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RESEARCH PAPER

The consumer genome: Willingness to share and accept genetic data in marketing

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Abstract
Genetic marketing presents novel challenges for marketing, namely how its implementation impacts consumers' attitudes. The current study is grounded on the privacy calculus and theory of planned behavior theories to understand how consumers are willing to accept the use of genetic data for marketing purposes. A total of 309 consumers were surveyed about their perceptions of using genetic data. The study shows that creating benefits for the disclosure of information, establishing a positive reputation for the organization, and building systems that empower consumers in terms of control over their genetic data will help consumers accept genetic marketing practices.

Keywords Genetic data · Genetic marketing · Personal data privacy · Privacy calculus · Acceptance

JEL M30 · M31

Introduction

Consumer genetic testing is growing in popularity worldwide driven by companies such as 23andMe and AncestryDNA. The DNA testing market was valued at $340 million in 2022, marking a growth of nearly 20% since 2021 (Statista, 2023). Genetic testing services enable individuals to explore their ancestry, connect with relatives, and, in some cases, gain insights into their health. For example, 23andMe (23andMe, 2023a) offers both ancestry information and health-related reports that provide consumers with data on genetic predispositions to certain conditions. These services illustrate the dual appeal of genetic testing: understanding one's heritage and taking pre-emptive steps in healthcare. These tests' benefits are not limited to personal insights but also extend to broader applications of tailored health products, such as supplements formulated to address genetic predispositions (e.g., vitamin deficiencies), or the development of skincare products targeted at individual customers. Communicating these personalized offers can be done through digital channels that allow targeted advertising based on genetic predispositions. One example is Nutrigenomix (2024), which uses genetic profiles to develop personalized nutrition services that are then communicated using targeted advertising channels such as podcasts and health-related blogs to reach each segment. Individuals with genetic markers linked to vitamin D deficiency might also be targeted to receive tailored ads or emails promoting vitamin D supplements or dietary plans enriched with this nutrient. Another example is SkinDNA (2024), a company that formulates skin products adapted to each person's skin sensitivity and makes a one-to-one marketing communication strategy to focus on each customer's specific needs. However, these advantages are accompanied by significant concerns regarding data privacy and protection (Ahmed & Shabani, 2019).

Research on the psychological dimensions of intention to share personal data has been conducted for years—involving areas such as social media, internet behavior, and medical devices (Ajzen, 1991; Bansal et al., 2010; Gerber et al., 2018; Jayawardhena et al., 2009; Li et al., 2016; Trepte et al.,

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2017; Zhang et al., 2018). However, there is a notable scarcity of studies addressing the use and acceptance of genetic data for marketing purposes. Genetic data for marketing purposes covers the total of activities involved in the transfer and use of genetic data, including the segmentation of products/services tailored to specific groups, targeted advertising, personalized brand positioning, and storing or selling private data to third parties (Daviet et al., 2022). Understanding the factors that drive consumer acceptance is crucial not only for companies aiming to leverage genetic data ethically but also for policymakers concerned with protecting consumer rights in an emerging market with vast implications. By identifying these factors, businesses can better align their strategies with consumer expectations, including using them for targeting segmentation and positioning (Daviet et al., 2022), while regulators can develop guidelines that address potential privacy concerns.

While Daviet et al. (2022) explore the impact of genetic data on marketing and Toussaint et al. (2022) investigate retail fairness in direct-to-consumer (DTC) genetic testing services, most research on genetic testing focuses on regulations rather than consumer perception of such use. Given the sensitive nature of genetic data and the importance of consumer perception, the current study seeks to answer the following research question: What factors influence consumers' acceptance of using their genetic data for marketing purposes? To address this question, we employ the privacy calculus theory (Serenko, 2014), which suggests that individuals weigh perceived benefits against potential risks when deciding to disclose personal information. By applying this framework to the context of genetic data, we aim to provide a comprehensive understanding of the tradeoffs consumers consider in this decision-making process.

This study contributes to the literature by highlighting the factors that drive consumers' decisions to share genetic data in marketing contexts. Our findings aim to inform marketers on how to responsibly approach data-driven strategies while respecting consumer privacy. Additionally, our insights may guide future regulatory frameworks that balance innovation with the protection of individual rights.

Background

Genetic data

Genetic data, according to the General Data Protection Regulation (GDPR) codified by the European Union and adopted by the present research, is defined as "personal data relating to the inherited or acquired genetic characteristics of a natural person which result from the analysis of a biological sample from the natural person in question, in particular chromosomal, deoxyribonucleic acid (DNA) or ribonucleic acid (RNA) analysis, or from the analysis of another element enabling equivalent information to be obtained" (European Parliament & Council of the European Union, 2016). This kind of data's potential uses and applications are far-reaching and potentially dangerous, particularly regarding breaching personal data privacy (Molteni, 2018; Turner, 2005). Such danger is linked to the unique characteristics of genetic data, one of which is its unparalleled identification accuracy that surpasses other biometric identifiers (Erlich & Narayanan, 2014). This uniqueness can potentially lead not only to a person being identified but also to their relatives, owing to the hereditary nature of DNA. Another characteristic of genetic data is that it does not change over time. Therefore, once compromised, the privacy risk remains indefinitely (Gymrek et al., 2013).

Direct-to-consumer (DTC) genetic testing is one method of acquiring this data from the population and exploiting its numerous applications. Private organizations conduct tests on consumers and analyze the resulting data to provide insights into health, personal ancestry, and other factors (Horton et al., 2019). Although healthcare professionals can also collect this type of data for diagnostic purposes, private organizations began gathering it through DTC genetic testing. This data can then be used for various business purposes and sold and resold, leading to concerns about personal data privacy similar to those with social media, mobile devices, and other healthcare domains (Nill & Laczniak, 2022).

