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Personalising with Purpose – How Transparency Disclosures Shape Consumer Responses

An Experimental Investigation of Dynamic Landing Pages

by

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Abstract

Purpose: This thesis explored how consumers respond to GenAI-enabled personalisation in the context of landing pages. The focus lies on their intention to continue using the service after the first encounter. Given the paradoxical nature of personalisation, the mediating roles of perceived usefulness and privacy concerns are examined. Furthermore, this study explores how the presence or absence of a transparency disclosure moderates these effects.

Research Question: This study followed three aims: How does the strength of GenAI enabled personalisation on landing pages effect continuance intention, what role does the personalisation-privacy paradox play in this effect and how does personalisation transparency affect this relationship?

Methodology: A quantitative, experimental survey design was adopted, in which 206 participants were randomly assigned to one of four conditions, evaluating an online pharmacy across varying levels of personalisation and the presence or absence of a transparency disclosure. The moderated mediation model was analysed using regression.

Findings/Conclusion: The study revealed that GenAI-enabled personalisation did not have a total effect on continuance intention. This is explained by the two opposing mediating pathways that demonstrate comparable strength: personalisation increases perceived usefulness while simultaneously heightening privacy concerns. These findings are consistent with Approach-Avoidance Theory, which describes the paradox. Furthermore, disclosures exhibit a moderating effect by reducing privacy concerns. Interpreted through Attribution Theory, this suggests that transparency primarily influences affective dimensions of consumer evaluation.

Theoretical and Managerial Contributions: Both theories were successfully extended to the context of GenAI-enabled personalisation. From a managerial perspective, it must be recognised that stronger personalisation does not necessarily improve outcomes. Proactively disclosing personalisation practices represents an attractive strategy for firms.

Keywords: Personalisation, Personalisation-Privacy Paradox, Transparency, GenAI, Dynamic Landing Pages, Approach-Avoidance Theory, Attribution Theory, Mediated Moderation

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1 Introduction

This chapter aims to set the scene for the study at hand. We explain the background and highlight the research problem. Next, the research aim and objectives are elaborated and a brief overview of the study's structure is provided.

1.1 Background

The digitalisation of commerce has disrupted how firms interact with consumers (Strycharz & Segijn, 2022). With the rapid advancement of recommendation algorithms, consumers increasingly expect personalised and relevant experiences that reflect their individual preferences and needs (Arora et al., 2021). Even more drastically, consumers begin to reject generic, static recommendations from firms online (Hardcastle et al., 2025). Empirical evidence underlines this shift: 71% of consumers expect firms to deliver personalised interactions, while 76% report frustration when this is not provided (Arora et al., 2021).

The emergence of Generative Artificial Intelligence (GenAI) has transformed the way firms are able to respond to the demand for tailored experiences (Sun et al., 2025). While previous AI technologies were only able to analyse vast datasets and identify complex behavioural patterns, GenAI is additionally capable of generating highly personalised content at scale and in real time, in a cost-effective way (Sun et al., 2025). As superior customer experience is a highly effective asset in e-commerce for firms, the leverage of GenAI is widely praised in research and practice (Scarpi et al., 2022).

But the transformative power of GenAI regarding personalisation practices does not come without friction (Hardcastle et al., 2025). On the one hand, personalisation practices have the potential to significantly improve consumer experience and serve as a competitive differentiator (Gao & Liu, 2022). Despite that, consumers tend to react ambivalently towards these practices (Hardcastle et al., 2025). This is majorly driven by concerns surrounding privacy (Saura, 2024). For example, the TRUSTe Privacy Index (2016) reported that 92% of U.S. internet users have concerns about how their data is collected and used, and Cisco's consumer survey found that

75% of consumers do not buy from organisations they do not trust with their data (Cisco, 2024). The evolution of digital technologies has impacted the scope and complexity of consumer privacy concerns, as the possibilities for collecting and processing customer data are increasing rapidly (Scarpi et al., 2022; Strycharz & Segijn, 2022). Personalisation practices might therefore be appealing as a concept, but their implementation as a business tool proves difficult (Salonen & Karjaluoto, 2016).

This phenomenon has been conceptualised as the "personalisation-privacy paradox", as consumers desire personalised content yet feel uneasy when it intrudes too much on their privacy (Gupta et al., 2025). As Kim et al. (2018, p. 35) note, "personalisation can be both an effective but also ineffective marketing strategy [...]." A critical context in which these effects can be witnessed is dynamic landing pages, which play an essential role in converting visitors into recurring customers by enabling traffic to be channelled toward specific actions (Meslem & Abbaci, 2022). Dynamic landing pages leverage GenAI to create consumer-specific, personalised website content in real-time, taking into account their previous behaviour, attributes and shared data, and also inferring more tailored psychological aspects (Loureiro et al., 2023). This can be perceived as more relevant and useful, thus increasing continuance intention and customer satisfaction (Gao & Liu, 2022). On the other hand, excessive or insensitive personalisation can undermine consumer trust and reduce the overall effectiveness of dynamic landing pages (Ayhan et al., 2018).

One of the key effectiveness metrics in e-commerce, especially for dynamic landing pages, is continuance intention (Gosh et al., 2024; Bhattacherjee, 2001). Continuance intention describes an individual's decision to continue using a specific information technology after their initial adoption (Nabavi et al., 2016). This serves as a foundation for consumer satisfaction and loyalty and paves the way for future revenue opportunities (Gosh et al., 2024; Bhattacherjee, 2001). Acquiring new customers can cost up to five times as much as retaining existing customers, highlighting the importance of continuance intention to firms (Bhattacherjee, 2001; Kumar, 2022). With the continuance intention as a primary objective, the personalisation-privacy paradox in GenAI-enabled contexts, such as dynamic landing pages, solidifies as a pressing issue for firms.

In the light of these challenges, transparency disclosures about GenAI-enabled personalisation practices have emerged as a potential strategy to counteract negative consumer reactions (Segijn et al., 2021). Such disclosures inform consumers about how and why personalised content is shown, for example, through banners and pop-ups such as “Why am I seeing this ad?” (Strycharz & Segijn, 2022). While some firms are concerned that drawing attention to their data collection practices may put off customers, research on personalised advertising indicates the opposite (Kim et al., 2019). Kertai (2025) demonstrated that when AI systems operate fairly and transparently, consumers are more likely to trust and engage with them. Trust, in turn, is a critical determinant of consumer acceptance of personalisation practices and can reduce privacy concerns (Larsson, 2023). These overall developments also align with recent regulatory developments, such as the General Data Protection Regulation (GDPR) in the European Union and the California Consumer Privacy Act in the U.S. (Gupta et al., 2025).

1.2 Research Problem

Given the relative novelty of GenAI-enabled personalisation, research has only partially explored its impact on consumer behaviour, focusing mainly on insights from personalisation prior to the advent of GenAI technologies. These studies reveal important insights, such as the paradoxical effects of personalisation and privacy, as well as the impact of trust-building activities on consumer behaviour. However, these findings are only partially applicable to GenAI-enabled personalisation practices, which offer unprecedented ways to tailor and infer customer preferences. Before that, personalised content was mainly based on segments and templates (Vinerean & Opreana, 2024). As a result, personalisation was limited to clustering users based on rules rather than true personalisation at an individual level (Vinerean & Opreana, 2024). With GenAI, dynamic generation of content in infinite, personalised variations became possible (Tang et al., 2025; Grewal et al., 2025), thereby altering the way e-commerce can be conducted from the ground up.

This includes a new relationship between consumer data disclosure and how companies can use it. Data processing without disclosure by GenAI algorithms is a highly covert practice that allows limited control over how exactly consumers' data is processed and, more importantly, which inferences the algorithm draws (Loureiro et al., 2023). This change in data disclosure challenges existing theories that aimed to explain the paradoxical perceptions of personalisation and privacy. The acknowledged “privacy calculus” as an example describes a cost-benefit trade-off in consumer evaluation and assumes a possibility for consumers to decide if and how they want to self-disclose their data (Dinev & Hart, 2006; Bol et al., 2018; Gupta et al., 2025).

If data collection and processing are covert, as in the case of GenAI algorithms, this cannot be applied. Attempts to explain the personalisation-paradox in a GenAI-enabled context remain sparse to date. This calls for a reinvestigation of previous findings and validation of suitable theories to explain the paradoxical nature in a GenAI context. First attempts have been made by Sun et al. (2025) by drawing upon Approach-Avoidance Theory, but further empirical validation is needed.

On top of that, a strong focus has been placed on the effects of personalised advertisements, neglecting the importance of other touchpoints such as dynamic landing pages, which are key levers in converting leads into recurring sales for firms (Meslem & Abbaci, 2022). Insights on personalised advertisements are only partially applicable to dynamic landing pages and their objective to maximise continuance intention, as much focus is placed on willingness to click, click through rates and ad effectiveness in prior studies (Bleier & Eisenbeiss, 2015; Tucker, 2014; Kim et al., 2019). However, understanding the reasons for contingency is important for the long-term success of technologies and firms (Nabavi et al., 2016).

To date, the moderating role of personalisation transparency has not been fully examined in the context of the personalisation-privacy paradox in dynamic landing pages, necessitating a closer study of the phenomenon. As dynamic landing page content is usually presented with little information about its creation or underlying processes (Kim et al., 2019), these developments make a clear and urgent call for research.

All in all, the upcoming and inherently ambivalent nature of GenAI-enabled personalisation practices demands more detailed investigations into how consumers respond to them in the context of dynamic landing pages. Additional insights are needed on how personalisation transparency moderates consumers' perceptions, as this could be a crucial asset in balancing the paradoxical nature of personalisation and privacy, which is essential for effective, respectful customer journeys (Hardcastle et al., 2025).

To guide our research, we investigate the following research questions:

Research Question 1 (RQ1): *To what extent does the strength of personalisation on dynamic landing pages impact continuance intention?*

Research Question 2 (RQ2): *What role does the personalisation-privacy paradox play in the impact of dynamic landing pages on continuance intention?*

Research Question 3 (RQ3): *How does personalisation transparency affect the relationship between dynamic landing pages and continuance intention?*

1.3 Research Aim and Objectives

We aim to contribute to research on personalisation and privacy concerns by quantifying the effect of personalisation transparency and by expanding the Approach-Avoidance Theory to the context of dynamic landing pages. Our proposed moderated mediation model expands the theoretical understanding about the effect of dynamic landing pages on continuance intention mediated through perceived usefulness and privacy concerns and how the transparency regarding the data collection and usage affects this relationship.

We aim to contribute to the literature by addressing the gap identified by Sun et al. (2025) regarding "whether explicitly displaying information about the methods and technical principles used in AI-generated [content] can reduce the perceived threat associated with [them]" (p. 253) through an Attribution Theory perspective. Furthermore, we aim to deepen understanding of consumers' internal affective and cognitive states when responding to GenAI-enabled personalisation by evaluating the dynamics with competing moderators, building on the Approach-Avoidance Theory.

By addressing this gap, we provide practical relevance to firms designing their customer experience effectively and responsibly, in addition to our theoretical contributions. For marketing practitioners, we aim to deepen their understanding of how to navigate consumers' privacy concerns when developing and operating dynamic landing pages. While GenAI is enabling more and more personalised experiences across all touchpoints of the customer journey, a more multifaceted understanding of how to be transparent about personalisation may lead to a competitive edge and more effective digital strategies. Finally, our thesis aims to provide policymakers with insights into effective data transparency and GenAI use legislation, thereby following the call for greater policy implications in business research by Eby and Facteau (2023).

1.4 Outline of the Thesis

This thesis is divided into six chapters. We began by introducing the topic, the empirical setting, and the background of dynamic landing pages and personalisation transparency. Based on this, we present the research purpose and question and the aimed contributions for theory, marketing practitioners, and policymakers. In the second chapter, we review literature streams, which are relevant to our study. In the third section, we present the theoretical frame of this thesis, based on which we formulate five hypotheses. After that, we lay out our research methodology in chapter four, including the research philosophy, research design, data collection, and the approach to analysis. In chapter five, the results of our analysis are presented and the hypotheses discussed. We conclude this thesis in chapter six with contributions to theory and practice, limitations, and lastly, future research directions.

2 Literature Review

This chapter outlines the key concepts of this study. First, we will provide an overview of digital customer journeys and continuance intention, followed by a review of personalisation literature. Then, conflicting consumer reactions towards personalisation practices are discussed, and the personalisation-privacy paradox is introduced. Building on this, we examine transparency disclosures. Lastly, the different streams of literature are placed in the context of recent technological developments, specifically the emergence of GenAI as a personalisation lever.

2.1 Digital Customer Experience and Continuance Intention

To understand how digital marketing activities shape consumer behaviour, an understanding of the digital customer journey is necessary. The customer journey describes the process of how a consumer moves through different stages and touchpoints that together shape their experience with a firm (Lemon & Verhoef, 2016). The concept of customer journey is closely related to customer experience, which is defined as the cognitive, emotional, sensory and social consumer responses to a firm's offerings (Lemon & Verhoef, 2016). Becker and Jaakkola (2020) expand this definition by postulating that customer experience is a spontaneous response to the firm's activities encountered during the journey across different touchpoints.

Digital technologies and their adoption have significantly impacted how consumers engage and interact online (Güngör & Cadirci, 2022; Pereira et al., 2025). The proliferation of digital touchpoints has shifted consumer decision-making from linear to interlinked, interactive and journeys (Pereira et al., 2025). The concept of a journey stems from research on buyer decision-making (Howard & Sheth, 1969), with the core idea that there are distinct stages. Lemon and Verhoef (2016) defined the stages of the customer journey as the pre-purchase, purchase and post-purchase. While Lemon and Verhoef (2016) view the customer journey as a more linear process, Court et al. (2009) characterise it as cyclical, introducing the loyalty loop, in which a positive post-purchase experience leads the customer to a repurchase stage. This perspective underscores the importance of a positive initial experience and the long-term value generated by repeated purchases. As digitalisation is making customer journeys more complex, firms that can positively shape the customer experience through these new touchpoints can gain a competitive edge (Homburg et al., 2017).

Customer journey research has identified the importance of how positive experiences across digital touchpoints are important in building a loyalty-loop and leading to repeat purchases (Homburg et al., 2017; Court et al., 2009; Lemon & Verhoef, 2016). With the intensification of competitiveness in e-commerce, companies invest in innovative strategies to differentiate themselves and retain customers (Pereira et al., 2025). As customer experience plays a crucial role in purchasing decisions in e-commerce, the integration of digital technologies has a direct impact (Pereira et al., 2025).

The integration of digital technologies to touchpoints is a central factor to customer retention (Pereira et al., 2025). The initial adoption of new technologies is not enough to keep consumers in the market (Franque et al., 2020). Instead, continuous use is necessary (Franque et al., 2020). As e-commerce is characterised by low switching costs for consumers, retaining consumers and building long-term relationships have never been more important (Chen et al., 2012; Zhou, 2013; Pereira et al., 2025). In the literature, researchers argue that continuous use is more important than initial use because attracting new customers is far more costly than retaining existing ones (Rahi & Ghani, 2019; Nabavi et al., 2016). As firms are required to continuously invest in the digital transformation of their touchpoints, consumer retention becomes an even greater concern (Zhou, 2013). Technology investments need frequent usage to pay off, not only initial acceptance (Nabavi et al., 2016). User retention is therefore a critical issue in technology-driven businesses such as e-commerce, as every touchpoint can be a potential moment of retention or churn (Nabavi et al., 2016). Continuance intention serves as a key indicator of this ambition (Bhattacherjee, 2001).

Continuance intention can be understood as a prolonged or sustained use of information technology over time (Bergmann et al., 2022). Continuance intention has been defined by Bhattacherjee (2001) as "[...] consumer's intention to continue using e-commerce services" (p. 202). The behaviour occurs after the consumer has their first experience with information technology (Franque et al., 2020; Rahi & Ghani, 2019). For this study, we adopt the definition of Nabavi et al. (2016) that continuance intention can be defined as a consumer's decision "[...]

to carry on using a specific [technology] that an individual has already been using." (p. 58). Chen et al. (2012) argue that continuance intention can be seen as a manifestation of customer satisfaction and loyalty, indicating long-term usage (Franque et al., 2013).

Studies on continuance intention have used a wide range of theories to explain the phenomenon, including the Expectation-Confirmation Model (Bhattacherjee, 2001), the Technology-Acceptance Model (Davis, 1989), and the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003). Therefore, a wide variety of factors from different theories and contexts have been identified to influence continuance intention in e-commerce (Franque et al., 2020). These factors include attitudes, trust and perceived behavioural control (Franque et al., 2020; Bergmann et al., 2022; Zhou, 2013). Van der Heijden (2004) also demonstrated that affective constructs such as perceived enjoyment positively influence continuance intention. Rahi and Ghani (2019) underlined the original proposal by Bhattacherjee (2001) that perceived usefulness and service satisfaction positively influence consumers' continuance intention. Perceived usefulness in this context can be defined as the consumer's subjective probability that the information technology will increase their performance. At the same time, satisfaction describes the consumer's affective response (i.e., feelings) towards the service (Bhattacherjee, 2001). While different factors persist, common ground in antecedents of continuance intention can be found in the fact that the technology in question needs to provide benefits to the consumer in order to be successful (Bergmann et al., 2022).

2.2 Personalisation

One frequently claimed strategy to increase continuance and improve customer experience is Personalisation (Lamberton & Stephen, 2016; Pereira et al., 2025; Bol et al., 2018). Personalisation is a method of acknowledging each customer's uniqueness by suggesting content that resonates with their preferences (Chandra et al., 2022). The overall objective of personalisation is to enhance the consumer experience and influence consumers' perceptions and decisions (Bol et al., 2018; Chandra et al., 2022). Personalisation is based on active procedures for learning about customer preferences and synthesising insights (Tang & Zhang, 2020). By using customer data, firms can create tailored, personalised experiences across touchpoints, manage relationships, and achieve a competitive advantage (Hardcastle et al., 2025; Chandra et al., 2022).

Personalisation is labelled a customer-oriented marketing strategy that strives to "[...] deliver the right content to the right person at the right time, to maximise immediate and future business opportunities" (Kim et al., 2019, p. 35). Bol et al. (2018) define personalisation as "the strategic creation, modification, and adaptation of content and distribution to optimise the fit with personal characteristics, interest, preferences, communication styles, and behaviours" (p. 373).

The roots of personalisation in marketing predate digital technologies (Salonen & Karjaluoto, 2016). The emergence of one-to-one marketing by Peppers and Rogers (1993) paved the way for personalisation to be acknowledged as a competitive strategy in marketing. Yet, a critical distinction needs to be applied between personalisation, customisation, segmentation and targeting (Chandra et al., 2022; Salonen & Karjaluoto, 2016). While personalisation is a strategic marketing choice by firms, customisation occurs when consumers proactively specify elements of their preferred marketing mix (Chandra et al., 2022). Segmentation precedes personalisation and underpins it technically (Chandra et al., 2022). Segmentation aims to identify groups with similar traits and interests to customise elements of the marketing mix accordingly (Chandra et al., 2022). Targeting builds on the segmentation logic by referring to the selection of an audience to whom these elements will be delivered (Chandra et al., 2022). Personalisation, as defined by Chandra et al. (2022), aims to go further by creating a unique experience for individual customers.

Personalisation has proven to be a desirable marketing strategy for both consumers and firms (Salonen & Karjaluoto, 2016). From a consumer perspective, personalisation reduces cognitive overload and the time spent making choices (Kim et al., 2019; Chandra et al., 2022). Additionally, consumers can enjoy content more relevant to them and filter through the abundance of information online (Bol et al., 2018). Firms benefit from personalisation, as it can positively impact attitudes, loyalty, and engagement (Walrave et al., 2017; Sun et al., 2025). Personalisation also grants opportunities to charge higher prices (Vesanen, 2007).

Generally, personalisation increases customer satisfaction by offering products and services that fit their needs (Teepapal, 2025). The success of personalisation depends on accurately detecting and responding to consumer preferences, which are complex and highly context-dependent (Salonen & Karjaluoto, 2016). It is therefore essential for firms to learn about their customers to make meaningful inferences about their preferences (Aguirre et al., 2015). The strategies employed by firms to collect data can be classified into overt (informing consumers) and covert (not informing consumers) strategies (Murthi & Sarkar, 2003).

