INSTITUTO
UNIVERSITÁRIO
DE LISBOA

The role of value propositions in consumers' willingness to share personal data in digital marketing

Matilde dos Reis Mendes Amaro da Costa

Master in Management

Supervisor:

PhD, Alexandra Etelvina Martins Marques Fernandes,
Associate Professor with Habilitation

Iscte – Instituto Universitário de Lisboa

October, 2025

BUSINESS
SCHOOL

Department of Marketing, Operation and General Management

The role of value propositions in consumers' willingness to share personal data in digital marketing

Matilde dos Reis Mendes Amaro da Costa

Master in Management

Supervisor:

PhD, Alexandra Etelvina Martins Marques Fernandes, Associate Professor with Habilitation

Iscte – Instituto Universitário de Lisboa

October, 2025

Acknowledgment

To my supervisor, Professor Alexandra Fernandes, for the guidance, availability, expertise, valuable feedback, professionalism, and kindness throughout the development of this dissertation.

To my family, especially my parents, my sister and my aunt for all the inspiration, encouragement, and for always believing in me.

To my friends, for their companionship, and for bringing lightness and laughter to this journey.

This achievement would not have been possible without each of you. Thank you for being part of this path.

Resumo

A recolha e utilização de dados pessoais tornaram-se elementos centrais de qualquer estratégia de marketing digital, especialmente nas redes sociais. Neste contexto, compreender os fatores que levam os consumidores a partilhar os seus dados pessoais é fundamental para as marcas possam desenvolver relações mais éticas, transparentes e sustentáveis com os sus públicos. No entanto, apesar da crescente relevância do marketing oreintado por dados, são escassos os estudos que analisam de forma integrada o impacto das diferentes propostas de valor, como a personalização, transparência, confiança e valor experiencial, na tomada de decisão de partilhar informação pessoal. De forma a colmatar esta lacuna, a presente investigação analisou o papel das propostas de valor na intenção de partilha de dados pessoais nas redes sociais, bem como o efeito da confiança e da perceção de justiça nessa relação. Para tal, foi realizado um inquérito online a 220 utilizadores de redes sociais, com recurso a uma metodologia quantitativa. Os resultados evidenciam que o principal fator principal fator para o aumento da predisposição para partilhar dados pessoais é de facto a personalização das experiências e conteúdos digitais. A confiança contribui positivamente, embora funcione como uma condição essencial de segurança e credibilidade e não como elemento diferenciador. Por outro lado, a transparência, quando analisada isoladamente, não aumenta significativamente a vontade de partilhar, mas aparenta ser mais mais eficaz quando associada a experiências emocionais, interativas ou exclusivas. Do ponto de vista teórico, esta investigação reforça a importância de integrar as dimensões racionais e emocionais nas propostas de valor digitais. Do ponto de vista prático, fornece orientações concretas para que as marcas possam desenvolver e desenhar estratégias de marketing de dados mais humanas, transparentes e justas, assentes na promoção de relações de confiança e partilha responsável no ambiente digital.

Palavras-chave: marketing digital; redes sociais; partilha de dados; proposta de valor; personalização; transparência; confiança do consumidor; ética.

Códigos de Classificação JEL: M15 – IT Management, M31 – Marketing, M37 – Advertising

Abstract

The collection and use of personal data have become central elements of any digital marketing strategy, particularly within social media platforms. In this context, understanding the factors that lead consumers to share their personal data is essential for brands to develop more ethical, transparent, and sustainable relationships with their audiences. However, despite the growing importance of data-driven marketing, few studies have examined in an integrated way the impact of different value propositions, such as personalization, transparency, trust, and experiential value, on consumers' decisions to share personal information. To address this gap, the present research analyzed the role of value propositions in consumers' willingness to share personal data on social media, as well as the influence of trust and perceived fairness in this relationship. For that, an online survey was conducted with 220 social media users, applying a quantitative research approach. The results show that personalization is the main factor that increases individuals's willingness to share personal data. Trust also contributes positively, functioning as an essential condition for security and credibility, rather than as a differentiating element. Conversely, transparency alone does not significantly enhance the willingness to share, but appears to be more effective when combined with emotional, interactive, or exclusive experiences. From a theoretical perspective, this research reinforces the importance of integrating both rational and emotional dimensions within digital value propositions. From a practical point of view, it provides concrete guidelines for brands to design more human, transparent, and fair data-driven marketing strategies, grounded in the promotion of trust and responsible data-sharing relationships in digital environments.

Keywords: Digital Marketing; Social Media; Data Sharing; Value Proposition; Personalization; Transparency; Consumer Trust; Ethics.

JEL Classification System: M15 – IT Management, M31 – Marketing, M37 – Advertising

Index

Acknowledgment i
Resumo iii
Abstract iv
1. Introduction 1
2. Literature review 7
2.1. Value propositions in the digital context 7
2.1.1. Social media in digital value context 8
2.2. The role of data in digital marketing 10
2.2.1. Regulations and ethical considerations 11
2.3. Social media as a channel for data-driven value propositions 12
2.3.1. Mechanisms of value proposition in social media 13
2.3.2. Data collection techniques embedded in social media UX 15
2.4. The privacy paradox and data sharing behavior 16
3. Conceptual model and hypotheses 17
3.1. Proposed conceptual framework 17
3.2. Research hypotheses 18
4. Methodology 20
4.1. Research strategy 20
4.2. Population and sample 21
4.3. Data collection instrument 21
4.4. Operationalization of variables 23
4.5. Data collection procedures 25
4.6. Data analysis techniques 25
4.7. Methodological limitations 28
5. Results 29
5.1. Descriptive analysis 29
5.2. Reliability analysis 31
5.3. Bivariate correlation 32
5.4. Exploratory factor analysis (EFA) 34
5.5. Cluster analysis 36
5.5.1. Cluster profiles 37
5.6. Trust vs. Actual consumption of digital platforms 39
5.7. Hypotheses testing 40
6. Discussion 44

6.1. Theoretical implications 44
6.2. Practical implications 46
6.3. Limitations and suggestions for future research 48
7. Conclusions 49
References 51
Appendices 54
A1. Survey questionnaire 54
A2. Additional results 60
Suplementary table 1. Descriptive statistics for the main variables. 60
Suplementary table 2. Descriptive statistics and reliability for the main constructs. 61
Suplementary table 3. Pearson bivariate correlations between all study items 62
Suplementary table 4. Comparison of trust and actual consumption across digital platforms 63
Suplementary table 5. Binary logistic regression models predicting willingness to share personal data based on perceived personalization and transparency 64
Suplementary table 6. Binary logistic regression models predicting willingness to share personal data based on perceived personalization and trust 65
Annex Table 7. Binary logistic regression models predicting willingness to share personal data based on perceived personalization and experiential value 66
Annex Table 8. Binary logistic regression models predicting willingness to share personal data based on perceived transparency and experiential value 67

Tables Index

Table 1. Questionnaire items by construct 22
Table 2. Operationalization of Variables 24
Table 3. Sociodemographic characterization of the participants 29
Table 4. Mean and standard deviation of the main constructs 31
Table 5. Reliability statistics of the independent and dependent variables 32
Table 6. Pearson bivariate correlations for the main constructs 34
Table 7. Factor analysis 35
Table 8. Profiles of consumer clusters 37
Table 9. Comparison of consumer clusters based on social media usage and data-sharing attitudes 38

Figures Index

Figure 1. Conceptual framework of the study 18
Figure 2. Participants' consumption intensity (a) and social media usage frequency (b). 30
Figure 3. Declared preference vs. Actual consumption by platform 40

1. Introduction

More than ever, our society lives in a digital era. The Internet, computers, smartphones, and tablets have become omnipresent today (Müller & Hopf, 2017). As technology continues to evolve rapidly, digital marketing, particularly on social media, has developed new ways to capture individual's attention. Social media platforms have become central tools for exchanging value and gathering data (Spiller, 2020; Kotler, 2021). In this context, obtaining consumers' personal data has become a cornerstone of digital marketing strategies. As Quach et al. (2022, p. 1299) state, "Modern marketing practice requires the use of digital technologies, and the customer data they generate, to create value".

As businesses increasingly rely on data to personalize marketing, improve customer experiences, and optimize products, consumers' willingness to share their personal information often depends on the perceived value they they expect in return. Consumers tend to share their data more willingly when they perceive clear benefits, like personalized offers, improved services, or tangible rewards. As Ackermann et al. (2022, p. 378) point out, this willingness depends on the type of reward offered and how identifiable consumers become through the data they share.

Furthermore, Faroukhi et al. (2020, p. 2) emphasize that "value creation is the rational goal of any organization. However, in a changing world, in terms of data, it is very difficult to find strategies to sustainably generate new value and improve operations". These insights illustrate that while data-driven marketing creates new opportunities to deliver value, it also brings complex strategic and ethical challenges.

Understanding the factors that drive these decisions is essential for businesses that aim to build trust with customers while respecting their privacy. The value proposition and the benefits offered in exchange for consumer personal data play a key role in shaping users' willingness to share. A strong value proposition can encourage data disclosure, while a weak or unclear one may make consumers hesitant or unwilling. Sophisticated use of consumer data allows for personalized product offerings and recommendations, price discounts, free services, and more relevant marketing communication (Martin & Murphy, 2017, p. 136). These perceived benefits form the foundation of the value exchange and strongly influence consumer behavior. Trust further reinforces this effect, increasing consumers' willingness to share data when they believe the company will

fulfill its side of the value exchange (Martin & Murphy, 2017, p. 138). In this sense, value propositions in social media play a crucial role in establishing trust, as brands realize that a strong brand must be human, relatable, and engaged (Burgess & Burgess, 2020).

Personal data have thus become a strategic resource powering personalization, recommendation systems, and targeted communication. Digital marketing increasingly depends on users' willingness to disclose information that enables firms to design value propositions tailored to individual preferences. Yet, while personalization enhances relevance and convenience, it also raises ethical and privacy-related concerns, creating tension between consumer empowerment and data vulnerability.

This dynamic is changing concurrently with growing worries about data ethics and digital privacy. Regulatory frameworks such as the General Data Protection Regulation (GDPR) have transformed the legal and operational environment for businesses. While stronger regulations at global, national, and regional levels protect consumers, they also increase compliance costs for firms and establish strict penalties for noncompliance (Quach et al., 2022, p. 1300). In addition to these legislative changes, consumers are now more conscious of the dangers of revealing personal information online. High-profile data scandals and increased media scrutiny have raised public consciousness, decreasing trust and engagement (Rosário & Dias, 2023, p. 6), and reinforcing the need for companies to act with greater transparency, accountability and ethical responsability. The adherence to minimal ethical standards of information usage, storage, and collection is essential to regaining consumer trust (Hemker et al., 2021, p. 5). Indeed, the extensive gathering of information from users' activities to personalize advertisements and communication activities can greatly intrude on customers' online privacy.

The real challenge, therefore, lies not only in identifying which types of value are most effective, but also what circumstances make customers feel comfortable sharing their data. In particular, within the context of value propositions, factors such as trust, perceived fairness, and a sense of control play an important role in consumer decision-making, even though they are often not taking in consideration as they should by brands.

It is thus essential to investigate how consumers perceive and respond to different types of value propositions in data-sharing contexts. The aim of this research is not to explain technological mechanisms or legal compliance, but instead to explore the human side of this exchange — the expectations, motivations, and concerns that shape consumer decisions in digital context; in other words, what actually leads consumers to either share or retain their personal data.

As data-collection practices continue to evolve, particularly on social media, this research gains increasing relevance. By examining how different types of value propositions influence consumers' willingness to share personal data, this study provides insights that can help brands to design trust-based, transparent and enganging digital marketing strategies.

Despite extensive research on digital personalization, existing studies remain fragmented. Previous work has explored the impact of personalization on engagement (Hollebeek & Macky, 2018), the role of trust in online environments (Mosteller & Poddar, 2017), and the influence of transparency on ethical perceptions (Martin & Murphy, 2016).

However, limited empirical evidence explains how these constructs interact simultaneously to shape consumers' willingness to share data. As Quach et al. (2022) observed, "we still lack a systematic, integrative, research-based view of privacy tensions across all three involved entities, specifically in relation to digital technologies and the unique customer data they generate" (p. 1300). This highlights the need for comprehensive models that integrate different determinants of consumers' data-sharing behavior, rather than addressing them in isolation.

First, there is limited evidence on which types of value propositions (transactional, personalized, or experiential) are most effective in encouraging data sharing on social media. Although previous studies have examined aspects such as trust, personalization, and transparency in digital contexts, "existing research effectively outlines privacy tensions from consumers' and firms' perspectives but without addressing the complex, interrelated positions of firms, consumers, and regulators simultaneously" (Quach et al., 2022, p. 1300). In the same line, Faroukhi et al. (2020) emphasize that "most of these studies propose basic model[s] … and completely ignore indispensable phases … such as exposition and monetization" (p. 13), indicating that research on data value and exchange remains fragmented and lacks integrative perspectives.

Overall, the literature tend to focus on isolated factors or theoretical discussions, rather empirically comparing different value dimensions. As Quach et al. (2022) note, "research into internal privacy mechanisms such as privacy paradoxes … cannot establish a triadic view of the privacy tensions created by digital technologies that link all these groups" (p. 1300).