Third-party genetic interpretation services can also examine this information and offer insights to physicians and DTC genetic testing companies on the raw data they have collected, raising concerns about data management due to the limited regulations in place, particularly in the USA (Guerrini et al., 2019). Consumers have limited benefits to gain by disclosing their genetic data beyond obtaining insights into their ancestry and possible health concerns. However, this situation may change due to the emergence of "DNA data marketplaces," which allow individuals to sell their data to interested parties, thereby empowering them to manage their data and derive benefits from it (Ahmed & Shabani, 2019).

Genetic data market

The genetic data market is a rapidly evolving sector across many industries, including healthcare, biotechnology, and consumer genetics. This market has led to significant applications in medicine, drug development, and DNA tracing (Zhang et al., 2024; Meng et al., 2024; Kim et al., 2024; Stoeklé et al., 2019; Esmonde et al., 2023). Companies like 23andMe and Ancestry.com have pioneered direct-to-consumer genetic testing and have monetized this data through partnerships with companies that assist brands in developing products and services that better align with consumer demands (23andMe, 2023a; AncestryDNA, 2023). In 2023, the direct-to-consumer genetic testing market was valued at USD 1.98 billion. It is expected to grow at a compound annual growth rate of 15.80% from 2024 to 2033, reaching over USD 8.57 billion by the end of the period (Precedence Research, 2024), which shows strong potential in the near future.

The genetic data market involves the commercialization of genetic information that, once collected, can be made anonymous, aggregated, and shared with third parties—as long as consumers agree with such share—so that, for example, genetic markers can be used for predicting patient responses for specific treatments. Despite the importance of this hyper-personalization, the use of this data raises significant ethical and privacy concerns because, most of the time, consumers are not fully aware of the extent to which their genetic information can be used in the future (Erlich & Narayanan, 2014).

The market has been regulated by the General Data Protection Regulation (GRPD) in Europe, which imposes strict guidelines for sharing personal data, including genetic information (Shabani & Borry, 2018). Due to the characteristics of genetic information, there are specific steps that need to be considered to protect individual privacy rights. One such step is to ensure the pseudonymization of data—processing genetic information so that it cannot be attributed to a specific and identifiable individual—to guarantee that the genetic market can bring benefits without risking privacy (Pormeister, 2017).

Consumer data privacy

The concept and definition of personal data are still being debated, with varying approaches in academia and the law. These approaches depend on the specific context of each country and region (Gellert, 2021). Understanding personal data implicates understanding the types of data that can be collected about groups or individuals. There are three types of personal data: first-party data, which is information obtained firsthand by the organization from their audience for their use; second-party data, which is about their audience and obtained secondhand from another partner entity; and third-party data, which is obtained through external sources about any group of individuals or audience (Bernazzani, 2021). In the context of personal data, genetic data represents a particularly sensitive category that extends beyond traditional first-, second-, or third-party data classifications. Genetic information is inherently unique and immutable, carrying with it details about an individual and their relatives and descendants.

The extant literature predominantly focuses on using and monetizing third-party data, a category of information that can be bought, sold, and repurposed for various applications such as targeted advertising. This data transaction often occurs without the explicit knowledge or informed consent of the individuals to whom the data pertains (Sponder & Khan, 2017). The pervasive trade and use of third-party data have significantly contributed to the extensive research on personal data privacy, highlighting numerous ethical and legal issues (Miller & Tucker, 2018; Stoeklé et al., 2019). The handling of genetic data is subject to increasing scrutiny, particularly concerning its use in commercial contexts for purposes of marketing such as segmentation, targeting and brand positioning. While researchers have begun to explore the implications of using genetic data for personalized marketing, with concerns centered around privacy, misinformation, and the potential for discrimination (Daviet et al., 2022), these considerations underscore the necessity for the theoretical frameworks and concepts discussed in the subsequent sections of this paper.

Table 1 shows the most prominent studies (those that are published in journals ranked in Q1 and Q2) based on a query on Scopus that searched for articles on ("genetic data" OR "genetic testing") AND (marketing OR "direct-to-consumer") on the "business, management, and accounting" category to show how research has evolved on the use of genetic data for marketing purposes.

Theoretical framework and conceptual model

Serenko (2014) defined privacy calculus as a theory that suggests "that an individual's intention to disclose personal information is based on a risk–benefit analysis. According to privacy calculus theory, individuals compare perceived risks and anticipated benefits." (p. 1). This theory has become fundamental when dealing with personal data. Still, it provides the central perspective on which the privacy concerns of individuals are evaluated in many fields and subjects, from healthcare to social media to websites of varied natures (Bol et al., 2018).

Studies show that the degree of individualism, collectivist thinking, uncertainty avoidance, and the importance of social gratifications are all cultural factors that impact the risk–benefit analysis. Other factors, such as concerns and attitudes towards privacy, perceived risk, and behavioral intention, are also evidenced to impact the outcome of the privacy calculus (Gerber et al., 2018).