In the literature, perceived usefulness plays a central role in determining the effectiveness of personalised marketing activities (Nysveen & Pedersen, 2004). It is defined as "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989, p. 320). Information overload is a common burden for consumers when shopping online, due to the increase in the volume and complexity of product recommendations (Lai et al., 2019). Personalisation helps to decrease this struggle and meet users in a way that resonates with their needs, thus increasing perceived usefulness (Wang et al., 2024; Bleier & Eisenbeiss, 2015).

2.2.1 Personalisation-Privacy Paradox

Nevertheless, the implementation of personalisation practices in marketing does not guarantee success. On the contrary, personalisation provides conflicting evidence on its effectiveness (McKee et al., 2023). Canhoto et al. (2023) describe the phenomenon as the "personalisation-privacy paradox", stating that personalisation not only creates benefits, but can also cause feelings of discomfort.

The process of data collection and usage often leads customers to experience privacy concerns, expressed as discomfort due to feelings of vulnerability (Baek & Morimoto, 2012; Aguirre et al., 2015). Many studies highlight privacy concerns as a pertinent issue that prevents consumers from enjoying personalised applications (Sutanto et al., 2013). Building on Westin's concept of privacy (1967), Baek and Morimoto (2012) define privacy concerns as "the degree to which a consumer is worried about the potential invasion of the right to prevent the disclosure of personal information to others" (Baek & Morimoto, 2012, p. 63). Other authors have defined privacy concerns as "the desire to keep personal information out of the hands of others" (Buchanan et al., 2007, p. 158) or "the ability of the individual to control the terms under which personal information is acquired and used" (Westin, 1967, p. 7). Privacy concerns are a construct originally researched in an age before the internet by Westin (1967) and Smith et al. (1996), among others. This led to a differentiation by Malhotra et al. (2004), who argued that a new construct is required due to the nature of the online environment. Today, almost all personalisation research concentrates on online personalisation. While we acknowledge the term online privacy concerns used by some scholars (e.g., Bol et al., 2018), we call the construct privacy concerns due to this being the common term in recent marketing literature.

Since consumers are usually unaware of data collection, analysis, and use, privacy concerns remain untriggered until they are targeted by marketing materials that leverage this data (Aguirre et al., 2015; Bleier & Eisenbeiss, 2015). Personalised communication is one of the primary causes of privacy concerns identified in existing marketing literature (Malhotra et al., 2004; Sheehan & Hoy, 2000). While privacy concerns have both affective and cognitive aspects (Bol et al., 2018), we build in this study on the dominant paradigm in the literature and treat privacy concerns as a more affective construct (Bol et al., 2018; Bleier & Eisenbeiss, 2015), according to which privacy concerns reflect the negative emotional attitude felt when personal rights, information or behaviour get regressed by others (Dienlin & Trepte, 2015).

This effect has been well researched in the context of personalised online interactions (Chellappa & Sin, 2005; Kobsa, 2007; Taylor et al., 2009) and personalised advertisements (Bleier & Eisenbeiss, 2015; Aguirre et al., 2015; Sun et al., 2025). Bleier & Eisenbeiss (2015) found in their research that higher personalisation depth, meaning how closely ads match interests, increases privacy concerns even further, because it signals the firm knows more about the consumer. Similar results were found by Sun et al. (2025), who distinguished three levels of personalisation (low/mid/high) and found that more personalised advertisements lead to stronger privacy concerns. Higher privacy concerns lead to unwanted consequences for firms, such as lower click-through intentions (Bleier & Eisenbeiss, 2015), negative personalisation attitudes (Sun et al., 2025), and lower consumer engagement (Teepapal, 2025).

Privacy concerns are central to many attempts to describe the paradoxical effects of personalisation. Saura (2024) presents the “privacy-personalisation paradox”, stating that consumers value the relevance of content but also fear the misuse of their personal data. Likewise, Barnes (2006) describes a “privacy paradox” as there is a visible inconsistency between privacy attitudes and privacy behaviours. Scarpi et al. (2022) pick up on that term and define it as “[...] the discrepancy between consumers expressed privacy concerns and their digital behaviour” (p. 1687). Other variations of the phenomenon exist in the form of labels such as the “privacy-benefit paradox” or the “personalisation-privacy paradox” (McKee et al., 2023; Soni, 2024; Chandra et al., 2022).

A common denominator behind these labels is that whenever personalisation comes into play, positive and negative attitudes towards the practice coexist (Sun et al., 2025). The Privacy-Calculus Theory, originally introduced by Dinev and Hart (2006), is a prominently used theory to capture the contradicting effects of personalisation (Bol et al., 2018; Gupta et al., 2025; Wang et al., 2024). Essentially, the theory describes the conception that consumers disclose personal information on the basis of a cost-benefit trade-off (Dinev & Hart, 2006; Krasnova et al., 2010). The theory is based on Laufer and Wolfe's (1977) proposal that an individual's willingness to disclose personal information is based on a purely cognitive calculus of behaviour. Consumers appear as rational decision-makers (Dinev & Hart, 2006). The trade-off describes the perceived benefits consumers expect from disclosing personal data relative to the perceived risks they associate with such disclosure (Cloarec, 2024). The Privacy-Calculus Theory is applied to explain attitudes and behaviours to personalised marketing in different contexts and situations (McKee et al., 2023; Chandra et al., 2022; Hayes, 2021). Yet, the theory primarily focuses on the willingness to self-disclose data (Laufer & Wolfe, 1977).

2.2.2 Personalisation Transparency

Simultaneously decreasing privacy concerns and increasing personalisation benefits present a significant challenge to firms (Wang et al., 2024). Due to online privacy becoming a major concern for consumers and rising regulatory pressure (e.g., GDPR in Europe, CCPA in the US, DPDP in India), transparency regarding data collection and processing has been gaining the attention of practitioners and scholars. Segijn et al. (2021) identify in their literature review that this transparency has a sender-side (the firm) and a receiver-side (the consumers), and thus they differentiate between personalisation transparency and personalisation awareness. Building on the conceptualisation of Kim et al. (2019), the authors define personalisation transparency as "the degree of disclosure of how firms collect, process, or share personal data to generate personalised communication" (Segijn et al., 2021, p. 123). Personalisation awareness, on the other hand, focuses on the degree to which individuals are aware of the data collection, processing, and sharing (Segijn et al., 2021). While personalisation transparency has been gaining relevance as a construct, research on the topic is heavily fragmented. Many strongly related constructs are covered by scholars, for example, ad transparency (Kim et al., 2019), overt data collection (Aguirre et al., 2015), and privacy control as implicit transparency (Tucker, 2014).

The source of the personalisation transparency disclosure matters when informing consumers about data collection and processing. When the disclosing party is not trustworthy, or the motives are perceived as insincere, personalisation transparency can lead to lower behavioural intentions toward personalised advertising (van Ooijen, 2022). Related to this, Gupta et al.

(2025) found in their qualitative study on GenAI-enabled personalisation in India that transparency is a key antecedent of trust.

When comparing overt and covert data collection, Aguirre et al. (2015) found that highly personalised advertisements lead to high perceived vulnerability and lower click-through intentions when firms are not transparent about how they gain user data. By communicating the collection and processing of data via cookies, this effect can be mitigated (Aguirre et al., 2015). In another study, Kim et al. (2019) found that the acceptability of information flows strongly influences the performance of personalised advertising, with acceptability depending on whether data are collected explicitly or implicitly. Disclosing unacceptable data-collection practices heightens privacy concerns and reduces behavioural intentions, underscoring the importance of personalisation transparency for consumers (Kim et al., 2019).

Additionally, individual characteristics moderate the effect of personalisation transparency in the context of personalised websites and advertisements. One study found that the consumers' need for cognition influences how cookies, as a form of personalisation transparency, moderate the relationship between personalisation and perceived control (Lambillotte et al., 2022). The authors argue that while personalisation transparency signals data collection and use, no difference was found between implicit and explicit data collection methods, and future research should examine personalisation transparency further in the context of personalised websites (Lambillotte et al., 2022).

While the existing literature has conceptualised personalisation transparency well, and initial studies have found that it affects consumer responses and perceptions of personalisation, the construct remains severely understudied across multiple contexts. While the disclosure of data collection and processing is gaining more and more importance, studies on transparency have been focusing mainly on compliance-side conceptualisations of personalisation transparency, such as cookies (e.g., Aguirre et al., 2015, Lambillotte et al., 2022) and the “why am I seeing this ad” button (e.g., Kim et al., 2019). Results from published papers suggest that these disclosures have positive effects on consumer behaviour, but no studies have analysed the potential benefits of disclosures going beyond compliance. With personalisation becoming common practice in the digital environment due to the accessibility of GenAI technologies, further research is required to determine whether these benefits also apply to personalisation transparency disclosures in light of current technological developments.

2.2.3 Personalisation Practices in the context of GenAI

Generally, personalisation closely intersects with the domains of computer science and information systems and therefore must be examined in relation to technological advancements (Chandra et al., 2022; Salonen & Karjaluoto, 2016). The breakthrough of GenAI changed personalisation practices profoundly (Peltier et al., 2023). GenAI can personalise consumer-firm interactions in unprecedented ways, enabling real-time, context-aware individualisation that goes beyond static profiles (Hardcastle et al., 2025; Hollebeek et al., 2021). GenAI is capable of understanding and anticipating consumers' needs, wants and preferences (Hollebeek et al., 2021).

This is enabled through sophisticated algorithms that process vast datasets to deliver highly relevant, customised content to consumers (Raji et al., 2024). Before the introduction of GenAI, personalised content, specifically ads, was based on segmentation and templates (Vinerean & Opreana, 2024). Segment-based personalisation relies on demographical information, browsing history or returning vs new users (Vinerean & Opreana, 2024). Personalisation was limited to user clustering rather than true individualisation (Vinerean & Opreana, 2024). In addition, content was mainly template-driven and validated through manual A/B tests or rule-based triggers (Grewal et al., 2025). Most notably, personalisation was based on predicted preferences using machine learning algorithms, but did not involve the dynamic generation of new content (Grewal et al., 2025). With the rise of GenAI, personalisation at an individual level is now feasible and scalable, including unique text, visuals, and layouts presented to the user (Grewal et al., 2025). GenAI takes personality traits, motivations, and values into account, enabling persuasion tailored to individuals' characters and incorporating more than simply their online behaviour (Grewal et al., 2025). The reliance on post-hoc A/B testing is no longer relevant, as infinite variations are deployed (Tang et al., 2025).

With GenAIs potential to enrich personalisation experience, previous insights into consumers attitudes and behaviour towards personalisation are only partially applicable as GenAI-enabled personalisation offers unprecedented opportunities to tailor content on an individual level in real time, with the capability to generate and display deeper and more targeted inferences of consumers (McKee et al., 2023). This is especially distinctive in GenAI's tendency to collect data covertly, as recommendation algorithms are designed not to disrupt the customer experience (Loureiro et al., 2023; Aguirre et al., 2015). Covert data collection practices exacerbate the feeling of vulnerability and discomfort towards personalised content (Tucker, 2012). The scepticism around privacy is likely to be more present in GenAI-enabled contexts (Hollebeek et al., 2021). This also calls for validating previous insights on the effect of personalisation transparency, as Kim et al. (2019) demonstrated that information flows that misalign with consumer values heighten privacy concerns and reduce personalisation effectiveness.

A noticeable gap can be observed in the current state of literature about the characteristics of the personalisation-privacy paradox in a GenAI-enabled context. The Privacy-Calculus Theory assumes an unhindered ability of consumers to control and influence the self-disclosure of their data. However, GenAI excels at creating personalised output through more covert data collection practices and can add inferences, interpretations, and meanings to data beyond the original information consumers may have disclosed (Loureiro et al., 2023). These technological characteristics of GenAI-enabled personalisation limit consumers' ability to self-disclose their data under the Privacy-Calculus Theory. Additionally, Privacy-Calculus Theory assumes fully rational consumer behaviour, without accounting for emotional or subconscious reactions. This contradicts perspectives on privacy concerns being not only a cognitive state, but also an affective construct that is formed instinctively and without in-depth thinking (Bol et al., 2018; Bleier & Eisenbeiss, 2015; Aguirre et al., 2015). All in all, new approaches are required to conceptualise the personalisation-privacy paradox in a GenAI-enabled context.

Sun et al. (2025) were among the first to propose a different conceptualisation of the paradox by introducing the “PUTD” (Perceived Utility - Perceived Threat) concept, which mediates the impact of Personalisation on consumer attitudes. It is based on the Approach-Avoidance Theory by Elliot (2006). Approach-Avoidance Theory integrates approach motivation, driven by the prospect of positive stimuli, and avoidance motivation, driven by mitigation of negative stimuli (Elliot, 2006). PUTD describes the paradox as a dynamic psychological mechanism (Sun et al., 2025). Unlike Privacy Calculus Theory, PUTD predicts a non-linear relationship between personalisation and attitudes (Sun et al., 2025). A sharper increase in threat perceptions is visible for higher levels of personalisation (Sun et al., 2025). This results in a distinctive attitude pattern of an inverted U-shape (Sun et al., 2025). PUTD successfully captures nonlinear effects and explains the backlash against overpersonalisation (Sun et al., 2025). This makes it especially suitable for AI-driven marketing contexts. Furthermore, PUTD treats perceived utility and threat not as separate mediators but captures them to represent the underlying trade-off mechanism applied by consumers (Sun et al., 2025).

While the focus on AI-driven personalisation and its impact on consumers is better explained with PUTD, the concept depicts some distinctive shortcomings. Approach-avoidance motivation theory was designed to explain the behaviour of organisms (Elliot, 2006). The possibility of also applying it to consumer attitudes is novel and not further validated except for the research done by Sun et al. (2025). To summarise, the usage of the Approach-Avoidance Theory needs further corroboration in the field.

So far, little theory exists to explain the paradox in consumers' behaviours successfully in the context of GenAI-enabled personalisation. Additionally, research on the personalisation-privacy paradox has mainly focused on advertisements (Vesanen, 2007; Bleier & Eisenbeiss, 2015; van Ooijen, 2022; Sun et al., 2025; Aguirre et al., 2015; Tang et al., 2014). Personalisation effects of advertisement have been investigated in many different contexts, and much insight is available on different moderating and mediating factors, as seen in *Table 2* and *Table 3*,

While advertisements are of great significance to the customer journey, they are only one possible touchpoint to deploy effective personalisation. Recognition in personalisation research is missing, as GenAI has transformed almost every touchpoint of the customer journey (Hardcastle et al., 2025; Meslem & Abbaci, 2022). Landing pages pose a promising field for GenAI-enabled personalisation as they offer many different possibilities to successfully incorporate personalised content, products, prices, promotions and nudges tailored towards individual customers (Meslem & Abbaci, 2022; Gao & Liu, 2022). These landing pages are also referred to as "dynamic landing pages", as they utilise GenAI to instantly adapt pages based on user intent and context information such as location, time and behaviour (Grewal et al., 2025). Dynamic landing pages can be utilised to maximise e-commerce KPIs such as purchase or continuance intention (Gao & Liu, 2022; Campbell et al., 2020).

Tables 1 to *Table 6* summarise the key extant studies and how they relate to our research. It becomes clear that prior research in this area is not fully applicable to the context of GenAI-enabled personalisation.

Table 1 Key Literature Digital Customer Journey and Continuance Intention

Authors (Year)	Focus	Theory	Metho-dology	Findings	Shortcomings in relation to study
Lemon & Verhoef (2016)	Conceptualisation of customer journeys and integration with customer experience	Customer Journey	Concep-tual review and theory-building article.	Propose a three stage customer journey (pre purchase, purchase, post purchase) and identified four-category touchpoint typography (brand-/partner-/customer-owned/social)	No empiric testing of proposed touchpoints, predates AI in personalisation, stage logic depends on linearity
Bhatta-cherjee (2001)	Examination of factors influencing user' s intention to continue using information system after initial adoption	Expectation-Confirm-ation Theory	Quantitativ e field survey	Continuance intention is determined by user satisfaction and perceived usefulness, with satisfaction being shaped by prior expectations and perceived usefulness	Tested information system not comparable to current technological standards, no specific focus on personalisation
Gosh et al. (2024)	Investigation of network externalities and trust-related attributes shape mobile payment application continuance intention	Post-adoption framework incorporatin g six mobile application attributes	Quantitativ e survey	Technological and legal backend of mobile applications need to deliver meaningful experiences to increase continuance	Only mobile applications investigated, no specific focus on personalisation

Table 2 Key Literature Personalisation in Marketing

Authors (Year)	Focus	Theory	Metho-dology	Findings	Shortcomings in relation to study
Chandra et al. (2022)	Comprehensive review of publications around personalised marketing to map structure, key topics and future research	-	Biblio-metric literature review	Six major themes revealed, proposal of future research among others to focus on AI and big data as well as emerging issues like personalisation paradox and vulnerability.	Transparency not reflected, no empirical validation of insights.
Baek & Morimoto (2012)	Identification of potential determinants of advertising avoidance of Personalised advertisements.	Psychologi-cal reactance theory	Self-administ-ered survey	Ad avoidance is determined by perceived personalisation, privacy concerns and ad irritation, with the latter one having a direct positive effect and the first one a negative.	Focus only on online advertising, insights precede GenAI applications.

Table 3 Key Literature Personalisation-Privacy Paradox

Authors (Year)	Focus	Theory	Metho-dology	Findings	Shortcomings in relation to study
Bol et al. (2018)	How consumers decide to share personal information online across different website contexts.	Privacy-Calculus	Scenario-based online experiment	Higher perceived benefits and trust increase willingness to self-disclose, higher privacy risk perceptions decrease it. Applied theory holds in all three contexts.	Contradictory findings on personalisation impact on trust (negative), assumption of data control by consumer.
Aguierre et al. (2015)	Examination of personalisation - privacy paradox and effect of data collection strategy on ad relevance and feelings of vulnerability.	Psycholog-ical ownership theory	Explorat-ory field experiment secondary data and 3 online experi-ments	Higher personalisation increases click-through only when data collection is overt. Negative reactions towards covert data collection can be mitigated through trust building information icons.	Focus only on online advertising, insights precede GenAI applications, impact of transparency disclosures not investigated
Bleier & Eisenbeiss (2015)	Effect of consumer trust in retailer on effectiveness of personalised online advertising, moderated through perceived usefulness, reactance and privacy concerns	Conceptuali-zation of personalisati on depth	Field data from real retargeting campaigns and laboratory experiment	Trusted retailers can increase ad effectiveness without raising reactance or privacy concerns when deploying narrow personalisation depth.	Focus only on online advertising, insights precede GenAI deployment, impact of transparency disclosures not investigated.

Table 4 Key Literature Personalisation Transparency

Authors (Year)	Focus	Theory	Metho-dology	Findings	Shortcomings in relation to study
Kim et al. (2019)	Effect of ad transparency on ad effectiveness, depending if revealed data use aligns with consumer's privacy norms.	Contextual information norms	Inductive survey and multiple experim-ents (lab, online, field)	Unacceptable information flows like cross-site tracking and interred attributes reduce ad effectiveness by heightening privacy concerns.	Focus only on online advertising, insights precede GenAI deployment, impact of transparency disclosures not investigated.
Segijn et al. (2021)	Review of articles on personalisation transparency, control and the role of awareness.	Transparen-cy-Awareness-Control Framework	Literature Review	Creation of common understanding of transparency and control paradigm as well as identification of further research.	Insights precede GenAI deployment, no empirical validation of insights and no consideration of personalisation-privacy paradox.
Lambill-otte et al. (2022)	Understanding of the underlying process of Personalisation on privacy concerns and impact of information transparency on websites.	Signaling Theory	Experim-ental studies	Perceived control is lower on personalised websites which leads to privacy concerns. The negative effect can be mitigated through transparency messages for consumers in low need of cognition.	No reflection on GenAI deployment and consideration of personalisation-privacy paradox.