The present study seeks to address this empirical and conceptual gap by testing an integrated model that explores how these variables (personalization trust, experience, transparency) jointly influence data-sharing intentions.

Second, although trust and transparency are frequently highlighted as critical factors, their combined role as boundary conditions in consumers' decisions remains underexplored. Faroukhi et al. (2020) also note that "few researches have considered the monetization concerns in a Big Data context … many efforts should be addressed to identify suitable strategies for an efficient data monetization approach" (p. 18), reinforcing that the interplay between fairness, value creation, and willingness to share data is still insufficiently examined.

Finally, concepts such as perceived fairness have been discussed but are rarely tested as mechanisms linking experiential value delivery and willingness to share. As Faroukhi et al. (2020) point out, "there is not enough academic research in Big Data Monetization … [and] the existing ones do not consider all big data aspects" (p. 19), further evidencing the lack of empirical analysis on fairness and other mediating factors. This gap is also a scientific motivation of the present research.

Addressing these gaps, the central research question guiding this dissertation is:

> *How do transparent and personalized value propositions shape consumers' willingness to share personal data in social-media environments?*

To answer this question, the study sets out four specific objectives:

(1) To examine how transparent and personalized value propositions influence consumers' willingness to share data.

(2) To assess whether trust in the platform strengthens the effect of personalization on that willingness.

(3) To analyse whether experiential mechanisms of value delivery, such as gamification, exclusivity, and influencer interaction, enhance consumers' perceived fairness in data exchange;

(4) To determine whether perceived transparency moderates the relationship between perceived value and willingness to share data.

These objectives are operationalized through four hypotheses, empirically tested using a quantitative survey of social-media users. The findings are expected to provide both theoretical and managerial insights: theoretically, by clarifying the interplay between trust, transparency, and fairness in data-exchange contexts; and practically, by helping marketers design ethical and transparent personalization strategies that respect users' perceptions of fairness and control.

This dissertation is relevant because it explores how value propositions influence consumers' willingness to share personal data and contributes to the emerging debate on

responsible data-driven marketing, aligning consumer-centric value creation with transparency and trust-building practices, central issues in today's digital economy (Quach et al., 2022, p. 1299). From an academic perspective, it tries to clarify which types of value propositions are most effective, and highlights the role of trust and perceived fairness in this process. From a practical standpoint, it offers guidance for companies to understand how to adapt their value propositions in ways that encourage consumers to share data more willingly, while ensuring transparency and responsibility (Quach et al., 2022, p. 1309). In this way, the study aims to provide both theoretical insights and practical guidance for organizations seeking to build trust-based and effective data-driven strategies.

The dissertation is structured as follows. The introduction presents the relevance of and scope of the topic. The literature review offers a comprehensive overview of the key concepts related to value propositions, consumer behavior, and data sharing in digital and social media environments. The conceptual model and research hypotheses are then detailed, followed by the methodology, which explains the design, data collection, and analysis procedures. The results are then presented and discussed in light of the theoretical framework. Finally, the dissertation concludes with reflection on the main contributions, limitations, and suggestions for future research, as well as practical recommendations for professionals working in data-driven marketing.

2. Literature review

2.1. Value propositions in the digital context

The Customer Value Proposition (CVP) is a central element of marketing strategy and enables brands to stand out and gain a competitive edge. As Payne, Frow, and Eggert (2017, p. 478) explain, “CVPs capture the essence of marketing strategy decisions, affect marketing strategy implementation, and determine the firm’s competitive advantage”. This perspective highlights that the CVP plays an important role in linking business goals to the value perceived by customers.

A CVP can be defined as “a strategic tool facilitating communication of an organization’s ability to share resources and offer a superior value package to targeted customers” (Payne, Frow & Eggert, 2017, p. 472). This definition underscores that the CVP aligns what the company offers with what the market values. It works both as a promise of value and as a mechanism of differentiation within competitive markets.

It is equally important to distinguish the CVP from the Unique Selling Proposition (USP). While the USP typically focuses on one single benefit in an explicit and advertising-driven way, the CVP is broader, multidimensional, and more strategic in nature. As explained by Payne, Frow & Eggert (2017, p. 470), “Unlike the USP concept from advertising, the CVP may include more than one benefit, incorporates some consideration of price, is not necessarily communicated to the customer, and may be ‘an implicit promise a company makes’”. Thus, the CVP integrates both tangible and intangible dimensions of value, extending beyond product features to encompass customer experience, service quality, and relational factors.

Besides being a strategic tool, the CVP also shapes how customers perceive, evaluate, and engage with a brand. When a CVP is clear and well designed, it helps customers understand the value, set the right expectations, and see the benefits and costs of choosing a brand. As noted by Payne, Frow & Eggert (2017, p. 477), “CVPs have positive impacts on customers’ value perceptions and subsequent satisfaction; they set appropriate expectations and clarify the superior benefits and costs of engaging with the supplier firm and its market offerings”.

This sense of relevance can even be more important than privacy concerns, as people often focus on immediate usefulness rather than long-term risks (Jung, 2017, in Eg et al., 2023, p. 11; Van den Broeck et al., 2020, in Eg et al., 2023, p. 6)". Nevertheless, such

perceptions of value are frequently accompanied by consumer ambivalence, where individuals acknowledge the benefits of personalization but simultaneously express discomfort with losing control over their personal data (Youn & Kim, 2019, in Eg et al., 2023, p. 11).

CVP can also be created at different levels: for the whole company, for specific customer segments, or even for individual customers. Each level has a different role and brings benefits to both the business and the consumer. “CVPs can be formulated at different levels of granularity, such as the firm level, customer segment level, or individual customer level. On each level, the CVP fulfills a different purpose, for the company and the customer” (Payne, Frow & Eggert, 2017, p. 478).

These dimensions are especially important in digital environments, where CVP are continuously communicated, co-created, and reshaped across multiple channels. Social media, in particular, plays a decisive role in this process: has become a key space where value is shown, understood, and even shaped by users. This idea will be explored further in the next section. From this point onward, the term value proposition will be consistently used throughout the dissertation to refer to the concept of customer value proposition (CVP).

2.1.1. Social media in digital value context

In the digital era, social media has emerged as a pivotal space for brands to communicate, adapt, and co-create customer value propositions. Traditionally defined as the overall promise of value that a company delivers to its customers, it now reflects a dynamic process of co-created value between brands and consumers. In digital contexts, value propositions rely not only on product or service attributes but also on the ability to offer *personalized, interactive, and experiential* engagements that align with individual needs and expectations (Payne, Frow & Eggert, 2017).

Social media platforms are more than just communication tools. They are active spaces where people interact with content, form opinions, and decide whether to trust and engage with brands. These platforms enable companies to deliver value through personalization, relevance, and emotional engagement. As Hollebeek and Macky (2018, p. 27) note, “Digital content marketing (DCM) aims to foster consumers' brand engagement and trust by delivering relevant, valuable brand-related content rather than

directly persuading them to purchase". Unlike traditional advertising, which pushes messages to the audience, social media content is often part of an inbound strategy that aims to attract people by offering value, such as entertainment, useful information, or inspiration

This shift from persuasion to value creation shows that the digital value proposition is no longer a one-way message. They no longer operate as static messages but as adaptive experiences, continuously refined through customer data and feedback. This transition underscores how personalization can increase the perceived fit between brand offerings and user identity, thereby strengthening engagement and loyalty With tools like quizzes, blogs, videos, and influencer collaborations, brands can offer more personal and authentic value experiences (Hollebeek & Macky, 2018, p. 33).

These personalized experiences are powered by algorithms that constantly analyze user interactions to adjust and improve content delivery in real time (Rassameeroj & Wu, 2019, in Eg et al., 2023, p. 2; Aydin, 2018, in Eg et al., 2023, p. 2).

Trust plays a central role in this process. As Mosteller and Poddar (2017, p. 31) point out, "Trust in social media websites positively relates to social media engagement". When users feel that they have transparency and control over their personal data — like through clear privacy settings or easy-to-understand consent options — they are more likely to engage with brands and accept digital value exchanges. Trust is essential for building long-term relationships between consumers and brands, especially when personalization is based on data. However, people often go along with these models more because of the immediate value they see than because they fully think through the privacy risks (Jung, 2017, in Eg et al., 2023, p. 11).

Moreover, social media enables brands to communicate their value propositions with a level of immediacy and flexibility that traditional media lacks. Real-time interactions, user-generated content, and algorithmic personalization all contribute to a value proposition that is not only communicated but also experienced by the user in contextual, meaningful ways.

In this context, the line between brand and consumer is becoming increasingly blurred. Consumers are no longer just passive receivers of a value proposition —they actively help shape and validate it through likes, shares, comments, and creating content. This co-creation makes the brand message feel more real and adds value for others in the network. Social media platforms use tools like mobile sensors, GPS, and contextual data

to personalize experiences even more. Still, this also brings challenges about how accurate and representative the collected data truly is (Martí et al., 2019, pp. 161–163).

In short, social media platforms have become essential arenas for the development and communication of digital value propositions. They increase reach, allow real-time personalization, and offer ways to engage users that are key to shaping how consumers see brands. As brands enhance personalization, they increasingly depend on access to personal data — raising concerns regarding privacy, fairness, and ethical use of consumer information. Understanding how users perceive these personalized value propositions therefore becomes essential to designing strategies that are both effective and responsible. In the end, these elements help encourage people to share their personal data willingly, as the next chapter will explore.

2.2. The role of data in digital marketing

In the digital era, data has become one of the most valuable resources for businesses. It helps personalize experiences, improve efficiency, and drive innovation. As Quach et al. (2022) and Faroukhi et al. (2020) point out, companies are using data more and more to create, deliver, and capture value by turning raw information into useful insights. This has also led to the direct monetization of data, either by selling it or using it to create information-based products and services (Hanafizadeh & Harati Nik, 2020, pp. 18, 24).

Using models like the Data Value Chain (Faroukhi et al., 2020), companies are turning data into economic value. This can be done by selling data directly or by using it to enhance customer experiences and improve internal operations. Data allows businesses to tailor their products and services to individual needs, making marketing efforts more targeted and effective (Hemker et al., 2021; Rosário & Dias, 2023). A good example is the use of cookies to track user preferences and behavior online, which enables personalized recommendations and smarter decision-making (Rodríguez-Galán & Torres, 2024, p. 771).

Social media platforms represent a particularly dynamic environment for data-driven marketing strategies. These platforms are more than just tools for communication and branding. They also play a key role in collecting data and creating value through exchange. As Spiller (2020) and Kotler (2021) observe, social media has evolved into a space where consumers and companies engage in continuous interaction, often

exchanging personal information for perceived benefits such as entertainment, personalization, or convenience.

Consumers' willingness to share data is frequently influenced by their perception of the value they receive in return. Personalized recommendations, discounts, access to exclusive content, or enhanced services can all motivate data sharing (Ackermann et al., 2022). However, trust is a key determinant: when users believe that a company will honor the terms of the exchange and use their data responsibly, they are more likely to engage (Martin & Murphy, 2017). Still, users often struggle with the trade-off between enjoying personalized experiences and feeling like they're losing control. Many end up making what feels like a 'forced compromise' (Schmidt et al., 2019, in Eg et al., 2023, p. 6).

Nevertheless, not all consumers react in the same way. While some are more open to sharing information, others are increasingly concerned about privacy, lack of transparency, and potential misuse of their data. These concerns lead to varying levels of engagement and create distinct consumer segments with different privacy preferences and expectations (Gimpel et al., 2018; Rosário & Dias, 2023).

In this context, a company's value proposition becomes a crucial mechanism for building trust and encouraging participation. A clear and trustworthy value proposition can help manage expectations, reduce doubts, and encourage more open and ethical data sharing (Payne, Frow & Eggert, 2017). On the other hand, when the message is unclear or confusing, it can lead to less engagement, resistance, or even negative reactions from consumers

Ultimately, data is more than just a resource. It's a way through which the relationship between consumers and companies is built and managed. To act responsibly and effectively in data-driven environments, companies need to understand how perceived value, trust, and digital behavior all connect.

2.2.1. Regulations and ethical considerations

As data-driven practices become increasingly widespread, regulatory and ethical considerations have become central to digital marketing strategies. The introduction of the General Data Protection Regulation (GDPR) in the European Union marked a significant shift in the way companies must handle consumer data. As noted by Martin & Murphy (2017) and Ackermann et al. (2022), GDPR emphasizes transparency, consent,

and consumer empowerment, placing strict obligations on firms and heavy penalties for non-compliance. The goal of regulation is to bring more balance to data relationships, but it often puts the responsibility on users. This shows one of the main limits of current legal approaches (Reviglio & Agosti, 2020, in Eg et al., 2023, p. 11).

Beyond legal compliance, ethical concerns about how data is collected, stored, and used are becoming more important. Hidden tracking, sharing data with third parties, or overly personalized ads can reduce trust and damage a brand's image (Faroukhi et al., 2020; Hemker et al., 2021). Also, when algorithms shape people's experiences without clear consent, it increases distrust and makes users feel powerless (Perez Vallejos et al., 2021, in Eg et al., 2023, p. 6).

As Rosário & Dias (2023) emphasize, when consumers perceive a lack of transparency, their engagement with digital platforms tends to decline.