In the personal data privacy literature, the privacy calculus is used to evaluate a variety of behavioral reactions and attitudes in individuals, from the adoption of wearable healthcare devices to information-sensitive mobile app adoption (Pentina et al., 2016; Li et al., 2016; Smith et al., 2011). These attitudes are closely related to acceptance, a variable of interest for this research. In these studies, perceived privacy risk and perceived benefits, critical

Table 1 Most prominent papers on genetic data for marketing purposes

Year	Title	Author	Source
2005	Critical junctures in genetic medicine the transformation of DNA lab science to commercial pharmacogenomics	Turner, S.S	Journal of Business and Technical Communication
2006	Strategic risk management using complementary assets: Organizational capabilities and the commercialization of human genetic testing in the UK	Hopkins M.M.; Nightingale P	Research Policy
2008	Challenges for corporate ethics in marketing genetic tests	Williams-Jones B.; Ozdemir V	Journal of Business Ethics
2008	The ethical challenges of direct-to-consumer genetic testing	Berg C.; Fryer-Edwards K	Journal of Business Ethics
2014	Direct-to-Consumer Advertising of Predictive Genetic Tests: A Health Belief Model Based Examination of Consumer Response	Rollins B.L.; Ramakrishnan S.; Perri M	Health Marketing Quarterly
2020	Making Knowledge Hereditary: Public–Private Partnership Drives Progress in Rare Disease Community	Mulally A.; Bias V.; Konkle B.; Watson C.; Yellen I.; Maxwell A	Social Marketing Quarterly
2021	Biobanks and Individual Health Related Findings: from an Obstacle to an Incentive	Lekstutiene J.; Holm S.; Gefenas E	Science and Engineering Ethics
2021	Forty years of assisted reproductive technologies (ARTs): the evolution of a marketplace icon	Takhar J.; Rika Houston H	Consumption Markets and Culture
2022	Direct-to-Consumer Genetic Testing and Its Marketing: Emergent Ethical and Public Policy Implications	Nill A.; Laczniak G	Journal of Business Ethics
2022	Perceived fairness of direct-to-consumer genetic testing business models	Toussaint P.A.; Thiebes S.; Schmidt-Kraepelin M.; Sunyaev A	Electronic Markets
2022	Examining the perceived transparency of DTC genetic testing company communication and its impact on consumer trust, attitude and behavioral intentions	Abitbol A.; Lee N.M.; VanDyke M.S	Journal of Communication Management
2022	Genetic Data: Potential Uses and Misuses in Marketing	Daviet R.; Nave G.; Wind J	Journal of Marketing
2023	A social and ethical framework for providing health information obtained from combining genetics and fitness tracking data	Esmonde K.; Roth S.; Walker A	Technology in Society

elements of the privacy calculus, negatively and positively influence adoption, respectively. In the case of perceived privacy risk, it is, indeed, affected by the perceived level of regulation in the sector and the degree of risk avoidance by the person who is willing to share the data (Chang et al., 2018; Hong et al., 2021; Miltgen & Smith, 2015). Thus, we suggest the same effect occurs for genetic data by building upon these findings. Hence, the following hypotheses are proposed:

H1: The perceived level of regulation is negatively affected by the perceived privacy risk of using genetic data.
H2: Risk avoidance is positively related to the perceived privacy risk of using genetic data.
H3: Perceived privacy risk negatively affects the acceptance of genetic data for marketing purposes.
H4: Perceived benefits positively affect the acceptance of genetic data for marketing purposes.

Along with privacy calculus, the privacy paradox has become a robust and consensual framework in topics about personal data. It describes the dichotomy between individuals' intention to protect their privacy and their actual behavior, which breaches their privacy (Barth & de Jong, 2017). In other words, people claim to care about disclosing their personal information but do not back these claims with actions that preserve their privacy (Bongiovanni et al., 2022). This paradox can be witnessed in disclosing personal information throughout the Internet, where individuals' behavior contradicts their concerns over their privacy after sharing their data in places such as social networking sites (Taddicken, 2013). However, despite being a consensual approach, there are other interpretations suggested to understand the concept of privacy paradox, which Kokolakis (2017) states to be derived from "social theory, psychology, behavioral economics and, in one case, from quantum theory." Additionally, other researchers also propose that there are issues in privacy paradox literature that put into question its validity and existence, claiming that there are methodological flaws in the literature that do not account for the causal nature of the phenomenon, suggesting that more research on causal relations is necessary to comprehend better the privacy paradox (Dienlin et al., 2021).

Research has uncovered key points to understand the privacy paradox and why people contradict their concerns. One key point is that the paradox is constituted by a temporally discounted balance between concerns and rewards, where psychologically near activities involving a privacy breach have more weight than psychologically distant concerns (Hallam & Zanella, 2017). Furthermore, as the additional investigation about mobile app adoption suggests, these concerns mentioned above do not influence the adoption or use of apps requiring sensitive personal data (Pentina et al., 2016). The authors further elaborate on the positive influence of personality traits such as agreeableness and extraversion on the benefits of using those apps, which affects the privacy calculus and further justifies the breach inherent to the privacy paradox.

Explaining the factors that influence consumer acceptance of their data usage is critical to understanding the literature on personal data privacy. Zeng et al. (2021) elaborated on the opportunity presented by data personalization, which positively drives acts of self-disclosure and their intensity if accompanied by declarations of privacy assurance. Li et al. (2016) demonstrated that the privacy calculus, and therefore behavioral attitudes, are influenced by several elements such as information sensitivity, personal innovativeness, legislative protection, perceived prestige, perceived informativeness, and functional congruence, in the context of the adoption of wearable healthcare devices. The authors also identified that perceived benefits negatively impact privacy risk within the privacy calculus.

Hence, we suggest that the same occurs in genetic data:

H5: The perceived benefits of sharing genetic data negatively affect the perceived privacy risk of using genetic data.