Table 5 Key Literature GenAI-enabled Personalisation

Authors (Year)	Focus	Theory	Metho-dology	Findings	Shortcomings in relation to study
Hardcastle et al. (2025)	How consumers experience and respond to AI-driven personalised recommendations and advertising with focus on customer empowerment.	Customer Journey Concept	Semi-structured interviews and Customer Journey Mapping	Technological capabilities of AI mediate brand-customer relationship, importance of preserving customer autonomy and ethics.	Ads remain key focus of investigation even though CJ is reflected as a whole.
Sun et al. (2025)	Determination of appropriate degree of personalisation in AI-generated ads and its impact on consumer attitudes.	Approach-Avoidance Theory	Scenario-based online experim-ents	Moderate personalisation leads to the most favorable attitude. The effect is mediated by the net difference of perceived utility and perceived threat, with privacy concerns moderating the mechanism.	Focus only on online advertising, impact of transparency disclosures not investigated.
Teepapal (2025)	Impact of GenAI-enabled personalised ads on consumer engagement in social media marketing.	Stimulus-Organism-Response Model	Self-adminis-tered survey	GenAI-enabled personalisation positively influences trust, privacy concerns and perceived usefulness. GenAI-enabled personalisation does not significantly influence consumer engagement, but perceived usefulness and trust are significant mediators.	Focus only on online advertising, impact of transparency disclosures not investigated.

2.3 Summary of Literature Gaps

To summarise, digitalisation has significantly reshaped customer journeys. The adoption of new information technologies has changed consumer behaviour, and the importance of retaining customers is a primary objective among firms in e-commerce. Continuance intention thereby serves as a key metric to ensure long-term success. Personalisation can act as a key lever to this ambition, as it demonstrates promising potential to enhance customer experiences.

Nevertheless, there are ambiguous empirical findings regarding successful implementations, mainly due to the paradoxical effect of personalisation, where customers appreciate increased usefulness but are simultaneously concerned about their privacy. This phenomenon is labelled the "personalisation-privacy paradox" and has been investigated from a theoretical perspective most prominently under the lens of the "Privacy-Calculus Theory". Personalisation transparency has emerged as a potential lever to mitigate privacy concerns within the paradox, as available insights into a firm's data processing may foster consumer trust and acceptance of personalised content.

The impact of GenAI-enabled personalisation on consumer behaviour remains underexplored, given the novelty of the phenomenon. On top of that, existing research is only partly applicable to GenAI-enabled personalisation, as significant differences in the underlying technologies exist. As demonstrated, GenAI-enabled personalisation offers one-to-one personalisation at scale, is able to infer deeper levels of meaning behind customer data and indulges more heavily in covert data collection. This contrasts with segment- and rule-based practices of personalisation before the advent of GenAI.

The theoretical interpretation of consumers' responses to GenAI-enabled personalisation is unclear so far. So far, literature streams have revealed a scarcity of applied theories to understand the paradoxical effect of personalisation in a GenAI-enabled field. The established Privacy-Calculus Theory has limited applicability to the technology, as it assumes a high degree of control over consumers' data disclosure. As the data processing of GenAI is predominantly covert and results are rather inferred than reproduced, a limited amount of control is accessible to consumers over their data. As the Privacy-Calculus Theory falls short in acknowledging this, further investigation and validation of suitable alternatives to explain the paradoxical effects are necessary.

Additionally, insights into personalisation research have primarily focused on personalisation practices in advertising, neglecting crucial conversion touchpoints such as landing pages. Dynamic landing pages that incorporate GenAI to deliver highly personalised content in real-time demonstrate promising results in converting consumers into recurring visitors. Insights on personalised advertising are only partly applicable to this touchpoint, as different performance measurement models are typically used for it. Especially, the impact of personalisation transparency on dynamic landing pages remains vastly understudied.

To conclude, the ambivalent nature of personalisation has not been investigated in detail in the context of GenAI-enabled personalisation. Previous findings from personalisation research are only partly applicable due to the underlying technological differences and require an in-depth study.

3 Theoretical Background and Hypotheses Development

In this chapter, we outline the theoretical basis of the present study. We begin by introducing the Approach-Avoidance Theory and Attribution Theory, from which hypotheses are deduced related to our research questions.

3.1 Approach-Avoidance Theory

The paradoxical consumer reactions regarding personalisation stimuli can be explored through the Approach-Avoidance Theory (Sun et al., 2025). The Approach-Avoidance Theory by Elliot (2006) describes that individuals are motivated by two primary drivers: approach motivation and avoidance motivation. While approach motivation directs behaviour towards desired outcomes or positive stimuli, avoidance motivation aims to steer behaviour away from negative stimuli and experiences (Elliot, 2006). Behavioural responses can be defined as "[...] manifested actions that occur in response to changes in emotional states elicited by environmental stimuli" (Tang et al., 2014, p. 514).

In more detail, approach motivation can be defined as the energisation and direction of behaviour towards positive stimuli (Elliot, 2006). "Energisation" describes a spring to action that gives orientation to an organism in a general way (Elliot & Sheldon, 1997). "Direction" refers to the guidance of behaviour towards a specific way (Elliot, 2006). Approach motivation not only aims to bring positive stimuli closer, but also encompasses keeping the present positive stimuli close (Elliot, 2006).

Similarly, avoidance motivation can be defined as both the energisation of behaviour and the direction of behaviour away from negative stimuli, such as objects, events, and possibilities (Elliot, 2006). This includes the avoidance of threats and risks (Sun et al., 2025). Avoidance motivation aims to keep stimuli away and to rectify existing negative situations (Elliot, 2006). This motivation can be experienced as stressful and negatively impacts enjoyment (Elliot &

Sheldon, 1997). From an Approach-Avoidance Theory perspective, consumers evaluate and weigh desired outcomes while simultaneously aiming to prevent negative experiences. Individuals constantly evaluate their circumstances based on these two parameters, intending to maximise overall benefit (Carver, 2006). The relative strengths of both parameters ultimately shape the behavioural response (Sun et al., 2025).

The definitions of positive and negative stimuli can vary depending on the context (Elliot, 2006). Stimuli can encompass concrete and observable objects, events and possibilities, but can also represent abstract, internally-generated representations of such objects, events and possibilities (Elliot, 2006). As the concept of approach and avoidance has been used in the literature across varying contexts to describe differences between human motivation and actual behavioural responses, its applicability to the personalisation-privacy paradox becomes evident (Tang et al., 2014; Sun et al., 2025). When applied to the context of dynamic landing pages, the phenomenon becomes clear: both approach and avoidance motivations influence consumer responses to GenAI-enabled personalisation practices.

For GenAI-enabled personalisation, benefits are often framed in terms of relevance, convenience and satisfaction (Canhoto et al., 2023). Personalisation reduces cognitive overload and simplifies decision-making, thereby increasing perceived usefulness (Bleier & Eisenbeiss, 2015). Consumers' perceived usefulness of dynamic landing pages, therefore, drives approach motivation as they expect positive outcomes such as efficient product searches and valuable information (Sun et al., 2025).

At the same time, privacy concerns are frequently attributed as a key threat drawn up by consumers to personalisation practices (George, 2004; Canhoto et al., 2023). This includes feelings of loss of control and vulnerability, which can result in resistance or disengagement (Awad & Krishnan, 2006; Kim & Huh, 2017; Teepapal, 2025). From an avoidance motivation perspective, privacy concerns therefore drive consumers' avoidance motivation when encountering dynamic landing pages.

To summarise, the personalisation-privacy paradox in the context of Approach-Avoidance Theory is a cumulative outcome of subconscious processes and conscious evaluations of perceived usefulness and privacy concerns. The balance between the two motivations reflects consumers' trade-off between benefits and threats, ultimately determining their behaviour towards personalisation practices.

3.2 Attribution Theory

While the Approach-Avoidance Theory conceptualises consumers' motivational forces towards or away from a stimulus, it does not specify how these motivations are shaped by the individual's interpretations of the underlying motives behind the stimulus. To interpret this and explore the boundary conditions of the consumer responses, we draw on Attribution Theory (Heider, 1958).

Heider (1958) theorised that individuals continuously aim to understand the causes of events and behaviours to make sense of their environment, attributing them to internal and external drivers. Internal attributions link the stimulus to the traits, motivations, or intentions of the actors, while external attributions link the stimulus to situational factors that the actor cannot control (Heider, 1958; Kelley, 1973). Building on Heider's seminal work, Weiner (1985) extended the theory by introducing the causal dimensions locus, stability and controllability, which influence how individuals respond to different attributional causes. According to Attribution Theory, individuals do not respond to a stimulus as such, but rather to the underlying meaning they attribute to it, making the attributional process critical for understanding behavioural responses when the actor's motives are unclear.

While the Attribution Theory stems from social psychology, it has been widely applied in consumer behaviour research to understand how consumers interpret and respond behaviourally to actions by firms (e.g., Forehand & Grier, 2003; Folkes, 1988; Sohaib & Han, 2023). Confronted with a marketing stimulus, such as a dynamic landing page, consumers do not simply accept it, but instead, they attribute it to a motive behind the firm's behaviour. The attributed motives are typically internal, as the drivers of marketing activities typically lie within the firm.

Thus, the central question is not whether an action was internally or externally motivated, but rather what the underlying internal motives are. As an illustration, a firm's activity can be attributed as more positive by consumers if they are under the impression, it addresses a concern of theirs (Forehand & Grier, 2003; Yoon et al., 2006). If an activity is rather attributed to a typical firm's interest, e.g. profit maximising or reputation management, this is not the case (Forehand & Grier, 2003; Yoon et al., 2006).

The implications of Attribution Theory are particularly relevant in settings where a firm's motives are not directly observable and the same marketing activity can elicit divergent consumer responses. Dynamic landing pages are such a setting, paved by the personalisation-privacy paradox, where consumers benefit from the experience, but at the same time, they are confronted with the data collection and processing. Recent research has shown that stronger personalisation may lead to unwanted behavioural outcomes, since consumers attribute it to the firm's self-serving motives, such as commercial exploitation (Sun et al., 2025; Aguirre et al., 2015). To combat this, firms can choose to disclose their data collection and processing practices. This personalisation transparency steers the attributions by the consumers towards more positively evaluated intrinsic motives, such as service improvement and consumer benefit (Kim et al., 2019; Segijn et al., 2021). Furthermore, Forehand and Grier (2003) found that consumers react with less skepticism towards negatively perceived intrinsic motives when they are clearly stated, indicating the potential benefit of disclosure for ambiguous activities.

3.3 Hypotheses Development and Research Model

Building on the findings of previous research as well as the Approach-Avoidance Theory and the Attribution Theory, we formulate the following five hypotheses. To support each hypothesis, we present a synopsis of relevant theory and literature. Our research model is depicted in *Figure 1* to offer an overview of the relationships between the constructs.

Different theories and constructs can be integrated into the context of continuance intention (Franque et al., 2020). The impact of personalisation on continuance intention can be attributed to several factors and cannot be exclusively assigned to cognitive dimensions such as perceived usefulness. Instead, perceptions, emotions and hedonic value triggered by personalisation have shown to exert positive influence on continuance intention (Zhang et al., 2025). Positive internal consumer responses triggered by GenAI-enabled personalised landing pages have been shown to mediate behavioural intentions, including continued website use (Zhang et al., 2025). This aligns with the overall concept of Approach-Avoidance-Theory as they can be viewed as a positive affects. Affective reactions encompass emotional responses of individuals to external stimuli (Benlian, 2015). Proven positive affects on continuance intention include algorithm appreciation, perceived value, consumer satisfaction and perceived enjoyment (Zhang et al., 2025; Li & Liu, 2014; Irmawan et al., 2025; Benlian, 2015). As the consideration of the multitude of factors proven to influence continuance intention would exceed this study's frame, we thus postulate:

H1: More strongly personalised landing pages will increase continuance intention.

H2 is grounded in the approach dimension of the Approach-Avoidance Theory (Elliot, 2006). This theory states that positively perceived stimuli lead to desirable behavioural outcomes. In this framework, continuance intention can be seen as a direct behavioural expression of the approach-avoidance evaluation consumers make when encountering dynamic landing pages. GenAI-enabled personalised landing pages reduce cognitive overload and simplify decision-making for consumers through adapting content to individual preferences (Kim et al., 2019; Chandra et al., 2022). Prior research has shown that personalised advertisements increase perceived usefulness by presenting content more relevant to consumer needs (Aguirre et al., 2015; Sun et al., 2025). In the context of dynamic landing pages, perceived usefulness is reflected by the extent to which the personalisation supports consumers in accomplishing their goals more efficiently than non-personalised versions (Nysveen & Pedersen, 2004). This aligns with Prendergast et al. (2010) and Tang and Zhang (2020), who state that, in the context of online shopping, the effects of dominant approach motivation can be seen in consumers staying in the shopping environment, for example, by browsing, choosing, or purchasing. Perceived usefulness represents a cognitive aspect of the internal processing of external stimuli. Thus, we hypothesise that stronger personalised landing pages will increase perceived usefulness, which then increases continuance intention:

H2: More strongly personalised landing pages will increase continuance intention, mediated through perceived usefulness.

H3 draws on the avoidance dimension of the Approach-Avoidance Theory (Elliot, 2006). Avoidance motivation directs behaviour away from negatively perceived stimuli, such as threats and risks. While personalisation benefits the consumers, it also signals that a firm collects and uses personal data (Aguirre et al., 2015; Strycharz & Segijn, 2022). By becoming aware of this process, privacy concerns may be triggered. Empirical evidence indicates that higher levels of personalisation are associated with stronger privacy concerns in the context of product banners (Bleier & Eisenbeiss, 2015) and advertisements (Sun et al., 2025). The result of dominant avoidance motivation can be seen in consumers moving away from the shopping environment, for example, by delaying, deferring or leaving without a purchase (Prendergast et al., 2010; Tang & Zhang, 2020). Privacy concerns represent an affective internal state that captures the avoidance motivation triggered by strong personalisation, leading to unwanted behavioural outcomes. Thus, we hypothesise that stronger personalisation on landing pages increases privacy concerns, which in turn decreases continuance intention:

H3: More strongly personalised landing pages will decrease continuance intention, mediated through privacy concerns.

H4 is based on Attribution Theory (Heider, 1958), and its application to personalisation in marketing. Consumers who engage with personalised landing pages attribute this to certain motivations of the firm (Forehand & Grier, 2003). Through personalisation transparency, a firm can choose to interfere with this attribution by disclosing its data collection and use practices. This indicates to consumers more transparent and acceptable practices rather than exploitative ones, leading to more positive attributions (Kim et al., 2019). Such favourable attributions may enhance the approach motivation by increasing the perceived usefulness of the personalised landing page. When consumers understand the process behind the personalisation, it can increase the perceived person-product fit (Summers et al., 2016). Aguirre et al. (2015) found that overt data collection increased click-through intentions. Personalisation transparency affects the effect of the stimulus on the internal response by altering how the dynamic landing page is perceived. We hypothesise that personalisation transparency will strengthen the positive effect of more highly personalised landing pages on perceived usefulness:

H4: Personalisation transparency will strengthen the positive effect of more strongly personalised landing pages on perceived usefulness.

H5 draws also on Attribution Theory (Heider, 1958) while focusing on the avoidance motivation path. When consumers view dynamic landing pages, they are implicitly confronted with data collection and processing, which triggers privacy concerns (Aguirre et al., 2015). A more strongly personalised landing page leads to a more negative evaluation of the underlying motives (Sun et al., 2025). By disclosing data collection and processing through personalisation transparency, firms can inform consumers about the rationale behind the personalisation (Segijn et al., 2021). Through this transparency, consumers attribute the personalisation to more legitimate and acceptable motives rather than surveillance or manipulation (Forehand & Grier, 2003), which may lead to lower privacy concerns. Gupta et al. (2025) support this reasoning, proposing that transparency is a key driver of trust and the reduction of negative perceptions towards personalisation. We hypothesise that personalisation transparency will weaken the negative effect of more strongly personalised landing pages on privacy concerns:

H5: Personalisation transparency will weaken the negative effect of more strongly personalised landing pages on privacy concerns.

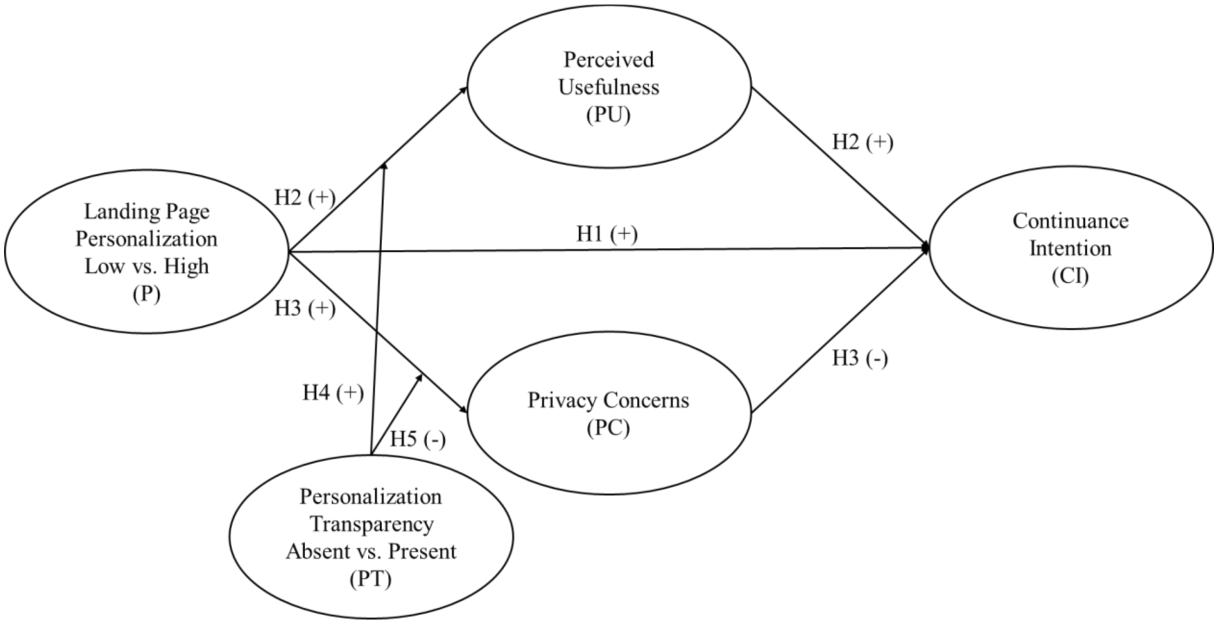


Figure 1 Research Model

The five hypotheses, taken together, operationalise the three research questions (RQ) of our study, with each layer of our model addressing one question. H1 addressed RQ1, which asked to what extent the strength of personalisation influences consumers' continuance intention, focusing on the direct effects of personalisation on continuance intention. H2 and H3 are related to RQ2 by specifying the role of the personalisation-privacy Paradox in the relationship between dynamic landing pages and continuance intention. In H4 and H5, we address RQ3 by postulating that personalisation transparency moderates the indirect effect of more strongly personalised landing pages on continuance intention. *Table 7* summarises these relationships between the research questions and the hypotheses.

Table 6 Relationship between Research questions and Hypotheses

Research Question	Description	Hypothesis	Description
RQ1	To what extent does the strength of personalisation on dynamic landing pages impact continuance intention?	H1	More strongly personalised landing pages will increase continuance intention.
RQ2	What role does the personalisation - privacy paradox play in the impact of dynamic landing pages on continuance intention?	H2	More strongly personalised landing pages will increase continuance intention, mediated through perceived usefulness.
		H3	More strongly personalised landing pages will decrease continuance intention, mediated through privacy concerns.
RQ3	How does personalisation transparency affect the relationship between dynamic landing pages and continuance intention?	H4	Personalisation transparency will strengthen the positive effect of more strongly personalised landing pages on perceived usefulness.
		H5	Personalisation transparency will weaken the negative effect of more strongly personalised landing pages on privacy concerns.

4 Methodology

In this chapter, we outline the research methodology deployed to answer the research questions. Based on the critical realist ontology, soft positivist epistemology, and the hypothetico-deductive approach, we introduce the research design, empirical setting, quantitative measurement scales of the latent variables, and data collection methods. Additionally, we discuss the criteria for validity and reliability of the results.

4.1 Research Philosophy

For this study, we adopt a critical realist ontological position, which provides a structured approach to understand underlying psychological mechanisms based on empirical self-reported measurements (Bhaskar, 1978; Ackroyd & Fleetwood, 2000), setting the frame for the analysis and discussion presented in Chapter 5.