In response, scholars and practitioners advocate for a more responsible and consumer-centric approach to data use. This includes fostering transparency, offering users meaningful control over their information (Mosteller & Poddar, 2017), and ensuring that value exchanges are perceived as fair and mutually beneficial (Payne, Frow & Eggert, 2017). Ethical marketing is no longer a choice. It's a key requirement for long-term success in a market where people are more aware and regulations are getting stricter.

Importantly, the balance between personalization and privacy remains a key challenge. While consumers appreciate tailored experiences, they also demand clarity on how their data is used and expect brands to act with integrity. As Hemker et al. (2021, p. 5) state, "the adherence to minimal ethical standards of information usage, storage, and collection […] is of great importance in gaining consumer trust".

In conclusion, as digital marketing becomes more reliant on data, companies need to keep up with changing laws and rising ethical expectations. Being transparent and offering fair value will be key to building trust and keeping strong relationships with consumers in a society that's increasingly aware of data issues.

2.3. Social media as a channel for data-driven value propositions

Social media platforms have become strategic enablers of data-driven marketing. Far from their original purpose of social connection, they now serve as infrastructures for capturing behavioral data, personalizing experiences, and sustaining platform-centric

business models. As Spiller (2020, p. 416) highlights, platforms like Facebook, Instagram, TikTok, or LinkedIn are central channels for marketing operations, allowing companies not only to distribute content but also to collect and process user data for targeted communication. These platforms often use behavioral cookies and algorithms to track clicks, content viewed, and time spent on posts. This data is used to build user profiles for targeted ads and engagement (Rodríguez-Galán & Torres, 2024, pp. 765–766)

Within this context, the logic of exchanging free access for personal data has become dominant. According to Martin and Murphy (2017, p. 136), many platforms operate with an implicit value proposition: "users receive access to services and content at no direct monetary cost, while companies obtain valuable data about their behaviors, interests, and preferences". This shared value model helps brands understand their audiences better and offer more relevant messages and products. When messages are personalized based on interests shown through browsing or past interactions, users are more likely to see the data exchange as fair (Rodríguez-Galán & Torres, 2024, p. 766).

This model is based on the idea that people will share their data if they feel they're getting something in return, like personalized content, special offers, or unique experiences. But this exchange isn't always clear. As Quach et al. (2022, p. 1303) explain, users often don't know who sees their data or how it's used. Still, their behavior shows a kind of silent acceptance, especially when the value offered is clear or emotionally appealing.

On the other hand, this data-based relationship can be weakened by privacy worries, lack of transparency, or feeling manipulated. That's why finding the right balance between value and trust is so important. As Hollebeek and Macky (2018, p. 32) note, trust on social media depends a lot on how users see the value they get and how clearly data is collected and used.

In this way, social media platforms are not just communication vehicles but structured environments for value exchange through the collection and activation of personal data. This often invisible value logic is at the heart of contemporary digital marketing practices and demands a critical look at the ethical and strategic implications involved.

2.3.1. Mechanisms of value proposition in social media

Value propositions in social media are implemented through different strategies that aim to capture attention, increase time spent on the platform, and encourage data sharing,

often in subtle ways These mechanisms are carefully designed to appear natural, playful, and advantageous, masking the underlying value transaction. Hollebeek and Macky (2018) argue that these interactions represent forms of value co-creation, in which users actively contribute to the construction of personalized experiences—while simultaneously generating relevant data for brands.

One of the clearest strategies is content personalization, which shows up in curated feeds, algorithm-based suggestions, and recommended products or friends. While users often see this as helpful, it depends on closely tracking their online behavior (Spiller, 2020, p. 419). Much of this happens without users fully realizing it, as it's built into system defaults and hidden tracking (Zuiderveen Borgesius et al., 2016, in Eg et al., 2023, p. 16).

Another mechanism is gamification, through rewards such as badges, levels, or rankings, which stimulate repeated behavior and emotional engagement. According to Gimpel et al. (2018), this dynamic strengthens the brand-user relationship while capturing behavioral data.

Exclusive access to content, such as giveaways, private livestreams, or early product releases, creates a sense of privilege that drives users to share more data in return. Simultaneously, interacting with influencers helps create an emotional bond that makes people feel more connected to the brand (Hollebeek & Macky, 2018, p. 33).

In addition, interactive tools such as quizzes, augmented reality filters, or automatic reactions not only entertain but also collect detailed psychographic information. This kind of emotional and experience-based value proposition is central to how social media platforms work today. It depends on constant user participation to turn behavior into profit**.** These systems often operate via "pre-selected personalization" and data capture that occurs without active user input, reinforcing the platform's predictive capabilities (Zuiderveen Borgesius et al., 2016, in Eg et al., 2023, p. 16).

The way users see this exchange as fair or not depends on how well they understand how algorithms work. This refers to their ability to make sense of the hidden processes behind recommendations and suggestions (Swart, 2021, in Eg et al., 2023, p. 6).
All of these mechanisms contribute to emotionally engaging, immersive experiences that frame data sharing as a fair and rewarding exchange.

2.3.2. Data collection techniques embedded in social media UX

"User experience (UX) on social media is carefully designed to keep people interacting, staying longer, and quietly collecting their data.. This process is not accidental. It's part of a planned strategy built into how users navigate, interact, and give consent on platforms. As Gimpel et al. (2018, p. 1) explain, digital services depend on large-scale data collection to build detailed user profiles based on behavior, preferences, and interactions. Much of this is done through cookies that track sessions, preferences, and clicks, allowing for very precise behavioral targeting (Rodríguez-Galán & Torres, 2024, pp. 765–766)".

A common technique is invisible tracking, including cookies, fingerprinting, scroll tracking, and web beacons. These practices often happen without users realizing it, allowing ongoing data collection without clear consent. Faroukhi et al. (2020, p. 3) describe these actions as part of the 'Data Value Chain,' where data is created, analyzed, and turned into profit. Cookies used for analytics collect information about how people use a service. This data is then used to improve content and features, aiming to offer a better user experience (Rodríguez-Galán & Torres, 2024, p. 766).

Another common practice is getting user consent in unclear or hidden ways, often through complex interfaces known as dark patterns. These designs lead people to accept terms without really understanding them. Ackermann et al. (2022, p. 376) warn that many users don't realize how much of their data is being shared, which hurts the feeling of transparency. Consent is often collected through confusing layouts or pre-selected choices, giving users a false sense of control (Zuiderveen Borgesius et al., 2016, in Eg et al., 2023, p. 16).

Even more subtly, data collection is integrated into playful and emotionally engaging experiences, such as quizzes, filters, or mini-games, which gather information about personality traits, preferences, or location in an entertaining way (Hollebeek & Macky, 2018, p. 33). These data can then be used to model user profiles that power recommendation systems, advertising segmentation, and persona development (Raj & Renumol, 2022, pp. 117–118).

The idea that access is free, combined with entertainment, helps make this kind of data exchange feel normal. Still, many people worry about privacy while continuing to share personal information. This contradiction is known as the privacy paradox (Martin

& Murphy, 2017, p. 136). On top of that, users often don't realize how valuable their data really is (Gimpel et al., 2018, p. 2).

All of these techniques contribute to a digital environment where transparency plays a central role in shaping users' perceptions of value and fairness.

2.4. The privacy paradox and data sharing behavior

Concerns about privacy have long been identified as one of the main barriers to online data disclosure. Surveys consistently show that users declare being highly concerned about the potential misuse of their personal information. Yet, despite this expressed concern, individuals continue to share personal data across digital platforms, a contradiction that has been termed the privacy paradox (Kokolakis, 2017, p. 2; Barth & de Jong, 2017, p. 1038). As Barth and de Jong (2017) note, "while users claim to be very concerned about their privacy, they nevertheless undertake very little to protect their personal data" (p. 1039). This paradox has significant implications for domains such as e-commerce, e-government, and, most notably, online social networking (Kokolakis, 2017, p.2).

Different theoretical perspectives have attempted to explain this discrepancy between privacy attitudes and actual behavior. From a rational perspective, the privacy calculus suggests that individuals perform a cost–benefit evaluation, disclosing information when perceived benefits outweigh expected risks (Kokolakis, 2017, p. 14; Gerber et al., 2018, p. 12). As Barth and de Jong (2017) emphasize, "users consciously weigh the disadvantages of privacy disclosure against the perceived benefits […] in most cases, benefits outweigh risks, which eventually leads to neglecting privacy concerns" (p. 1044). In the context of social networking sites, this trade-off often involves exchanging privacy for entertainment, social relationships, or identity construction (Kokolakis, 2017, p. 15).

Other explanations stress the role of cognitive biases and psychological limitations. Individuals frequently operate under conditions of incomplete information and bounded rationality, which leads them to prioritize immediate benefits over long-term privacy risks (Kokolakis, 2017, p. 19; Barth & de Jong, 2017, p. 1047). As Barth and de Jong (2017) argue, "situational cues mitigate potential risks in the distant future and emphasize immediate benefits […] this immediate gratification outweighs eventual privacy

concerns" (p. 1048). Optimism bias, in particular, reinforces this behavior, as individuals often believe they are less at risk compared to others (Kokolakis, 2017, p. 17).

Furthermore, the systematic review conducted by Gerber et al. (2018) found that perceived benefits, trust in the platform, and intentions to disclose are significant predictors of actual sharing behavior, whereas sociodemographic factors play only a minor role (p. 12). This indicates that the privacy paradox should not be interpreted as a strict contradiction, but rather as the result of a complex interaction between rational trade-offs, cognitive biases, social influences, and contextual factors (Gerber et al., 2018, p. 13; Barth & de Jong, 2017, p. 1049).

In sum, the privacy paradox highlights a central tension in digital marketing and social media: although consumers report being concerned about the protection of their personal data, they continue to disclose it when the perceived value of exchange is attractive enough. The reviewed literature provides a comprehensive overview of the theoretical foundations linking value propositions to data-sharing behaviour in digital marketing. It identifies four core dimensions:

- Personalization – enhances perceived relevance and consumer satisfaction.
- Trust – reduces perceived risk and facilitates openness to data exchange.
- Transparency – increases perceived fairness and control.
- Experiential value – transforms data sharing into an engaging and reciprocal process.

However, existing studies rarely combine these dimensions into a single empirical framework. This research therefore aims to fill that gap by testing a model that integrates personalization, trust, transparency, and experiential mechanisms as predictors of willingness to share personal data, with perceived fairness acting as a potential mediator.

3. Conceptual model and hypotheses

3.1. Proposed conceptual framework

Building on the theoretical foundations discussed in the previous sections, this study proposes a conceptual framework that links consumers' perceptions of personalization, transparency, trust, experiential mechanisms, and perceived value to their willingness to share personal data on social media platforms. The framework is grounded in the notion of the *privacy paradox*, which highlights the tension between consumers' expressed

concerns about privacy and their actual willingness to disclose information when attractive value propositions are offered.

Figure 1 presents the conceptual model developed for this study. It illustrates the independent variables (personalization, transparency, experiential mechanisms, perceived value), the dependent variable (willingness to share personal data), and the roles of trust (as a moderator) and perceived fairness (as a mediator). Each construct represents a key dimension of digital value exchange, reflecting both cognitive and relational factors that drive consumer decisions in data-based marketing contexts.

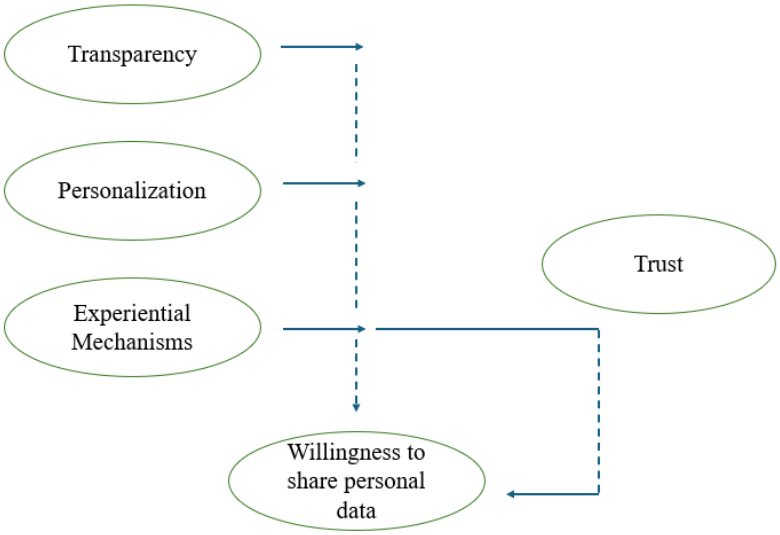


Figure 1. Conceptual framework of the study

The framework suggests that personalization and transparency form the basis of perceived value in digital interactions, while trust operates as a contextual moderator that amplifies positive effects. Experiential mechanisms are expected to influence perceptions of fairness, reinforcing the belief that data exchange can be mutually beneficial. Finally, perceived fairness and perceived value are proposed as key mediating processes linking value propositions to willingness to share personal data.

3.2. Research hypotheses

Based on the conceptual framework presented in Figure 1, this study formulates a set of hypotheses to empirically test the proposed relationships. These hypotheses are designed to capture how personalization, transparency, experiential mechanisms, and perceived value influence consumers' willingness to share personal data, as well as the moderating

role of trust and the mediating role of perceived fairness. Together, they provide a structured way to translate the theoretical model into testable propositions that can be examined through empirical research.

