UNIVERSITY OF GOTHENBURG
SCHOOL OF BUSINESS, ECONOMICS AND LAW

Genomarketing:
Hyper-personalized to You or Too Much to Share?

Michael Chrissos Anestis

Supervisor:

Jonas Nilsson

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Graduate School, School of Business, Economics and Law

University of Gothenburg, Sweden

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Abstract

Hyper-personalization represents a quantum leap beyond conventional marketing strategies by leveraging DNA data to highly tailor products and services to individual consumer profiles like never before. This shift toward genomarketing marks a substantial step forward in hyper-personalizing consumer experiences based on DNA data. This paper attempts to explore the impact of utilizing genomic data—consumer biology (i.e., genetic makeup) related to ancestry, health, and lifestyle preferences—in marketing, focusing on what drives consumer willingness-to-share their DNA data with third parties for hyper-personalized products and services. Through this lens, this research seeks to decode the hyper-personalization-privacy paradox, wherein the benefits of genetically tailored offerings are balanced against the potential risks to consumer privacy. Employing an online survey developed in partnership with a leading Swedish organization in genealogy research, this study utilizes Structural Equation Modeling (SEM) to analyze a sample of 582 Swedish consumers. Weighing a rational cost-benefit analysis of losses (privacy concerns) and gains (personalized benefits), the results reveal a cautious yet passive consumer stance toward sharing DNA data, with trust acting as the gateway mediating their willingness-to-share in hyper-personalized data. By uncovering these insights, this study contributes to the marketing literature through genetic science, expanding the toolkit for marketers and public policy decision-makers.

Keywords: Hyper-personalization, Genomarketing, DNA data, Hyper-personalization-privacy paradox, Consumer privacy, Third-party.

Introduction

Hyper-personalization represents the next step in the nexus of consumer-company interaction, encompassing both customization and personalization options (Rosenbaum *et al.,* 2021). In an era where "Your DNA is one click away" (Buiten, 2020), such hyper-personalization goes beyond conventional marketing metrics (Daviet & Nave, 2024), capitalizing on a consumer's unique genetic makeup, that is, their individual set of genes derived from DNA samples, typically from saliva, to tailor highly personalized products and services (Rosenbaum *et al.,* 2017; Rosenbaum *et al.,* 2021). This approach lies at the intersection of genetic science and marketing, transforming the Marketing 5.0 toolkit (Ivanova-Kadiri, 2022). In what is referred to as the "Technology 5.0" era, Kotler, Kartajaya, and Setiawan (2021) characterize this period as one focused on designing technology that serves humanity, highlighting a growing trend among consumers towards preferring increasingly personalized experiences. It should be noted that the consumption of new technology has not only moved the needle but has also expanded the possible scope of personal data to include biological and neurological markers, which are some of the most inherently personal and valuable as one's own biological composition. Driven by genetic data and technological advancements (Fumagalli, 2019), (hyper-)personalization is now redefining marketing strategies through enhanced segmentation, targeting, and positioning (Daviet, Nave & Wind, 2022; Daviet & Nave, 2024).

The premise is tantalizing: What if the music consumers listen to, the trips they take or the flights they book were all tailored to their genetic profiles? This leap towards utilizing genetic data to align consumers with products and services suggests that behavior might be predestined or genetically determined (Bhattacharjee, Berger & Menon, 2014; Zheng & Alba, 2021). Such a strategy reinforces the concept of biological determinism and may inadvertently strengthen beliefs in predestined behavioral traits (Condit, Ofulue & Sheedy, 1998). For example, Spotify, a Swedish music streaming service, uses genetic data tests to personalize music recommendations (Musical DNA). This approach illustrates an innovative use of genetic data in personalizing consumer experiences that "match their genetic ancestry" (Hassan, 2018; Moore, 2018). Following this, Airbnb, an online marketplace for renting and booking accommodations, curates cultural trips and experiences tailored to an individual's genetic heritage, offering a unique travel experience based on their DNA data. Similarly, Aeroméxico, Mexico's national air carrier, launched a "DNA Discounts" campaign, providing customers with flight discounts to Mexico that correspond to their percentage of Mexican DNA, established through a genetic test (Vora, 2019). At present, a few companies provide access to their customers' DNA data to third-party companies, which in turn can use the data to offer products and services tailored to consumer genomics (Fumagalli, 2019). Nonetheless, the early adoption of genetic data in marketing has predominantly catered to a relatively small market segment of consumers in cultural offerings that correspond with their genetic ancestry for purposes of self-discovery (Daviet & Nave, 2024). These actions mark the dawn of a new age, leveraging direct-to-consumer genetic testing (DTC-GT), where consumers can access their DNA data through genetic tests available directly in the consumer market without the mediation of medical providers, to offer unprecedented hyper-personalization previously unimagined (Ivanova-Kadiri, 2022).

Yet, this move towards hyper-personalization presents a dilemma, raising critical questions about the future course of human civilization: Will the advancement of technology be aligned with the principles of "technology for humanity," or will it veer towards "humanity for technology"? (Ivanova-Kadiri, 2022). Cutting-edge technologies have revolutionized data processing, increasing the amount of consumer data available for analysis (Blasco-Arcas *et al.,* 2022). This technological leap sets the stage for a neologism introduced by this study, "Genomarketing," which leverages genomic data to refine marketing strategies and enhance personalized consumer interactions. This development raises key concerns regarding data collection and usage (Aguirre *et al.,* 2016). Even as some consumers might welcome the use of their genetic data for benefits like tailored recommendations, which could save search costs, ethical and privacy issues remain largely unexplored in the marketing domain. The use of genetic data brings privacy concerns like those related to other data types (Daviet, Nave & Wind, 2022). In a pioneering vein, this continuous tension is termed the *hyper-personalization-privacy paradox*, extending the dialog beyond the conventional personalization-privacy paradox.

To date, marketing scholars have largely neglected the applications of genetics, with only a few exceptions (Daviet, Nave & Wind, 2022; Daviet & Nave, 2024; Fumagalli, 2019; Gabel, 2012; Ivanova-Kadiri, 2023; 2022; McGuire, 2023; Moorman *et al.,* 2024; Nill & Laczniak, 2022); Patsiaouras, 2017; Pearson & Liu-Thompkins, 2012; Zheng & Alba, 2021). Therefore, the current study would be a straightforward extension, aiming to contribute to the development of marketing theory (Daviet, Nave & Wind, 2022). To the best of my knowledge, this research represents one of the first empirical attempts to investigate hyper-personalization via DNA sequencing. Among the few exceptions, Rosenbaum *et al.* (2017) predicted nutrigenomics as a key digital evolution, underscoring the potential of DNA sequencing in personalizing nutrition and wellness. Building on this, Rosenbaum *et al.* (2021) further studied hyper-personalized wellness products as unconventional luxury products, where consumer goods are crafted using a consumer's DNA. Beyond Rosenbaum et al.'s focus on such personalized consumer goods, Daviet and Nave (2024) recently discovered the potential utility of genetic data in predicting consumer (taste) preferences through personalized health, nutrition, and wellness beyond demographics, behavioral variables, and/or even past consumption.

Against this background, this study advances consumer research by exploring the underlying factors that motivate consumers to disclose their DNA data with third parties for hyper-personalization purposes. To bridge these research gaps, this paper seeks to answer the following key research question: RQ: *What drives consumer willingness-to-share their DNA data with third parties for hyper-personalized products and services?* With this question in mind, this study contributes, in an exploratory manner, to the marketing literature by uncovering the role of DNA data in hyper-personalization.

The paper is structured as follows: Initially, a theoretical anchor is provided, reviewing and synthesizing relevant literature on the phenomenon of hyper-personalization-privacy paradox, including analyses through privacy calculus theory, trust, and perception of self. The subsequent section outlines the research methods employed and presents the key findings. Finally, theoretical, and practical implications of hyper-personalization through the DTC-GT lens are discussed, drawing conclusions, and offering final remarks.

Theoretical Anchor

All too often, we hear about DNA but not what it can and cannot tell us. DNA is often regarded as merely a biological blueprint, but its implications are far more this simplistic view. It contains unique and immutable identifiers that render it exceptionally sensitive and deserving of special consideration, a view known as "genetic exceptionalism" (Sulmasy, 2015). Unlike other types of sensitive data, DNA holds the keys to deeply personal insights into who we are, influencing not only our biological traits but also our understanding of heritage and health outcomes (Steverson, Leithauser & Wasson, 2024). Its influence, however, is inherently probabilistic, not definitive, offering possibilities rather than certainties about relatedness (i.e., ancestry), health, and traits (Nill & Laczniak, 2022). Throughout our lives, DNA continually interacts with environmental factors such as exposure to toxins, nutrition, and behavior (i.e., nature and nurture) that together shape our development and health (Klug *et al.* 2019). The genetic information encoded in an individual's DNA (i.e., genotype) lays out a range of possible characteristics (i.e., phenotype), which are then influenced by inherited epigenetic modifications and non-inherited environmental factors (Daviet, Nave & Wind, 2022). These epigenetic factors can change gene expression without altering the DNA sequence itself and can be passed down to future generations (Nill & Laczniak, 2022). Given DNA's complex and sensitive nature, consumer privacy must be scrutinized, particularly as biological mechanisms intersect with technological advancements in hyper-personalization.

Hyper-personalization-privacy paradox

The concept of personalization is defined as *the ability to proactively tailor products…to tastes of individual consumers based upon their personal and preference information* (Chellappa & Sin, 2005, p. 181). It mostly manifests in two forms: personalized advertising and personalized services (Awad & Krishnan, 2006). In both instances, companies construct consumer profiles using data that users either voluntarily disclose or gather through monitoring their behaviors (Chellappa & Sin, 2005). For the purpose of this study, the focus is on personalized services, emphasizing the effectiveness of targeting individual needs (Xu *et al.,* 2011; Chellappa & Sin, 2005). Unlike customization, where consumers modify products to their preferences, personalization involves tailoring products to match specific consumer profiles (Da Silveira, Borenstein & Fogliatto, 2001). Such personalization represents a transformative approach in marketing, where genetic science is seamlessly integrated with marketing strategies (Table 1), the so-called hyper-personalization merging both personalization and customization elements (Rosenbaum *et al.*, 2021).