Critical realism divides reality into three domains: the empirical domain, representing experiences and perceptions, the actual domain, composed of events and processes occurring whether observed or not, and the real domain, describing the underlying causal mechanisms that lead to events (Easterby-Smith et al., 2021; Bhaskar, 1978). This study aligns with this conceptualisation of reality by treating the self-reported survey measures as the empirical domain and the event of the survey participant viewing the landing page as the actual domain. The underlying psychological mechanisms theorised in *Chapter 3* form the real domain. While the approach-avoidance motivations and the Attribution Theory are not directly observable, they are discussed based on the findings from the empirical domain.

Epistemologically, critical realism lies between positivism, which assumes that reality exists independently of observers, and constructionism, which recognises that human access to reality depends on interpretation and context (Easterby-Smith et al., 2021). Aligned with the critical realist position, we assume that the underlying mechanisms possess causal powers but express themselves as tendencies rather than constant conjunctions, depending on the experimental conditions under which they operate (Bhaskar, 1978; Sayer, 2000). The moderated mediation analysis tests for observable patterns in the empirical domain and whether the theorised effects emerge under different conditions. Thus, the analysis follows a hypothetico-deductive approach, aligned with traditional positivist research models (Easterby-Smith et al., 2021). This logic serves as guidance throughout hypothesis formation, primary data collection, and statistical analysis. Statistical results are reported as evidence that the hypothesised mechanisms are expressing themselves under the experimental conditions, but not as confirmations of universal laws.

Methodologically, we employ a quantitative research approach, in line with the ontological and epistemological positioning. This was selected due to its suitability for hypothesis testing and its potential for statistical generalizability to uncover relationships between variables (Saunders et al., 2023). Moreover, previously established measurement scales for perceived usefulness, privacy concerns, personalisation transparency, and continuance intention are well-suited to quantitative research. Quantitative research enables solid predictive power, systematic evaluation and replicable findings (Easterby-Smith et al., 2021). The study follows a deductive logic, drawing on established theories such as Attribution Theory and Approach-Avoidance Theory, which are then tested through empirical data.

4.2 Research Design

This paper adopts a quantitative research survey design. A reactive online survey was deployed to test the hypothesis in a between-subjects, cross-sectional, vignette-based experimental design.

While we acknowledge the shortcomings of survey methods, such as the validity of questions, non-coverage and potentially low response rates (Hair et al., 2021; Easterby-Smith et al., 2021), several advantages persist. First of all, surveys are suitable to gather answers in a structured way from large samples (Saunders et al., 2023). This ensures consistency and enables advanced statistical analysis to identify patterns and, therefore, the investigation of underlying relationships that cannot be directly observed (Easterby-Smith et al., 2021). This is of special relevance to abstract concepts such as privacy concerns, perceived usefulness and our objective to measure subtle behavioural shifts in continuance intention (Hair et al., 2021). Surveys are often used in academic management research, including marketing, to understand the behaviour and characteristics of individuals (Easterby-Smith et al., 2021). Surveys can enable the generalisation of findings from a sample to a broader population (Easterby-Smith et al., 2021), resonating with our aim to generate broader assumptions about consumer behaviour towards GenAI-enabled personalisation and personalisation transparency.

The usage of online surveys allows the collection of standardised data from a large and diverse sample in a cost- and time-effective manner (Saunders et al., 2023). The online format of the survey enables participants to complete the survey at their own convenience and via their own devices, thereby increasing accessibility. Additionally, the self-administrative nature of online surveys reduces researcher effects and social desirability biases (Lavrakas et al., 2019). Lastly, online surveys allow an effective manipulation of the independent variable to create different conditions for testing, while controlling for exogenous influences (Lavrakas et al., 2019).

The use of a between-subjects, cross-sectional experimental design is a common approach in the domain of personalisation research in an e-commerce context (Bleier & Eisenbeiss, 2015; Sun et al., 2025; Salonen & Karjaluoto, 2016). Creating different, controlled experimental conditions allows an effective comparison of effects and their attribution to a setting (Lavrakas et al., 2019). The standardised format of the online survey enables a comparison of the conditions and consistency in measurement, thus enabling the statistical analysis of the hypothesis (Lavrakas et al., 2019).

The design encompasses four conditions: the investigation of the mediating effects of perceived usefulness and privacy concerns on continuance intention for 1) a low personalised dynamic landing page, 2) a more strongly personalised dynamic landing page as well as 3) a low personalised dynamic landing page with personalisation transparency and 4) a more strongly personalised landing page with personalisation transparency. This results in a 2x2 factorial matrix (see *Table 8*).

Table 7 Distribution of Experimental Groups

		Moderator	
		Absent Personalisation	**Present Personalisation**
Independent Variable	**Low Personalised landing pages**	Condition: low-personalisation/no-transparency	Condition: low-personalisation/ transparency
	More strongly Personalised landing pages	Condition: high-personalisation/no-transparency	Condition: high-personalisation/ transparency

4.3 Survey Design

The between-subjects, cross-sectional experimental, vignette-based survey consists of four sections and incorporates aspects of prior studies in the field. The complete survey can be found in *Appendix A*.

1. First, participants were presented with a short introduction that informed them of the study's aim, their voluntary participation and that there are no right or wrong answers. They were informed about the applied data privacy regulations and by continuing the survey, they confirmed that they are at least 18 years old.

2. The second section presented the experimental stimulus through a vignette by providing participants with a short descriptive scenario. The vignette methodology ensures that all participants experienced a consistent stimulus (Lavrakas et al., 2019). Next to that, a vignette enables the measurement of complex concepts through the usage of examples and enables the revelation of characteristics that may not be admitted or recognised by participants themselves (Vargas, 2008). In this study, the vignette asked participants to imagine themselves experiencing a specific health issue, researching online about it and concluding with the desire to visit the website of an online pharmacy. The vignette concluded with the information that participants would see the website in the next step,

and their task would be to explore it carefully before answering some questions about their impressions.

3. After reading the vignette, participants were randomly assigned to one of the four conditions. As seen in *Figure 2* and *Figure 3*, every condition entails a specifically designed dynamic landing page of an online pharmacy. For condition 1), participants would see a low personalised landing page, only depicting the most popular health products in the minerals segment, as well as a generic article on vitamins. For condition 2), participants would be presented with a more strongly personalised landing page. This includes recommendations of minerals for the specific condition the vignette described, as well as an informative article about the experienced symptoms of fatigue, an overview of recently viewed products and an advertisement of free delivery to Malmö, the participants' fictional residency. In Condition 3), participants would encounter the same, low personalised content as in Condition 1), but with a banner explaining how their experience was Personalised, disclosing that the website uses data from the participants' location, previous visits and browsing behaviour. In condition 4), the same more strongly personalised content as in Condition 2) would be presented, but with the addition of the mentioned banner from condition 3).

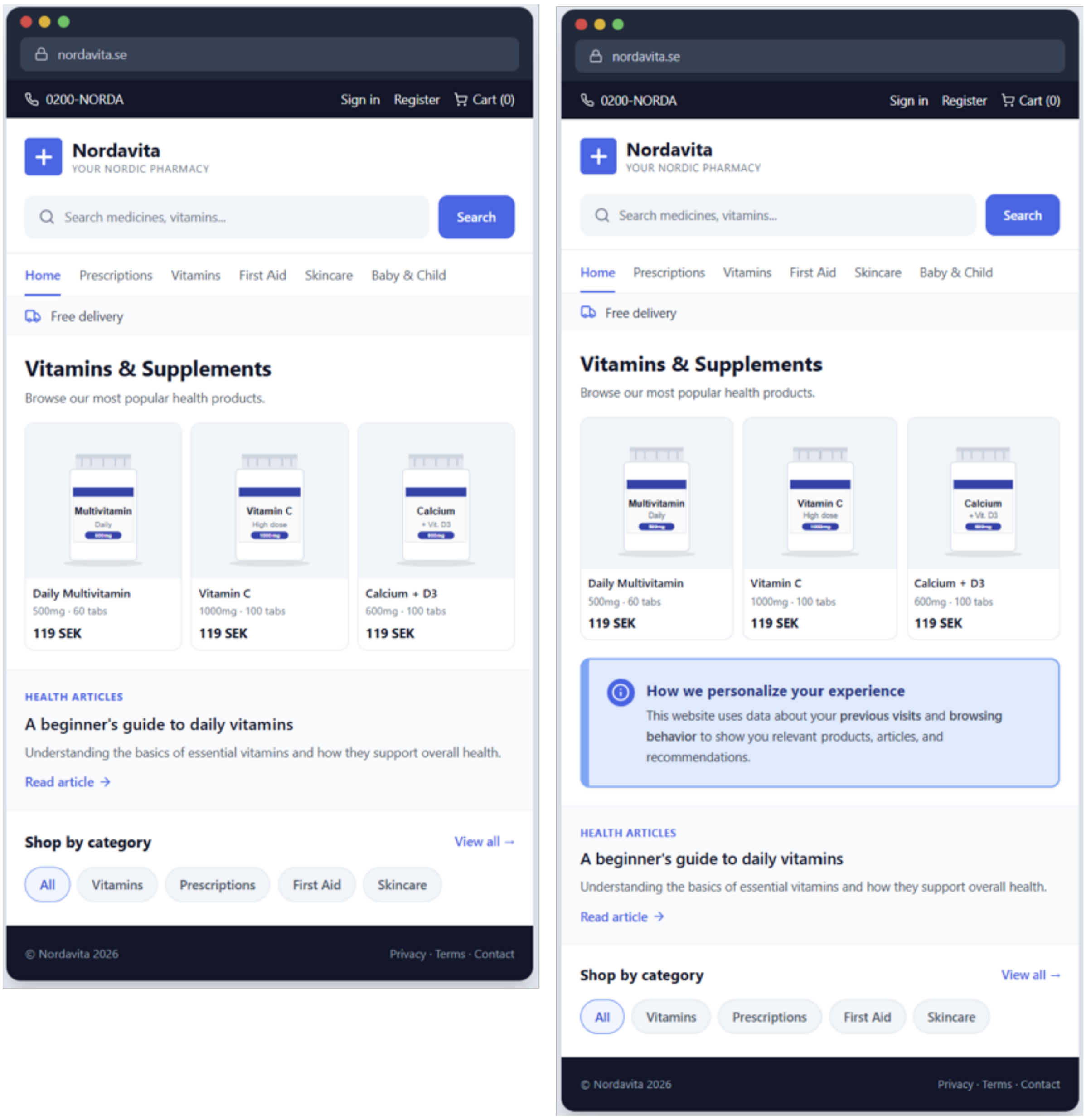


Figure 2 Survey Design low personalisation with and without banner

The content of the website was held constant across conditions 1) and 3) as well as 2) and 4) to ensure that any observed differences could be attributed to differences in personalisation degree and/or the presence of a transparency disclosure and not the website content itself. By doing so, an effective evaluation of the influences on continuance intention can be realised.

After the presentation of the random condition, participants were tasked to answer questions about the dynamic landing page. The displayed questions entailed the operationalised mediating, moderating and dependent variables. The survey consisted primarily of rating questions to collect participants' opinions (Saunders et al., 2023). This offers advantages regarding comparability, speed, and participants' effort in completing the questions (Saunders et al., 2023). As advised in the literature, existing scales have been used and minimally adapted for this research context (Saunders et al., 2023). Additionally, a manipulation check for personalisation level and personalisation transparency was included, as well as an attention check. The manipulation check was designed to verify that the experimental manipulation of different degrees of personalisation worked as intended. The attention check helped determine whether participants answered the questions with sufficient thoroughness (Huang et al., 2012).

4. In the last part of the online survey, demographic information was collected to understand the sample composition and ensure transparent reporting. This included information on age and gender, with any respondents under 18 years of age excluded from the sample. By doing so, a descriptive overview of the participants as well as an assessment of the generalizability of the findings became possible (Lavrakas et al., 2019).

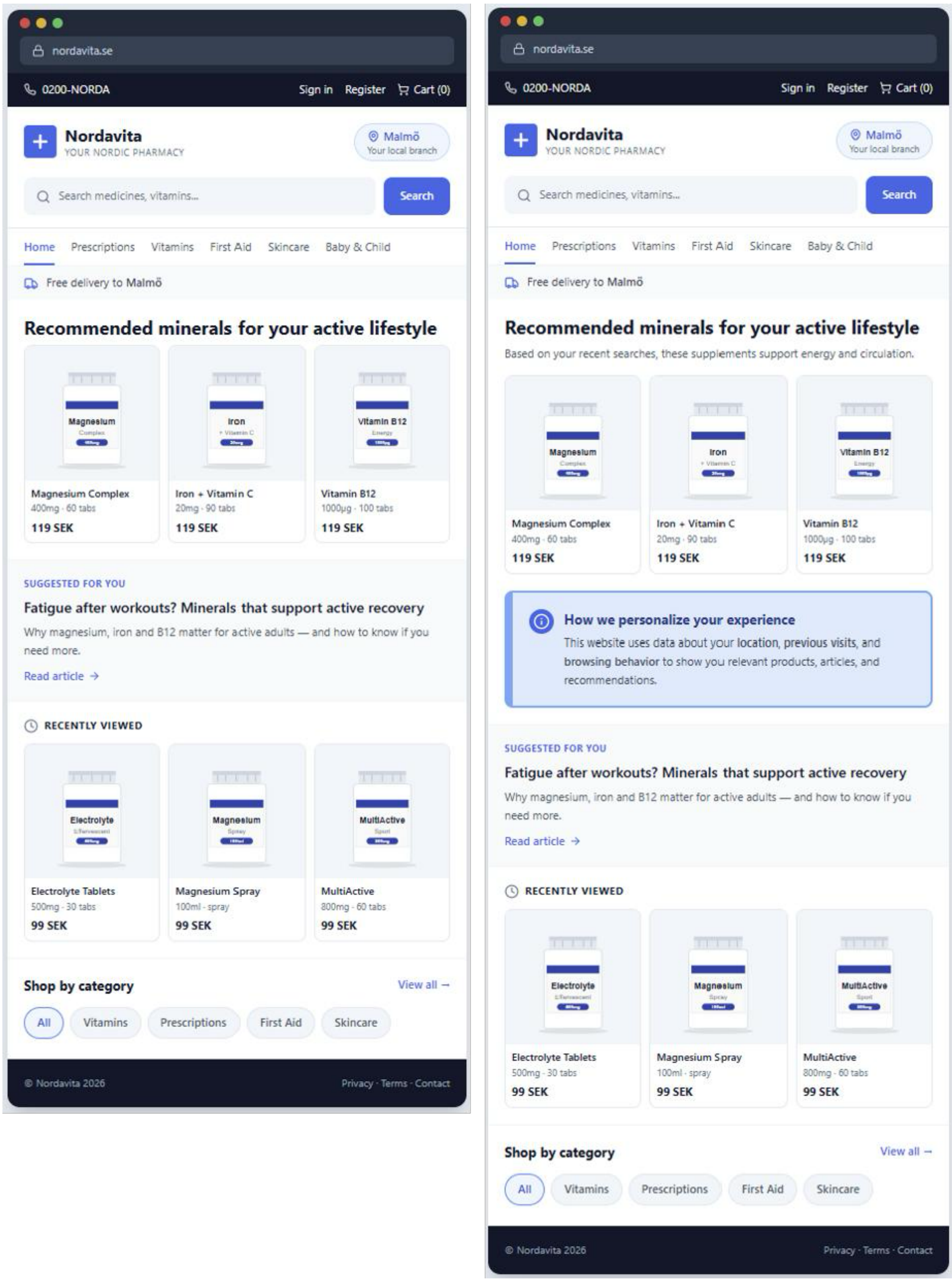


Figure 3 Survey Design high personalisation with and without banner

4.4 Empirical Setting: Online Pharmacies

For the survey, the empirical setting of online pharmacies was chosen. This environment was selected because it offers great potential for dynamic landing pages while defusing the ambiguity around personalisation practices and privacy concerns. By choosing this context, we aim to establish a relatable yet sensitive context to the research questions that would support authentic reactions from respondents.

Pharmacies play a critical role in healthcare systems and can serve as buffers to shortages in trained professionals (Fernández del Río et al., 2024). The advancement of online pharmacies has introduced a new era for consumers and the industry (Spanakis et al., 2019). Information technologies have gained significant traction in modern pharmaceutical care and have been proclaimed repeatedly as a way to improve health services (Liu et al., 2023; Lapão et al., 2017). This includes more effective, patient-centred and accessible healthcare (Spanakis et al., 2019). Additionally, purchasing medications online offers a more convenient shopping experience than traditional methods (Nistal-Nuño, 2022). Online pharmacies can overcome the typical time and space constraints of pharmaceutical care, especially when there is a disparity between licensed pharmacies and the population (Liu et al., 2023).

Yet, the adoption of AI technologies by online pharmacies remains limited, and long-term success remains characterised by uncertainty (Nistal-Nuño, 2022; Lapão et al., 2017). AI has been proposed as a key technology to provide more personalised, more efficient and user-friendly services for online pharmacies (Nistal-Nuño, 2022). Personalisation practices are of great relevance in pharmaceutical commerce as medications are highly individual, based on a person's specific characteristics, and suggestions from other consumers' profiles may be unsuitable (Nistal-Nuño, 2022). On top of that, personalisation practices can help counteract the information overload online regarding medications (Nistal-Nuño, 2022). First steps towards implementing dynamic landing pages have proven successful, as GenAI algorithms demonstrate strength in delivering a personalised experience with limited consumer data available (Nistal-Nuño, 2022). Common applications of AI in online pharmacies include recommending products and helping consumers find information (Nistal-Nuño, 2022). Nistal-Nuño (2022) demonstrated that GenAI-enabled pharmacies can quickly and consistently achieve high accuracy in predicting medication categories needed by patients, enabling them to reduce time and mental effort. Simultaneously, they unlock benefits for firms. Fernández del

Río et al. (2024) proposed an AI-enabled platform to enhance user journeys in online pharmacies and were able to demonstrate significant increases in basket size. The elevated levels of convenience and efficiency were found to be a critical factor in influencing consumers' adoption of online pharmacies (Ma, 2021).

Yet, privacy concerns are among the most crucial factors contributing to resistance to online pharmacy adoption, especially in the context of GenAI adoption in the field (Ashrafi et al., 2024; Hasan et al., 2024). Health records contain sensitive personal data, and their protection is therefore crucial (Hasan et al., 2024). Customers are therefore especially sensitive to potential risks, such as the privacy of their information when shopping at online pharmacies (Ma, 2021).

The high sensitivity to privacy concerns provides a clear case for avoidance motivation, while the perceived usefulness of the sites represents significant approach motivation. This creates a potentially strongly receptive experimental context for the effects of personalisation transparency.

4.5 Operationalisation of Constructs

4.5.1 Dynamic Landing Pages

The independent variable in our model is the GenAI-enabled, personalised landing page (dynamic landing page). We operationalise the independent variable as a binary manipulation (low vs high) to clearly highlight the exacerbating effects of higher levels of personalisation on perceived usefulness, privacy concerns, and continuance intention.

To stimulate personalisation, participants are exposed to a condition vignette. In the condition, participants were looking to buy nutritional supplements fitting their specific lifestyle. Depending on a random selection, participants were shown either a low- or a more strongly personalised landing page.

Vignette:

Imagine the following situation. You are currently living in Malmö, Sweden and pursue an active, sporty lifestyle. Lately, you have been suffering from dizziness and fatigue after your workouts.

You researched online about your symptoms and possible causes. You read some articles online and consulted with an AI Chatbot. You come to the conclusion that some additional nutritional minerals next to your usual intake of supplements might help you best in your situation. Therefore, you open an online pharmacy website that you have visited before to browse for a product that fits your needs.

In the next step, you will be shown a website of an online pharmacy. Take your time to carefully examine the website as if you were making a real purchase evaluation.

To differentiate between high and low personalisation, the differentiation approach by Sun et al. (2025) was adopted and adjusted. While the low personalised landing page would display two personalised items, the high personalised landing pages would display five personalised items. The personalised items displayed on the dynamic landing pages are derived from literature and encompass frequently mentioned personalised design elements (Desai, 2019; Vinaykarthik & Mohana, 2022; Märtin et al., 2021). In general, research distinguishes between the design aspects of personalised landing pages: information personalisation, presentation personalisation, and navigation personalisation (Tam & Ho, 2006). *Table 9* displays the implementation in our study. For a post-experimental manipulation check, three items were adapted from Baek and Morimoto (2012) to measure perceived personalisation on a seven-point Likert scale.