Accordingly, the following hypotheses are formulated:

- **Hypothesis 1**: When brands offer clear and relevant value, consumers are more likely to disclose personal data in exchange for personalized experiences or convenience. Although privacy concerns remain, users tend to exchange personal information when they perceive a clear benefit, illustrating the so-called privacy paradox (Garcia-Rivadulla, 2016, p. 229).

  H1: Transparent and personalized value propositions increase consumers' willingness to share personal data.

- **Hypothesis 2:** Trust plays a key role in shaping consumers' attitudes toward personalization. When individuals trust the platforms that collect and use their data, they tend to perceive personalization as beneficial rather than intrusive. In fact, trust in online firms is strongly associated with a greater preference for personalized content (Stevenson & Pasek, 2015, p. 1).

  H2: Trust in the platform strengthens the effect of personalization on consumers' willingness to share personal data.

- **Hypothesis 3:** Experiential mechanisms of value delivery, such as gamification, exclusivity, or influencer interaction, can create a more engaging and fair environment for data exchange. These mechanisms enhance users' sense of control and enjoyment, leading to greater satisfaction and perceived fairness in sharing personal data. As shown by Hajarian et al. (2025, p.11), gamified experiences encouraging privacy personalization significantly increased users' satisfaction and reduced negative experiences online.

  H3: Experiential mechanisms of value delivery (e.g., gamification, exclusivity, influencer interaction) positively influence consumers' perceived fairness in exchanging personal data.

- **Hypothesis 4:** Transparency messages play a key role in shaping how consumers evaluate data-driven personalization. When customers understand how their data are collected and used, they feel greater control and perceive personalization as more legitimate. As Lambillotte, Bart, and Poncin (2022, p.394) demonstrate, transparency messages can mitigate the negative impact

of personalization by increasing perceived control and reducing privacy concerns.

H4: Perceived transparency in data collection moderates the relationship between perceived value and willingness to share personal data, such that the relationship is stronger when transparency is high.

These hypotheses collectively form the analytical foundation of this dissertation. They reflect how personalization, trust, transparency, and experiential mechanisms shape data-sharing behaviour, while fairness and value mediate consumers' ethical evaluation of digital exchanges.

4. Methodology

4.1. Research strategy

To meet the goals of this research, a quantitative method was used through a self-administered online questionnaire. In this study, the online survey format was particularly appropriate because the research problem is directly related to consumer behavior on digital platforms and social media. Since the target population is already active in online environments, applying the questionnaire digitally reflects the natural context where data sharing decisions take place. This not only increases the ecological validity of the study but also facilitates access to a broader and more diverse sample of social media users. The online format allows participants to respond at their own pace and in conditions of privacy, which is essential when addressing sensitive topics such as personal data, trust, and transparency (Ball, 2019).

Quantitative methods not only allow for the testing of predefined hypotheses and the identification of statistical relationships between variables, but also enable more confident generalizations, since "the larger the number of cases … the surer data analysts can be that what they observe is not a random occurrence" (John, 2008, p. 268). By contrast, qualitative approaches are "ideal for exploratory analysis" and more useful when research is focused on "a single case (or event) or a small number of cases" (Gerring, 2017, p. 20).

According to Rattray & Jones (2007), surveys provide a systematic and organized means of gathering quantitative data from a defined sample, allowing for generalization of the findings to the wider population. In addition, the anonymity of questionnaires encourages more honest and open answers, which is especially important when dealing with sensitive topics like leadership or organizational climate.

4.2. Population and sample

The target population of this study consists of active social media users, who interact with brands and content online. A convenience sampling strategy was applied, since participants were recruited based on accessibility through the researcher's social networks. As Alvi (2016, p. 30) explains, convenience sampling "includes those participants who are easy or convenient to approach," which makes it inexpensive and efficient, although it is also prone to sampling biases. To extend the reach and heterogeneity of the sample, a snowball technique was also used, encouraging participants to share the questionnaire with others in their networks. According to Alvi (2016, p. 35), snowball sampling is "useful in approaching the type of population which is not readily available," even though it can be affected by biases due to network connections.

A total of 220 valid responses were obtained.. Participants completed the survey voluntarily, and no identifying information was recorded. The sample size is sufficient for reliability and correlation analyses but should be interpreted with caution when generalizing results.

A brief summary of participants' demographics (gender, age, education level, and most-used social-media platforms) is provided in the Descriptive Analysis section. The sample predominantly includes young adults aged 18–35, with an average age of 36.4 years old, reflecting the demographic group most active in social media usage.

4.3. Data collection instrument

For this research, data were gathered using an structured questionnaire distributed online through Google Forms. The questionnaire was structured into three sections with a total of 20 questions, combining closed-ended and scaled items.

The questionnaire included items to measure the main constructs of the study (personalization, transparency, trust, experiential mechanisms, perceived fairness, perceived value, and willingness to share personal data). All items were measured on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). To provide a clearer overview of how each construct was measured, Table 1 summarizes the main questionnaire items.

Table 1. Questionnaire items by construct

Construct	Question	
Personalization	11. Think about how you usually interact with brands on social media. Indicate the extent to which the following statements correspond to your usual behavior:	The personalization of offers and content makes me consider the sharing of my personal data fair.
		I am more willing to share my personal data when a brand offers me personalized benefits.
		I prefer brands that clearly communicate how they use my data.
		Understanding exactly how my data will be used makes me feel more comfortable sharing it.
Trust	12. Think about the level of trust you feel when using social media and interacting with brands in those spaces. Indicate the extent to which the following statements reflect your usual perception or behavior:	I trust the social media platforms I use regularly.
		I trust brands I already know, even when they ask for personal data.
		When I trust a brand, I more easily accept that content is personalized based on my data.
		The trust I have in a platform influences my decision to share personal data.
Discomfort with Data Sharing	13. Think about situations in which you distrust brands or platforms on social media. Indicate the extent to which the following statements reflect your usual perception:	I have had previous negative experiences that made me more cautious.
		I become suspicious when the origin of a page or content is unclear.
		I feel hesitant when the information provided by the brand is insufficient.
		I believe many brands use data for purposes that are not clearly communicated.
Experiential Mechanisms	14. Think about experiences you have had with brands on social media — such as campaigns, contests, exclusive content, or interactions with influencers. Indicate the extent to which the following statements correspond to what you usually feel or do:	Accessing exclusive content makes me more willing to share data.
		When I take part in contests or interactive campaigns, I agree to share more personal data.
		My interaction with digital influencers affects my perception of fairness in exchanging data with a brand.
		I feel that data exchange is fair when I receive unique experiences in return.
Transparency	15. Think about how brands communicate about the collection and use of your personal data. Indicate the extent to which you agree with the following statements based on your experience on social media:	The more transparent a brand is about the data it collects, the more value I recognize in its proposal.
		Transparency in data collection makes me more receptive to the benefits offered.
		I feel that a lack of clarity about data collection reduces the perceived value of a brand's proposal.
		Even if a proposal seems advantageous, if it is not transparent, I hesitate to share my data.

The structure followed a logical progression from general perceptions to specific attitudes. In addition, the questionnaire included control variables to characterize the respondents, such as age, gender, education level, consumption habits, frequency of social media use, and most frequently used platforms.

Respondents were informed about the research purpose, assured of anonymity, and provided informed consent before proceeding.

4.4. Operationalization of variables

To ensure a clear connection between the research hypotheses and the questionnaire, an operationalization matrix was developed. The construction of an operationalization matrix is a fundamental step in any academic research, as it establishes a clear link between hypotheses, variables, and data collection instruments. As Andrade (2021, p. 178) explains, "variables need to be operationalized; that is, defined in a way that permits their accurate measurement". In this sense, operationalization ensures that each abstract concept or hypothesis is translated into observable and measurable indicators. The importance of this process lies in the fact that poorly defined variables lead to weak measurements, which compromise the validity and reliability of the study: "much thought should be given to the operationalization of variables because variables that are carelessly operationalized will be poorly measured; the data collected will then be of poor quality, and the study will yield unreliable results" (Andrade, 2021, p. 179). Moreover, the same variable can be operationalized in different ways, thereby enriching the understanding of the phenomenon under investigation: "it is also permissible to operationalize the same variable in many different ways […] because conceptualizing variables in different ways can help understand the subject of the study in different ways" (Andrade, 2021, p. 179). Finally, clearly defining how a variable will be measured ensures objectivity and uniformity in data collection: "when the way in which a variable will be measured is defined, measurement of that variable becomes more objective and uniform" (Andrade, 2021, p. 179).

The hypotheses tested involve independent, dependent, moderating, and mediating variables. Each set of survey items is directly associated with one or more hypotheses, thereby ensuring that the theoretical constructs are translated into measurable indicators and can be empirically tested. Table 2 below summarizes this correspondence:

Table 2. Operationalization of Variables

Construct / Variable	Conceptual Definition	Survey Items (5-point Likert Scale)	Variable Type	Source/Theoretical Basis	Hypothesis(es)
Perceived Personalization	Degree to which consumers perceive that digital content, offers, and communications are tailored to their personal preferences.	1. Personalized offers and content make me consider sharing my data as fair. 2. I am more willing to share my personal data when a brand provides personalized benefits.	Independent Likert scale	Hollebeek & Macky (2018); Payne, Frow & Eggert (2017)	H1, H2
Perceived Transparency	Extent to which consumers believe that brands are open and clear about how personal data is collected, stored, and used.	1. I prefer brands that clearly communicate how they use my data. 2. Knowing exactly how my data will be used makes me more comfortable sharing it. 3. The more transparent a brand is about its data practices, the more value I perceive in its offer. 4. Even if an offer seems beneficial, if it is not transparent, I hesitate to share my data.	Independent / Moderator Likert scale	Martin & Murphy (2016); Hemker et al. (2021); Rosário & Dias (2023)	H1, H4
Trust	Degree of confidence and perceived reliability that users have in brands and social media platforms to act ethically when handling personal data.	1. I trust the social media platforms I regularly use. 2. I trust well-known brands, even when they request personal data. 3. When I trust a brand, I am more accepting of personalized content based on my data. 4. My level of trust in a platform influences my willingness to share personal data.	Moderator Likert scale	Mosteller & Poddar (2017); Ackermann et al. (2021)	H2
Distrust / Privacy Concern	Level of scepticism or concern about how transparently data is collected and used by brands.	1. I become suspicious when the source of a page or content is unclear. 2. I am hesitant when I feel the information provided by a brand is insufficient. 3. I believe many brands use personal data for purposes that are not transparently communicated.	Control / Negative Variable Likert scale	Kokolakis (2017); Barth & de Jong (2017)	—
Experiential Mechanisms	Strategies that deliver experiential or emotional value (e.g., gamification, exclusivity, influencer interaction) and enhance engagement and perceived fairness in data exchange.	1. Accessing exclusive content makes me more willing to share my data. 2. When I take part in interactive campaigns or contests, I am more open to sharing my data. 3. Interactions with influencers make data exchange feel fairer. 4. I feel data sharing is fair when I receive unique experiences in return.	Independent Likert scale	Hollebeek & Macky (2018); Gimpel et al. (2018)	H3
Perceived Value	Perceived utility, benefit, or advantage associated with sharing personal data in digital interactions.	1. I believe sharing data on social media can be advantageous for me. 2. I am willing to share my data in exchange for real benefits. 3. My decision to share data depends on my relationship with the brand.	Mediator / Independent Likert scale	Ackermann et al. (2021); Quach et al. (2022)	H4
Willingness to Share Personal Data	Stated intention of users to share different types of personal information with brands on social media.	1. I am willing to share my personal data on social media. 2. I believe that data sharing can bring me benefits. 3. Please indicate to what extent you would share: contact details, location, preferences, browsing history, interactions, photos, permissions.	Dependent Binomial / Likert scale	Martin & Murphy (2016); Ackermann et al. (2021)	H1–H4

4.5. Data collection procedures

The data collection procedures were designed to ensure both methodological rigor and ethical standards. The link to the questionnaire was disseminated via social media platforms (e.g., WhatsApp, Instagram). To increase reach and heterogeneity, participants were also encouraged to share the survey within their own networks, generating a snowball effect. The study had no specific participation requirements, and participants were not paid to take part. The data collection period lasted for approximately 4 weeks, during September 2025.

Before starting the questionnaire, they were informed about the purpose of the study and told that their participation was voluntary and their answers would remain confidential. Consent was given by selecting 'yes' or 'no' on the first page of the survey, and only those who agreed were able to continue.

4.6. Data analysis techniques

A descriptive analysis was conducted to examine all variables, including means, standard deviations, skewness, and kurtosis. In addition, a summary analysis was performed to describe the sociodemographic characteristics of the sample and to provide an overview of participants' consumption habits and social media activity. These summary statistics offer an initial understanding of the dataset and its variables, while categorical variables were described using frequencies and percentages.Before testing the hypotheses, composite indices for each construct (mean of the corresponding items) were computed and the internal consistency of the scales assessed through Cronbach's alpha (α). In line with Gomes and Cesário (2014), values above .90 will be considered very good, between .80–.90 good, between .70–.80 acceptable, and between .60–.70 weak, with .60 as the minimum acceptable threshold. Each construct will be tested separately (e.g., personalization, transparency, trust, experiential mechanisms, perceived fairness, perceived value, and willingness to share personal data).