Without any means to determine whether a DTC-GT firm is acting in its own best interests (Christofides & O'Doherty, 2016; King, 2019), consumers may resist hyper-personalization, perceiving the collection and utilization of personal data that underpin hyper-personalization as too invasive (e.g., Moore *et al.,* 2015). Known as the "privacy paradox", first coined by Barnes (2006), it underscores the incongruity between consumer concerns about personal privacy and their behaviors. Such privacy concerns potentially threaten consumers' sense of autonomy by implying that preferences might be genetically predetermined, thereby undermining the perception of free choice in consumption decisions (Wertenbroch *et al.,* 2020). More specifically, in this study, this manifestation of the privacy paradox evolves into a more complex paradox—the hyper-personalization-privacy paradox. As a new phenomenon, it reflects growing consumer concerns towards privacy and willingness-to-share DNA data with third-party services for interpretation (Guerrini *et al.,* 2020) and product/service recommendations (Daviet, Nave & Wind, 2022). The exchange of DNA data for hyper-personalized services constitutes a "Faustian bargain" for consumers, who might not fully realize that the data they provide, once shared, becomes irrevocable, potentially more valuable than the hyper-personalized services they receive in return (Raz *et al.,* 2020).

Under the hyper-personalization-privacy paradox, some consumers are willing to sacrifice their privacy in exchange for benefits (e.g., personalization), yet paradoxically, consumers view their privacy as a fundamental right and resist any compromises (Smith, Dinev & Xu, 2011). This dichotomy implies that reactive loss of privacy may lead to privacy risks, whereas proactive loss of privacy may result in personalized benefits (Wang *et al.,* 2024). In this paper, privacy concerns and personalization are emphasized as two salient facets.

Privacy calculus theory

Privacy calculus theory (PCT), originally proposed by Laufer and Wolfe (1977), has been extensively studied as one of the most foundational frameworks to examine privacy (e.g., Wang *et al.,* 2024) and to understand behavioral reactions toward data sharing (Kim *et al.,* 2019). Although numerous studies have empirically supported its application (Dinev & Hart, 2006; Xu *et al.,* 2009), PCT has not yet been applied to DTC-GT consumer privacy in the existing literature. Nonetheless, prior studies highlight a similar decision-making process in DTC-GT, where consumers weigh the personal and social benefits against the privacy costs (Grandhi & Plotnick, 2022; Hendricks-Sturrup & Lu, 2020; 2019; King, 2019; Saha *et al.,* 2020). The present research suggests that the decision to share data involves a calculus where consumers assess the trade-offs, weighing the costs of privacy loss against the benefits gained from data sharing (Chellappa & Sin, 2005). This calculated judgment embodies the cornerstone of Exchange Theory (Bagozzi, 1975), frequently applied in understanding privacy-related decisions (Culnan & Bies, 2003). Building on this notion, Carlsson Hauff and Nilsson (2023) contribute to the understanding of this privacy-related behavior trade-off, highlighting how consumers balance the loss of privacy against benefits. Turning to the context of DTC-GT, the potential benefits and their ability to outweigh the concerns remain in question (Daviet, Nave & Wind (2022).

From a rational perspective, consumers consciously and rationally evaluate the cost-benefit ratio of data disclosure (Simon, 1955). Others have questioned this rational view by arguing that individuals are bound in their rational decision-making by several cognitive biases, resulting in a pre-determinable cost-benefit calculation (Simon, 1997). In this cost-benefit analysis, consumers are viewed as rational economic agents, making calculated decisions after sharing their information and forming perceptions of the personalized service (Awad & Krishnan, 2006; Chellappa & Shivendu, 2010; John, Acquisti & Loewenstein, 2011; Pavlou, 2011). This rational assessment and deliberate decision process underscores that the willingness-to-share private data is a cognitive, rather than affective, concept (Aguirre *et al.,* 2015). Recognizing this, the current research is aligned with a PCT's rationalist approach. Notably, Chellappa and Sin (2005) observed that the value of personalized benefits and privacy concerns might be orthogonal to consumers' decision-making. That is, the two constructs operate independently rather than in a straightforward trade-off mechanism. In doing so, it aims to illuminate the hyper-personalization versus privacy paradox, where consumer reactions exhibit when hyper-personalized benefits are weighed against privacy concerns provided by DTC-GT (Aguirre *et al.,* 2015).

DNA-based personalized benefits

Consumer perceptions often lean more favorably towards the benefits from DTC-GT, with risk playing a lesser role in their decision-making process (Grandhi & Plotnick, 2022). These tests, ranging from uncovering forgotten family histories to identifying genetic predispositions towards certain health conditions, appeal to cognitive-driven consumers' views (Daviet, Nave & Wind, 2022). Nill & Laczniak (2022) classify DTC-GT into eight distinct types: Ancestry, relatedness (e.g., Baig *et al.,* 2020; Ruhl *et al.*, 2019; Saha *et al.,* 2020), nutrigenetic, talent and athletic ability, prenatal tests, diagnostic tests, personalized medicine, carrier testing (e.g., King, 2019). Specifically, Toussaint *et al.* (2022) streamline these into three broader groups: Health, Relationship (or Ancestry), and Lifestyle. Such classifications not only segment the primary consumer bases, health enthusiasts, specific genetic information seekers, and consumers with concerns over chronic health conditions or genetic risks, but also enhance consumers' understanding of the diverse offerings of the proposed service, underscoring the critical, sometimes life-altering, benefits of personalized health services (Bol *et al.,* 2018).

For the purpose of this study, ancestry-based benefits were explicitly highlighted as an example. Owing to the popularity of genealogy its practical applications, the so called "genealogy craze" has driven consumer interest (Barnwell, 2013) in learning about ancestors, mapping a family tree, and identifying both new and long-lost biological relatives (Baig *et al.,* 2020). Indeed, DNA data offers a new means of "knowing thyself" by connecting individuals with previously unknown genetic relatives and fostering connections to their ancient family histories (Tutton, 2004).

Additionally, DNA testing stands out as an exponential advancement over traditional over traditional information-seeking methods. Traditional methods, such as historical records and parish registers to compile names and dates of birth and death, often provide limited information and may encounter missing or conflicting records (Darby & Clough, 2013; Duff & Johnson, 2003). There are, at the very least, two key benefits to opting for DNA testing. Firstly, it provides a rock-solid “peace of mind” by confirming suspicions or clarifying uncertainties about one’s ancestry, allowing individuals to understand their roots more clearly (Hazel *et al.,* 2021). Secondly, it helps overcome “brick wall”, points at which traditional methods fail due to missing or conflicting records. By uploading DNA results into an ecosystem, DNA testing offers new leads and connections that traditional documentation might not uncover.

DNA-based privacy concerns

As consumers increasingly seek personalized benefits, privacy costs simultaneously surface. Notwithstanding, the question remains as to which kind of privacy cost is most pertinent to consumers’ willingness-to-share their DNA data for such purposes. To date, privacy studies have characterized these costs in terms of such as privacy risk beliefs, perceived privacy risk or privacy concerns (Bol *et al.,* 2018). In an attempt to be as straightforward as possible within this framework, the term privacy concerns will consistently refer to the cost factor within the PCT throughout the rest of this paper (Chen, 2018; Dienlin & Trepte, 2016; Li, Cho & Goh, 2019) in negatively shaping consumer reactions (Baruh, Secinti & Cemalcilar, 2017; Dinev *et al.,* 2013). From the standpoint of PCT, the term privacy concerns is rooted in fear of opportunistic behavior of data misuse (Karwatzki, 2017) and unease about potential risks when sharing private data (Cherif, Bezaz & Mzoughi, 2021). Among these concerns, the possible misuse of DNA data (Baig *et al.,* 2020; Grandhi & Plotnick, 2022) and the fact that databases of DNA testing companies are often shared with third parties are paramount (Ioan & Hanganu, 2023; Nelson, Bowen & Fullerton, 2019). Carlsson Hauff and Nilsson (2023) linked this cost to a third party acting opportunistically, where personal information collectors may act in ways contrary to the consumer’s interests in sharing, a concern that can sometimes overshadow the benefits of personalization (Awad & Krishnan, 2006).

To this end, the PCT posits that consumers weigh the trade-off between the potential loss of privacy and the gains of personalized services and discounts (Sultan, Rohm & Gao, 2009). Thus, privacy is treated as a commodity whose value can be quantified (Hann *et al.,* 2007). Within this framework, the marketing potential of DNA data is closely intertwined with fundamental privacy concerns (Daviet, Nave & Wind, 2022). Consumers who have already undergone DTC-GT typically manifest lower privacy concerns than non-users, particularly those averse to future testing (Christofides & O’Doherty, 2016; Grandhi & Plotnick, 2022).

To complicate matters further, even when DNA data are labeled as anonymized might still enable reidentification attacks (Gymrek *et al.,* 2013; Saha *et al.,* 2020). This identifiable and predictive nature of DNA data not only pertain to one’s genomic data but also, to some degree, to one’s nongenotyped relatives (Buiten, 2020; Daviet, Nave & Wind, 2022; Daviet & Nave, 2024; Grandhi & Plotnick, 2022; Haeusermann *et al.,* 2018; Ioan & Hanganu, 2023; Nill &

Laczniak, 2022). By its nature, DNA data, inherently familial, has the potential to reveal data about consumers beyond those who consented to testing (Klug *et al.,* 2019; Webborn *et al.,* 2015), effectively serving as a lifelong identifier for both consumers tested and their biological relatives (Nill & Laczniak, 2022). Once leaked, DNA data becomes an irreversible action, with no feasible means to retract or shield this deeply personal information from being accessed and utilized by others, often overlooking regulations or ethical norms. This permanent exposure not only subjects test-takers but also their genetic circle to perpetual privacy vulnerabilities, leaving their most personal genetic data open to potential misuse (Daviet, Nave & Wind, 2022).