Table 8 Characteristics of Dynamic Landing Pages

Items	Low personalisation of dynamic landing page	High personalisation of dynamic landing page
Information Personalisation: Product recommendations	Generic bestseller in the product category of supplements	Explicitly need-based
Information Personalisation: Editorial content	Generic articles about the product	Individually tailored articles
Information Personalisation: Self-referential content (Location)	Absent	Present
Presentation Personalisation: Homepage Layout	Uniform	Individually tailored
Navigation Personalisation: Continuity features	Absent	“Recently viewed” Module

4.5.2 Personalisation Transparency

We operationalised the moderating variable, personalisation transparency, as a binary manipulation (absent vs present). Participants in the transparency condition were exposed to a transparency disclosure. Building on the conceptualisation by Segijn et al. (2021), the disclosure included information about the data collection and processing, embedded in the dynamic landing page. This approach was deemed appropriate due to the realistic nature, improving the managerial implications of our findings. To verify successful manipulation of the moderator, a single-item manipulation check was included in the survey following the stimulus. Participants were asked on a binary scale whether they were informed about data collection and processing for personalisation.

4.5.3 Perceived Usefulness and Privacy Concerns

To measure the mediating effects of perceived usefulness and privacy concerns, we modified the operationalisation of Bleier and Eisenbeiss's (2015) model to the context of dynamic landing pages. Both mediating factors have been applied to similar research models (Bleier & Eisenbeiss, 2015), enabling a suitable transferability to the research design of this study. Perceived usefulness and privacy concerns are measured through a seven-point Likert scale.

4.5.4 Continuance Intention

As a dependent variable, we aim to investigate the effect of personalisation and transparency disclosures on continuance intention. Continuance Intention can be described as a consumer's decision to carry on using a specific information technology he has already been using (Rahi & Ghani, 2019). It is relatively difficult to measure actual continuance usage, which is why continuance intention is a suitable substitute (Zhou, 2013). While concerns regarding the discrepancy between behavioural intentions and actual behaviours need to be acknowledged (Tang & Zhang, 2020), it is well documented that intentions are a major predictor of actual behaviour (Bagozzi, 1981).

Adapted from Bhattacherjee (2001) and Gosh et al. (2024) we operationalised continuance intention using three items and measuring them on a seven-point Likert scale, with one reverse-coded item.

4.5.5 Summary of Items

Table 10 presents the operationalisations of the latent construct through the items. All scales are measured on a seven-point Likert scale, ranging from strongly disagree to strongly agree, and are validated through prior quantitative peer-reviewed research.

Table 9 Operationalisations of Latent Constructs

Ref	Item	Source
PP	Perceived Personalisation	
PP1	This landing page makes purchase recommendations that match my needs.	Baek & Morimoto (2012)
PP2	Overall, this landing page is tailored to my situation.	Baek & Morimoto (2012)
PP3	I believe that this personalised landing page is customized to my needs.	Baek & Morimoto (2012)
PU	Perceived Usefulness	
PU1	The landing page enables me to accomplish shopping tasks more quickly.	Bleier & Eisenbeiss (2015)
PU2	The landing page improves my shopping task performance.	Bleier & Eisenbeiss (2015)
PU3	The landing page enhances my effectiveness in my shopping task.	Bleier & Eisenbeiss (2015)
PU4	The landing page makes it easier to do my shopping task.	Bleier & Eisenbeiss (2015)
PC	Privacy Concerns	
PC1	It bothers me that the firm is able to track information about me.	Bleier & Eisenbeiss (2015)
PC2	I am concerned that the firm has too much information about me.	Bleier & Eisenbeiss (2015)
PC3	It bothers me that the firm is able to access information about me.	Bleier & Eisenbeiss (2015)
PC4	I am concerned that my information could be used in ways I could not foresee.	Bleier & Eisenbeiss (2015)
CI	Continuance Intention	

CI1	I intend to continue using the website in the future.	Bhattacherjee (2001)
CI2	I want to continue using this website rather than use any alternative.	Gosh et al. (2024)
CI3	If I could, I would like to discontinue the use of this website.	Gosh et al. (2024)

4.6 Data Collection and Sampling

As Easterby-Smith et al. (2021) lay out, quantitative research usually draws upon two main types of data: primary data gathered for the purpose of the research or secondary data, drawn from pre-existing sources. For this study, primary data were used solely, as the literature review identified shortcomings in existing datasets on the impact of GenAI-enabled personalisation and personalisation transparency. In contrast to secondary data, primary data also enables causal inference and control over the data (Easterby-Smith et al., 2021).

There are various methods of primary data collection in marketing, such as observation and experimentation. An online survey method was chosen for the data as it was able to cater to the several latent variables and intangible constructs of the research model. The online survey was created using www.soscisurvey.de, as this platform ensured alignment with the European General Data Protection Regulation and allowed all necessary manipulations and randomisations of the survey.

The development of the sampling frame is a crucial process in the survey design (Easterby-Smith et al., 2021). We followed a non-probabilistic sampling strategy, which refers to sampling in which the likelihood of each population entity is unknown (Easterby-Smith et al., 2021). The non-probabilistic sampling strategy used convenience and snowball sampling. Convenience sampling describes samples in which entities are included based on their ease of access (Easterby-Smith et al., 2021). Snowball sampling includes participants identifying further members of the sample (Saunders et al., 2023).

Although non-probabilistic samples limit the generalisability of findings and snowball sampling likely leads to more homogeneous samples (Saunders et al., 2023), it was deemed appropriate, as this study serves an exploratory purpose to investigate behavioural patterns within a limited timeframe and with constrained access to participants (Easterby-Smith et al., 2021). As the investigation of moderation and mediating effects requires sufficient sample sizes (Lavrakas et al., 2019), the quantity of participants was prioritised over a probabilistic sampling strategy. For this reason, the online survey did not entail any demographic exclusion criteria with regard to age (except below 18), gender or place of residence to increase the likelihood of attracting participants from a range of social groups. In addition, several studies have shown that effect sizes in online convenience samples are similar to those observed in probability-based studies (Berinsky et al., 2017; Mullinix et al., 2015). While sampling has to be acknowledged as a crucial part of research, it can be noted that "[...] the key factor for good experimental designs is not the random selection of respondents, but rather a well-established experimental design, combining an adequate set-up of vignettes which contain the experimental stimuli and are randomly allocated to respondents (Lavrakas et al., 2019, p. 374).

To accommodate the convenience and snowball sampling approaches, personal networks were approached and encouraged to share the survey further. Additionally, participants were recruited online (through digital platforms) and in person using QR codes. No incentives for participation were provided except the opportunity to contribute to academic research. The study was conducted in alignment with established ethical research standards. Voluntary participation was ensured, as well as transparency on the research purpose and data use. The online survey was designed to be completed anonymously and the possibility to withdraw from the survey was given at any time.

Before the data collection, we conducted an a-priori power analysis using GPower (Faul et al., 2007) to calculate the minimum sample size required for the mediated moderation analysis. Since GPower does not have a separate setting for moderated mediation, we calculated the sample size for the mediator equation containing three predictors, which is the basis of our hypothesis testing. To do this, we used the linear multiple regression (F-test for R^2 deviation from zero) module with the parameters $\alpha = 0.05$ and power = 0.80. We anticipated an effect size of $f^2 = 0.06$, which lies between Cohen's (1988) small and medium effect size conventions. This was deemed appropriate, since interaction effects of moderated mediation are typically smaller than main effects, for which $f^2 = 0.15$ would have been sufficient. GPower calculated a minimum sample size of $N = 186$. Data collection took place from the 24th of April to the 5th of May and included 270 participants. After exclusions, the final sample included $N = 206$, meeting the required minimum sample size.

4.7 Data Analysis

After data collection, the survey responses were restructured in Microsoft Excel for analysis, with each row representing a unit of analysis (survey participants) and each column representing a survey question. To analyse different experimental conditions, binary-coded dummy variables were added to the columns for the degree of dynamic landing page personalisation and the transparency disclosure.

Statistical tests in our analysis were conducted using jamovi (jamovi, 2024; Rosseel, 2012), including descriptive statistics, the Welch's t-test as a manipulation check for the personalisation conditions, confirmatory factor analysis, model validity analysis, and correlation calculations. The analysis of the moderated mediation to test our hypotheses was done in jamovi using the Advanced Mediation Models module (Gallucci, 2020).

Throughout our data analysis, we evaluated the statistical significance of regression coefficients and Welch's t-test results using the conventional alpha level of $\alpha = 0.05$. For hypothesis testing in the jamovi Advanced Mediation Models module, effects were considered significant if the 95% confidence interval, computed via bootstrapping with 5,000 resamples, did not include zero. This corresponds to established criteria for significance for moderated mediation models (Preacher & Hayes, 2008; Hayes, 2022). For the Index of Moderated Mediation (Hayes, 2015) and its confidence interval, we used Python to conduct a Monte Carlo simulation with 100,000 repetitions (Preacher & Selig, 2012; MacKinnon et al., 2004). To ensure stability and reproducibility of our results for the Index, we used a fixed random seed in Python 3.14.5 (np.random.seed(123)).

4.8 Research Quality Criteria

This study was designed with reliability and validity as central considerations, as they lay the foundation for the credibility, replicability and practical relevance of empirical research (Saunders et al., 2023).

Reliability concerns itself with the robustness of the survey and the consistency of measurement procedures to produce consistent findings at different times and under different conditions (Saunders et al., 2023; Easterby-Smith et al., 2021). On the one hand, internal reliability was strengthened through a well-documented and systematic research approach, carried out collaboratively by two authors. This enhances transparency and accountability in instrument development and data handling. On the other hand, external reliability (replicability) was ensured by providing full access to all stimuli, scales and measurement items. Internal consistency of the measurement scales was ensured through Cronbach's α and McDonald's ω, which were compared against accepted thresholds to confirm that the individual items measure the same underlying concept. Furthermore, external reliability was ensured through a pilot test with non-Swedish participants to verify that the Swedish-based vignette and dynamic landing page are applicable to an international audience.

Validity builds upon reliability, as unreliable measurements evoke errors that can distort the interpretation and replicability of results (Lavrakas et al., 2019). Validity can be defined as the aim to ensure a study measures the intended objectives (Easterby-Smith et al., 2021). Several sub-dimensions of validity exist and need to be recognised when conducting a quantitative study. Internal validity in a survey refers to the ability of the method to measure the intended objective (Saunders et al., 2023). Internal validity was established through several measures. For one, the condition-based online survey enabled a controlled comparison of the manipulated independent variable and the moderator's influence. Furthermore, random assignment of conditions allows the elimination of alternative explanations because all other factors were equivalent except for the desired manipulations (Lavrakas et al., 2019). This strengthens internal validity, as certainty can be established that the relationship between the measured variables is causal and not due to randomness (Lavrakas et al., 2019). A Welch's t-test further confirmed the successful manipulation.

Potential threats to internal validity, such as misunderstandings of the survey, were addressed through a pilot study ($N = 7$) prior to the data collection. This serves as a way to check the survey's design for coherence, understandability and potential misleadings. Additionally, it enables the initial assessment of the validity and reliability of the questions and the data (Saunders et al., 2023). Several points of feedback were implemented, including shortening the introduction and vignette, as well as addressing the user experience of the survey tool and the overall structure. All participants of the pilot study were excluded from the actual data collection. Lastly, internal validity was additionally ensured through an attention check in the study. That way, the collected data reflect only participants who were actually exposed to the manipulation as intended, reducing sampling error.

Construct validity can be defined as the extent to which the measurement questions measure the presence of the intended constructs (Saunders et al., 2023). To ensure alignment with the theoretical construct of interest, only well-established measurement scales from prior research were used for all variables. The use of a reverse-coded item for the dependent variable (continuance intention) also contributes to construct validity, as it counteracts the tendency for participants to agree with statements regardless of their content and to give uniform responses. In addition, construct validity was quantified via Confirmatory Factor Analysis (CFA). Convergent and discriminant validity were assessed using Average Variance Extracted (AVE) and the Heterotrait-Monotrait Ratio of Correlations, both of which met established thresholds.

Due to the measurement of all constructs being conducted through self-reported Likert seven-point scales, common method bias was considered as a potential threat to the validity of our results (Podsakoff et al., 2003). The common method bias describes how shared measurement methods, such as repeated scale formats, can artificially inflate or deflate observed relationships among the variables measured (Podsakoff et al., 2003). Following the procedural recommendations of Podsakoff et al. (2003) for survey design, we only used established scales, ensured anonymous participation, informed the participants that there were no correct or incorrect answers and included a reverse-coded item. Furthermore, the common method bias was statistically addressed using Harman's single-factor test.

External validity is met with some limitations in this study. The non-probabilistic sampling strategy restricts generalizability and demonstrates a higher risk of sampling errors. However, accessibility to participants was among the key objectives of the research design, which is why the approach can nevertheless be deemed as appropriate. The reactive nature of the study can also impact social desirability bias in participants' responses as described in the Hawthorne effect (Adair, 1984). By emphasising that there are no right or wrong answers in the introduction and anonymising the participation, steps were implemented to navigate this effect.

5 Analysis and Discussion

In the following, we analyse the sample and discuss the results of the analysis. We begin by exploring the characteristics of the sample, then conduct a manipulation check for the two levels of personalisation (low vs high). After this, the measurement model is presented, including internal reliability and confirmatory factor analysis. Additionally, we address the common method bias. Followed by the descriptive statistics and correlations, we test our hypotheses and discuss the results.

5.1 Sample Characteristics

5.1.1 Final Sample and Experimental Conditions

The collected sample for our study consisted of 270 responses, of which three did not finish the survey and were thus excluded by default. Out of the remaining responses, 10 failed the Q13 attention check. To ensure that the final sample successfully analyses personalisation transparency, respondents were asked to identify whether personalisation transparency was disclosed on the landing page. In total, 56 respondents failed to do so correctly, falling into two categories. 21 out of 129 (16.3%) respondents who were shown the personalisation transparency did not register it, while 35 out of 138 (25.4%) who were shown no disclosure reported the landing page included personalisation transparency. Since both failure types indicate failed manipulation, all 56 out of 267 (21%) were excluded to ensure the validity of the reported results. Five respondents failed both the attention check and the personalisation transparency identification, resulting in a total of 61 unique respondents being excluded, leaving the final sample at N = 206.

The conditions of the final sample were balanced, with low-personalisation/no-transparency (n = 52), low-personalisation/transparency (n = 57), high-personalisation/no-transparency (n = 48) and high-personalisation/transparency (n = 49). Missing data was only an issue for the gender of 3 participants, which we set as “Prefer not to say”, and the age of two participants, who were left out of the demographic analysis. The balanced experimental conditions and exclusion strategy ensure the internal validity of the following analysis.

5.1.2 Demographics

The demographic profile of the final sample (N = 206) reflects the sampling methods of this study, with the mean exceeding the median due to convenience and snowball sampling of university students and older family members. (mean = 29.3, SD = 11.5, range = 19-73, median = 25). The gender distribution was 52.4% female, 42.7% male and 4.9% other/prefer not to say. While convenience sampling methods limit the representativeness of the sample to the specific population, the sample's demographic profile was deemed appropriate for an exploratory study of consumer responses to GenAI-enabled personalised landing pages. *Table 11* presents the demographic profile of the final sample.

Table 50 Demographic Profile of the Final Sample

Characteristic		**Counts**	**% of Total**
Gender	Female	108	52.40%
	Male	88	42.70%
	Non-Binary	4	1.90%
	Prefer not to say	6	2.90%
Age	18-24	97	47.10%
	25-34	75	36.40%
	35-44	5	2.40%
	45-54	11	5.30%
	55-64	12	5.80%
	65+	4	1.90%
	Missing	2	1.00%

5.2 Manipulation Check

The manipulation check aimed to verify that participants in the treatment conditions perceived the dynamic landing page with the intended level of personalisation (low/high). To ensure this, we measured perceived personalisation with a three-item scale and conducted a Welch's t-test. Due to Welch's t-test robustness to unequal variances and because it does not rely on the homogeneity assumption (Derrick & White, 2016), we used this test rather than a Student's t-test. This approach was consistent with the results of Levene's test, which indicated that the assumption of equal variances was violated (Levene's $F(1, 204) = 16.5$, $p < 0.001$).

Results confirmed a statistically significant difference in perceived personalisation between the groups ($t(202) = 8.57$, $p < 0.001$, $d = 1.19$). Participants exposed to the low personalisation conditions ($n = 109$, $M = 3.89$, $SD = 1.65$) reported substantially lower perceived Personalisation than those exposed to the high personalisation dynamic landing page ($n = 97$, $M = 5.67$, $SD = 1.33$). Thus, the manipulation was deemed successful. *Figure 4* graphically presents the means of perceived personalisation with 95% confidence intervals.

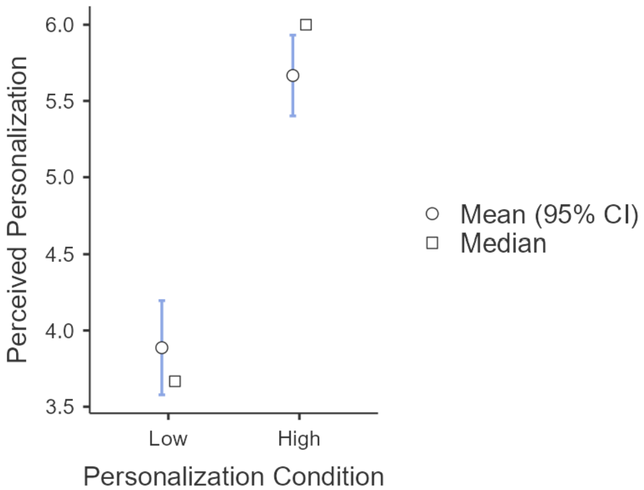


Figure 4 Welch's t-test for Perceived Personalisation (Source: jamovi)

5.3 Measurement Model

5.3.1 Internal Reliability

To assess the scale reliability of our constructs, we use Cronbach's α and McDonald's ω, with the established thresholds $\alpha > 0.7$ and $\omega > 0.7$ (Hair et al., 2021). Both Cronbach's α and McDonald's ω report to what extent the items from the questionnaire measure the same underlying latent variable, with values closer to 1 indicating stronger internal reliability.

All constructs were well above these thresholds, indicating strong internal consistency for perceived usefulness ($\alpha = 0.962$, $\omega = 0.963$), privacy concerns ($\alpha = 0.962$, $\omega = 0.963$) and continuance intention ($\alpha = 0.849$, $\omega = 0.858$). Additionally, we measured the scale reliability of the manipulation check for personalisation ($\alpha = 0.951$, $\omega = 0.951$), to ensure that the prior Welch's t-test is supported by consistent scales, with the values again exceeding relevant thresholds. Thus, our questionnaire consistently measured the same constructs using its items. *Table 12* summarises the scale reliability of the latent variables.

Table 61 Scale Reliability

Construct	Mean	SD	α	ω
Perceived Personalisation	4.72	1.75	0.951	0.951
Perceived Usefulness	4.71	1.64	0.962	0.963
Privacy Concerns	4.28	1.97	0.962	0.963
Continuance Intention	4.06	1.42	0.849	0.858

5.3.2 Confirmatory Factor Analysis

To assess the factor structure of our measurement model, we conducted a confirmatory factor analysis (CFA) with maximum likelihood estimation. The CFA aims to evaluate the model fit, meaning how well our model reproduces the patterns actually observed in the sample data. Mardia's test indicated deviation from multivariate normality (skewness $\chi^2(286) = 751$, $p < 0.001$; kurtosis $z = 11.5$, $p < 0.001$), which is why we applied Huber-White robust standard errors, which enable a CFA for a sample that is not normally distributed and ensure the validity of test statistics.