Next, a Pearson correlation matrix was used to identify relationships between variables..

To better understand the structure of the constructs and confirm that the questionnaire items accurately represent the intended dimensions, an exploratory factor analysis (EFA)

was conducted. This analysis helps reveal the underlying factors captured by the items and ensures that the statements cluster consistently within their respective constructs. As noted by Hooper (2012, p. 1), “factor analysis examines the inter-correlations that exist between a large number of items and in doing so reduces the items into smaller groups, known as factors”.

The adequacy of the data for this procedure will be verified through the Kaiser–Meyer–Olkin (KMO) test and Bartlett’s test of sphericity, which assess sampling adequacy and correlation strength between variables. As noted by Amerioun et al. (2018, p.1526), “results of the Kaiser-Meyer-Olkin (KMO = 0.973) and Bartlett's test at significance level of < 0.01 [...] suggest that factor analysis was suitable for these statements” , indicating that KMO values above .70 and significant Bartlett’s tests ($p < .05$) confirm the appropriateness of the data for factor analysis.

In addition, a cluster analysis was performed to identify different consumer profiles based on their attitudes toward data sharing and perceived value exchange. As stated by Dalmaijer, Nord, and Astle (2022, p-1), “cluster algorithms are gaining in popularity in biomedical research due to their compelling ability to identify discrete subgroups in data, and their increasing accessibility in mainstream software”, which supports the use of this method to uncover distinct consumer patterns. The analysis will begin with a hierarchical clustering method (Ward’s method with squared Euclidean distance) to explore the optimal number of clusters. Then, a k-means clustering will be applied to refine these groups and describe each profile according to the main variables of the study. This procedure aligns with the idea that “statistical power in cluster analysis [is] the probability of correctly detecting that subgroups are present” (Dalmaijer et al., 2022, p. 5).

To identify discrepancies between intention and behaviour at the individual level, declared preference and actual usage for eight major digital platforms (Instagram, Facebook, TikTok, LinkedIn, YouTube, Snapchat, WhatsApp, and Twitter/X) were analysed. Each platform was coded as a binary variable (1 = yes; 0 = no). Each row in the dataset corresponded to an individual participant, enabling paired comparisons between what each respondent reported preferring and what they effectively used. Paired t-test and the Wilcoxon signed-rank test ($p < .05$) were used highlight significant diferences between intention–action gap observed in digital behaviour studies. Concordance between preference and usage was assessed using Cohen’s Kappa (κ) (measure the degree of agreement between declared trust and actual use; values were considered < 0.20 = poor; 0.21–0.40 = fair; 0.41–0.60 = moderate; 0.61–0.80 = substantial; > 0.81 = almost perfect),

McNemar's test (detect significant asymmetries between the proportions of users who trust but do not use a platform and those who use but do not trust), and F1 metrics (harmonic mean between Precision - proportion of trusted platforms that are actually used - and Recall - proportion of used platforms that were also trusted, representing the overall balance between trust and behaviour) (Appendix A2, Table 3).

To examine the relationships proposed in the research hypotheses, a series of binary logistic regression analyses were conducted. This method was selected because the dependent variable — consumers' willingness to share personal data — was dichotomous (0 = unwilling; 1 = willing). Logistic regression allows estimating the probability that a respondent falls into one of two categories based on one or more independent variables, without assuming normal distribution of residuals or linear relationships between predictors and the outcome. Each hypothesis was tested using a separate logistic regression model, progressively adding predictors and interaction terms to examine direct and moderating effects.

The general form of the model is expressed as:

$$\ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n$$

where:

- p= probability of being willing to share personal data (Y = 1),
- β_0= intercept,
- β_i= regression coefficients for predictor X_i,
- $\frac{p}{1-p}$= odds ratio (likelihood of sharing vs. not sharing).

The exponential of each coefficient, Exp(B), represents the odds ratio, indicating how a one-unit increase in the predictor affects the likelihood of data-sharing.

The Enter method was used for variable inclusion, allowing simultaneous estimation of all predictors. Each model was evaluated sequentially to test both the individual effects and combined influence of the variables on the likelihood of sharing data. For each research hypotheses, the regression was performed in five main steps, corresponding to different research hypothesis: (1) the constructs related with the research hypothesis; (2) the constructs related with the research hypothesis and its interaction; (3) the constructs related with the research hypothesis and sociodemographic variables (age, gender and education), as a robustness check; (4) the constructs related with the research hypothesis and age, the only control sociodemographic variable significant; (5) the constructs related

with the research hypothesis, its interaction, and age, the only control sociodemographic variable significant (Appendix A2, Table 5 to 8).

To assess the global significance of each model, the Omnibus Test of Model Coefficients was applied. A significant result ($p < .05$) was considered as an indicative that the model with predictors fits significantly better than a null model containing only the intercept. Classification accuracy (percentage of correctly predicted cases) was also examined, alongside pseudo-R^2 statistics (Cox & Snell, Nagelkerke) to estimate explanatory power. All models achieved high classification accuracy (80–85%) and significant omnibus χ^2 values ($p < .001$), confirming their predictive validity.

All analyses will be performed in SPSS (version 28), adopting a two-tailed significance level of $\alpha = .05$.

4.7. Methodological limitations

Online surveys present certain limitations that need to be acknowledged. Coverage error may arise "when not all members of a target population have an equal chance of being selected in the survey sample […], under-coverage of the population represents the main barrier to switching to web surveys of nationally representative samples" (Roberts, 2007, p. 7). In addition, response rates in self-administered online modes "tend to be considerably lower […], increasing the likelihood of response bias" (Roberts, 2007, p. 8). Another limitation concerns measurement error, since "respondents [may] modify the true answer […] in order to present themselves in a more favourable light" (Roberts, 2007, p. 8). Errors may also result from satisficing, when participants "choose a 'merely satisfactory' response rather than an optimal one" (Krosnick, 1991, as cited in Roberts, 2007, p. 12).

Moreover, the sampling strategy applied in this study (convenience and snowball sampling) does not guarantee representativeness of the entire population of social media users, which limits the generalizability of the findings. Finally, the data are based exclusively on respondents' self-reported perceptions rather than on observed behaviors, which may not fully reflect actual practices.

Although this method has some limitations, it allows for a large number of responses and helps achieve broader representation across different sectors, organization sizes, and regions.

5. Results

This chapter presents the results of the quantitative analysis conducted using IBM SPSS Statistics 28. The findings are organized into four main parts: (1) reliability analysis, (2) exploratory factor analysis (EFA), (3) correlation analysis, and (4) cluster analysis. Together, these analyses provide a comprehensive assessment of the relationships among the variables and the degree of support for the research hypotheses.

5.1. Descriptive analysis

The presentation of results begins with a descriptive overview of the dataset. This section summarizes participants' sociodemographic characteristics and their patterns of social media use, followed by descriptive statistics for the main study variables. These variables provide a comprehensive profile of the respondents and allow for a deeper understanding of the sample's demographic and behavioral characteristics.

Regarding sociodemographic characteristics, most respondents were female (67.3%), while 32.7% identified as male. In terms of age, the largest group of participants was 25 years old or younger (31.8%), followed by those aged 31–50 years (25.5%), 26–30 years (20.0%), and 51 years or older (22.7%). Regarding education level, the largest group had completed a bachelor's degree (49.5%), followed by 33.2% with a master's degree or PhD, and 17.3% with secondary education (Table 3).

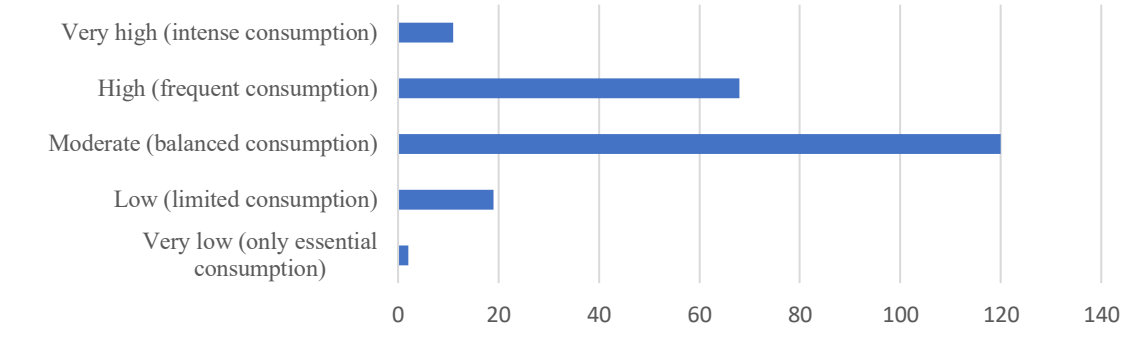
Table 3. Sociodemographic characterization of the participants

Variables	Groups	Percentage(%)
Age (Years) 36.4±15.3	≤25	31,8%
	26 - 30	20,0%
	31 - 50	25,5%
	≥ 51	22,7%
Gender	Female	67,3%
	Male	32,7%
Education	Secondary education	17,3%
	Bachelor/Degree	49,5%
	Master/PhD	33,2%

To further characterize the sample, participants were asked about their general consumption level. Results showed that 54.5% reported a moderate consumption pattern, while 35.9% reported high or very high consumption and 9.5% described their

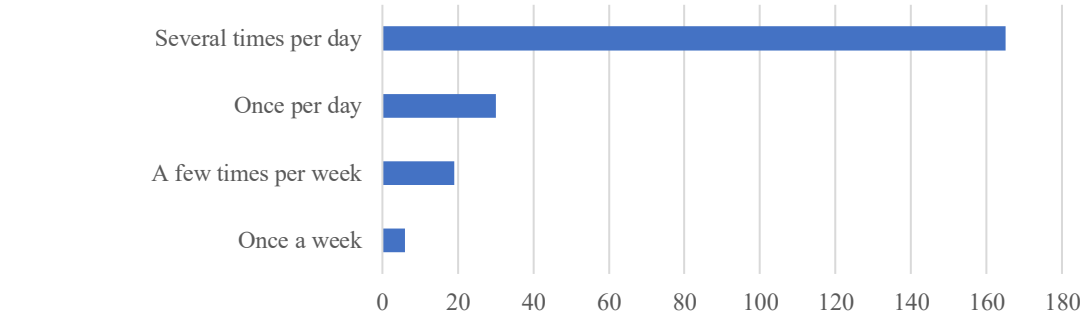
consumption as low or very low (Figure 2a). In terms of social media habits, the majority of respondents reported using social media several times a day (75.0%), followed by once a day (13.6%) and a few times a week (8.6%) (Figure 2b).

When asked about the platforms they used most frequently, Instagram was the most mentioned (90.5%), followed by YouTube (53.6%), TikTok (40.9%), and LinkedIn (39.5%), while smaller proportions of participants indicated platforms such as Snapchat, Twitter/X or Whatsapp.



	Very low (only essential consumption)	Low (limited consumption)	Moderate (balanced consumption)	High (frequent consumption)	Very high (intense consumption)
How would you describe your usual level of consumption? (intensity scale, not related to income)	2	19	120	68	11

(a)



	Once a week	A few times per week	Once per day	Several times per day
How often do you use social media?	6	19	30	165

(b)

Figure 2. Participants' consumption intensity (a) and social media usage frequency (b).

Before testing the hypotheses, descriptive statistics (means and standard deviations) were calculated for all main constructs in the model (Table 4). A detailed breakdown of the sample characteristics is presented in Appendix A2 (Table 2).

Table 4. Mean and standard deviation of the main constructs

	Mean	Standard deviation
Perceived Personalization	3,87	0,84
Trust	3,55	0,85
Discomfort	3,91	0,72
Previous brand experiences	3,12	1,17
Transparency	4,40	0,69

The construct *Perceived Personalization* (M = 3.87, SD = 0.84) presented relatively high mean values, suggesting that participants generally expressed agreement with statements related to the personalization of content and communication by brands.

Trust in social media platforms and brands showed a moderate mean score (M = 3.55, SD = 0.85), indicating a balanced distribution of responses, with participants neither fully trusting nor distrusting the platforms and brands they engage with.

The construct *Discomfort* with data sharing recorded a mean of M = 3.91 (SD = 0.72), showing a slight tendency toward agreement with statements expressing caution or concern regarding data sharing on social media.

For *Previous brand experiences* on social media, the mean was M = 3.12 (SD = 1.17), representing moderate agreement levels and suggesting that responses were more evenly distributed across the scale.

Finally, *Transparency* presented the highest mean among the constructs (M = 4.40, SD = 0.69), reflecting consistent agreement with statements related to brands' clear and transparent communication about data usage.

Overall, these descriptive results provide an overview of the main constructs' central tendencies and variation, serving as the basis for further inferential analysis.

5.2. Reliability analysis

Before proceeding with hypothesis testing, the reliability and validity of the measurement scales were examined to ensure that the dataset was adequate for further statistical analyses. This preliminary step aimed to confirm that all constructs were measured consistently and that the data met the assumptions required for factor analysis.

All scales demonstrated strong reliability, with values above the recommended threshold of 0.70 (Hair et al., 2019) (Table 5). These results demonstrate that all

dimensions included in this study were measured reliably and can be confidently used in subsequent analyses.