As such, one consumer's decision to share genomic data could inadvertently expose familial ties and susceptibility risks to relatives, imposing unintended consequences on them (Buiten, 2020). Arguably, the identifiable and predictive nature of DNA data could enable genomic companies to target individuals and their relatives without consent, raising concerns about privacy (Daviet, Nave & Wind, 2022). This encroachment is problematic not only because it could force consumers to confront their "genetic destiny," limiting their personal freedom and possibly infringing on their fundamental right to self-determination (Nill, Laczniak & Thistle, 2019). In line with Jonas (1985), this is the ethical criticism of the "right to not know." This refers to the ethical dilemma of whether consumers should have the right to refuse certain genetic information, even if it could futher be beneficial or life-saving. Notably, 34% of consumers willing to purchase a DTC genetic test evoked concern about discovering unwelcome aspects of their genetic profile (Friend *et al.,* 2018). Such concerns are substantial enough to deter consumers from utilizing DNA kits (Grandhi & Plotnick, 2022).

In short, the PCT highlights consumers' dilemma: seeking personalized benefits while concurrently grappling with increased risks associated with a loss of privacy (Awad & Krishnan, 2006; Sultan *et al.,* 2009; Sutanto *et al.,* 2013).

On the verges of vulnerability

Vulnerability is a critical aspect of privacy concerns (Bandyopadhyay, 2009; Dinev & Hart, 2004) and is particularly salient when considering the use of DNA data in marketing, which offers personalized benefits but is also fraught with risks (Daviet, Nave & Wind, 2022). Raab and Bennett (1998) describe vulnerability as the perceived risks associated with compromised personal information. Martin, Borah, and Palmatier (2017) defined vulnerability as "*perceptions of susceptibility to harm due to unwanted uses of their personal data, such as those that can result from data breaches or identity theft.*" For the purpose of this study, perceived vulnerability is explicitly focused on consumers' subjective sense of exposure and risk when commercializing their genetic information (Haeusermann *et al.,* 2018).

Recent observations by Steverson, Leithauser, and Wasson (2024) reveal that DNA ancestry companies often employ "genetic essentialism" in their marketing strategies, glamorizing genomic science as definitive scientific "proof" of identity (Nordgren & Juengst 2009). This strategic positioning can raise concerns about manipulation and exploitation of consumers (e.g., Susser, Roessler & Nissenbaum, 2019), particularly those who are susceptible to pseudo-scientific marketing claims that capitalize on the perceived scientific authority of genetics (Buiten, 2020; Daviet & Nave, 2024).

For example, companies could leverage genetic data to identify and target teenagers who have a genetic predisposition towards certain behaviors, such as addictions. Specifically, ecigarette companies might use this data to market their products to teenagers who are genetically more likely to develop nicotine addiction (Richtel & Kaplan, 2018). Much like with other types of data, using DNA data in marketing is overshadowed by misinformation. Misleading marketing messages often overclaim the utility of applications relying on genetic-based recommendations, which consumers might uncritically accept as scientifically validated (Daviet & Nave, 2024; Fumagalli, 2019).

The disclosure of such sensitive information can leave consumers feeling defenceless, facing potential issues of discrimination. Discrimination based on actual or assumed genetic makeup is a possible source of distress, exclusion, and loss of opportunities (Billings *et al.,* 1992), followed by social stigma (Ioan & Hanganu, 2023). For instance, Aeroméxico's DNA, as mentioned earlier discounts campaign, is an example of what essentially amounts to genetic-based price discrimination. It remains unclear whether consumers truly benefited from these DNA-based discounts (Daviet, Nave & Wind, 2022).

Through an overoptimistic view, consumers may underestimate their vulnerability to privacy risks due to cognitive biases and heuristics that distort their understanding of such threats (Xie, Fowler-Dawson & Tvauri, 2018). Given the study focus, however, overoptimism is not framed as an independent variable but as a key element that shapes consumer vulnerability. Consumers often exhibit an overly optimistic perception of the benefits of DNA testing, which consequentially leads them to underestimate the inherent concerns associated with the disclosure of their DNA data (Grandhi & Plotnick, 2022; King, 2019; Saha *et al.,* 2020). Ironically, this skewed perception towards underestimating the immutable nature of DNA information increases their vulnerability to privacy risks (Buiten, 2020). Thus, the following hypotheses are generated:

> **H1a** — *The higher the perceived consumer vulnerability with respect to the use of DNA tests, the lower the personalized benefits.*
> **H1b** — *The higher the perceived consumer vulnerability with respect to the use of DNA tests, the higher the privacy concerns.*

Do consumers know what they think they know?

The inherent complexity of DNA tests makes them difficult for the lay public to understand and use (Nill & Laczniak, 2022). Consumers' poor intuitive understanding of probabilities may lead them to overestimate their knowledge of genetic-based recommendations, even when the probabilistic nature of these recommendations is communicated (Tversky & Kahneman, 1983). Consumer knowledge, which refers to the data that consumers possess when making purchasing decisions (Brucks, 1985), is distinguished in the literature between what consumers know and what they think they know (subjective knowledge) and what consumers actually know as measured by some sort of test (objective knowledge) (Carlson *et al.,* 2009; Raju Lonial & Mangold, 1995; Park *et al.,* 1994). According to Pearson and Liu-Thompkins (2012), it is evident that consumers' perceived knowledge, rather than actual knowledge, influences their attitudes and purchase intentions. In view of this research, the role of subjective knowledge is examined, the metacognitive feeling of knowing (Alba & Hutchinson, 2000) and how it is influenced by consumers' literacy and the calibration of their knowledge towards DTC marketing of genetic tests (Pearson & Liu-Thompkins, 2012).

Generally speaking, consumers tend to overestimate their knowledge levels, a tendency that leans more towards overestimation than underestimation (Alba & Hutchinson, 2000). Many consumers mistakenly overestimate their capability of accurately interpreting these results, leading to ethical and privacy dilemmas (Liu & Pearson, 2008; Nill & Laczniak, 2022), which in turn significantly influences consumer reactions to DTC-GT (Daviet, Nave & Wind, 2022). This phenomenon, reflected in the "illusion of knowing" (Glenberg, Wilkinson & Epstein, 1982; for review, see also Pearson & Liu-Thompkins, 2012), stems from consumers being "unaware of their own ignorance of genetics" (Liu & Pearson, 2008) and is intensified by consumer reactions that presuppose genetic-based recommendations to be scientifically validated, regardless of whether such claims are explicitly made (Zheng & Alba, 2021).

In this context, high subjective knowledge can markedly increase the likelihood of consumers sharing data (Donoghue, Van Oordt & Strydom, 2016; Oh & Abraham, 2016; Utkarsh, Sangwan & Agarwal, 2019) and viewing themselves to be experts, they are more prone to advise and sway their friends' purchasing decisions due to a belief in their superior product knowledge (Utkarsh, Sangwan & Agarwal, 2019). Interestingly, Hadar and Sood (2014) point out a paradoxical behavior where consumers with low subjective knowledge are more inclined to make purchases when presented with more choices, adhering to the "more is better" philosophy. In contrast, those with high subjective knowledge prefer fewer options, a reflection of the well-documented phenomenon of choice overload. However, it is crucial to differentiate between one's confidence in their own knowledge and one's confidence in their decisions. The former can be construed as a measure or manifestation of subjective knowledge, whereas the latter is often a consequence of possessing such knowledge (Hadar, Sood & Fox, 2013). For example, a consumer who perceives themselves as subjectively knowledgeable about DNA testing is likely to feel confident about their knowledge of the subject.

Immersed in perceived knowledge, consumers may disregard the future applications of their genetic data, a reflection of "hyperbolic discounting," where immediate benefits are prioritized over future risks (Buiten, 2020). Research showed that consumers often rely on their subjective knowledge to guide their future behavior, with those having high subjective knowledge more likely to make risky decisions (Hadar, Sood & Fox, 2013). These future applications of DNA data highly promote uncertainty, underscoring the unpredictable nature of genetic data's role in personalization and targeting over the next thirty years (Miller & Tucker, 2018). Subjective knowledgeable consumers are more likely to share their DNA data with third parties without fully appreciating the privacy risk (Nill & Laczniak, 2022). This often stems from consumers' subjective confidence that overshadows objective measures of their understanding (Miron-Shatz *et al.*, 2014), resulting in suboptimal decision-making (Alba & Hutchinson, 2000), exemplified in genetic test-related searches and purchases (Liu & Pearson, 2008; Nill & Laczniak, 2022). Hence, the next hypothesis is proposed:

> **H2** — *The higher the consumer subjective knowledge with respect to the use of DNA tests, the higher the personalized benefits.*

Trust dilemma - To share or not to share

Trust, a fundamental concept defined as *the intention to accept vulnerability based on positive expectations of the intentions or behaviors of another* (Rousseau *et al.*, 1998, p. 395), plays a crucial role in the context of DTC-GT. Not surprisingly, scholars have integrated trust into their privacy calculus models; however, this integration needs to be more present in DTC-GT research. Moreover, prior research has incorporated the concept of trust, in its diverse manifestations, alongside the personalization-privacy paradox (e.g., Aguirre *et al.,* 2015; Guo, Zhang & Sun, 2016; Cloarec, Meyer-Waarden & Munzel, 2022; 2024), but not in the specific context of DTC-GT.