Our research model fit the data well, with $\chi^2(41) = 56.9$, $p = 0.050$, CFI = 0.994, TLI = 0.991, RMSEA = 0.043, 90% CI [0.000, 0.069], RMSEA p = 0.636, SRMR = 0.028. All indices met the established thresholds of CFI > 0.95, TLI > 0.95, RMSEA < 0.08 and SRMR < 0.08 (Hu & Bentler, 1999). These results support a successful operationalisation. The items from the survey map onto perceived usefulness, privacy concerns and continuance intention as three distinct latent constructs. The good model fit statistics indicate that our model is highly consistent with the sample data. *Table 13* summarises the model fit indices for the measurement scales.

Table 72 Model Fit Indices for Measurement Scales

Index	Saturated Model	Threshold	Interpretation
χ^2	56.90 (p = 0.05)	> 0 (p ≥ 0.050)	Acceptable fit
CFI	0.994	> 0.95	Good fit
TLI	0.991	> 0.95	Good fit
SRMR	0.028	< 0.08	Good fit
RMSEA	0.043	< 0.08	Good fit

5.3.3 Convergent Validity

The convergent validity of our model was assessed using the average variance extracted (AVE) for each construct. AVE represents the proportion of variance of the latent construct captured by the individual survey items, relative to the amount caused by measurement error. Values above AVE > 0.50 indicate that the construct accounts for more variance in the survey items than measurement error does (Fornell & Larcker, 1981), suggesting that the survey questions reliably measure the theoretical constructs rather than random statistical error. For our study, the AVEs for each construct support convergent validity, with perceived usefulness (AVE = 0.866), privacy concerns (AVE = 0.869), and continuance intention (AVE = 0.671) all exceeding the threshold.

5.3.4 Discriminant Validity

To ensure that the latent variables in our research model are empirically distinct, we examined the Heterotrait-Monotrait ratio of correlations (HTMT), which compares the between-construct item correlations to within-construct item correlations (Henseler et al., 2015). All HTMT values in our model fell below the conservative threshold of < 0.85 (Henseler et al., 2015), with perceived usefulness/privacy concerns = 0.117, perceived usefulness/continuance intention = 0.583, and privacy concerns/continuance intention = 0.519, supporting discriminant validity. The low HTMT-value between perceived usefulness and privacy concerns suggests that the two mediators in our model are conceptually very distinct internal responses of the consumer to the personalisation. *Table 14* summarises the HTMT ratio of correlations.

Table 83 Heterotrait-Monotrait Ratio of Correlations

	Perceived Usefulness	**Privacy Concern**	**Continuance Intention**
Perceived Usefulness			
Privacy Concerns	0.117		
Continuance Intention	0.583	0.519	

5.3.5 Common Method Bias

Since all measures in this study were collected through a self-reported online survey, the common method bias was considered. Following the recommendation of Podsakoff et al. (2003), a Harman's single-factor test was conducted, forcing all measured factors into a single, unrotated exploratory factor (Harman, 1976; Podsakoff et al., 2003).

The results, presented in *Table 15*, show that this single factor accounted for 39.4% of the total variance, lying below the 50% threshold. This indicates that the common method bias is unlikely to distort the relationships analysed. In addition to this test, we followed further recommendations by Podsakoff et al. (2003), for example, stating that there are no correct answers, making participation anonymous and including a reverse-coded item (CI3).

Table 94 Harman's Single-Factor Test

Factor	**SS Loadings**	**% of Variance**
1	4.34	39.4

5.4 Descriptive Statistics and Correlations

5.4.1 Construct-Level Descriptives

Regarding univariate descriptive statistics for the latent variables, skewness is reported to evaluate the symmetry of the distribution, with 0 indicating perfect symmetry, and kurtosis to evaluate the tailedness relative to a normal distribution, with 0 indicating a normal distribution (Sarstedt et al., 2017). Skewness ranged from -0.449 to 0.0907 and kurtosis from -1.41 to -0.541. All values lay well within the recommended thresholds of |2| for skewness and |7| for kurtosis (Sarstedt et al., 2017). *Table 16* presents the distributional properties of the sample. While bootstrap-based inferences used in hypothesis testing remain robust under non-normal distributions (Preacher & Hayes, 2008), these results support the validity of the parametric tests reported throughout our analysis, as no construct strongly indicates a non-normal distribution.

Table 105 Skewness and Kurtosis

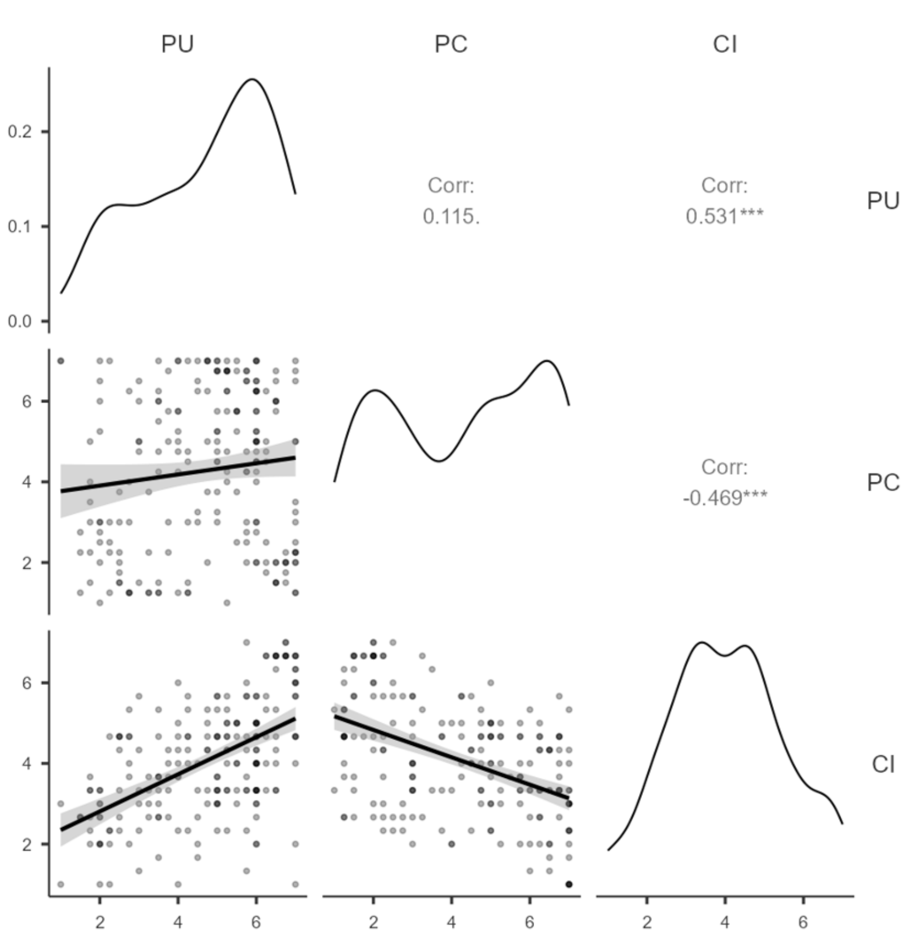
	Skewness	SE Skewness	Kurtosis	SE Kurtosis
Perceived Usefulness	-0.449	0.169	-0.957	0.337
Privacy Concerns	-0.125	0.169	-1.41	0.337
Continuance Intention	0.091	0.169	-0.541	0.337

5.4.2 Inter-Construct Pearson Correlations

Before we tested the hypotheses, we evaluated the Pearson correlations to measure strength and direction of correlation between the constructs in our research model, with $r \approx |0.3|$ indicating weak correlation, $r \approx |0.5|$ moderate and $r \approx |0.7|$ strong (Evans, 1996).

Perceived usefulness was positively correlated with continuance intention ($r = 0.531$, $p < 0.001$) and privacy concerns were negatively correlated with continuance intention ($r = -0.469$, $p < 0.001$). Perceived usefulness and privacy concerns were only very weakly and insignificantly correlated ($r = 0.115$, $p = 0.099$). The significant positive correlation between perceived usefulness and continuance intention and the significant negative correlation between privacy concerns and continuance intention support the hypothesised directions of our model. These results also align with the Approach-Avoidance Theory, with perceived usefulness as an approach path and privacy concerns as an avoidance path. *Figure 5* presents the results from the Pearson correlation matrix.

These results also indicate a non-normal distribution of privacy concerns across all conditions, suggesting that different levels of personalisation have polarising effects on consumers and that moderators may affect the emerging privacy concerns.



PU = Perceived Usefulness, PC = Privacy Concerns, CI = Continuance Intention

Figure 5 Pearson Correlation Matrix (Source: jamovi)

5.4.3 Cell-level Descriptives

Cell-level descriptives report the mean (M) and standard deviation (SD) of each variable for the four experimental conditions, formed by personalisation (low vs high) and personalisation transparency (absent vs present). The descriptives aim to allow for direct comparison of the variables before hypotheses are tested.

Participants in the high-personalisation/transparency condition reported the highest perceived usefulness (M = 5.59, SD = 1.49) and continuance intention (M = 4.69, SD = 1.86). At the same time, their privacy concerns (M = 4.14, SD = 2.08) were higher than those in both low-personalised conditions. The high-personalisation/no-transparency condition reported the highest privacy concerns (M = 5.44, SD = 1.71), with slightly lower perceived usefulness (M = 4.91, SD = 1.31) and continuance intention (M = 3.68, SD = 1.14). The low-personalisation/no-transparency condition reported the lowest perceived usefulness (M = 3.80, SD = 1.73) and continuance intention (M = 3.58, SD = 0.979), and low privacy concerns (M = 3.85, SD = 1.53). Finally, the low-personalisation/transparency condition reported the lowest privacy concerns (M = 3.82, SD = 2.08), which were still close to the low-personalisation/no-transparency condition, indicating that personalisation transparency did not strongly lower privacy concerns when personalisation was low. The perceived usefulness (M = 4.61, SD = 1.52) and continuance intention (M = 4.26, SD = 1.32) in the low-personalisation/transparency condition were in the mid-range of the sample. Values are summarised in *Table 17* below.

Figure 6 visualises the cell means for each latent variable, with a separate line for each transparency condition. The plots for the constructs followed different patterns, indicating possible moderating effects. While perceived usefulness ran approximately parallel across both transparency conditions, rising with higher personalisation, privacy concerns diverged between the transparency conditions under high personalisation. These results suggest an asymmetric effect of personalisation transparency on the mediated pathways. Perceived usefulness rises under high personalisation across both personalisation transparency conditions, indicating no moderating effect. On the other hand, privacy concerns strongly increase under high personalisation with no transparency. But with transparency disclosure present, the increase is only moderate. This supports a possible moderating effect and the Attribution-Theory perspective, that personalisation transparency weakens the formation of avoidance-motivations, such as privacy concerns. For continuance intention, the mean rises with higher personalisation in the condition with personalisation transparency, but remains relatively flat with no personalisation transparency. This suggests that potentially the total effect of personalisation on continuance intention only rises when a transparency disclosure is present.

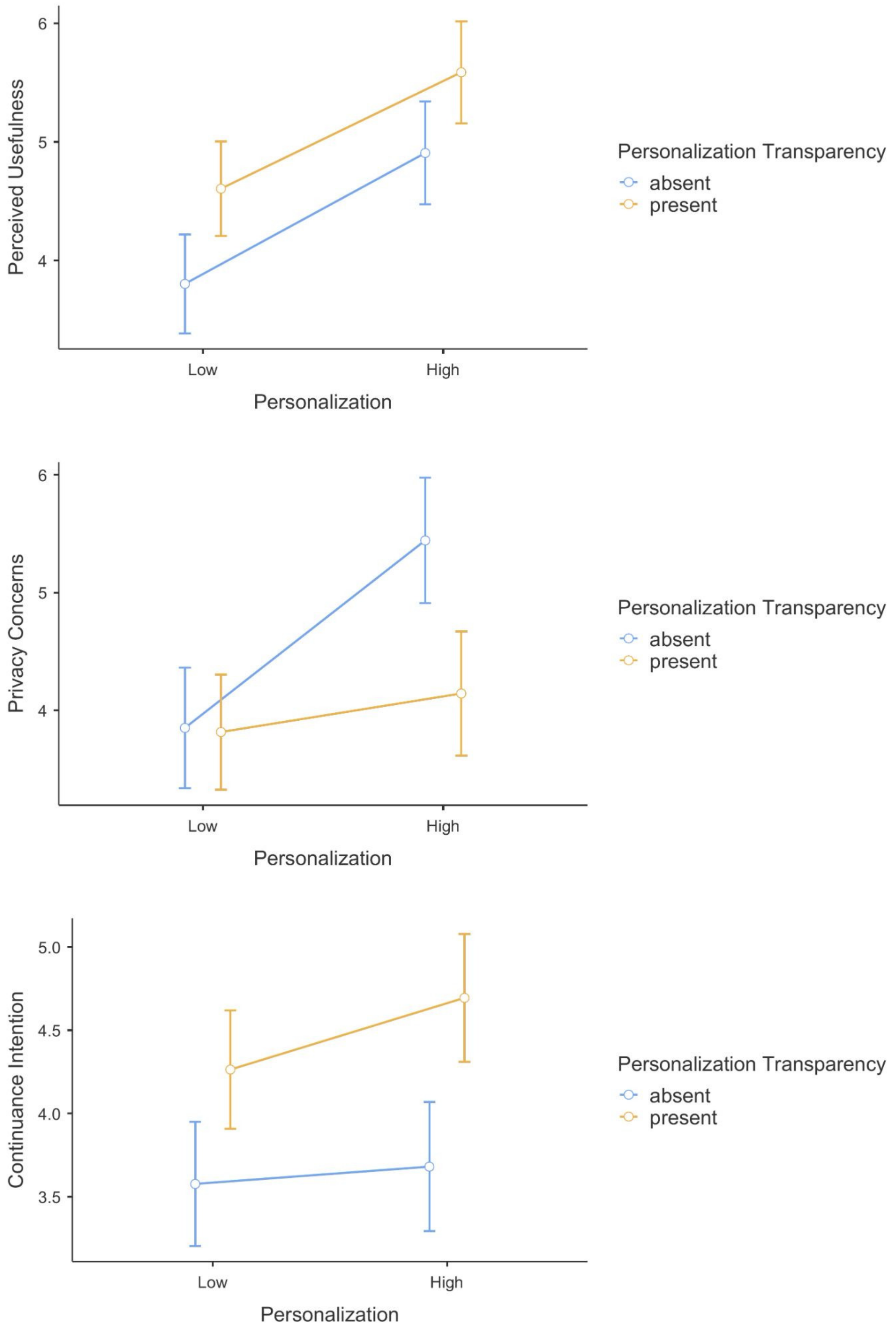


Figure 6 Interaction plots of the latent variables across conditions (source: jamovi)

Table 116 Descriptive Statistics per Condition

Metric	Personalisation	Personalisation Transparency	Perceived Usefulness	Privacy Concerns	Continuance Intention
N	Low	absent	52	52	52
		present	57	57	57
	High	absent	48	48	48
		present	49	49	49
Mean	Low	absent	3.80	3.85	3.58
		present	4.61	3.82	4.26
	High	absent	4.91	5.44	3.68
		present	5.59	4.14	4.69
Median	Low	absent	3.50	3.88	3.33
		present	4.75	4.25	4.67
	High	absent	5.25	6.25	3.33
		present	6.00	4.25	5.00
Standard deviation	Low	absent	1.73	1.53	0.979
		present	1.52	2.08	1.32
	High	absent	1.31	1.71	1.14
		present	1.49	2.08	1.86

5.5 Hypothesis Testing

5.5.1 Total, Direct and Indirect Effects

While the regression analysis does not test the hypotheses, the coefficients for the indirect effects reported with the hypothesis tests are based on the regression equations. To ensure replicability, the regression equations are included in Appendix B. For the moderated mediation analysis, we estimated three regression equations simultaneously, with two equations predicting the effects of personalisation (low vs high) and personalisation transparency (absent vs present) and their interaction, on the mediators perceived usefulness and privacy concerns. The third equation predicted the effect of perceived usefulness, privacy concerns and the direct effect of personalisation on continuance intention.

The equations of the regression analysis explained 15% of the variance of perceived usefulness ($R^2 = 0.150$), 11% of the variance of privacy concerns ($R^2 = 0.110$) and 56.9% of the variance of continuance intention ($R^2 = 0.569$). Furthermore, the personalisation × transparency interaction was significant for privacy concerns (b = -1.265, p = 0.016), but nonsignificant for perceived usefulness (b = -0.122, p = 0.775), suggesting an asymmetric moderating effect.

To test hypotheses 1, 2 and 3, the total, direct and indirect effects of personalisation on continuance intention were analysed. The total effect of personalisation on continuance intention was small and not significant (b = 0.257, 95% CI [-0.140, 0.651]). The direct effect was also small and non-significant (b = 0.115, 95% CI [-0.188, 0.416]). Hypothesis 1, predicting a positive direct effect of personalisation on continuance intention, is therefore not supported.

The non-significant total explained can be explained by the mediation by two effects of similar strength in opposite directions, suppressing each other (MacKinnon et al., 2007). The indirect effect of personalisation on continuance intention mediated through perceived usefulness was positive and significant (b = 0.526, 95% CI [0.310, 0.764]), supporting H2 and the approach-pathway. At the same time, the indirect effect of personalisation on continuance intention, mediated through privacy concerns, was negative and significant (b = -0.379, 95% CI [-0.608, -0.174]), supporting H3 and the avoidance pathway. Taken together, hypotheses 2 and 3 support the personalisation-privacy paradox and the assumptions of the Approach-Avoidance Theory, according to which the two paths can be activated at the same time, independently of one another. *Table 18* presents the total, direct and indirect effects of personalisation on continuance intention.

Table 127 Total, Direct and Indirect Effects of Personalisation of Continuance Intention

Effect	Pathway	b	Boot SE	95% CI
Total effect	P → CI	0.257	0.198	[−0.140, 0.651]
Direct Effect (H1)	P → CI | PU, PC	0.115	0.142	[−0.188, 0.416]
Indirect Effect (H2)	P → PU → CI	0.526	0.115	[0.310, 0.764]
Indirect Effect (H3)	P → PC → CI	−0.379	0.107	[−0.608, −0.174]

P = Personalisation, PU = Perceived Usefulness, PC = Privacy Concerns, CI = Continuance Intention

5.5.2 Conditional Indirect Effects

In hypothesis 4, we postulated that personalisation transparency strengthens the indirect effects of personalisation on continuance intention, mediated through perceived usefulness and in hypothesis 5, we predicted that personalisation transparency would weaken the indirect effect, mediated through privacy concerns. To test these hypotheses, we analysed the conditional indirect effects and the Index of Moderated Mediation for both pathways. The conditional indirect effects test the strength of the indirect effects in each personalisation transparency condition (absent vs present), and the Index of Moderated Mediation represents the differences in the moderated indirect effect across the personalisation transparency conditions as a single number with a 95% bootstrap confidence interval (Hayes, 2015). Moderating effects are considered significant if the confidence interval excludes zero (Hayes, 2015).

The indirect effect of personalisation on continuance intention, mediated through perceived usefulness, was positive with and without personalisation transparency (personalisation transparency absent: $b = 0.556$, 95% CI [0.240, 0.876]; personalisation transparency present: $b = 0.495$, 95% CI [0.189, 0.795]). The Index of Moderated Mediation for this path was small and non-significant (Index = -0.062, 95% CI [−0.485, 0.363]). Thus, hypothesis 4, which predicted that personalisation transparency would strengthen the indirect effect through perceived usefulness, is not supported.

For privacy concerns, the indirect effect without personalisation transparency was negative and significant (personalisation transparency absent: $b = -0.629$, 95% CI [−0.925, -0.362]), but with personalisation transparency, this indirect effect was less strong and non-significant (personalisation transparency present, $b = -0.129$, 95% CI [−0.443, 0.188]). The Index of Moderated Mediation for the privacy concerns path was positive and significant (Index = 0.499, 95% CI [0.096, 0.922]), indicating that personalisation transparency suppresses emerging privacy concerns. Thus, hypothesis 5 is supported, which predicted that personalisation transparency would weaken the negative indirect effect of personalisation on continuance intention, mediated through privacy concerns. These results suggest that personalisation transparency only moderates the effect of personalisation on continuance on the avoidance pathway. *Table 19* summarises the conditional indirect effects and the Index of Moderated Mediation.