Also related to healthcare, it was found that individuals' health concerns and their perceived vulnerability positively influence their privacy concerns. Such concerns are negatively affected by the perception of the control consumers have over their privacy (self-efficacy) and the effectiveness of privacy protection mechanisms (response efficacy) (Zhang et al., 2018). Indeed, control over personal information is a significant factor in privacy literature, going back to the theory of planned behavior, where perceived behavior control is shown to have an essential role over intentions and actual behavior (Ajzen, 1991). Lack of control leads to another relevant factor, which is risk avoidance. This factor is a barrier to acceptance, negatively influencing youth consumers' acceptance of mobile marketing in China (Gao et al., 2012).

Therefore, we propose that the level of control in how genetic data is used can be an important factor in accepting of the use of genetic data.

H6: The perceived level of control in genetic data positively affects the acceptance of using genetic data for marketing purposes.

It was also shown that the disclosure intention of personal data is influenced by trust, the sensitivity of the information, and the level of privacy concerns (Bansal et al., 2010). Additionally, trust is, in turn, influenced by antecedents such as risk beliefs, health status, and personality traits. In the case of genetic data, we suggest that data provider reputation (related to organizations that sell genetic data to third parties) and company reputation (the company that holds the data) can be important factors in explaining how consumers perceive the benefits they receive, due to the importance of trust in reducing privacy risks. Thus, the following hypotheses are presented based on the literature:

H7: The company's reputation positively affects the perceived benefits of sharing genetic data.
H8: The data provider's reputation positively affects the perceived benefits of sharing genetic data.

Figure 1 shows the proposed conceptual model.

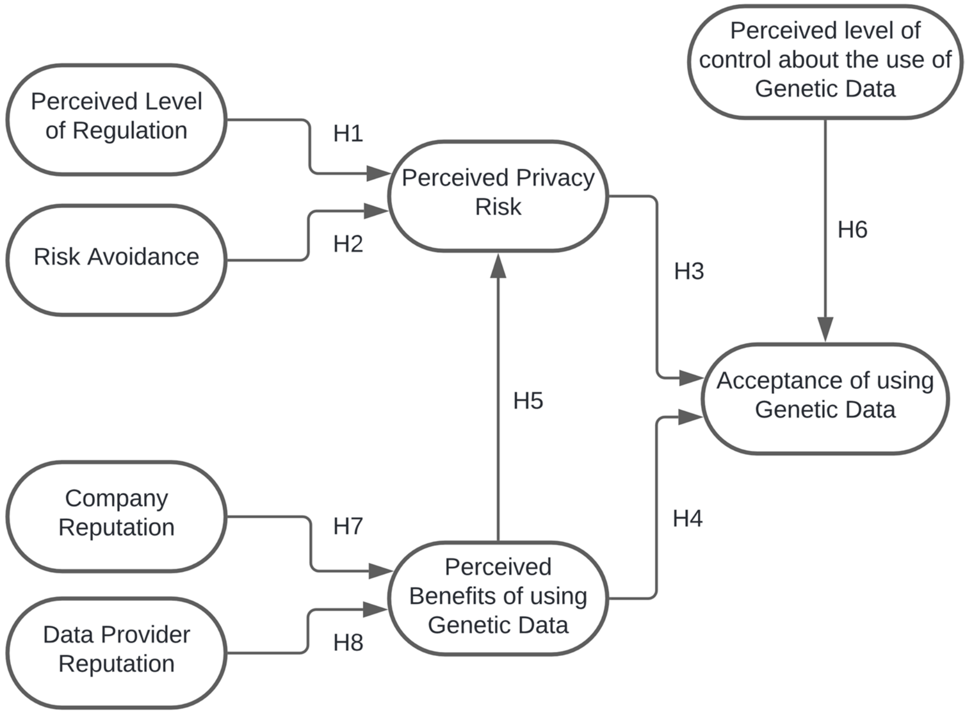
Methodology

Measures and scales

A survey was developed based on questions and scales found in related literature that allowed for an adequate measure of the variables in the research model. The questions were subsequently adapted to fit the research topic while maintaining internal consistency in logic and purpose.

The survey started by clarifying the purpose of the study and the definitions of genetic data and genetic marketing. Second, demographic questions were asked, such as age, gender, and average monthly income. Third, we asked participants to answer questions about genetic data. All the scales in this study were seven-point Likert scales (1 = strongly disagree, 7 = strongly agree). A scale by Wirtz et al. (2007) measured the perceived level of

Fig. 1 Proposed research model



regulation. Another seven-point Likert scale by Dinev et al. (2013) measured the perceived level of information control. A scale by Gao et al. (2012) captured respondents' level of risk avoidance. A scale by Suh and Han (2003) measured both data provider reputation and company reputation, creating a distinction between the two to obtain different perspectives on the same items. Another two scales by Dinev et al. (2013) captured perceived benefits and perceived privacy risks. Another scale by Suh and Han (2003) measured acceptance of genetic marketing. Appendix A shows the items used for each scale.

In terms of demographic variables, gender was measured between "male," "female," "other," and "rather not say." Age was divided into five groups: under 18; 18 to 29; 30 to 49; 50 to 65; over 65. Education was measured and divided into seven groups: 9th grade; 12th grade; bachelor's; master; Ph.D.; post-graduate; technical professional degree. Household income was divided into four groups, measured in euros: under 1500; 1500 to 2500; 2500 to 5000; above 5000. Finally, the professional situation was measured and divided into six groups, capturing respondents' current professional status: student; student-worker; full-time worker; part-time worker; unemployed; retired. To ensure validity and reduce bias, the survey ensured participants that their responses were confidential and entirely anonymous. This step was relevant when collecting behavioral and attitudinal data from self-report questionnaires to mitigate common method bias (Podsakoff et al., 2003; Chang et al., 2010).