Trust assumes a complex and critical role, acting as a key mediator between personalized benefits and consumer privacy concerns (Guo, Zhang & Sun, 2016; Wu & Xu, 2023). The potential of personalization to erode trust becomes apparent when consumers perceive their privacy to be at risk (Bol *et al.,* 2018). This resonates with consumers, inclined towards perceiving more benefits from data sharing, who were particularly willing-to-share their data for research, while risk perceptions were less influential. Trust in data recipients increased people's willingness-to-share directly (Bearth & Siegrist, 2020). Furthermore, trust is associated with the positive benefits that individuals anticipate from disclosing their data (Cloarec, Meyer-Waarden & Munzel, 2024). External entities' efforts toward enhancing trust serve as promotive mechanisms, in contrast to efforts to reduce privacy concerns, which are reactive mechanisms (Wirtz & Lwin, 2009). Thus, trust assumes a complex role, especially when it concerns the sharing of sensitive genetic information (e.g., Bearth & Siegrist, 2020; Juga, Juntunen & Koivumäki, 2021; Middleton *et al.,* 2020; Milne *et al,* 2021). Consumers voiced a distrust in DTC-GT companies and concerns that they will intentionally share data with third parties (Critchley *et al.,* 2015). In this study, trust is not only seen as a precursor to privacy concerns but also as a central mediator influencing consumers' willingness-to-share sensitive information (Martin & Murphy, 2017), even to the point of providing companies with their DNA (Rosenbaum *et al.*, 2021).

Extensive literature has been focused on consumer data-sharing willingness, either for altruistic scientific or commercial purposes. Research have consistently shown that consumers are aware of the secondary uses of their DNA data (Baig *et al.,* 2020; Mladucky *et al.,* 2021; Saha *et al.,* 2020). This willingness-to-share, however, is not uniform and varies significantly with the intended purpose behind data utilization. Altruistically, previous studies have revealed that consumers feel comfortable with the use of DNA data for research purposes (Mladucky *et al.,* 2021; Ruhl *et al.,* 2019), especially when it contributes to advancements in science and medicine (Haeusermann *et al.,* 2018; Saha *et al.,* 2020). In contrast, other studies observed low willingness among individuals to donate DNA for research, attributing this hesitance to low trust levels in data-sharing practices (Middleton *et al.*, 2020). Looking at it commercially, consumers seem to be resistant to the idea of third parties profiting from personal DNA data (Baig *et al.,* 2020; Critchley *et al.,* 2015; Mladucky *et al.,* 2021). The core of this centers on the key question: How does this willingness-to-share shift for hyper-personalization purposes? Awad and Krishnan (2006) highlighted a notable reluctance among consumers to be subjected to online profiling for personalization, presenting a paradox for companies that invest heavily in personalized services. Trust can positively influence consumers' willingness-to-share information for personalization purposes (Cloarec, Meyer-Waarden & Munzel, 2024).

In all, trust is seen as a central mediator influencing consumers' willingness-to-share DNA data with companies for such purposes, rendering the following hypotheses:

H3 — *The higher the personalized benefits with respect to the use of DNA tests, the higher the trust for hyper-personalization.*
H4 — *The higher the privacy concerns with respect to the use of DNA tests, the lower the trust for hyper-personalization.*
H5 — *The higher the consumer's trust with respect to the use of DNA tests, the higher their willingness-to-share DNA data for hyper-personalization.*

Age differences

Age differences are still relatively under-researched in the DTC-GT, with even fewer studies in hyper-personalization literature related to ancestry-based factors. Age frequently influences how older adults are willing to provide different types of information to various requesting entities (Kim & Choi, 2019). Existing studies indicate a divergence in acceptance intention among younger and older potential users. Younger individuals tend to be more accepting, with their intentions largely driven by perceived personalization (Guo, Zhang & Sun, 2016). Conversely, Awad and Krishnan (2006) highlighted a reluctance among consumers, particularly older ones, to undergo online profiling for personalization. This pattern suggests that older consumers exhibit lower engagement in hyper-personalized data sharing. They are selective about sharing their personal information, depending on the specific type of information and the entities requesting it when using technologies and relevant services (Kim & Choi, 2019). One plausible explanation is that the senior population, which has yet to grow up with ubiquitous computing, are less inclined to embrace new technologies for sharing personal information (Guo, Zhang & Sun, 2016). In Sweden, the elderly population may be less engaged due to digital unfamiliarity or lower internet technology usage (Anderberg *et al.,* 2020). Consistent with prior research, older adults are less willing to self-disclose personal information (Bol *et al.,* 2018). Hence, the next hypothesis is articulated:

H6 — *The older the consumers, the lower their willingness-to-share DNA data for hyper-personalization.*

On the basis of these hypotheses the following schematic research model was developed to serve as a summary of the proposed pathways' predictions:

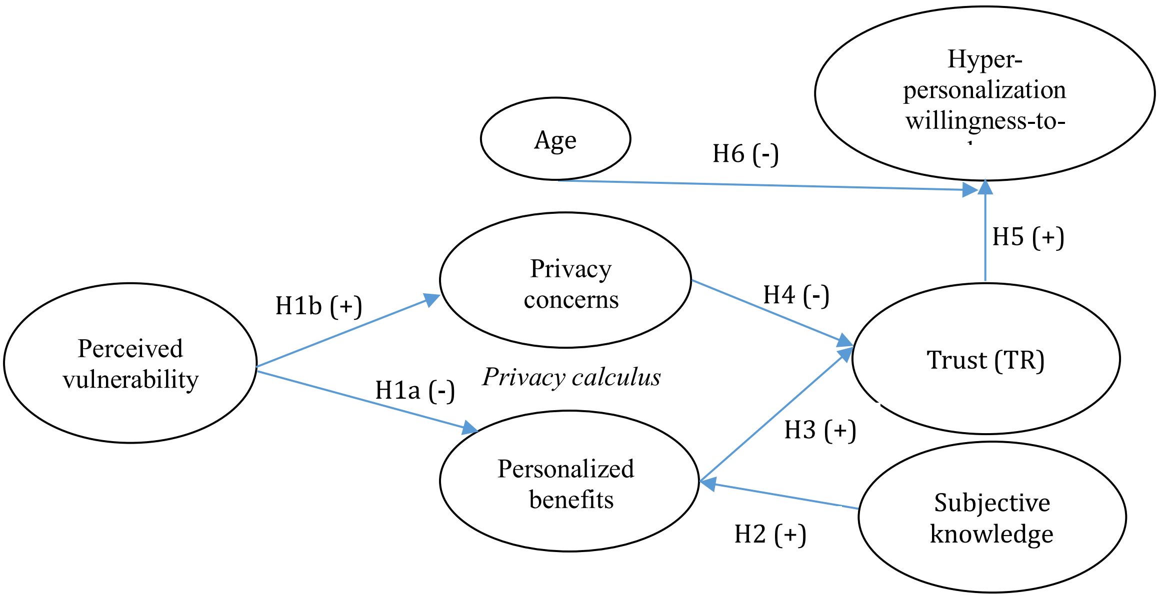

Fig. 1 Research model

Table 1. Applications of DNA data in Marketing Research

Author(s)	Main contributions
Gabel (2012)	Advocating balanced regulatory measures in DNA marketing. Exploring ethical marketing dimensions and risks associated with DNA testing. Addressing the risks of genetic profiteering and misinformation.
Pearson and Liu-Thompkins (2012)	Examining consumers' genetic literacy and calibration, the gap between consumers' actual knowledge and how much they think they know. Revealing how consumers perceived rather than actual knowledge levels drove attitude and purchase intention.
Patsiaouras (2017)	Unveiling a digital genetic data marketplace that shapes biological consumer identities and belonging. Analyzing 'consumer empowerment' and 'choice' in genetic test ads. Suggesting ethical guidelines to improve consumer genetic understanding.
Fumagalli (2019)	Examining the influence of personalized products in DTC DNA testing on marketing strategies and technology. Encouraging debate on ethics versus profit in genetic testing markets.
Zheng and Alba (2021)	Understanding biological underpinnings' influence on marketing stakeholders. Distinguishing between biological and lay perspectives on genetics. Examining self-control through a biological lens in marketing.
Daviet, Nave, and Wind (2022)	Examining the potential uses and misuses of genetic data in marketing. Observing exponential growth in consumer genetic testing and data collection. Proposing a framework to integrate genetic data into consumer behavior theory.
Ivanova-Kadiri (2022)	Presenting genetic marketing and DNA-based customer segmentation theories. Highlighting consumer willingness to share genetic data. Introducing the concept of hyper-personalization for precise targeting in genetic marketing.
Nill and Laczniak (2022)	Discussing ethical and policy challenges in DTC genetic test marketing. Advocating for ethical guideline development and systemic adjustments. Reviewing literature for policy change proposals in DTC genetic test transactions.
Ivanova-Kadiri (2023)	Personalizing products and services with genetic data integration. Utilizing customer genetic data for sustainable product development. Aligning hyper-personalized marketing with environmental benefits.
McGuire (2023)	Developing a gene-centric theoretical framework for marketing. Creating cognitive maps to identify thematic relationships in genomics marketing. Outlining a research agenda and discussing marketing implications in genomic data.
Moorman *et al.* (2024)	Opening new pathways for marketing's role in healthcare and genetics. Disrupting marketing healthcare exchanges among providers, producers, consumers. Shifting the healthcare market towards consumer empowerment via genetic profiling.
Daviet and Nave (2024)	Stressing how genetic data can predict consumer preferences beyond conventional metrics such as demographics, behaviors, or past consumption. Affirming its accuracy of segmentation, targeting, and personalization.

Note: The main contributions listed summarize the authors' work on applying DNA data in marketing research.