Table 5. Reliability statistics of the independent and dependent variables

Variables	α	Cronbach's Alpha Based on Standardized Items	N of Items
Perceived personalization	.778	.775	4
Trust	.832	.834	4
Discomfort	.755	.781	4
Previous brand experiences	.925	.925	4
Transparency	.830	.837	4

5.3. Bivariate correlation

Before estimating the models, a Pearson bivariate correlation analysis was was performed to examine the relationships among all study variables (Appendix A2, Table 3). As expected, perceptions of personalization were strongly connected to trust and transparency/value judgements. The item "*personalization makes data sharing fair*" correlated very highly with "*availability to share when benefits are personalized*" ($r = .886$, $p < .01$), and showed positive associations with "*trust in platforms"* ($r = .532$, $p < .01$), "*trust in known brands"* ($r = .621$, $p < .01$), "*acceptance of content personalization when trusting a brand"* ($r = .707$, $p < .01$), and the "*influence of platform trust on sharing decisions"* ($r = .465$, $p < .01$). It was also positively related to transparency/value items—"*transparency increases perceived value*" ($r = .354$, $p < .01$) and "*transparency makes me more receptive to advantages*" ($r = .445$, $p < .01$)—while showing negative correlations with opacity/concern items (e.g., "*I distrust unclear sources*": $r = -.187$, $p < .01$; "*insufficient information makes me reluctant*": $r = -.145$, $p < .05$), as expected.

Experiential mechanisms were consistently and positively associated with willingness/benefit appraisals: "*accessing exclusive content"* ($r = .753$, $p < .01$), "*interactive campaigns"* ($r = .687$, $p < .01$), "*influencer relations"* ($r = .668$, $p < .01$), and "*receiving unique experiences"* ($r = .745$, $p < .01$) all correlated with the personalization–fairness item. These experiential variables also showed robust ties with the "*willingness to share"* and "*perceived advantage measures"* (e.g., with "*I am willing to share in exchange for real benefits*": rs from .701 to .801, all $p < .01$; with "*data sharing can be advantageous for me*": rs from .641 to .748, all $p < .01$).

Regarding transparency and perceived value, clarity about data practices related positively to value recognition (*"clear communication about data use increases value":* r = .654 with *"comprehend exactly how data will be used"*, $p < .01$; r = .559 with *"clarity makes me comfortable"*, $p < .01$) and negatively to opacity/concern items (e.g., *"insufficient information"* and *"unclear source"*: rs between −.335 and −.589, all $p < .01$). The item *"even if a proposal seems advantageous, if it is not transparent I hesitate"* correlated positively with the opacity/concern block (rs up to .560, $p < .01$) and negatively with experiential drivers (e.g., r = −.296 with *"experiences make exchange fair"*, $p < .01$), reinforcing the central role of transparency.

Perceived willingness and value exchange clustered together as expected. *"Willing to share for real benefits"* correlated very strongly with *"data sharing can be advantageous"* ($r = .748$, $p < .01$) and with the decision depending on the brand relationship ($r = .601$, $p < .01$). The single-item question on general willingness *("would you share your data with brands on social media?"*) showed negative correlations with these positive appraisals (e.g., with "*willingness for real benefits"*: r = −.664, $p < .01$; with perceived advantage: r = −.605, $p < .01$), reflecting its response direction.

Finally, acceptance of specific data types followed a coherent gradient. Willingness to share preferences/interests correlated very highly with the broader willingness/advantage indicators (e.g., with *"willing to share for real benefits"*: r = .724, $p < .01$; with *"advantageous for me"*: r = .753, $p < .01$). Contact data also showed strong positive links (e.g., r = .595 with perceived advantage, $p < .01$). By contrast, real-time location was negatively associated with transparency/value and intention measures (e.g., r = −.388 with *"even if advantageous, if not transparent I hesitate"*, $p < .01$; r = −.348 with the general willingness item, $p < .01$), indicating a higher sensitivity around this data category.

Overall, the correlation patterns support the proposed relationships. Personalization, trust, experiential mechanisms, and transparency move together with perceived fairness and willingness to disclose, whereas discomfort and opacity indicators move in the opposite direction. Inter-item associations generally remained below conventional multicollinearity thresholds; the highest observed coefficient (r = .886) occurred between conceptually similar personalization items, confirming the internal coherence of the measurement model.

Table 6 presents the Pearson bivariate correlations among the main constructs of the study. The results reveal some interesting and coherent patterns in the way people relate

to brands and data sharing. *Willingness to share* shows strong and positive links with perceived personalization ($r = .593$, $p < .001$), trust ($r = .546$, $p < .001$) and *previous brand experiences* ($r = .619$, $p < .001$). In simple terms, participants who feel that brands understand them, communicate transparently and inspire confidence are much more likely to share their personal data. Positive past interactions also seem to make a clear difference — trust built over time encourages users to open up more easily. Conversely, *discomfort* correlates negatively with *willingness to share* ($r = –.263$, $p < .001$), reminding that privacy concerns or feelings of mistrust can quickly undermine users' readiness to share information. *Transparency*, although showing a smaller correlation ($r = .150$, $p < .05$), still plays a role in fostering a sense of fairness and safety in data exchange. Overall, these findings mirror what has been observed in previous studies on digital trust and privacy, reinforcing the internal consistency of the research model and paving the way for deeper analyses in the following sections.

Table 6. Pearson bivariate correlations for the main constructs

Variables		Willigness to share	Perceived personalization	Trust	Discomfort	Previous brand experiences
Willigness to share	r					
	Sig.					
Perceived personalization	r	,593**				
	Sig.	0,000				
Trust	r	,546**	,740**			
	Sig.	0,000	0,000			
Discomfort	r	-,263**	-0,069	-0,073		
	Sig.	0,000	0,305	0,280		
Previous brand experiences	r	,619**	,763**	,661**	-,363**	
	Sig.	0,000	0,000	0,000	0,000	
Transparency	r	,150*	,242**	0,107	,457**	-0,031
	Sig.	0,026	0,000	0,115	0,000	0,648

5.4. Exploratory factor analysis (EFA)

To evaluate the suitability of the data for factor analysis, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity were performed. The KMO value of .900 indicated an excellent level of sampling adequacy, suggesting that correlations among the variables were sufficiently strong to justify factor analysis. Likewise, Bartlett's test was significant ($\chi^2 = 3362.494$, $df = 171$, $p < .001$), rejecting the null hypothesis that the correlation matrix is an identity matrix. Taken together, these results confirmed that the data was appropriate for factor analysis.

An Exploratory Factor Analysis (EFA) was then conducted using principal axis factoring as the extraction method. The initial analysis suggested a three-factor structure; however, the third factor did not present any meaningful loadings, leading to a refined two-factor model. The final two-factor solution accounted for 64.7% of the total variance, indicating a strong and coherent representation of the data structure (Table 7).

Table 7. Factor analysis

Factor	Variance explained	Cronbach's alpha	Item	Loadings
F1	39.2%	0.934	The personalization of offers and content makes me consider the sharing of my personal data fair.	0,923
			I am more willing to share my personal data when a brand offers me personalized benefits.	0,922
			Understanding exactly how my data will be used makes me feel more comfortable sharing it.	0,936
			I trust the social media platforms I use regularly.	0,933
			I trust brands I know well, even when they ask for personal data.	0,929
			When I trust a brand, I am more likely to accept that content is personalized based on my data.	0,925
			The trust I have in a platform influences my decision to share data.	0,934
			Accessing exclusive content makes me more willing to share data.	0,924
			When I take part in contests or interactive campaigns, I am more willing to share personal data.	0,926
			The relationship with digital influencers influences my perception of fairness in data exchange with a brand.	0,927
			I feel that data exchange is fair when I receive unique experiences in return.	0,925
			Transparency in data collection makes me more receptive to the benefits offered.	0,936
F2	25.5%	0.879 without item (DESCEXP), or 0.848 with all items	I prefer brands that clearly communicate how they use my data.	0,876
			I become suspicious when the source of a page or its content is not clear.	0,857
			I become hesitant when I feel that the information provided by the brand is insufficient.	0,857
			I believe that many brands use data for purposes that are not communicated transparently.	0,864
			The more transparent a brand is about the data it collects, the more value I perceive in its offer.	0,870
			I feel that a lack of clarity about data collection reduces the value of a brand's offer.	0,847
			Even if an offer seems advantageous, if it is not transparent, I hesitate to share my data.	0,858

Global FMLSS Cronbach's alpha: 0.900 with or without item (DESCEXP) (Sig. <0.0001)

5.5. Cluster analysis

To identify distinct consumer profiles based on their perceptions of trust, privacy, and willingness to share personal data with brands on social media, a cluster analysis was conducted.

The procedure began with a hierarchical cluster analysis using Ward's method and squared Euclidean distance to explore the potential number of clusters. The dendrogram suggested a three-cluster solution, which was then refined through a K-Means cluster analysis to optimize group classification and minimize within-group variance.

This two-step procedure ensured both conceptual interpretability and statistical robustness. Each cluster represents a group of respondents who share similar attitudes toward social media interactions, confidence in brands, and data-sharing behavior.

Prior to interpretion, several statistical tests were conducted to confirm the adequacy and validity of the grouping solution. The Shapiro–Wilk test indicated that all variables deviated from normality ($p < .05$), supporting the use of non-parametric tests for further comparisons. In addition, Levene's test for homogeneity of variances revealed significant heterogeneity across clusters ($p < .05$), justifying the use of the Tamhane post-hoc test for pairwise comparisons.

The Kruskal–Wallis test was then applied to examine whether significant differences existed between clusters. The results indicated statistically significant differences across most variables ($p < .05$), particularly in:

- frequency of social media use
- confidence in social media platforms
- willingness to share personal data
- perceived value of personal data
- privacy concerns and trust in brand communication

These findings confirm that the identified clusters represent meaningfully distinct consumer segments. The combination of hierarchical and non-parametric validation methods strengthens the reliability of the segmentation and supports its conceptual relevance for understanding diverse patterns of trust, transparency, and willingness to share data in social-media contexts.

5.5.1. Cluster profiles

Based on the K-Means results, three distinct consumer segments were identified. Each cluster represents a specific pattern of interaction with brands and distinct attitudes toward privacy, trust, and data sharing on social media. Table 8 below the profiles and main characteristics of the three groups.

Table 8. Profiles of consumer clusters

Cluster	Profile	Main Characteristics
Cluster 1 – Confident Sharers	Representing the largest group (approx. 52% of respondents), these users are confident, brand-oriented and open to interaction.	They report the highest frequency of social media use (especially on Instagram and Facebook), strong trust in brands, and a high willingness to share personal data. They tend to perceive data sharing as beneficial when it leads to personalized offers, exclusive content, or tangible advantages.
Cluster 2 – Cautious Skeptics	The smallest group (around 12%) characterized by low engagement and limited trust.	These individuals are less active on social media and and display strong privacy concerns. Their reluctance to share data often stems from previous negative experiences or from lack of confidence in how transparently brands communicate their data practices.
Cluster 3 – Critical Observers	Comprising roughly 36% of the sample, this group combines moderate social media use with high privacy awareness.	They use social media moderately but are highly attentive to data protection issues. While they may interact with brands, they only do so when communication is transparent and the value exchange is clear. They view personal data as highly valuable and demand control over how it is used.

Overall, these clusters reveal three distinct behavioural profiles that differ in their levels of trust, engagement, and privacy sensitivity. The results illustrate how varying perceptions of transparency, fairness, and control shape consumers' willingness to share

personal data on social media. To better understand these behavioral differences, Table 9 compares the three identified clusters in terms of their social media usage, perceived trust, and willingness to share personal data.