Sample and data collection

Between March and May 2022, 310 people from Portugal participated in a survey and responded to a questionnaire shared online via social media (Facebook). Respondents clicked on the survey available on social media and were redirected to a Qualtrics form. Of these, 309 responses were valid, resulting in an effective response rate of 99%. There was no compensation for participating in the study. Among these valid questionnaires, 65.4% of the respondents were women, 34% were men, 0.3% identified as another gender, and 0.3% would rather not say. Additional demographic information on the respondents is presented in Table 2.

Results

A partial least square structural equation modeling (PLS-SEM) run with SmartPLS 4 was used to test the model. PLS-SEM is considered adequate for this research due to the relatively complex nature of the model and to test its predictive power (Hair et al., 2012; Sarstedt et al., 2014). This research evaluates the research model in two steps: the outer model (measurement model) and the inner model (structural model) (Henseler et al., 2015b). A bootstrapping method with 5000 samples was used to validate the support of each hypothesis.

Table 2 Demographic information

$N = 309$	Demographic	%
Age	< 18	1.6%
	18–29	46.6%
	30–49	33.3%
	50–65	12.7%
	> 65	5.8%
Gender	Male	34%
	Female	65.4%
	Other	0.3%
	Rather not say	0.3%
Income	< 1500	24.6%
	1500–2500	36.6%
	2500–5000	27.8%
	> 5000	11%
Education	9th grade	3.2%
	12th grade	18.1%
	Bachelor's	50.8%
	Masters	23.1%
	PhD	2.9%
	Professional	1.6%
	Post-graduate	0.3%
	Student	28.5%
	Student-worker	14.6%
Professional situation	Full-time	45.3%
	Part-time	2.9%
	Unemployed	2.6%
	Retired	6.1%

Outer model

When evaluating the measurement model, the first three aspects to consider are internal consistency reliability, composite reliability, and convergent validity. Cronbach's alpha is used to determine the internal reliability of the model and should be above 0.70 for each construct (Hair et al., 2010). In terms of composite reliability, outer loadings should be above 0.70, and if their deletion improves composite reliability, they should be removed (Hair et al., 2010). All outer loading indicators show composite reliability above 0.70, except for ACC2. Deleting this item improved the composite reliability of the construct from 0.911 to 0.934. For convergent validity, the average extracted variances (AVE) should be above 0.50 for all constructs, indicating convergent validity (Hair et al., 2010; Urbach & Ahlemann, 2010). These results are shown in Table 3.

In order to establish discriminant validity, it is important to ensure that the square roots of the average variance extracted (AVE) values for each construct are higher than the correlations with any other constructs, as per the Fornell-Larcker criterion (Henseler et al., 2015a, b). Upon examination of Table 4, it is evident that the square root of AVE values for all constructs exceeds the correlations with the other constructs, indicating the presence of discriminant validity. Another method for assessing discriminant validity is through the Heterotrait-Monotrait (HTMT) ratio of the correlation, which should be below 0.850. The results, which are also shown in Table 4 in parentheses, indicate satisfactory discriminant validity within the data (Henseler et al., 2015b). All VIF values are also less than 10, ranging from 1.243 to 6.051, which is considered acceptable in terms of potential multicollinearity (Hair et al., 2010).

Inner model

The standardized mean root residual (SRMR) is 0.074, below the recommended threshold of 0.08. This indicates that the proposed model fits the data well (Henseler et al., 2015b). Additional evaluations of the structural model involve examining R^2 estimates, Stone-Geisser's Q^2 value, effect size (f^2), path coefficients (β), and p-values. These details are presented in Fig. 2 and Table 5.

All the hypotheses except for H3 are supported by the study and the model predicts a 55.6% variance in acceptance of the use of genetic data for marketing purposes, 31.8% variance in perceived privacy risk, and 28.1% variance in perceived benefits of using genetic data, all of which indicate moderate prediction (Henseler et al., 2009).

Results show that the perceived level of regulation is negatively related to perceived privacy risk ($\beta = -0.220$, $p < 0.001$), thus supporting H1. Therefore, as consumers perceive that the use of genetic data is more regulated, they also consider the risk to be lower. Risk avoidance is positively related to perceived privacy risk ($\beta = 0.359$, $p < 0.001$), which denotes that people who avoid risk are also more aware of the risks that genetic data may unravel and supports H2. H3, which tested the effect of perceived privacy risk on acceptance, is not statistically significant, having a p-value larger than 0.05. Perceived benefits negatively affect perceived privacy risk ($\beta = -0.196$, $p < 0.01$), but positively affect acceptance ($\beta = 0.644$, $p < 0.001$), thus supporting both H4 and H5. This means that benefits can affect the degree to which consumers understand the risks. The more benefits they have, the less risk is perceived. H6 is also supported, and the results show that the perceived level of control positively affects acceptance ($\beta = 0.211$, $p < 0.001$). If consumers have increased control over their genetic data, they are more willing to accept its use. Finally, the study shows that both company reputation ($\beta = 0.343$, $p < 0.001$) and data provider reputation ($\beta = 0.217$, $p < 0.05$) have a positive effect on the perceived benefits of allowing companies to use genetic data. Therefore, H7 and H8 are supported.