Methodology

Sample

An online survey was conducted on the Qualtrics platform in two phases. In the first phase, a pilot study was executed with 40 participants of Swedish origin. The purpose of the pilot test was to establish the reliability and clarity of the questionnaire, mainly focusing on the concept of "hyper-personalization", referred to herein as "high tailoring" due to produced anomalous replies. Alongside the pilot study, expert consultation further refined the questionnaire design, enhancing the accuracy of terminologies and cultural sensitivity.

In the second phase, the primary survey was rolled out in partnership with Föreningen DIS, an acronym for *"Datorhjälp i Släktforskningen"* (=computer assistance in genealogy), a Swedish non-profit organization with over 40 years of engagement with genealogy enthusiasts. By leveraging its network, the survey was able to reach a targeted Swedish segment interested in genealogy and ancestry. A notice was placed in their newsletters, while at the same time, an email was sent to connect with individuals. To ensure linguistic accuracy and cultural relevance, the English version of the survey was translated into Swedish and vetted by the organization before distribution. Sweden was selected due to its active role in global genetic research, including national genome projects (Swede, Stone & Norwood, 2007), making it an ideal setting for DTC-GT studies (Daviet, Nave & Wind, 2022). Participation in the survey was entirely voluntary, underscoring ethical research practices. To boost response rates while ensuring the exclusivity of the participants, a single reminder message was sent out (Sheehan, 2001), reflecting the Swedish ethos of "lagom," meaning "just the right amount." This moderate approach avoids non-compliant behavior (Kittleson, 1997) and aligns with the principle of balance, respecting participants' privacy and time.

The participant selection process within the Föreningen DIS's membership was unbiased, avoiding deliberate inclusion or exclusion and aiming for a sample that representing the association's demographic. Using a non-probability method, participants were chosen for their relevance to the study's aims, not randomly. Representative sampling was confirmed by assessing participants' knowledge about DTC-GT. Following Flynn and Goldsmith (1999), this was measured with the general statement of consumer knowledge ("I know pretty much about DNA testing"), resulting in a high average knowledge score (M=3.39), indicating the sample's strong suitability for addressing the research questions effectively.

A total of 2,031 participants were recruited to participate in the study. Following the removal of 31 responses (~5%) due to random or careless manner such as response time (Meade & Craig, 2012), 582 valid responses were obtained. This yields a valid response rate of 29.1% for online surveys compared to other survey modes (Manfreda *et al.,* 2008). The survey achieved a balanced gender distribution between males (50.5%) and females (47.9%). To ensure confidentiality and integrity, the survey omitted identifying details (e.g., names and email addresses), and to prevent duplicate responses, the survey link was shared for one-time use only. Among these respondents, 46.3% are older adults aged between 70 and 79, with 35.6% holding some college degree. Table 2 shows the demographic profiles of the respondents.

In examining sharing behavior, the survey found that a substantial majority of participants (66.5%) engaged in actual sharing behavior, i.e., consumers who have undergone a DNA test. Primarily, these consumer gained insights into their ancestry through DTC-GT. They might perceive information about ancestry and finding relatives as more informative than health-related results (Ruhl *et al.*, 2019; Wang *et al.,* 2018). Moreover, FamilyTreeDNA emerged as the provider of choice for 45.9% of these respondents, followed by AncenstryDNA with 21.6%, underscoring the study's focus on genealogy. This aligns with Kirkpatrick and Rashkin (2017), who state FamilyTreeDNA and AncestryDNA are key players in DTC ancestry testing for genealogical purposes. The trend shows that 40.9% of the participants underwent only one DNA test, with 25.3% not updating their testing in five years or more, suggesting a period of early adoption followed by a plateau. Interestingly, it is evident that retracting DNA data from databases is a rare practice (65.3%). In contrast to actual sharing behavior, perceived willingness-to-share behavior, i.e., consumers who have not (yet) undergone a DNA test stood at 33.5%, with a smaller fraction (10.3%) expressing an aversion, highlighting a divide in attitudes towards genetic data exchange.

Table 2. Characteristics of respondents

Measure	**Valid sample (N=582)**	
	Frequency	**Percent**
Gender		
Male	300	50.5
Female	279	47.9
Prefer not to say	3	0.50
Age		
Under 49 years	5	0.86
50-59 years	48	8.26
60-69 years	148	25.47
70-79 years	269	46.3
80 years and older	111	19.10
Education		
Less than high school	40	6.9
High school graduate or equivalent	149	25.6
Some college or vocational training	207	35.6
Bachelor's degree	74	12.7
Graduate or professional degree	112	19.2
Actual sharing behavior (i.e., undergone a DNA test)	387	66.5
Number of tests		
One-time test	238	40.9
2 tests	75	12.9
3 tests	37	6.4
4 tests	12	2.1
More than 5 tests	25	4.3
Last DNA test		
1 year ago or less	63	10.8

Table 2. (continued)		
2 years ago	54	9.3
3 years ago	62	10.7
4 years ago	61	10.5
5 years or more ago	147	25.3
DNA testing providers		
FamilyTreeDNA	267	45.9
MyHeritage	148	25.4
Ancestry	126	21.6
23andMe	25	4.3
LivingDNA	19	3.3
Other	12	2.1
DNA testing categories		
Ancestry	384	66.0
Health	25	4.3
Lifestyle	7	1.2
Perceived willingness-to-share behavior (i.e., not undergone a DNA test)	195	33.5
Not consider at all (1)	26	4.5
(2)	34	5.8
(3)	47	8.1
(4)	36	6.2
Absolutely consider (5)	52	8.9

Measurement

For this study, a structured questionnaire was crafted, consisting of three parts. Categorically, the first part introduces the purpose and the context of the research, orienting respondents to the study's objective. The second part contains a screening section determining participants' prior experience with a DTC-GT and statement-like items rated on a five-point Likert scale anchored by (1) = *strongly disagree* and (5) = *strongly agree*. Such a scale offers a granular (step-by-step) spectrum of selections, granting respondents the autonomy to read out the complete list of scale descriptors (Dawes, 2008) and considering that the target sample may include participants inexperienced with online questionnaires. To the extent possible, all constructs were established based on prior research and reframed to suit the present research context, except for personalized benefits (PB). This original construct was developed from prior qualitative studies (Grandhi & Plotnick, 2022; Baig *et al.*, 2020; Saha *et al.*, 2020; King, 2019; Ruhl *et al.*, 2019) owing to the absence of pre-existing scales. Privacy concerns (PC) was operationalized by adapting a four-item scale from Xu *et al.* (2011). Key objective of this study was to delve into consumer responses to the hyper-personalization-privacy paradox through these two lenses. Perceived vulnerability (PV) was conceptualized around a five-item scale from Martin, Borah, and Palmatier (2017), while consumer subjective knowledge (SK) was measured using a subset of five items from the nine-item scale by Flynn and Goldsmith (1999). In alignment with Guo, Zhang, and Sun (2016), trust (TR) was posited as the central mediator of the hyper-personalization-privacy paradox for this study, measured using a five-item scale adapted from Malhotra, Kim, and Agarwal (2004). As an outcome, hyper-personalization willingness-to-share (HPW) was innovatively adapted from Culnan and

Armstrong's (1999) two-item scale of willingness-to-share for personalization (for review, see also Awad & Krishnan, 2006), refined to emphasize hyper-personalization. This adaptation sets it apart from broader willingness-to-share measures (e.g., Xu *et al.,* 2011) by explicitly giving emphasis on the sharing of highly personal data. An attempt has been made to counterbalance the sequence of the questions about the different measures for avoiding respondent fatigue (Podsakoff *et al.,* 2003). Finally, the third part covers standard demographic elements of participants on gender and educational background presented as closed-ended, multiple-choice questions and uniquely asks participants' birth years rather than age intervals to improve data accuracy. This categorization facilitates an accessible interpretation of age-related trends within the cohort. Notably, respondents were given the opportunity to leave comments in an open-ended question section for any additional insights or feedback, enhancing the depth of the collected data. All items are listed in Table 3 below.

Table 3. Construct and measurement item

Constructs[1]	**Mean**	**SD**
Personalized benefits (PB)[2] Grandhi & Plotnick (2022); Baig *et al.,* (2020); Saha *et al.* (2020); King, (2019); Ruhl *et al.* (2019)	**3.81**	**0.824**
PB1 – Undergoing a DNA test is beneficial as I can learn more about genealogy and ancestry.	4.32	.942
PB2 – Undergoing a DNA test is beneficial as I can find family members and relatives.	4.29	.930
PB3 – Undergoing a DNA test is beneficial as I can learn more about myself.	2.81	1.253
Privacy concerns (PC) Xu *et al.* (2011)	**3.28**	**1.241**
PC1 - I am concerned that the DNA data I submitted to genetic testing companies could be misused.	3.31	1.239
PC2 - I am concerned that unauthorized people can find personal DNA data from genetic testing companies.	3.31	1.228
PC3 - I am concerned about having provided DNA data to genetic testing companies because of what others might do with it.	3.23	1.267
PC4 - I am concerned about having provided DNA data to genetic testing companies because it could be used in ways I did not foresee.	3.26	1.231
Perceived vulnerability (PV) Martin, Borah, and Palmatier (2017)	**3.15**	**1.280**
PV1 - The DNA data that the company holds about me makes me feel *insecure*	3.25	1.243
PV2 - The DNA data that the company holds about me makes me feel *exposed*	3.16	1.295
PV3 - The DNA data that the company holds about me makes me feel *threatened*	2.93	1.320
PV4 - The DNA data that the company holds about me makes me feel *vulnerable*	3.22	1.295
PV5 - The DNA data that the company holds about me makes me feel *susceptible*	3.19	1.248
Subjective knowledge (SK) Flynn and Goldsmith (1999)	3.26	1.249
SK1 - I know pretty much about DNA testing.	3.39	1.151
SK2 - I know how to judge the quality of a DNA testing service.	3.22	1.236
SK3 - I think I know enough about DNA testing to feel pretty confident when I make a purchase.	3.52	1.180
SK4 - Among my circle of friends, I'm one of the "experts" on DNA testing.	2.80	1.395
SK5 - I have heard of most of the new developments in DNA testing that are around.	2.88	1.282
Trust (TR) Malhotra, Kim, and Agarwal (2004)	**2.86**	**1.166**
TR1 - The company is trustworthy in handling the DNA data.	2.96	1.139
TR2 - The company tells the truth and fulfil promises related to the DNA data provided by me.	2.83	1.172

Table 3. (continued)		
TR3 - I trust the company to keep my best interests in mind when dealing with the DNA data.	2.73	1.194
TR4 - The company is generally predictable and consistent in its usage of the DNA data.	2.90	1.128
TR5 - The company is always honest with consumers when it comes to using the DNA data that I provide.	2.90	1.148
Hyper-personalization willingness-to-share (HPW) Culnan and Armstrong (1999)	**1.71**	**1.034**
HPW1 - I am interested in having my personal information used by the genetic testing company for hyper-personalization of products and services.	1.75	1.066
HPW2 - I am likely to provide my personal information to the genetic testing company to receive hyper-personalized recommendations of products and services	1.67	1.003

[1] The development of this measurement scale is an original construct, synthesizing and expanding upon prior research.