Table 9. Comparison of consumer clusters based on social media usage and data-sharing attitudes

Item	Cluster 1 n=114 Mean ± SD				Cluster 2 n=27 Mean ± SD				Cluster 3 n=79 Mean ± SD				Teste Kruskal Wallis Sig.	
Level of consumption	3,29	±	0,700		3,22	±	1,013		3,35	±	0,680		0,542	
Frequency of use	**3,82**	**±**	**0,603**	**a**	**3,48**	**±**	**0,893**	**b**	**3,35**	**±**	**0,833**	**c**	0,000	***
Which of these platforms do you use most frequently?														
Instagram	**0,99**	**±**	**0,094**	**a**	0,81	±	0,396	b	0,81	±	0,395	b	0,000	***
Facebook	**0,05**	**±**	**0,224**	**a**	**0,67**	**±**	**0,480**	**b**	**0,47**	**±**	**0,502**	**c**	0,000	***
TikTok	**0,61**	**±**	**0,489**	**a**	**0,11**	**±**	**0,320**	**b**	**0,22**	**±**	**0,414**	**c**	0,000	***
LinkedIn	**0,43**	**±**	**0,497**	**a**	0,41	±	0,501		**0,34**	**±**	**0,477**	**b**	0,467	
YouTube	0,58	±	0,496		0,44	±	0,506		0,51	±	0,503		0,363	
Snapchat	**0,06**	**±**	**0,241**	**a**	0,04	±	0,192		**0,01**	**±**	**0,113**	**b**	0,244	
Whatsapp	0,04	±	0,185	a	0,07	±	0,267	a	**0,01**	**±**	**0,113**	**b**	0,282	
Twitter/X	**0,11**	**±**	**0,308**	**a**	0,00	±	0,000	b	0,00	±	0,000	b	0,003	**
On which of these platforms do you feel most confident sharing your personal data?														
None	**0,02**	**±**	**0,132**	**a**	**0,15**	**±**	**0,362**	**b**	**0,06**	**±**	**0,245**	**c**	0,016	*
Low	0,00	±	0,000	a	**0,04**	**±**	**0,192**	**b**	0,00	±	0,000	a	0,028	*
Same	0,01	±	0,094		0,00	±	0,000		0,00	±	0,000		0,628	
Instagram	0,44	±	0,498		0,30	±	0,465		0,42	±	0,496		0,402	
Facebook	**0,03**	**±**	**0,161**	**a**	0,22	±	0,424	b	0,13	±	0,335	b	0,001	**
TikTok	0,05	±	0,224		0,04	±	0,192		0,03	±	0,158		0,639	
LinkedIn	0,49	±	0,502		0,30	±	0,465		0,44	±	0,500		0,186	
YouTube	**0,31**	**±**	**0,463**	**a**	0,00	±	0,000	b	0,15	±	0,361	b	0,001	**
Snapchat	0,04	±	0,185	a	0,04	±	0,192	a	**0,00**	**±**	**0,000**	**b**	0,240	
Twitter/X	**0,03**	**±**	**0,161**	**a**	0,00	±	0,000		**0,00**	**±**	**0,000**	**b**	0,245	
Share of personal data	**2,89**	**±**	**0,916**	**a**	**1,70**	**±**	**0,953**	**b**	**2,09**	**±**	**0,894**	**c**	0,000	*
Value of personal data	**4,46**	**±**	**0,654**	**a**	**4,70**	**±**	**0,542**	**b**	**4,89**	**±**	**0,358**	**c**	0,000	***
What are the main reasons why you are not willing to share your personal data? (you may select multiple options)														
Lack of trust in brands	**0,03**	**±**	**0,161**	**a**	**0,26**	**±**	**0,447**	**b**	**0,41**	**±**	**0,494**	**c**	0,000	***
Privacy and security	**0,06**	**±**	**0,241**	**a**	**0,89**	**±**	**0,320**	**b**	**0,53**	**±**	**0,502**	**c**	0,000	***
Past negative experiences	**0,06**	**±**	**0,241**	**a**	**0,52**	**±**	**0,509**	**b**	**0,32**	**±**	**0,468**	**c**	0,000	***
Lack of clarity	**0,00**	**±**	**0,000**	**a**	**0,04**	**±**	**0,192**	**a**	**0,10**	**±**	**0,304**	**b**	0,002	**
I don't see enough benefits	**0,01**	**±**	**0,094**	**a**	**0,33**	**±**	**0,480**	**b**	**0,37**	**±**	**0,485**	**b**	0,000	***

[a, b, c] Scores in the same row with different letters are significantly different at p<0.05 (*), p<0.01 (**) or p<0.001 (***) (post hoc Least Significan Difference and Tamhane multiple comparison tests)

5.6. Trust vs. Actual consumption of digital platforms

After analysing participants' general consumption habits, this section addresses a central question: *do users actually engage with the platforms they trust the most?* In other words, is there a a consistent relationship between users' confidence in a platform and their frequency of use?

In the questionnaire, respondents were first asked to indicate both their preferred or trusted platforms and then their actual frequency of use between eight major digital platforms: *Instagram, Facebook, TikTok, LinkedIn, YouTube, Snapchat, WhatsApp,* and *Twitter/X*. Based on these answers, two variables were defined:

- *Trust*, representing the platforms users platforms users reported preferring or trusting the most;
- *Actual consumption*, representing the platforms they reported using most frequently in their daily lives.

When comparing these two dimensions, the results reveal a noticeable difference. In general, participants reported more preferred platforms than those they actually used. Both the paired t-test and the Wilcoxon signed-rank test confirmed that this difference was statistically significant ($p < .05$), indicating that not all declared trust or preference translate into real usage behaviour. This finding highlights a typical intention–action gap observed in digital and consumer behaviour studies, where declared intentions often fail to manifest in actual actions (Viglia & Acuti, 2023, as cited in Borges-Tiago et al., 2024).

The overall level of agreement between trust and use, measured through Cohen's Kappa, was moderate (≈ 0.5). This means that although people express confidence in certain platforms, their daily behavior tends to be more selective and pragmatic. They might trust several platforms, but only a few truly fit into their routines.

Looking at each platform individually, distinct patterns emerge (Figure 3 and Appendix A2, Table 3). LinkedIn exhibits the highest consistency ($\kappa = 0.61$), indicating that users who trust LinkedIn also tend to use it frequently — likely because of its clear, professional purpose. Instagram shows a similar balance, between trust and use, with moderate-to-high concordance and a non-significant McNemar test, suggesting behavioural balance, meaning that trust and use of Instagram generally goes hand in hand. In contrast, TikTok ($\kappa = 0.12$) and Twitter/X ($\kappa = 0.39$) display much weaker alignment, with significant McNemar results pointing to a clear asymmetry between intention and

action. These are platforms people seem to *like* or *be curious about*, but don't necessarily use in a stable or continuous way.

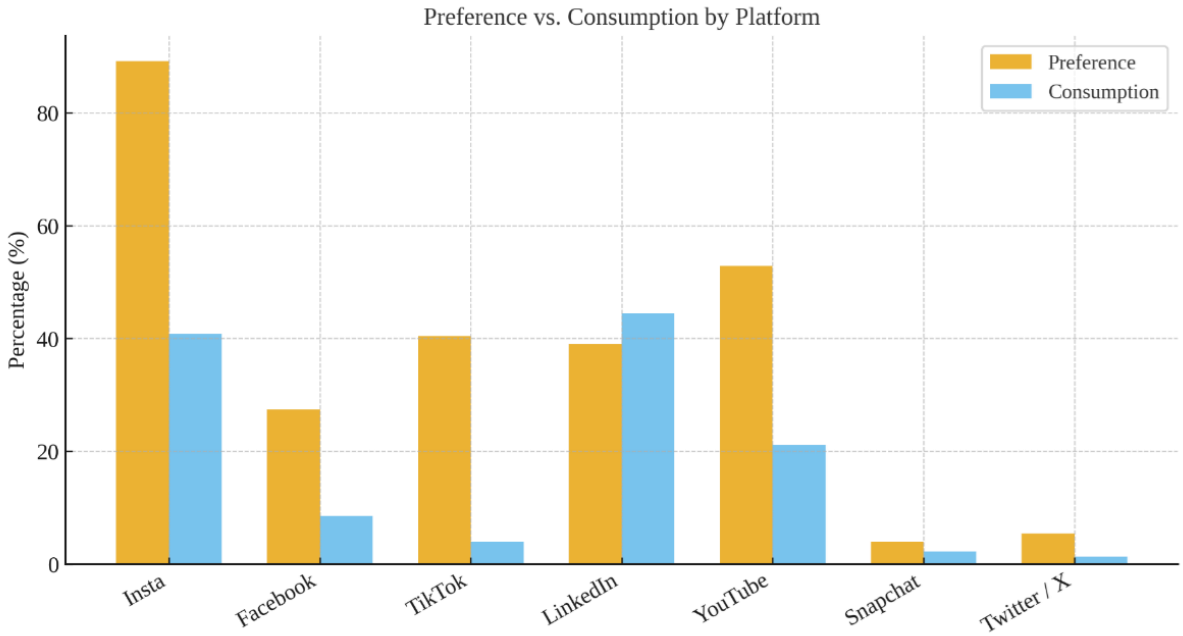


Figure 3. Declared preference vs. Actual consumption by platform

The F1 score, which combines both precision (how many of those who trust also use) and recall (how many of those who use also trust), reinforces these patterns. LinkedIn (F1 = 77.4) and Instagram (F1 = 62.1) achieved the highest balance between trust and behavior, while TikTok (F1 = 18.2) and Twitter/X (F1 = 40.0) showed the lowest, reflecting more occasional or passive forms of engagement.

Overall, these findings suggest that user's relationships with social media are purpose-driven and selective rather than impulsive or habitual. Platforms such as LinkedIn, Instagram, and YouTube seem to play a clearer and more stable role in users' digital lives, where trust aligns closely with usage. Conversely, platforms like TikTok or Twitter/X appear to spark interest or credibility, but not necessarily the kind of consistent engagement that translates into daily activity.

5.7. Hypotheses testing

Hypothesis 1 proposed that *transparent and personalized value propositions would increase consumers' willingness to share personal data*. To test this assumption, the

binary logistic regression with a higher predictive value was conducted including *perceived personalization, transparency*, and *age* as predictor (other sociodemographic variables were not significant) (Appendix A2, Table 5, Model 4).

The model was statistically significant ($\chi^2(3) = 98.144$, $p < .001$) and correctly classified 81.8% of the cases, showing a good ability to predict who is more likely to share their data.

Among the variables tested, *perceived personalization* stood out clearly. It showed a strong and significant effect (B = 2.117, p =.000), with an odds ratio of 8.303. In other words, participants who perceived higher personalization were *over eight times more likely* to share their personal data compared to those who did not.

By contrast, *transparency* did not show a meaningful influence on consumers' willingness to share (B = –.102, p = .751). This suggests that being clear about how data are collected or used, on its own, does not necessarily motivate users to share them.

Age also revealed a small but significant negative effect (B = –.027, p = .031), indicating that *older participants tend to be slightly less willing to share their data*.

To explore whether transparent and personalized propositions could reinforce each other, an interaction term between *perceived personalization* and *transparency* was added to the model (Appendix A2, Table 5, Model 2). However, this combined effect was not significant ($p > .05$), indicating that "being both transparent and personalized" does not create an additional advantage. The effect of personalization remains strong on its own, regardless of how transparent the brand is perceived to be.

Overall, these findings partially support Hypothesis 1. Personalization appears to be a key driver of data-sharing intentions, whereas transparency alone does not directly shape this behavior.

Hypothesis 2 proposed that *trust in the platform would strengthen the effect of personalization on consumers' willingness to share personal data*.

To test this, a binary logistic regression was conducted including *perceived personalization* and *trust* as predictors. The model was statistically significant ($\chi^2(2) = 102{,}511$, $p < .000$) and correctly classified 81.4% of the cases, demonstrating a strong predictive capacity (Appendix A2, Table 6, Model 1).

Both *perceived personalization* (B = 1.501, p = .000) and *trust* (B = 1.090, p = .002) had significant and positive effects on willingness to share personal data. This indicates that users who perceive higher personalization and greater trust in the platform are substantially more likely to share personal data. Specifically, the odds of being willing to

share data were about 4.5 times higher for personalization and almost 3 times higher for trust, holding other variables constant.

The interaction between personalization and trust was added to the model to test whether trust amplifies the effect of personalization (Appendix A2, Table 6, Model 2). However, the interaction was not significant (B = –.034, p = .940), indicating that trust does not strengthen or weaken the relationship between personalization and willingness to share. In other words, even though both factors are individually important, their combined effect does not create an additional advantage.

Adding *age* as a control variable (Appendix A2, Table 6, Model 4), the model remained significant ($\chi^2(3) = 109{,}498$, $p < .001$) and correctly classified 80.5% of the cases. *Perceived personalization* (B = 1.303, p = .001) and *trust* (B = 1.202, p = .001) continued to be strong predictors, while *age* showed a small negative effect (B = –.032, p = .009), suggesting that younger participants tend to be slightly more open to sharing their data.

Overall, these results show that both personalization and trust increase consumers' willingness to share personal data, but trust does not significantly moderate the relationship between personalization and data-sharing intention. Therefore, Hypothesis 2 was not supported, as trust and personalization independently increase willingness to share but their interaction produces no additional effect.

Hypothesis 3 proposed that *experiential mechanisms of value delivery, such as gamification, exclusivity, or interaction with influencers, would positively influence how fair consumers perceive the exchange of their personal data to be.*

To test this assumption, a binary logistic regression was conducted including *perceived personalization* and *experiential value* as predictors of willingness to share personal data. The model proved to be statistically significant ($\chi^2(2) = 112.363$, $p < .001$) and correctly classified 84.5% of the cases, which shows that it explains consumers' intentions with a high level of accuracy (Appendix A2, Table 7, Model 1).

Both predictors had a clear and positive impact. *Perceived personalization* (B = 1.154, p = .002) and *experiential value* (B = 1.074, p < .001) significantly increased consumers' willingness to share their data. In practical terms, participants who perceived stronger personalization or more engaging experiences were about three times more likely to feel comfortable sharing their personal information.

An additional step was taken to examine whether the combination of personalization and experiential value would have an amplified effect (Appendix A2, Table 7, Model 2).

The interaction term, however, was not significant (B = –.500, p = .164), indicating that these two factors operate independently. While both personalization and experience are important on their own, their combination does not seem to create a stronger or "synergistic" influence.

When *age*, was added as control variables, the model remained robust (84.5% correct classification) (Appendix A2, Table 7, Model 4). Both *perceived personalization* (B = 1.156, p = .002) and *experiencial value* (B = 1.070, p = .000) continued to show significant and positive effects, while the control variables had no meaningful impact.