Table 138 Conditional Indirect Effects of Index of Moderated Mediation

Pathway	Personalisation Transparency	Conditional indirect effect (b)	95% CI	Index of Moderated Mediation	95% CI
P → PU → CI	Absent	0.556	[0.240, 0.876]	−0.062	[−0.485, 0.363]
	Present	0.495	[0.189, 0.795]		
P → PC → CI	Absent	−0.629	[−0.925, −0.362]	0.499	[0.096, 0.922]
	Present	−0.129	[−0.443, 0.188]		

P = Personalisation, PU = Perceived Usefulness, PC = Privacy Concerns, CI = Continuance Intention

5.5.3 Summary of Hypotheses

Out of the five hypotheses deduced from the Approach-Avoidance Theory and Attribution Theory, three were supported and two hypotheses were rejected, as presented in *Table 20*. The hypothesised positive direct effect of personalisation of continuance intention (H1) was not supported. The hypothesised indirect effects of personalisation on continuance intention, mediated through perceived usefulness (H2) and privacy concerns (H3), were both significant, supporting the approach- and avoidance pathways. Since the direct effect was nonsignificant and the indirect effects were significant, the results implied indirect-only mediation through perceived usefulness and privacy concerns (Zhao et al., 2010).

The moderating effect of personalisation transparency on the indirect effect mediated through perceived usefulness (H4) was rejected, but the moderating effect of personalisation transparency on the indirect effect mediated through privacy concerns (H5) was supported, indicating that the attribution of the firm's motives behind the personalisation landing page only affected the avoidance pathway.

Table 19 Summary of Hypothesis Tests

Hypothesis	Predicted relationship	Result	Supported
H1	P → CI (positive direct effect)	b = 0.115, 95% CI [−0.165, 0.395]	No
H2	P → PU → CI (positive indirect effect)	b = 0.525, 95% CI [0.302, 0.762]	Yes
H3	P → PC → CI (negative indirect effect)	b = −0.372, 95% CI [−0.596, −0.159]	Yes
H4	PT strengthens the indirect effect through PU	Index = −0.062, 95% CI [−0.485, 0.363]	No
H5	PT weakens the indirect effect through PC	Index = 0.499, 95% CI [0.096, 0.922]	Yes

P = Personalisation, PU = Perceived Usefulness, PC = Privacy Concerns, CI = Continuance Intention, PT = Personalisation Transparency

5.6 Discussion

Our study aimed to explore how GenAI-enabled personalisation of landing pages affect the continuance intention of consumers, what mediating role the personalisation-privacy paradox has in this relationship and how personalisation transparency moderates this effect.

While personalisation itself had no significant total effect on continuance intention, the two indirect effects, mediated through perceived usefulness and privacy concerns, were significant. These two indirect effects operate independently in parallel, instead of two opposing sides of one dimension, as supported by the very low correlation and HTMT ratio between the two constructs. Our empirical findings also rejected the hypothesis of the positive direct effect of personalisation on continuance intention, indicating indirect-only mediation.

Furthermore, the moderating effect of personalisation transparency on the indirect effects was analysed and we found that it was significant only for the avoidance pathway, strongly and significantly mitigating privacy concerns, while not significantly affecting the effect mediated through perceived usefulness via the approach-pathway.

These findings provide an empirical validation of the personalisation-privacy paradox in the context of dynamic landing pages, which has not been tested in the existing literature. This study also offers findings on the moderating effect of personalisation transparency, which has not been tested in the context of dynamic landing pages, with empirical data supporting a suppressive effect on emerging privacy concerns on the affective side of the consumer's internal response.

Among other results, the findings on the indirect effects show that the approach- and the avoidance-motivations, reflected in the mediation through perceived usefulness and privacy concerns, are significant and activate simultaneously in opposite directions and with comparable strength, leading to a nonsignificant total effect of high personalisation on continuance intention by suppressing each other.

While similar effects of personalisation have been studied in the setting of banners (Bleier & Eisenbeiss, 2015), advertisements (Sun et al., 2025) and media environments (Bol et al., 2018), the dual-pathway of personalisation on behavioural outcomes has not been studied for dynamic landing pages, a context that Lambillotte et al. (2022) specifically identified as understudied. The findings of the present study are consistent with the bidirectional and independent approach- and avoidance-motivations conceptualized in the Approach-Avoidance Theory (Elliot, 2006). When consumers respond to personalisation as a stimulus, both internal pathways are activated. Thus, our study expands the empirical scope of the personalisation-privacy paradox and supports a parallel mediation approach chosen to study this phenomenon through the lens of Approach-Avoidance Theory. Approaches that summarise the paradox in a single construct (e.g., Sun et al., 2025; Xu et al., 2011) fail to capture consumers' bidirectional motivations.

Another central finding of this study stems from the asymmetric moderating effect of personalisation transparency. Strong and significant transparency in personalisation strongly and significantly reduced the indirect effect of personalisation on continuance intention, mediated by privacy concerns. This means that the conditional indirect effect strongly decreased with personalisation transparency present on the dynamic landing page. Additionally, with personalisation transparency, the entire avoidance pathway was no longer statistically significant. The indirect effect mediated through perceived usefulness was significant and similarly strong in both personalisation transparency conditions, and the moderating effect of personalisation transparency was non-significant. This asymmetry of personalisation transparency as the moderator is by itself already an important finding, contributing to the empirical understanding of the Attribution Theory and to the underlying domain of how consumers react to personalisation .

While hypothesising, we deduced from the Attribution Theory that personalisation transparency would moderate both indirect effects. The theory suggested that disclosing the collection and processing of data for personalisation would prevent consumers from attributing the personalisation to a firm’s self-serving motives (Forehand & Grier, 2003; Kim et al., 2019). Following this logic, we postulated that this shift in attribution toward more consumer-serving motives would strengthen perceived usefulness (approach pathway) and reduce privacy concerns (avoidance pathway) by framing personalisation as helping consumers have a better experience, while legitimising data collection through more acceptable practices. Our data only supports the moderating effect on the avoidance pathway, suggesting that the two parallel pathways are not affected by shifts in attribution in the same way.

While perceived usefulness is a cognitive, function-oriented aspect of the consumer's internal response, privacy concerns are an affective, more motive-dependent factor. Our interpretation of this data is that when consumers consider how functionally relevant the personalisation is to them, the underlying motives of the firm are not as important to them as when they are considering their online privacy and if the firm is exploiting them through unacceptable data collection and processing practices. These findings are aligned with similar results from the literature. For example, Aguirre et al. (2015) discovered that covert data collection practices strengthened the negative indirect effect of personalisation on click-through rates, mediated through perceived vulnerability, indicating that personalisation transparency affects more affective internal states of the consumer. Our findings contribute to the personalisation literature by showing that personalisation transparency does not operate through usefulness and by deepening the understanding of the mechanism in the context of dynamic landing pages.

6 Conclusion

This chapter presents the theoretical contributions and practical implications of this study. Additionally, limitations and future research possibilities are discussed.

6.1 Reflection on Research Aim and Objectives

We aimed to contribute to research on personalisation and privacy by exploring the personalisation-privacy paradox through the Approach-Avoidance Theory in the context of dynamic landing pages, and to gain a deeper understanding of the effects of personalisation transparency. With the introduction of GenAI technologies to marketing practices, personalisation research has not been able to fully keep up with the rapid technological advancements. In addition, dynamic landing pages as a key touchpoint in the customer journey have been severely understudied. Related to the aim of this study, the objectives were to quantify the effects of personalisation transparency, which set the boundary conditions for consumer responses to personalisation, and to validate the Approach-Avoidance Theory's dual-pathway conceptualisation of internal responses to GenAI-enabled landing pages. Additionally, this study had the objective to offer advice for marketing practitioners designing and operating dynamic landing pages. These objectives were conceptualised through three research questions.

In RQ1, we asked to what extent the strength of personalisation on dynamic landing pages affects the continuance intention of consumers. In our study, we found that stronger personalisation did not lead to a higher continuance intention of using the landing page. At first glance, it could indicate indifference on the consumer side towards personalisation, but the real mechanism uncovered goes deeper than that. This leads to RQ2, which asks what role the personalisation-privacy paradox plays in the relationship between personalisation and continuance intention. Our study shows that higher personalisation leads to higher perceived usefulness, which increases continuance intention, but also to higher privacy concerns, which decrease continuance intention. These two independent pathways, operating in opposite directions with comparable strength, were able to suppress the effects of each other, causing the nonsignificant total effect. These findings are consistent with the Approach-Avoidance Theory and empirically support the personalisation-privacy paradox in the context of dynamic landing pages. RQ3 examined personalisation transparency and its effects on the relationship between personalisation and continuance intention. Our study found that transparency disclosures had an asymmetric effect on the paradox, only affecting the avoidance pathway. We interpreted this result through the Attribution Theory, theorising that the attribution of the personalisation and the firm's underlying motives was only significant for the more affective internal response, privacy concerns, and not for the cognitive internal response, perceived usefulness. Based on these answers, the study fulfilled its aim and objectives, with the limitations of these findings being presented at the end of this chapter.

6.2 Theoretical Contributions

From a theoretical perspective, our findings advance the understanding of consumer responses to GenAI-enabled personalisation in multiple ways. We extend the application of Approach-Avoidance Theory to explain the underlying mechanisms of the personalisation-privacy paradox in a GenAI-enabled context. To date, Approach-Avoidance Theory has been primarily applied to evaluate personalised advertisements (Tang et al., 2014; Tang & Zhang, 2020; Loureiro et al., 2023). The application of dynamic landing pages provides a novum and extends the range of touchpoints that can be investigated through this theory. This poses a novel utilisation of the construct, and our statistical results support the proposal by Sun et al. (2025) to apply the theory to GenAI-enabled contexts.

Approach and avoidance are typical behavioural reactions of consumers when they are exposed to a new environment (Tang & Zhang, 2020). Within the literature, multi-faceted meanings of the concepts of approach and avoidance exist (Tang et al., 2014). Our study showed that perceived usefulness can be considered an approach motivation, while privacy concerns operate as an avoidance motivation. Our statistical results reinforce the overall notion among personalisation literature that privacy concerns play a crucial role in the effectiveness of targeted content (Loureiro et al., 2023). We provide evidence that privacy is a salient issue that can prevent consumers from responding positively to personalised applications (Sutanto et al., 2013). At the same time, we add evidence for the paradox by showing that approach and avoidance motivations are activated in parallel and can balance each other out.

Our research further challenges the relevance of the Privacy-Calculus Theory by demonstrating that the Approach-Avoidance Theory can act as a suitable alternative to capture the paradoxical effects of personalisation. This is particularly important, as our study investigated solely covert data collection practices. Privacy-Calculus claims that user disclosing behaviour depends on their evaluation of perceived risks and benefits (Wang et al., 2024). While Privacy-Calculus Theory assumes an option for consumers to decide on their information disclosure, we demonstrate that paradoxical tendencies also exist in covert data collection practices. Furthermore, the Privacy-Calculus assumes cognitive reasoning in consumers' trade-off decisions (Aguirre et al., 2015). Privacy-Calculus Theory, therefore, falls short in capturing affective consumer behaviours associated with covert data collection practices. This underscores the applicability and strength of Approach-Avoidance Theory to provide insights into the paradox.

Beyond identifying suitable theories to explain the personalisation-privacy paradox, we provide a pathway to mitigate the phenomenon. This answers calls from Sutanto et al. (2013) and Wang et al. (2024), who state that emphasis should not only be placed on investigating the phenomenon but also on looking into solutions and methods that mitigate the contradictory outcomes. Wang et al. (2024) propose that the dilemma can be addressed by recommending related products to consumers on e-commerce websites. Sutanto et al. (2013) present an IT solution that processes consumer information locally on their devices. We enrich the theoretical pathways to mitigate the personalisation-privacy paradox by demonstrating that personalisation transparency can lower privacy concerns in high-personalisation contexts.

This is achieved by expanding Attribution Theory into the realm of GenAI-enabled personalisation. While the theory stems from interpersonal psychology and was later applied to commercial settings, we contribute to the understanding of the theory by applying it to a setting in which consumers respond to the attribution of the motives behind complex and opaque GenAI systems and algorithms. The theory transfers to this setting, where disclosures provide the necessary attributional information for consumers viewing personalised content. Furthermore, our results let us speculate about the boundary conditions the Attribution Theory sets. While personalisation transparency affected the affective avoidance path, the cognitive approach path remained relatively constant across both transparency conditions. We interpreted this asymmetry as an indication of how consumers attribute a firm's motives. While the cognitive and functional perceived usefulness is not significantly affected by personalisation transparency, the affective privacy concerns can be mitigated through personalisation transparency. Therefore, we propose the general contribution to Attribution Theory, that attribution interventions, such as transparency disclosures, influence affective, motive-dependent consumer responses more strongly.

Our study contributes to the literature and theory additionally by connecting the Approach-Avoidance Theory with the Attribution Theory. Our results support that the attribution of the firm’s motives affects the motivational paths theorised by the Approach-Avoidance Theory. Avoidance motivations triggered by personalisation can be suppressed through personalisation transparency. This effect was deducted from the Attribution Theory. The insights from our study reveal a dynamic connection between the two theories. Avoidance motivation should not be seen as a static disposition within consumers but rather as an amendable inner state that can be influenced and altered. This adds to the general understanding of consumer behaviour theory by exploring how attributions of the firm's motives influence the formation of approach- and avoidance-motivations.

Furthermore, this study extends the current understanding of personalisation practices by investigating dynamic landing pages as focal touchpoints. This adds to the literature beyond the dominant context of personalised advertisements. We demonstrated how different levels of personalisation can be successfully manipulated in the context of dynamic landing pages. This provides important methodological guidance, as the manipulation can serve as a foundation for exploring other differences in moderating and mediating effects related to personalisation.

Lastly, we acknowledge the argument of Acquisti et al. (2015) that privacy behaviours are context-dependent. Our findings offer direct theoretical insights into the field of online pharmacies, as we show that the paradoxical attitude towards personalisation practices must be acknowledged. We also demonstrate that Approach-Avoidance Theory is a suitable theoretical construct for capturing these attitudes, while the mechanisms of Attribution Theory can be applied in the field of online pharmacies to mitigate privacy concerns.

6.3 Implications for Practice

Our study highlights several practical implications. When designing dynamic landing pages, firms need to be aware that stronger personalisation increases privacy concerns. This trade-off must be weighed when making decisions about GenAI recommendation algorithms. Our findings support Sun et al. (2025) in their observation that “the more personalised, the better” is, in fact,t not necessarily welcomed by the consumers. This is especially evident in the sensitive context of online pharmacies, a fact practitioners should be aware of in the field. In order to increase continuance intention, strongly personalised landing pages should incorporate transparency about the data processing.

Our insights on the effectiveness of personalisation transparency resonate with European legal requirements. Transparency over personal data is a well-acknowledged right, reflected in data protection legislation of the GDPR (Murmann & Fischer-Hübner, 2017). GDPR Articles 15 and 22 provide the framework for automated data processing, which includes the obligation of firms to inform consumers about how their data is being used (Wulf & Seizov, 2022). The GDPR has placed privacy policies as a legal obligation for firms rather than an optional practice (Fox et al., 2022). In this study, transparency in personalisation was implemented as an ex-post disclosure, providing insights into how data were collected and processed. Our recommendations also align with the IEEE (Institute of Electrical and Electronics Engineers), which states that the base of every algorithmic decision should be clearly identifiable (Shahriari & Shahriari, 2017). Our findings therefore positively reinforce the regulative environment firms operate in in European markets.

In our study, we also demonstrated that firms could potentially gain commercial benefits from disclosing their personalisation practices to consumers. The main cause of the negative perceptions of GenAI-enabled personalisation is the vulnerability consumers feel (Fox et al., 2022). The disclosure enables firms to reduce privacy concerns about their dynamic landing page content, thereby increasing continuance intention. As mentioned, continuance intention is a strong lever to ensure future revenues (Bhattacherjee, 2001). Personalisation transparency may therefore have the potential to unlock competitive advantage and serve as a long-term lever for success in eCommerce, as consumers appreciate being informed about how automated data processes affect them (Wulf & Seizov, 2022). This challenges the common notion that regulations primarily function as a hindrance to economic pursuits, showing that disclosures can also create competitive opportunities.

This is especially relevant, as the GDPR provides only limited guidance on how transparency should be established (Wulf & Seizov, 2022). The GDPR specifications remain vague and do not fully reflect the reality of data processed by AI (Wulf & Seizov, 2022). Data processed by GenAI is drastically more complex and opaquer due to the vast computing power and volumes of data (Wulf & Seizov, 2022). With regulations yet to catch up to these developments, transparency disclosures offer firms the opportunity to distinguish themselves as pioneers in the field and secure consumer trust from early on.

Our results indicated that personalisation transparency is a key driver, enabling commercial benefits through continued usage of highly personalised dynamic landing pages. This benefit depends on consumers noticing the disclosure, which cannot be assumed by the firms operating these dynamic landing pages. If consumers overlook or ignore the transparency disclosure, the observed effect might in reality be weaker than what our data showed, which is why a clear design and placement of the disclosure is crucial for firms. Existing research suggests that disclosures can be made salient to consumers through plain language and clear visual prominence (Fox et al., 2022; Wulf & Seizov, 2022; Murmann & Fischer-Hübner, 2017). Our results lay out the potential benefits of applying strategies from existing research and of informing consumers about data collection and processing.

6.4 Limitations

Several limitations need to be considered when interpreting the findings of our study. The first limiting factor of our study stems from the non-probabilistic convenience and snowball sampling methods, which do not guarantee the representativeness of the population (Saunders et al., 2023; Lavrakas et al., 2019).

In addition to the sampling methods used, the single-industry stimulus of online pharmacies limits generalizability, as the conclusions may not extend to other products or industries. As privacy behaviour is context-dependent, the same personalisation might be considered appropriate in one context but inappropriate in another (Acquisti et al., 2015). High-sensitivity contexts, such as online pharmacies, may amplify both the benefits of transparency as well as the negative consequences of over-personalisation. Our findings are therefore context-bound rather than universal.

A scenario-based approach limits ecological validity (Bol et al., 2018). While a vignette-based methodology is able to control for extraneous variables, the scenario is fundamentally different from real-life purchase behaviour under real privacy stakes, underscoring the intentions-behaviour gap. This is especially critical in the context of personalisation practices, as the paradoxical effects themselves are a prime example of actual behaviour diverging from proclaimed attitudes. Also, the explicit questions regarding personalisation, privacy, and transparency in the study might lead to hypersensitization of participants towards these constructs, thereby distorting actual perceptions and attitudes and threatening internal validity. No longitudinal effects are taken into account in the study's results. Continuance intention was measured at a single point in time rather than the actual return behaviour over time.

Lastly, the rate of the transparency manipulation check needs to be addressed, as 21% of the survey's respondents failed to notice the transparency disclosure in the conditions it was displayed and were therefore excluded from the analysis. While this was a deliberate methodological choice to analyse the moderating effect of personalisation transparency, if every fifth consumer misses the disclosure in actual deployment, the actual effects may differ from those in the research model.

6.5 Future Research

In this section, we identify directions for future research based on our findings. To begin, future research should address the methodological gaps of our study design. While online survey-based designs are common in the behavioural research literature, we propose repeating the study as an experimental design, incorporating actual operational dynamic landing pages. This could enable additional insights into consumers' perceptions, eye-tracking of the transparency disclosures and into the willingness to explore the dynamic landing page further. As Salonen and Karjaluoto (2016) suggest, longitudinal studies could also be considered, as they enable the tracking of actual return visits rather than relying on stated continuance intention, thereby closing the gap between intentions and actual behaviour.

Next, future research should apply qualitative approaches to uncover how the attribution of the firm's motives influences the motivations of the consumers. For our study, we deduced from the Attribution Theory how personalisation transparency shapes consumer responses, but we did not collect data on how this attribution functions internally. Our results support our theoretical contribution that attribution shapes only the affective and motive-dependent internal response, but further research is required to uncover the underlying consumer perceptions. Through think-aloud protocols or in-depth interviews, researchers could address the limitations of our study due to quantitative methods when it comes to researching motivations.