Data analysis

To examine the research model of this study, a three-step approach was utilized, employing SPSS 25.0. and STATA 18.0. Initially, descriptive analysis was employed to summarize the dataset's characteristics. Subsequently, exploratory factor analysis was performed to assess the adequacy of the measurement scales, particularly for the newly developed scale (PB). Based on the prior information from EFA, CFA was then applied to validate the construct validity of the scales, further refining the factor structure identified by the EFA. The final stage entailed assessing and analyzing the hypothesized relationship model through structural equation modeling (SEM).

Results

In the first step, descriptive analysis for all variables was conducted. As summarized in Table 3, each variable presents the means and standard deviations for each study variable. Notably, PB is generally perceived positively among consumers regarding DNA testing (M = 3.81, SD = 0.824). However, PC (M = 3.28, SD = 1.241), PV (M = 3.15, SD = 1.280), SK (M = 3.26, SD = 1.249) and TR (M = 2.86, SD = 1.166) among consumers showed varying levels. As expected, HPW (M = 1.71, SD = 1.034) exhibited a reluctance among consumers, with attitudes towards sharing behavior showing considerable variability.

Validity and Reliability

In the second step, exploratory factor analysis (EFA) was employed to uncover the underlying structure of the instrument. Principal component analysis with varimax rotation, a commonly used method that simplifies the factor structure by maximizing the variance of the squared loadings, initially extracted twenty-four observed variables across six reflective theoretical constructs. Varimax is a commonly used rotation method when the sample structure is clear (Corner, 2009).

Factor loadings below 0.4 were discarded to simplify a factor structure, exceeding the general rule for over 350 observatories (N=582). All items are loaded onto the expected factors. After inspecting the communality, however, PB3 did not meet the criterion <0.5, leading to its exclusion and a refined factor solution. By adopting the eigenvalue of 1, the revised factors, including PB, PC, PV, SK, TR, and HPW (Table 4) accounted for an increased total variance explained 80.340%. As such, the data demonstrated robust construct validity.

Bartlett’s test of sphericity demonstrated a significant correlation between the original variables (chi-square = 10869.323, $p < 0.001$), whereas the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy is close to 1 (KMO=0.839); together they indicate that the data are suitable for factor analysis (Hair *et al.,* 2013). Subsequently, reliability check was performed. Cronbach’s alpha (α) values were used to measure the internal consistency, ensuring that the observed variables were free of errors and accurately measured. All items scored well above the recommended cut-off of 0.70, ranging from 0.844 to 0.961 (Hair *et al.,* 2013). Briefly, the results of the analysis justify the use of the EFA as all the criteria were well exceeded.

Table 4. Construct measures and scale reliability.

Constructs	**Items**	**Component**								**Communality**	**Cronbach’s Alpha**
		1	2	3	4	5	6	7	8		
PB1	2	.906								.868	.844
PB2		.896								.862	
PC1	4			.905						.863	.961
PC2				.928						.904	
PC3				.928						.919	
PC4				.927						.896	
PV1						.821				.703	
PV2						.916				.876	
PV3	5					.912				.865	.939
PV4						.883				.824	
PV5						.853				.775	
SK1							.804			.663	
SK2							.882			.786	
SK3	5						.836			.754	.893
SK4							.817			.702	
SK5							.816			.678	
TR1								.837		.715	
TR2								.893		.815	
TR3	5							.859		.760	.922
TR4								.848		.738	
TR5								.884		.797	
HPW1	2								.920	.857	.834
HPW2									.920	.857	

Extraction method: Principal component analysis.
Rotation method: Varimax with Kaiser Normalization

a. Rotation converged in 6 iterations.

Overall model fit

Following EFA, the factor structure was further tested through confirmatory factor analysis (CFA). As shown in Table 5 below, the results of goodness-of-fit indices (GFI) for the SEM of hyper-personalization are displayed. The model yielded a chi-square CMIN/ df=3.37. Although this value exceeds the more stringent threshold of 3.00 (> 3.00), it remains below the permissible cut-off point of 5.00. This is considered acceptable, given the Chi-square test's sensitivity to large sample sizes (Byrne, 2013). To assess the overall model fit, four widely recommended fit indices were employed (Hu & Bentler, 1999): Root Mean Square Error of Approximation (RMSEA) =0.077 (<0.10) (Browne & Cudek, 1993), Comparative fit index (CFI) = 0.932 (> 0.90) (Hu & Bentler, 1995), Standardized Root Mean Square Residual (SRMR) = 0.04 (<0.10) (Bentler, 1995), Tucker–Lewis index (TLI) = 0.919 (> 0.90) (Bentler & Bonett, 1980). As a result, the indices demonstrated the model of goodness-of-fit in which the final model adequately fits the data.

Table 5. Fitness indices.

Name of category	Name of index	Model value	Recommended value
Absolute fit	Chisq	0.00	p >.05
	RMSEA	0.077	< .10
	SRMR	0.040	< .10
Incremental fit	CFI	0.932	> .95
	TLI	0.919	> .90
Parsimonious fit	Chisq/df	3.370	2-5 3.00

Measurement fit model

Once fit validity was established, construct validity was assessed through evaluations of both convergent and discriminant validity. Convergent validity was ascertained by inspecting the factor loadings (lambdas), which were found to be satisfactory (> 0.50) and highly significant across all constructs (Jöreskog & Sörbom, 1993) criteria. Additionally, the Composite Reliability of all constructs exceeded the 0.80 threshold, signifying their acceptability. The Average Variance Extracted (AVE) was also tested for all constructs. By computing AVE, all constructs surpass the cut-off value 0.50 (Hair *et al.,* 2019). Consequently, convergent validity was assured (Table 6). Additionally, discriminant validity was assessed. On the basis of Fornell and Larcker (1981), the analysis involved comparing the AVE with the squared estimated correlations between each construct. Since none of the squared correlations among the constructs surpassed the square root of the AVE from the constructs, it is evident that discriminant validity was successfully established.

Table 6. Summary for all constructs.

Construct	**Composite Reliability (CR)[a]**	**Average Variant Extracted (AVE)[b]**
Personalized benefits	0.84	0.73
Privacy concerns	0.96	0.86
Perceived vulnerability	0.94	0.76

Table 3. (continued)

Subjective knowledge	0.89	0.63
Trust	0.92	0.70
Hyper-personalization willingness-to-share	0.83	0.72

[a]Composite reliability = (Σstd. factor loadings)^2 / [(Σstd. factor loadings)^2 + Σe]

[b]Composite reliability = (Σstd. factor loadings)^2 / (Σstd. factor loadings^2 + Σe)

Construct model fit

For the structural model, the coefficient of determination (R^2) was employed to examine the consumer's willingness-to-share DNA data with third parties for hyper-personalization purposes. The R^2, which is close to one, can signify a strong predictive ability; the complexity of consumer behavior in privacy-sensitive data-sharing contexts often results in lower R^2 values. As expected, the results revealed a moderate level of influence of the independent variables on the dependent variables: personalized benefits (R^2_{PB} = 13.26%), privacy concerns (R^2_{PC} =16.57%), trust (R^2_{TR} =6.55%) and hyper-personalization willingness-to-share (R^2_{HPW} =4.7%). In (hyper-)personalization privacy paradoxes, it is expected to observe lower R^2 values due to the myriad influences on behavior. The tested model is depicted in Fig. 2, which detailed SEM results presented in Table 7. The model includes four latent-independent (exogenous) variables: PB, PC, PV, SK; one control variable: Age; one latent-dependent (endogenous) variable: HPW; one central latent-mediating variable: TR.