Table 3 Reliability and validity test for the complete data

Constructs	Items	Outer loadings	Cronbach's α	CR	AVE
Perceived level of regulation (4 items)	PLR1	0.888	0.891	0.924	0.755
	PLR2	0.904			
	PLR3	0.932			
	PLR4	0.738			
Perceived level of control (4 items)	PLC1	0.906	0.948	0.962	0.865
	PLC2	0.952			
	PLC3	0.941			
	PLC4	0.922			
Company reputation (6 items)	CR1	0.804	0.926	0.942	0.732
	CR2	0.884			
	CR3	0.853			
	CR4	0.882			
	CR5	0.802			
	CR6	0.902			
Data provider reputation (6 items)	DPR1	0.850	0.952	0.962	0.808
	DPR2	0.937			
	DPR3	0.894			
	DPR4	0.927			
	DPR5	0.853			
	DPR6	0.927			
Risk avoidance (3 items)	RA1	0.808	0.743	0.853	0.659
	RA2	0.771			
	RA3	0.855			
Perceived privacy risk (4 items)	PPR1	0.890	0.875	0.914	0.728
	PPR2	0.899			
	PPR3	0.803			
	PPR4	0.815			
Perceived benefits (3 items)	PB1	0.901	0.874	0.922	0.799
	PB2	0.873			
	PB3	0.907			
Acceptance (3 items)	ACC1	0.898	0.894	0.934	0.825
	ACC3	0.937			
	ACC4	0.889			

Table 4 Fornell-Larcker criterion analysis and HTMT ratios

	ACC	CR	DPR	PB	PLC	PLR	PPR	RA
ACC	**0.908**							
CR	0.644 (0.705)	**0.855**						
DPR	0.613 (0.659)	0.779 (0.824)	**0.899**					
PB	0.714 (0.807)	0.512 (0.564)	0.484 (0.524)	**0.894**				
PLC	0.376 (0.404)	0.566 (0.602)	0.511 (0.539)	0.241 (0.262)	**0.930**			
PLR	0.320 (0.358)	0.323 (0.356)	0.338 (0.368)	0.213 (0.238)	0.261 (0.291)	**0.869**		
PPR	−0.308 (0.345)	−0.394 (0.437)	−0.380 (0.419)	−0.338 (0.378)	−0.172 (0.193)	−0.369 (0.406)	**0.853**	
RA	−0.247 (0.302)	−0.305 (0.354)	−0.280 (0.319)	−0.265 (0.323)	−0.254 (0.293)	−0.298 (0.355)	0.476 (0.573)	**0.812**

HTMT ratios are in parentheses. The diagonal elements in bold are the square roots of the variance between the constructs and their measures (AVE)

Regarding effect size (f^2), perceived regulation and benefits have a moderate effect on perceived privacy risk, while risk avoidance has a strong effect. Company and data provider reputations moderately affect perceived benefits. Perceived control over information moderately affects acceptance, while perceived privacy risk weakly affects acceptance, and perceived benefits strongly affect acceptance (Cohen, 1988). Additionally, all dependent variables' Stone-Geisser's Q^2 values are above zero, confirming the model's predictive validity (Henseler et al., 2009).

Fig. 2 Research model with PLS algorithm and bootstrapping results. *p*-values are inside the parenthesis

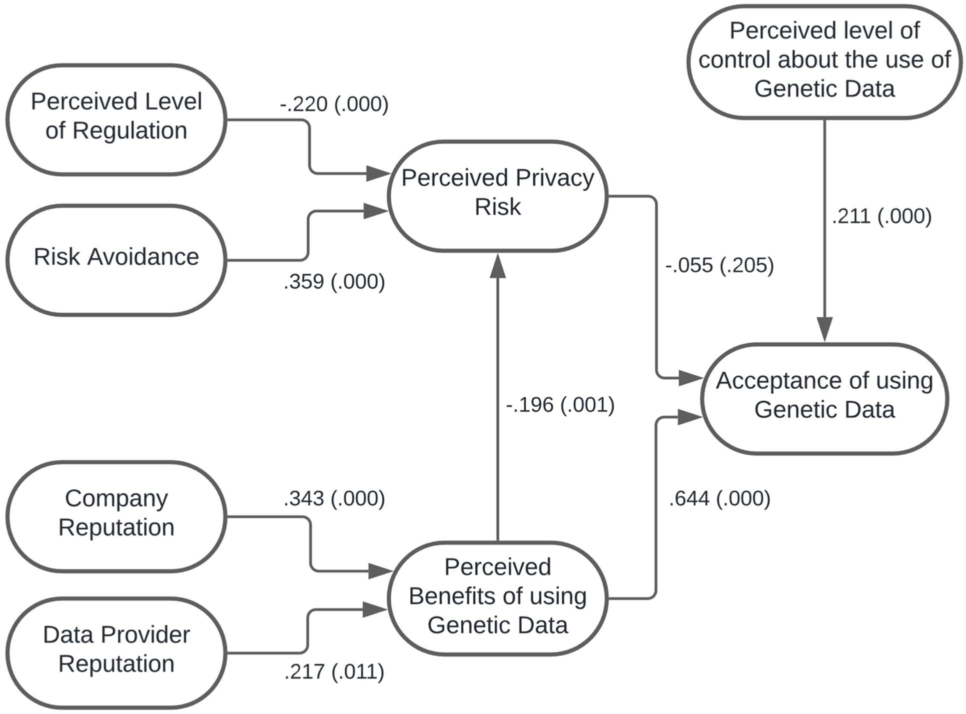


Table 5 Structural model results

Hypothesized relationship	Proposed effect	Path coefficient	f^2	Results
PLR—> PPR RA—> PPR	Negative	−0.220***	0.063	H1: supported
PPR—> ACC	Positive	0.359***	0.164	H2: supported
PB—> ACC	Negative	−0.055	0.006	H3: not supported
PB—> PPR	Positive	0.644***	0.796	H4: supported
PLC—> ACC	Negative	−0.196**	0.051	H5: supported
CR—> PB	Positive	0.211***	0.094	H6: supported
DPR—> PB	Positive	0.343***	0.064	H7: supported
	Positive	0.217*	0.026	H8: supported