Another direction for future research concerns the transparency disclosure itself. As Salonen and Karjaluoto (2016) point out, an understanding of design factors is crucial to understanding the personalisation of landing pages. In our study design, we used a disclosure format integrated into the personalised website. Researchers could incorporate differences in the level of detail of the disclosure, as well as effects related to the explicit statement of "GenAI usage". Thereby, insight could reveal which designs are most effective at reducing concerns, thus also decreasing failed manipulation checks regarding transparency awareness. Additionally, the timing of the personalisation transparency should be investigated further, since ex-ante and ex-post disclosures have been found to influence consumer responses differently (Murmann & Fischer-Hübner, 2017). This means that investigating ex-ante transparency on non-personalised landing pages could be beneficial, with disclosures informing the consumer that the website collects data and will present more personalised content in future visits.

A closer investigation of the sample's demographics could be insightful as well, potentially introducing age as a control variable in the model. From our data, a high variance within privacy concerns became apparent, leading to a non-normal distribution of the variable. This could indicate a polarising effect of personalisation, potentially explained by participants' demographic factors, such as age or gender. Overall, further validation of these individual-level moderators is needed. Related to this, it should be noted that, due to our sampling method, the survey participants are likely to be mainly European. Future research should consider replicating the study in regions where online privacy is less regulated than in the EU, such as the US, China, or India.

Furthermore, the model should be applied to other industries and products to identify context-dependent and independent factors. Our stimulus was a dynamic landing page for a fictional online pharmacy. Acquisti et al. (2015) argue that privacy concerns are a context-dependent phenomenon and we deliberately chose a setting where privacy concerns play a major role. Replicating our study in other empirical settings, such as entertainment, fashion, e-commerce, or hospitality, would enable testing of the asymmetric moderating effect of personalisation transparency and our proposed dual-pathway, potentially improving the generalisability of the results.

To conclude, it can be noted that GenAI continues to redefine the boundaries of personalization and transforms marketing. Therefore the question is no longer how firms can know their consumers better, but if they are willing to let their consumer know them back.

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Use of AI

For this thesis, Artificial Intelligence has been used to a limited extent to assist with the research and writing process. We used Anthropics' Claude model Opus 4.7, Grammarly and Consensus AI to assist with:

- Initial topic brainstorming and summarization of reviewed articles.
- Generating draft text proposals for the survey introduction and vignette.
- Generating mock dynamic landing pages for the survey.
- Improving the authors understanding of statistical methods.
- Assisting with Python code for the Index of Moderated Mediation.
- Refining spelling and clarity.

All AI-generated outputs were carefully reviewed, validated and revised by us to ensure accuracy, relevance, and academic integrity.

In accordance with ethical guidelines, no AI tool was used to generate original research ideas, core arguments, analytical interpretations or critical discussions. We take full responsibility for the content of this study.

Appendix A – Survey

Introduction

Dear Participant,

Thank you very much for taking part in this survey.

This study is conducted as part of a research project in the Master of International Marketing and Brand Management. Your participation is completely voluntary and anonymous. All responses will be treated confidentially and used solely for academic research purposes. The survey will take approximately 5 minutes to complete. There are no right or wrong answers — we are interested in your honest opinions and impressions.

This study is conducted in accordance with the General Data Protection Regulation (GDPR) Regulation (EU) 2016/679). By continuing, you confirm that you are at least 18 years old and agree to participate in this study.

Thank you for your valuable contribution to this research!

Vignette

Imagine the following situation. You are currently living in Malmö, Sweden and pursue an active, sporty lifestyle. Lately, you have been suffering from dizziness and fatigue after your workouts.

You researched online about your symptoms and possible causes. You read some articles online and consulted with an AI Chatbot. You come to the conclusion that some additional nutritional minerals next to your usual intake of supplements might help you best in your situation. Therefore, you open an online pharmacy website that you have visited before to browse for a product that fits your needs.

In the next step, you will be shown a website of an online pharmacy. Take your time to carefully examine the website as if you were making a real purchase evaluation.

Stimulus (randomized)

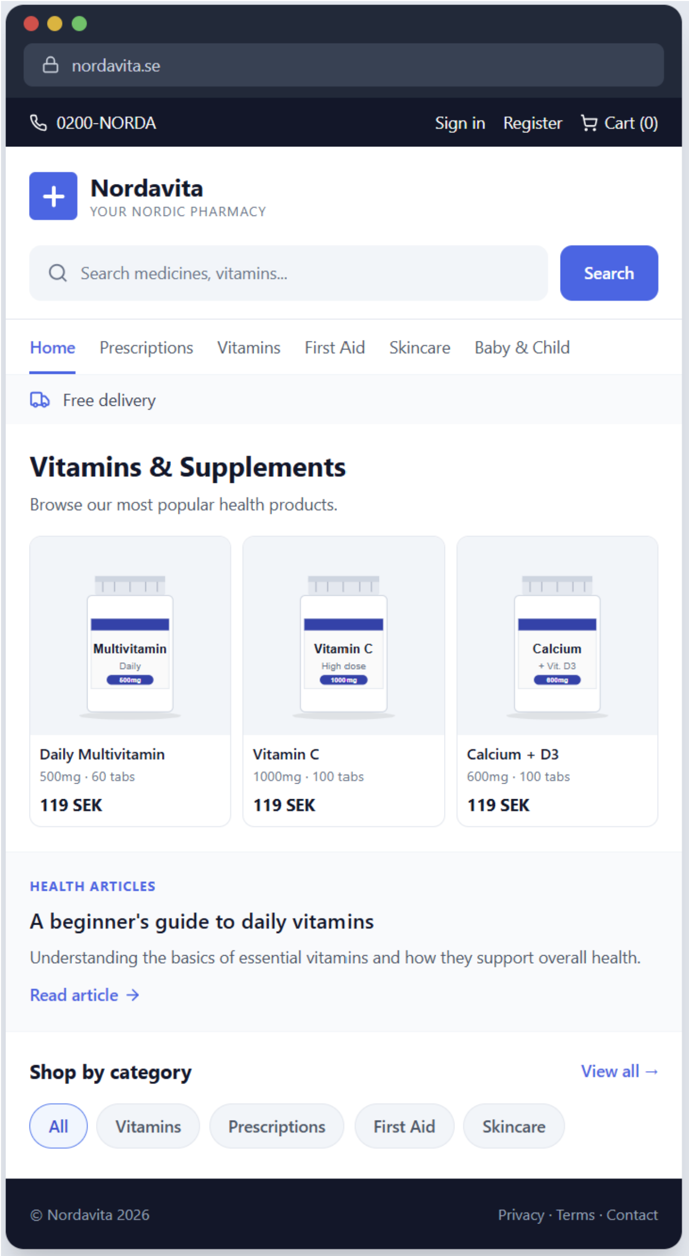

Figure 7 Stimulus 1: Low-Personalisation/no-transparency

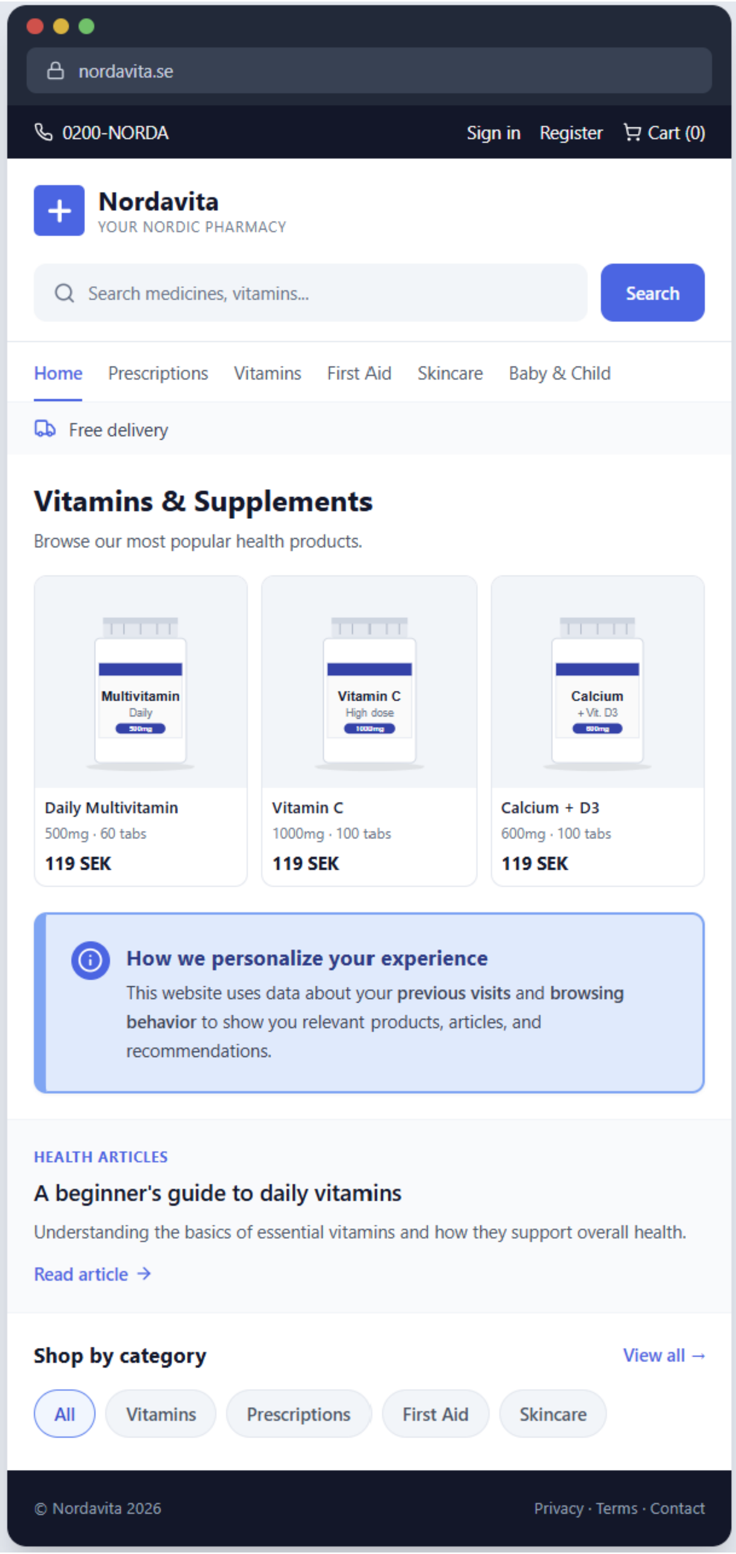

Figure 8 Stimulus 2: Low-Personalisation/transparency

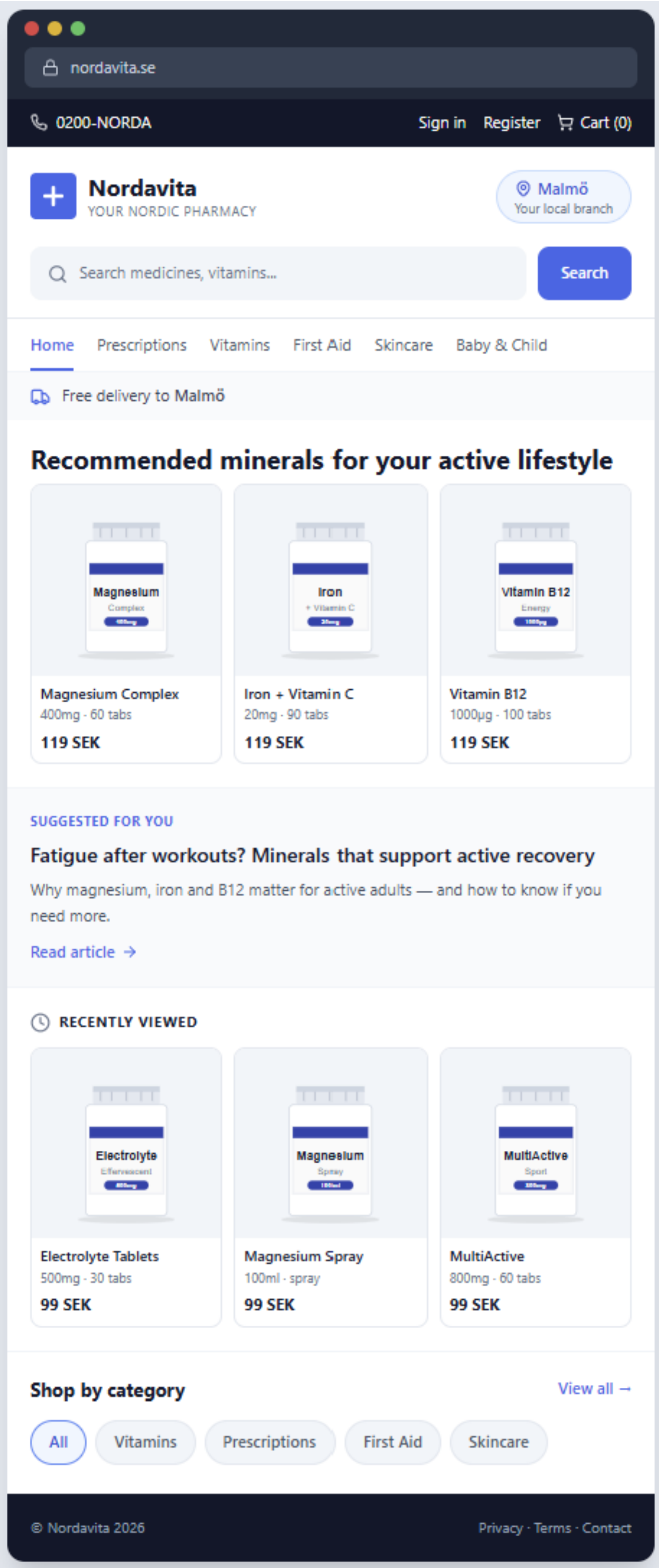

Figure 9 Stimulus 3: High-Personalisation/no-transparency

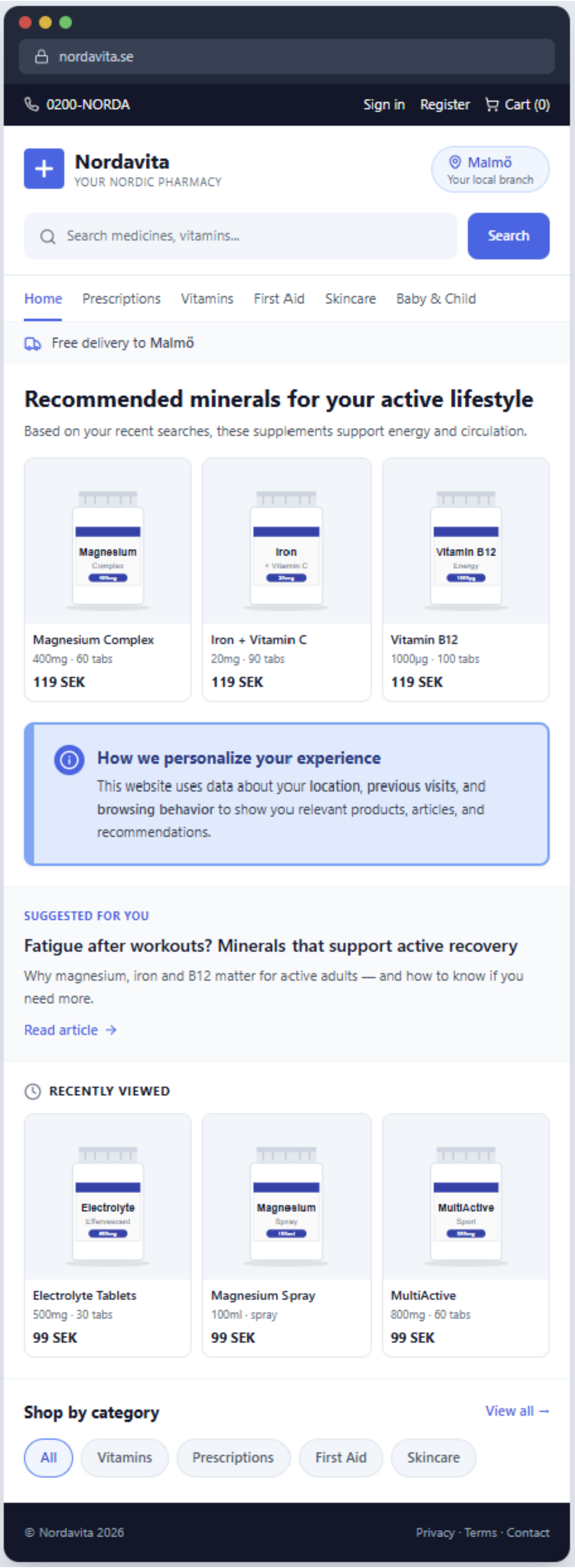

Figure 10 Stimulus 4: High-Personalisation/transparency

Questionnaire

Table 140 Questions Overview

No.	Question	Measurement
Q1	This landing page makes purchase recommendations that match my needs.	Likert-seven scale [Strongly Disagree - Strongly Agree]
Q2	Overall, this landing page is tailored to my situation.	Likert-seven scale [Strongly Disagree - Strongly Agree]
Q3	I believe that this personalised landing page is customized to my needs.	Likert-seven scale [Strongly Disagree - Strongly Agree]
Q4	The landing page enables me to accomplish shopping tasks more quickly.	Likert-seven scale [Strongly Disagree - Strongly Agree]
Q5	The landing page improves my shopping task performance.	Likert-seven scale [Strongly Disagree - Strongly Agree]
Q6	The landing page enhances my effectiveness in my shopping task.	Likert-seven scale [Strongly Disagree - Strongly Agree]
Q7	The landing page makes it easier to do my shopping task.	Likert-seven scale [Strongly Disagree - Strongly Agree]
Q8	It bothers me that the firm is able to track information about me.	Likert-seven scale [Strongly Disagree - Strongly Agree]
Q9	I am concerned that the firm has too much information about me.	Likert-seven scale [Strongly Disagree - Strongly Agree]
Q10	It bothers me that the firm is able to access information about me.	Likert-seven scale [Strongly Disagree - Strongly Agree]
Q11	I am concerned that my information could be used in ways I could not foresee.	Likert-seven scale [Strongly Disagree - Strongly Agree]
Q12	I intend to continue using the website in the future.	Likert-seven scale [Strongly Disagree - Strongly Agree]
Q13	Please select "2" to confirm attention.	Likert-seven scale [Strongly Disagree - Strongly Agree]
Q14	I want to continue using this website rather than use any alternative.	Likert-seven scale [Strongly Disagree - Strongly Agree]
Q15	If I could, I would like to discontinue the use of this website.	Reverse-coded Likert-seven scale [Strongly Disagree - Strongly Agree]

Q16	I was informed on the website of data collection and processing for Personalisation.	[Yes / No]
Q17	Please enter your age	[Text]
Q18	Gender	Multiple Choice [Male/Female/Nonbinary/Other/Prefer not to say]

End of the survey

=== Thank you for completing this questionnaire! ===

We would like to thank you very much for helping us.

If you have any question, feel free to contact us via email be5863ro-s@student.lu.se

Your answers were submitted, you may close the browser window or tab now.

Appendix B- Regression Coefficients

Table 151 Regression Coefficients

Predictor	b	SE	t	p	95% CI	β
Outcome: Perceived Usefulness (R^2 = 0.150)						
Personalisation	1.103	0.305	3.62	<0.001	[0.502, 1.690]	0.317
Personalisation Transparency	0.802	0.292	2.74	0.007	[0.226, 1.379]	0.227
Personalisation × Personalisation Transparency	−0.122	0.426	−0.29	0.775	[−0.962, 0.718]	−0.019
Outcome: Privacy Concerns (R^2 = 0.110)						
Personalisation	1.592	0.374	4.25	<0.001	[0.854, 2.330]	0.404
Personalisation Transparency	−0.035	0.359	−0.10	0.922	[−0.742, 0.672]	−0.009
Personalisation × Personalisation Transparency	−1.265	0.522	−2.42	0.016	[−2.295, −0.235]	−0.274
Outcome: Continuance Intention (R^2 = 0.569)						
Perceived Usefulness	0.504	0.042	11.94	<0.001	[0.421, 0.587]	0.581
Privacy Concerns	−0.395	0.034	−11.45	<0.001	[−0.463, −0.327]	−0.546
Personalisation (controlling for Perceived Usefulness and Privacy Concerns)	0.115	0.142	0.81	0.418	[−0.165, 0.395]	0.041