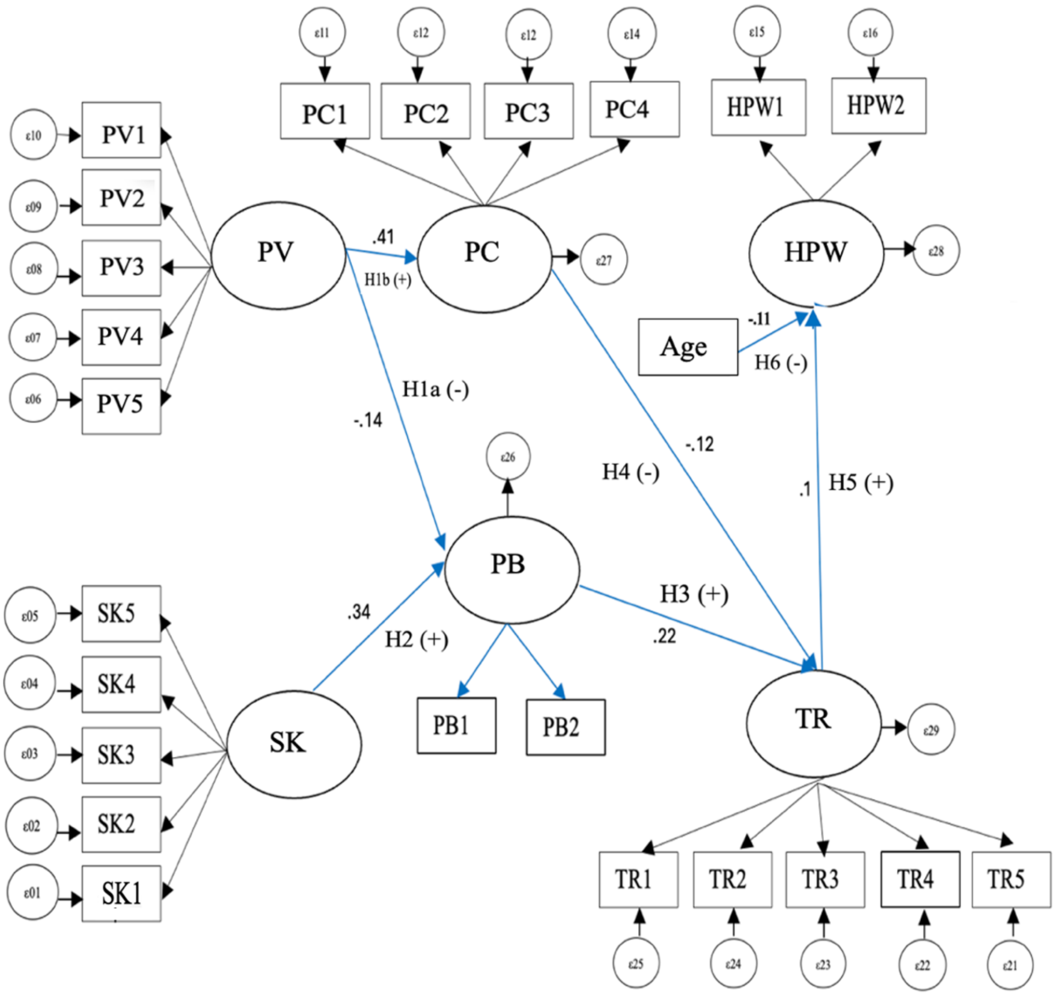

Fig. 2. SEM of Hyper-personalization

Hypothesis testing

To test the hypotheses and deepen understanding of (i) the hyper-personalization-privacy paradox and (ii) the mediation role of trust, both direct and indirect relationships were analyzed. Results revealed that perceived consumer vulnerability has a dual impact: it negatively influenced personalized benefits ($t = -3.17$, $p < 0.05$) and positively influenced privacy concerns ($t = 11.16$, $p < 0.01$), thereby supporting H1a and H1b. In support of H2, subjective knowledge was found to impact personalized benefits positively ($t = 7.69$, $p < 0.05$). Further supporting the model, personalized benefits were shown to positively influence trust ($t = 4.90$, $p < 0.01$), supporting H3. Conversely, privacy concerns had a negative effect on trust ($t = -2.75$, $p < 0.01$), which confirmed H4. As the central gate in this study, trust also positively influenced such hyper-personalization willingness-to-share ($t = 2.48$, $p < 0.05$), affirming H5. Among the demographic variables included in the analysis to control for potential confounding effects (i.e., gender, age, education), only age was found to exert a significant influence on hyper-personalization willingness-to-share negatively ($t = -2.56$, $p < 0.05$), thereby confirming H6. As summarized in Table 7, all hypotheses were well supported, and the proposed research model (Fig. 1) was empirically validated.

Table 7. Construct path estimates.

Relatioships	Path coefficient	*t-value*	*p*-value	Result
H1a: PV → PB	−0.139*	−3.17	0.002	Supported
H1b: PV → PC	0.407*	11.16	0.00	Supported
H2: SK → PB	0.336*	7.69	0.00	Supported
H3: PB → TR	0.220*	4.90	0.00	Supported
H4: PC → TR	−0.118**	−2.75	0.01	Supported
H5: TR → HPW	0.123**	2.48	0.01	Supported
H6: Age → HPW	−0.120**	−2.56	0.01	Supported

Note: $^*p < .01$, $^{**}p < .05$

Discussion

The paper illuminates the concept of hyper-personalization, examining it through the lens of genetic science. DNA-based applications in marketing, remains largely unexplored, leaving significant gaps, particularly in understanding the consumer's willingness-to-share information for (hyper-)personalized products and services (Awad & Krishnan, 2006; Cloarec, Meyer-Waarden & Munzel, 2024; Culnan & Armstrong, 1999). Toward this end, a novel research model was developed to decode the hyper-personalization-privacy paradox. The model, viewed through a privacy calculus lens, evaluates consumers by rationalizing and weighing the benefits of genetically tailored offerings against the potential risks to their privacy.

The first key finding reveals consumers manifested a high level of subjective knowledge about DTC-GT, reflecting a certain level of familiarity and confidence in their understanding of the subject matter. This high subjective knowledge positively influenced consumers' perceptions of personalized benefits. Aligned with Nill and Laczniak (2022), consumers who perceive themselves as knowledgeable about DNA testing are more likely to share their DNA data with third parties. This action could potentially lead to underestimating the associated privacy risks. This evidence supports the rationale of Buiten (2020) and Grandhi and Plotnick (2022), who prioritized benefits over costs in the DTC-GT landscape.

Prior research has underscored the significant role consumer vulnerability plays in shaping privacy concerns (Bandyopadhyay, 2009; Dinev & Hart, 2004) and realizing personalized benefits (Daviet, Nave & Wind, 2022). This dual influence, however, has yet to be quantified within the DTC-GT context in marketing. This study, however, takes a step further by quantifying this influence. A major finding is that high levels of perceived vulnerability significantly reduce personalized benefits (i.e., ancestry) from genetic-based marketing offers. At the same time, higher levels of perceived vulnerability corresponded with higher levels of privacy concerns. One conceivable reason is a general poor understanding among consumers about the ramifications of sharing their DNA data. For instance, companies like FamilyTreeDNA, AncestryDNA and MyHeritage market these DNA kits via gift certificates, which could trivialize the decision to purchase them. When a DNA test is purchased as a gift, the giver often fails to adequately inform the recipient about the full implications of using the test, leaving them without the necessary information to make an informed choice (i.e., consumers do not fully understand what they are actually agreeing to). This could make these consumers particularly vulnerable, as they may not recognize the nature of the gift itself, where DNA constitutes particularly sensitive personal information (King, 2019), leading to uninformed or misinformed (superficial) consent (O'Doherty *et al*., 2016; Schaper, Wöhlke & Schicktanz, 2019).

Moreover, this research brings to light the central role of trust in the calculus. Similar to Wu and Xu (2023) and Guo, Zhang and Sun (2016), trust acts as a mediator between personalized benefits and privacy concerns towards sharing behavior. Importantly, personalized benefits were found to have a positive influence on trust among consumers, particularly when it comes to the prospect of sharing data (Cloarec, Meyer-Waarden & Munzel, 2024). This suggests that individuals who perceive personalized benefits from DNA testing (e.g., learning about ancestry/genealogy or finding family members) are more likely to place trust in the companies handling their DNA data. Conversely, privacy concerns were observed to erode trust, indicating that fears about potential data misuse or unauthorized access can diminish consumer trust in these companies.

In turn, trust emerged as the central gateway of sharing behavior in exchange for hyper-personalized experiences. Meanwhile, beneath this willingness-to-share lies a cautious consumer stance, with trust tempering their willingness to engage in hyper-personalized data sharing. This finding lends support to Awad and Krishnan (2006), who highlighted a reluctance among consumers to undergo online profiling for personalization.

Interestingly, most consumers in this study engaged with these services more than five years ago and typically opted for a one-time testing service. This occasional engagement suggests that once consumers obtain their DNA results, they feel free of the need for additional tests. This behavior is reflected in the rarity with which consumers retract their DNA data from databases, an indication of a cautious yet passive attitude towards the management of stored data. Such trends support the view that consumers generally regard DNA testing as a one-off transaction rather than an ongoing relationship.

Alternatively, it might reflect a cautious approach to the use of such technologies, driven by an instinctive mistrust. This pattern arises from the specific age cohort of this study, with older consumers displaying lower engagement in hyper-personalized data sharing. One plausible explanation for this trend is that elderly consumers, having come of age without ubiquitous computing, are less likely to embrace new technologies for sharing personal information (Guo, Zhang & Sun, 2016; Kim & Choi, 2019) due to digital unfamiliarity or lower usage of internet technology in Sweden (Anderberg *et al.,* 2020).

Theoretical implications

This study contributes to the literature in various ways. First and foremost, this research enriches the literature body by bridging the gap between genetic science and marketing. This novel intersection, thinking outside the box, expands the toolkit available to marketers, enabling more advanced approaches in hyper-personalized markets. As one of the first empirical studies to explore hyper-personalization via DNA sequencing, this research addresses a notable gap in the existing literature, offering fresh insights into consumer sharing behavior through DNA data (Rosenbaum *et al.*, 2021). Although previous studies have acknowledged a decision-making process among consumers who weigh benefits against privacy concerns in DTC-GT settings (Grandhi & Plotnick, 2022; Hendricks-Sturrup & Lu, 2020; 2019; King, 2019; Saha *et al.,* 2020), the application of privacy calculus theory in this domain remains underexplored. In the wake of Daviet, Nave and Wind (2022), this study empirically answered the unresolved question concerning whether the potential benefits of DTC-GT indeed outweigh its privacy concerns. Lastly, the study extends the conventional personalization-privacy paradox, decoding the hyper-personalization privacy paradox. This new phenomenon arises from the use of highly sensitive and personal genetic data, contributing to an advanced understanding of consumer privacy in hyper-personalized contexts (e.g., genetics).