***$p<0.001$ **$p<0.01$ *$p<0.05$

PLR perceived level of regulation, *RA* risk avoidance, *PB* perceived benefits, *CR* company reputation, *DPR* data provider reputation, *PLC* perceived level of control, *PPR* perceived privacy risk, *ACC* acceptance

Discussion

Principal findings

The use of genetic services provided by companies such as 23andMe offers a wide range of applications. These include tracing ancestry, delivering health-related insights, identifying potential future medical conditions, and informing personalized healthcare strategies. Beyond individual insights, these tests offer broader opportunities, including creating customized health products and implementing targeted marketing approaches (Daviet et al., 2022). However, the use of genetic data also raises critical concerns regarding data privacy, potential re-identification, and misuse (Esmonde et al., 2023; Daviet et al., 2022), highlighting the need for robust protections to safeguard sensitive information (Ahmed & Shabani, 2019). Ethical considerations, such as fairness, transparency, and consumer consent, are pivotal in shaping public perception and acceptance of these technologies (Toussaint et al., 2022). However, as the field evolves, it becomes increasingly important to understand other factors that may influence the willingness or reluctance to share this sensitive data.

The findings of our study bring to light novel insights into the acceptance of genetic data for marketing purposes. By emphasizing the unique roles of perceived benefits, institutional reputation, perceived control, risk avoidance, and regulation, our research offers fresh perspectives for researchers and practitioners navigating the complex field of genetic data privacy and consumer acceptance. The alignment of our findings with those from related fields, such as healthcare and mobile device adoption (Pentina et al., 2016; Zhang et al., 2018), not only strengthens the validity of our results but also sets the stage for future research and practical applications.

Our study showed that the perceived level of regulation negatively influences perceived privacy risk (H1). This inverse relationship indicates that stronger legislative protection regarding personal data privacy reduces consumers' perceived risks. This finding is consistent with existing studies on other fields of data protection (Li et al., 2016) and shows the importance of robust regulatory frameworks in mitigating privacy concerns. The influence of regulatory protection is crucial, as highlighted by Chang et al. (2018), who demonstrated that enhanced legislative measures can substantially lower perceived privacy risks.

The psychological factor of risk avoidance was also shown to contribute positively to perceived privacy risks (H2), which is aligned with Miltgen and Smith (2015), who found that risk avoidance behaviors significantly impact perceived risks in data-sharing contexts. This means that individuals with a higher tendency to avoid risk are more likely to perceive higher privacy risks of using genetic data. This finding aligns with the broader privacy calculus literature, highlighting the role of risk aversion in shaping privacy perceptions.

The study shows a significant positive influence of perceived benefits on the acceptance of using genetic data for marketing purposes (H4). This suggests that consumers' acceptance levels increase when they perceive greater benefits from using genetic data. This reinforces the importance of emphasizing the positive outcomes and advantages of genetic data use in marketing strategies to enhance consumer acceptance. As noted by Li et al. (2016), perceived benefits play a critical role in the privacy calculus, often outweighing perceived risks when benefits are substantial.

Another relevant finding is the positive impact of the perceived level of control on acceptance (H6). This confirms the theory of planned behavior (TPB), which suggests a connection between perceived control and behavioral intention, a concept closely related to acceptance (Ajzen, 1991). Ensuring that consumers feel they have control over their genetic data can significantly enhance their acceptance of its use for marketing purposes. This finding is supported by Zhang et al. (2018), who found that perceived control (self-efficacy) over personal information significantly reduces privacy concerns and enhances acceptance.

The study also highlighted the critical and positive relationship between institutional reputation and perceived benefits (H7 and H8). This suggests that an organization's reputation significantly enhances consumers' perception of benefits. This finding is crucial for companies operating in the genetic data market, indicating that building and maintaining a strong, positive reputation can enhance consumer perceived value. This supports the notion that reputation is important in consumer data-sharing decisions (Bansal et al., 2010).

Finally, the literature suggests that perceived benefits negatively influence (H5) and that perceived privacy risk negatively affects acceptance levels (H3) (Li et al., 2016). Our study supports the first relationship, demonstrating that increasing perceived benefits decreases perceived risks. However, we did not find support for the negative effect of perceived privacy risk on the acceptance of genetic data use for marketing purposes. One possible explanation for this behavior is that only extreme levels of perceived privacy risk significantly impact behavior and acceptance (Pentina et al., 2016). The privacy paradox may also explain this discrepancy, where individuals' concerns do not always translate into protective behaviors (Barth & de Jong, 2017; Taddicken, 2013).

Theoretical contributions

The present study tests a comprehensive conceptual model for understanding the acceptance of genetic data use for marketing purposes and makes several contributions to the nascent field of genetic marketing.

First, the study identifies and explores the key factors influencing consumers' acceptance of genetic data use. By highlighting the role of perceived benefits, the research shows how consumers' recognition of tangible advantages can enhance acceptance levels and mitigate perceived privacy risks. This finding aligns with the privacy calculus theory (Serenko, 2014), which shows that individuals weigh perceived benefits against risks when deciding whether to disclose personal information. Our study extends this theory to the context of genetic data, demonstrating its applicability beyond traditional data types.

Second, the study explores the significant impact of institutional reputation on the perceived benefits of using genetic data. This contribution extends existing theories on consumer trust and risk perception by integrating institutional reputation as a crucial factor in the context of sensitive data sharing. From a research perspective, this finding invites researchers to explore how institutional credibility and reputation shape consumer behavior in digital and high-risk contexts, providing a valuable direction for future studies on privacy, trust, and data acceptance of genetic data.

Third, our research extends the applicability of the TPB (Ajzen, 1991) to genetic data, suggesting that consumers' perceived control over their data significantly influences their acceptance. This insight aligns with findings from Zhang et al. (2018), who noted that perceived control reduces privacy concerns and drives acceptance. The study also sheds light on the psychological dimension of risk avoidance and its impact on perceived privacy risks.

By showing that individuals with a higher tendency to avoid risk perceive greater privacy risks, our research contributes to a deeper understanding of the psychological factors in the privacy calculus. Our research also emphasizes the critical role of regulation in shaping consumer perceptions and acceptance of using genetic data. This relationship reinforces the importance of robust legislative frameworks in reducing privacy concerns (Chang et al., 2018; Li et al., 2016).

Finally, the study addresses the privacy paradox, where individuals' concerns about privacy do not always translate into protective behaviors (Barth & de Jong, 2017; Taddicken, 2013). Our finding that perceived privacy risk does not significantly affect acceptance levels suggests that only extreme levels of perceived risk may impact behavior in this case, which can present an area for further research.

Managerial contributions

This study's contributions extend beyond the theoretical and academic domains to practical and managerial applications.

First, this study shows the positive influence of perceived benefits on the acceptance of genetic data usage for marketing purposes. This significant finding suggests that managers and organizations pursuing genetic marketing should invest in implementing and effectively communicating the benefits associated with their practices. Specifically, these practices can improve products and services, enhance customization and product quality, and help consumers obtain desired products. For instance, 23andMe, a company specializing in genetic testing, provides health reports that can inform users about their predispositions to certain medical conditions (23andMe, 2023a). This valuable information allows consumers to take proactive measures regarding their health, a clear benefit of genetic marketing that improves consumer acceptance.

Second, the research highlights institutional reputation's essential and positive role in perceived benefits, focusing on data providers and company reputations. As these reputations increase, so do the perceived benefits for consumers. This finding indicates that companies interested in using genetic marketing should cultivate trustworthy reputations, especially in their promises and behaviors toward consumers. For instance, Helix Inc. has partnered with reputable institutions like the Mayo Clinic to provide reliable health information, enhancing its reputation and, consequently, the perceived benefits for users (Mayo Clinic, 2024). Companies should select genetic data providers with strong reputations, as poor reputations can negatively impact consumer acceptance of genetic marketing practices.

Finally, another important managerial implication is the positive influence of the perceived level of control over information on acceptance. The results indicate that managers and organizations should invest in measures that enhance consumers' perceived control over their personal information. This will directly impact their acceptance of using such information for marketing purposes. For example, 23andMe provides a comprehensive privacy center where users can control their data settings, choose how their information is shared, and even opt out of research studies (23andMe, 2023b). This approach aligns with best practices for data control, helping to increase consumer trust and acceptance.

Limitations and future research

Despite making significant contributions to genetic marketing theory and practice, this study also has some limitations, which open up new opportunities for future research in several areas. For example, the current study surveyed participants from Portugal, a country in the European Union, which already has strict laws on how to process and share genetic data. Also, the most popular direct-to-consumer genetic test companies, such as 23andMe, AncestryDNA, and MyHeritage (2023), can be found mainly in the USA. Therefore, we suggest that these findings can be replicated in other countries where laws for sharing and processing genetic data are less strict. Indeed, future studies can explore Hofstede's cultural dimensions theory to examine how cultural differences in individualism and uncertainty avoidance impact the acceptance of genetic data for marketing purposes (Hofstede, 1984).

The study predominantly focuses on the privacy calculus theory to explain consumer behavior. While this theory provides valuable insights, it does not explore all factors influencing consumer acceptance. Future research could integrate other theoretical frameworks, such as the elaboration likelihood model (ELM) (Petty et al., 1986), which could help understand how consumers process information about genetic data use and how this affects their acceptance.

Another limitation is the study's cross-sectional nature, which captures data at a single point in time. Consumer attitudes towards genetic data privacy and acceptance may evolve, especially as regulations and market conditions change. Longitudinal studies are needed to understand how these attitudes shift over time.

Conclusions

The current research contributes to a deeper understanding of how consumers perceive the use of private data for marketing purposes, where sensitive data like genetic information is increasingly used in commercial contexts. As genetic data continues to gain traction in various fields, including healthcare and personalized marketing, understanding these drivers is essential for developing ethical frameworks and public policies that address privacy concerns and ensure consumer adoption. The current study sheds light on the critical factors that influence consumer acceptance of genetic data used for marketing purposes, revealing the roles of perceived benefits, institutional reputation, perceived control, and the impact of regulatory frameworks.

Our findings show that perceived benefits significantly drive acceptance, and that strong institutional reputations and enhanced perceptions of control can lead to a higher degree of acceptance of using genetic data for marketing purposes. These insights provide practical guidance for companies seeking to ethically leverage genetic data and emphasize the importance of transparent and consumer-centered approaches in building trust in the use of private data.

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Data Availability The data that support the findings of this study are not openly available due to reasons of sensitivity and privacy but anonymized data can be made available upon reasonable request.

Declarations

Competing interests The authors declare no competing interests.

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