In terms of methodology, Daviet, Nave and Wind (2022) suggest the relevance of genetic ancestry in marketing through its noncausal correlation with environmental factors like language and culture, implying that while ancestry and cultural behaviors are linked, the former does not directly cause the latter. In contrast, to my knowledge, this research is the first to effectively employ a casual correlational analysis using an SEM approach within genetic ancestry in marketing. Mainly, this research introduces an innovative methodological approach to the Nordic context (e.g., Sweden), thereby paving the way for region-specific studies in marketing and genetics. After establishing the measurement constructs for validity and reliability, it can be asserted that they effectively capture the various dimensions, personalized benefits, privacy concerns, perceived vulnerability, subjective knowledge, trust, and hyper-personalized willingnes-to-share, within this converging context. Importantly, this study also makes a significant theoretical contribution by developing and validating a new construct for ancestry-based benefits, enhancing our understanding of how consumers perceive genetic-based hyper-personalization.

Practical implications

The study's findings also practically advance knowledge for marketers and public policy decision-makers. Marketers have already begun translating consumers' fascination with DNA to develop hyper-personalized marketing strategies that cater to individual preferences. Notably, Spotify's with AncestryDNA offers playlists that reflect users' ancestral origins, while Airbnb and 23andMe have partnered to curate travel experiences tailored to individuals' heritages. However, advancements in genetic and genomic technologies raised privacy concerns, which vary across age groups, affecting their willingness to disclose DNA data for hyper-personalized purposes (for review, see Guo, Zhang & Sun, 2016). Given the cautious mindset of elderly consumers toward sharing hyper-personalized data, marketers should consider implementing targeted educational initiatives. These programs could enhance digital literacy, helping to bridge the technology gap and making older consumers more comfortable with, and receptive to, online platforms. Education should address data privacy concerns and reassure elderly consumers about protective measures. Such education efforts are especially important in the DNA data marketplace, where similar educational materials on data sharing are lacking (Ahmed & Shabani, 2019).

As trust mediates the effects of privacy concerns and personalized benefits, it is crucial for marketers looking to gather such sensitive information to prioritize trust-building measures. These measures, when implemented effectively, can help alleviate ethical considerations and skepticism about the actual benefits of such practices. Bowen, Battuello, and Raats (2005, p. 676) argue that DTC-GT use today is like modern "snake oil," where deceitful con artists exploit the public with fraudulent remedies, partly due to the lack of regulation over the handling of consumer DNA data (Rosenbaum *et al.,* 2017). Due to consumers' reluctance to disclose their information, hyper-personalization faces similar skepticism, with uncertainties surrounding whether genomics truly offers more its physiological benefits over standard products and services (Rosenbaum *et al.,* 2021). Likewise, Patsiaouras (2017) highlights the ethical implications associated with promoting "'fault' genes and creating false needs?", which fuels public skepticism. To combat this perception and build trust, marketers must inform consumers about the science behind genetic testing and privacy protections. Educating consumers about the legitimate benefits of genomics, alongside transparent communication about these aspects, can help mitigate the view of hyper-personalization as modern "snake oil" (Rosenbaum *et al.,* 2021). By addressing these concerns proactively, marketers can foster a more trusting relationship with consumers and demonstrate the actual value of their hyper-personalized offerings.

To complicate this area, the proliferation of third-party genetic interpretation services, which assist consumers in understanding their DNA data and matching with genetic relatives, currently operates in a regulatory grey area. Thus far, this lack of clear oversight raises significant concerns about their accuracy, safety, and privacy practices. Though their positions may be limited, public policy-decision makers must establish clear guidelines and implement oversight to address these pressing issues (Guerrini *et al.,* 2020; Ioan & Hanganu, 2023).

Despite skepticism, hyper-personalization allows public policy decision-makers to foster trust-based relationships by enacting stringent privacy laws and effective oversight mechanisms. Daviet, Nave and Wind (2022) argue that the utilization of genetic data in marketing raises parallel concerns about privacy and discrimination. Apart from Spotify's and Airbnb's campaigns, Aeroméxico's DNA discounts campaign exemplifies genetic-based price discrimination. With minimal regulation and increased access to DTC-GT (Howard & Borry, 2012), the expansion of genetic science and technology may lead to discrimination, particularly in employment and insurance contexts (De Paor & Ferri, 2015). In Europe, the unified and appropriate regulatory framework surrounding DTC-GT is fragmented and insufficient, especially evident in Sweden (Hoxhaj *et al.,* 2020; Kalokairinou *et al.,* 2018; Soini, 2012). The Swedish Genetic Integrity Act (2006) primarily protects genetic privacy, mandates consent for genetic testing and regulates how genetic information can be collected, used, and stored (Hoxhaj *et al.,* 2020). However, this act fails to address discrimination or regulate marketing practices involving DNA data. Written consent is mandated for genetic tests conducted as part of medical screening (Lag [2006:351], 2006) but not for services tailored to individual consumer needs (Kalokairinou *et al.,* 2018). This regulatory gap (or loophole) leaves individuals vulnerable to discrimination under other circumstances, highlighting an urgent need for public policy decision-makers to intervene. By implementing regulations that govern the use of DNA data in marketing, they can ensure that discrimination based on genetic information is treated like other forms of discrimination.

Taking a cue from Daviet, Nave, and Wind (2022), this study also suggests the adapted four principles for DNA data to ensure best practices as an effective means of addressing privacy concerns: (1) training data privacy, which ensures that DNA data cannot be inferred from other available information, can enhance confidentiality; (2) input privacy, which protects a consumer's DNA data from observation by any third parties, can encourage consumers to share data for hyper-personalization; (3) output privacy, which restricts visibility of the model's output exclusively to the consumer being analyzed, demonstrating the truly personalized benefits they receive from sharing their data, can demystify the process and build trust; (4) model privacy, which secures the model throughout the lifecycle of the data (i.e., from collection to deletion), can protect it from theft by malicious entities (for the original review, see, Thaine & Penn, 2020). Notwithstanding, major market stakeholders may not adopt these practices without clear incentives. Public policy decision-makers should enact regulatory enforcement that could mandate the adoption of these technologies. That is, a legal framework might stipulate that all DTC-GT firms comply with these principles before being marketed.

This calls attention to the necessity for marketers and policymakers to steer the future of hyper-personalized marketing towards a more ethical and consumer-friendly direction. Such a collaborative approach will not only enhance consumer trust by transparently communicating the benefits and risks of genetic-based marketing but also help close existing legal loopholes.

Limitations and future research

The present study carries several limitations, which can guide avenues for future research. First, the uneven distribution of consumers who have undergone DTC-GT versus those who have yet to present a challenge in comparing cost factors between these groups. This bias could skew results since DNA-testers may perceive lower risks or concerns compared to non-testers (Christofides & O'Doherty, 2016; Grandhi & Plotnick, 2022). Addressing this limitation could involve employing sampling techniques to ensure a more balanced representation of both groups. Employing cluster analysis to map differences in actual sharing behavior across consumer segments based on their vulnerability would enable a more robust understanding of how different groups respond to marketing strategies in DTC-GT. Alternatively, future studies could explore positive and negative consumer reactions to DTC-GT, underlying mechanisms of satisfaction and regret, respectively.

Second, PCT is widely utilized to understand consumer decision-making processes. However, it is imperative to acknowledge its limitations in accurately predicting consumer behavior. Numerous researchers have highlighted that various factors and heuristics beyond the rational privacy calculus model influence consumer decision-making in this context (Cherif, Bezaz & Mzoughi, 2021; Kang & Namkung, 2019; Keith *et al.,* 2013; Wilson & Valacich, 2012). Consequently, there is potential for enhancing the theoretical framework in the future. In particular, this study on PCT leans heavily towards a cognitive-based framework, emphasizing consumer's willingness-to-share data (Martin & Murphy, 2017), while overlooking the role of affective-driven factors (Wang, Duongand & Chen, 2016) in understanding privacy behaviors (Anderson & Agarwal, 2011; Li, Sarathy & Xu, 2011). Recognizing this, future research could broaden the scope of PCT by integrating affective elements into the cost-benefit equation alongside cognitive ones.

Third, the study's focus on older consumers with a demonstrated interest in genealogy may limit its generalizability to the broader population. Along these lines, emphasizing ancestry-based benefits over health and lifestyle benefits could reflect the specific preferences of this sample rather than broader consumer motivations. Examining age differences in consumer engagement with hyper-personalization technology could yield valuable insights. Young consumers, who are often more tech-savvy and open to personalized experiences, may exhibit different behaviors and preferences compared to elderly generations.

Conclusion

As an exploratory study, this research provided empirical evidence on the drivers influencing consumer willingness-to-share DNA data for hyper-personalized products and services. At the heart of these findings lies the hyper-personalization-privacy paradox, where trust serves as a gateway for building sustainable relationships between consumers and marketers. The results highlight a cautious yet passive consumer stance towards sharing DNA data for hyper-personalized purposes. Positioned at the next frontier of "Genomarketing", this study serves as a cornerstone in bridging the gap between genetic science and marketing, offering practical implications for both marketers and public policy decision-makers. By prioritizing education and regulatory enforcement, stakeholders can collaboratively steer the future of hyper-personalized marketing towards more ethical consumption, fostering trust and closing existing legal loopholes in the process.

ORCID ID

Chrissos Anestis M. https://orcid.org/0000-0002-4178-8127

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