Overall, the results suggest that experiential mechanisms play a valuable role in shaping how consumers perceive the fairness of data exchange. Experiences that make users feel involved, rewarded, or emotionally connected to the brand seem to make data sharing feel more acceptable. However, the combination of these experiences with personalization does not further strengthen this perception. Therefore, Hypothesis 3 was supported in part, as experiential mechanisms positively influenced consumers' sense of fairness, but without a reinforcing effect when paired with personalization.

Hypothesis 4 proposed that *perceived transparency in data collection would moderate the relationship between perceived value and willingness to share personal data*, such that this relationship would be stronger when transparency is high.

To test this assumption, a binary logistic regression was conducted including *transparency* and *experiential value* as predictors (Appendix A2, Table 8, Model 1). The model was statistically significant ($\chi^2(2) = 106{,}200$, $p < .001$) and correctly classified 84.5% of the cases, indicating strong predictive accuracy. Both predictors were significant and positive: *transparency* (B = .695, p = .022) and *experiential value* (B = 1.605, p < .000). This means that participants who perceived higher transparency and more engaging experiences were substantially more likely to share their data.

To examine the moderating effect of transparency, an interaction term (Transparency × Experience) was added to the model (Appendix A2, Table 8, Model 2). The result was not significant (B = .091, p = .777), suggesting that transparency does not strengthen or weaken the effect of experiential value on willingness to share. Although both factors are individually important, their combination does not create a synergistic influence.

When *age* was introduced as a control variable, the model remained significant ($\chi^2(5) = 106{,}256$, $p < .001$) and accurately classified 84.5% of the cases (Appendix A2, Table 8, Model 4). Both *transparency* (B = 1.634, p = .000) and *experiential value* (B = .687, p =

.025) continued to show positive and significant effects, while the control variables had no significant impact.

In summary, the findings show that both transparency and experiential mechanisms independently increase consumers' willingness to share data, but transparency does not moderate the relationship between perceived value and willingness to share. Therefore, Hypothesis 4 was not supported.

6. Discussion

This study set out to explore how different types of value propositions affect people's willingness to share personal data in digital marketing contexts, with a particular focus on social media platforms. A conceptual model was proposed and tested across four main dimensions of perceived value — personalization, trust, transparency, and experiential engagement — to understand how each factor contributes to users' decisions to disclose personal information. The aim was also to see whether these elements could interact in ways that shape perceptions of fairness and reciprocity in data exchange.

The results reveal that is the strongest driver of willingness to share, clearly supporting the first hypothesis. Trust also exerts a positive and significanteffect, though it does not amplify the influence of personalization as initially expected. Experiential factors such as gamification, exclusivity, or interaction with influencers enhance users' sense of fairness in data exchange, aligning with the third hypothesis. However, transparency did not significantly influence the link between perceived value and willingness to share, suggesting that openness about data practices alone may not be sufficient to foster participation.

Overall, the findings suggest that emotional and experiential forms of value carry more weight than purely rational or informational factors when individuals decide whether to share personal data online. This highlights the importance of designing digital value propositions that engage users not only cognitively but also emotionally and experientially, fostering trust and a sense of fairness in the data-sharing process

6.1. Theoretical implications

This research brings several theoretical contributions. First, it expands the concept of the Customer Value Proposition by applying it to the context of data exchange on social

media. Traditional definitions usually describe value propositions as strategic mechanisms that connect what a company offers with what customers value (Payne, Frow & Eggert, 2017). However, this study shows that, in digital environments, value propositions extend beyond functional or economic benefits. They also encompass emotional and experiential dimensions of value, such as the feeling that something personalized for each individual, of being part of something exclusive, of joining playful or gamified experiences, or of interacting with influencers. These results support Hollebeek and Macky (2018) arguments that digital value propositions are not one-time offers but ongoing exchanges built on trust and engagement. In this way, this study shows that a digital value proposition includes different types of value, bringing together practical, emotional, and relational aspects that help explain how people judge whether sharing their data feels fair, meaningful, and worthwhile.

Second, the study contributes to the understanding of the privacy paradox, which is the discrepancy between individuals' stated privacy concerns and their actual online behaviour. The results indicate that individuals remain willing to share data despite privacy awareness, provided they perceive authentic value in return. This indicates that the paradox constitutes not merely a contradiction, but a trade-off between rational assessment and emotional gratification. Following Kokolakis (2017) and Gerber et al. (2018), the findings suggest that emotional experiences, including entertainment, recognition, or exclusivity, influence users' decision-making, leading them to perceive personal data sharing as acceptable or even desirable. Consequently, the privacy calculus appears to be more than a rational balancing of risks and rewards, but is also shaped by emotions, trust, and enjoyment that affect individuals' choices and judgements about data disclosure on social media.

Third, the results prompt a reconsideration of how trust and transparency are conceptualized in digital marketing theory. Although prior research highlights these elements as fundamental to ethical data practices (Martin & Murphy, 2017; Hemker et al., 2021), the present research reveals that transparency alone does not significantly affect users' willingness to share data. This contradicts the assumption that transparency automatically fosters trust. Instead, transparency seems to acquire importance when coupled with tangible or emotional rewards. While trust had a positive effect, it does not moderate other relationships within the model — suggesting that trust functions less as an amplifier and more as a baseline condition for meaningful connection. This insight contributes to refine existing trust models, showing that users' confidence in digital

transactions depends less on clear information and more on the sense of stability, empathy, and reliability that brands build over time.

Fourth, the study contributes to value co-creation theory by showing that consumers are active participants rather than passive recipients of value propositions. Through participation and data sharing, users co-create value by engaging in activities such as gamified experiences, influencer interactions, and exclusive access. These mechanisms generate emotional and relational value, not just utilitarian benefits. Such perspective help to better understand the co-creation theory by emphasizing that digital value comes that digital value emerges through experience and reciprocity, when users feel that the exchange between themselves and the brand is fair, participatory, and emotionally rewarding.

Finally, the research offers insights for data-driven and ethical marketing theories. It introduces a more human-centred perspective into Data Value Chain (Faroukhi et al., 2020), showing that value is not created solely by companies but also through the trust, consent, and engagement of individuals who share their data. The weak effect of transparency observed in this study suggests that ethical conduct, while necessary, is not sufficient: indeed, sustainable data relationships also need emotional resonance and perceived fairness to enhance people's emotions and sense of exchange. This aligns with Hemker et al. (2021) and Rosário and Dias (2023), emphasizing that the future of ethical digital marketing should balance transparency with emotional connection and perceived fairness. In sum, this study contributes to a deeper understanding of digital marketing, showing that value, emotion, and ethics jointly explain why individuals choose to share their personal data online.

6.2. Practical implications

Digital marketing today operates in a context where the exchange of personal data is central to value creation. Understanding how consumers perceive and respond to different types of value propositions is therefore essential for organizations seeking to design digital experiences that are more transparent, engaging, and trustworthy. The findings of this study provide practical guidance for brands and marketers who want to build stronger relationships with users and create data exchanges that are perceived as fair, and mutually beneficial.

Since personalization strongly affects users' willingness to share data, companies should focus on creating value propositions that feel rewarding rather than intrusive. This involves tailoring content and offers based on individual preferences and contexts, while also making sure they know how their data is being used and have control over it. When personalization is accompanied by tangible benefits — such as exclusive content, recognition, convenience, or a sense of belonging — data sharing becomes a fair and reciprocal exchange rather than a one-sided transaction.

The results also show that trust is still essential in digital relationships, though it functions more as a baseline expectation than as a differentiating advantage. Because of this, companies should focus on building trust over time, gradually and consistently, by offering real and genuine benefits in exchange for using personal data. Communicating transparency emotionally — through empathy, clear language, and relatable storytelling — helps transform compliance into connection.

Furthermore, the significant role of experiential mechanisms, such as gamification and influencer interaction, suggests that emotional engagement is a powerful driver of perceived value. Brands and platforms should make data-sharing experiences feel more interactive, meaningful, and participatory. For example, adding playful elements, social interaction, or moments of recognition, where users feel valued and part of a community can turn data sharing into a positive experience instead of something that feels purely transactional.

From both ethical and business perspectives, organizations should rethink their data strategies to combine responsibility with a more engaging and human approach. Privacy messages and consent can be designed in more creative, user-centred ways, using visuals, tone, and interactivity that capture attention and make people feel stronger connected with the brand, rather than just completing a formal step.

The findings also highlight that effective digital strategies come from integrating and combining emotion, ethics, and value in every interaction. Marketers should look at the customer value proposition as a holistic system, one that aligns personalization, transparency, and experiential engagement to build trust and enjoyment simultaneously. Maintaining this balance allows organizations to create sustainable, trust-based relationships with consumers and turn data sharing into a collaborative process that benefits both sides.

6.3. Limitations and suggestions for future research

Although this study provides relevant insights into how different types of value propositions influence users' willingness to share personal data on social media, some limitations must be acknowledged.

One of the main limitations concerns the sample size and demographic composition. The respondents were mostly young adults, which restricts the generalization of the results to broader populations. Since perceptions of personalization, trust, and privacy may differ across generations or cultures, future studies should more diverse and representative samples to capture potential differences in how various audiences perceive the fairness and benefits of data exchange.

A second limitation relates to the use of self-reported data. Because participants were asked to describe their own attitudes and intentions, their answers may not fully reflect how they actually behave online. Some individuals might have said they are more careful or selective about sharing data than they really are in practice, while others may not even be fully aware that they are regularly allowing social media platforms to collect and use their personal information. Future studies could mitigate this bias by using behavioral or experimental methods, such as observing real interactions on social media, analysing digital footprints, or testing how users respond to different value propositions in controlled environments.

Third, the conceptual model focused on four core variables: personalization, trust, transparency, and experiential engagement. While these constructs capture major aspects of perceived value, other elements may also influence users's decisions to share personal data. Factors such as perceived control, privacy concerns, emotional connection to brands, or perceived risk could be examined in future studies to provide a more comprehensive understand of what motivates or discourages individuals from disclosing personal information online.

Another limitation that should be considered concerns the way this study approached data-sharing behavior. While the research focused on users' perceptions of value, it did not account for how interface design and visual cues on social media might influence these perceptions and decisions. In many cases, users may share personal information not because they consciously choose to, but because the interface makes the process extremely easy or appealing, for example, by using large "accept" buttons or requiring only one or two clicks to give consent. Future studies could experimentally test how

different visual and interactive formats affect users' awareness and willingness to share data, offering new insights into the role of design in shaping online behavior.

Lastly, although this study compared how people use and trust across social media platforms, it did not not explore the underlying reasons behind those differences. Future research could explore how each platform's purspose, community norms, and communication style influence perceptions of trust and fairness in data sharing. Investigating user's familiarity, emotional connection, or perceived identity alignment with a certain platform could also explain why ome environments are perceived as ore trustworthy or ethically sound than others.

Expanding the research in these directions would contribute to a deeper understanding of the drivers of data-sharing behaviours, supporting brands in developing digital experiences that transparent, engaging, and grounded in mutual trust.

7. Conclusions

The aim of this study was to investigate how different types of value propositions influence consumers' willingness to share personal data on social media. The results demonstrate that personalization is the main factor that encourages people to share their data. When users perceive clear and relevant benefits, such as offers, content, or experiences that feel designed for them, they become more comfortable disclosing personal information. Trust also plays a positive role, functioning less as a differentiator between brands and more as a foundational condition that enables users to feel safe and confident. In contrast, transparency alone did not increase the willingness to share, which suggests that merely explaining data policies is insufficient. It becomes more effective when combined with emotionally engaging experiences, such as exclusive content, interactive campaigns, or collaborations with influencers, which create a sense of connection and reciprocity.

This study deepens the understanding of how emotions and relationships shape digital value. Individuals do not decide to share data only through logic or rational evaluation; their choices are also guided by feelings of recognition, belonging, and fairness. For marketers, this implies that value propositions should be both responsible, relevant, and emotionally resonant. Personalization must relate with the feeling of genuine and

rewarding, and communication about data use should be clear, creative, and human-centered.

Although the study offers useful insights, it also has some limitations. The sample was composed primarily young adults, which restricts the generalization of the results. Future research could include more diverse age groups and cultural contexts and/or employ experimental methods to observe how individuals actually behave online. It could also examine additional factors such as perceived control, privacy concerns, or emotional attachment to brands to to provide a more comprehensive view on what motivates people to share or protect their data.

Ultimately, this study suggests that the future of digital marketing depends on balancing value, emotion, and ethics. When brands make data sharing feel transparent, fair, and meaningful, they can foster deeper trust, strengthen long-term relationships with consumers, and create a more sustainable and human-centered digital ecosystem.

References

Ackermann, K. A., Burkhalter, L., Mildenberger, T., Frey, M., & Bearth, A. (2021). Willingness to share data: Contextual determinants of consumers' decisions to share private data with companies. Journal of Consumer Behaviour, 21(2), 375–386. https://doi.org/10.1002/cb.2012

Alvi, M. H. (2016). A manual for selecting sampling techniques in research. Munich Personal RePEc Archive (MPRA Paper No. 70218). University of Karachi, Iqra University. https://mpra.ub.uni-muenchen.de/70218/

Amerioun, A., Alidadi, S., Zaboli, R., & Sepandi, M. (2018). Dataset for factor analysis of barriers of health system research utilization in Iran. Data in Brief, 19, 1522–1529. https://doi.org/10.1016/j.dib.2018.05.152

Ball, H. L. (2019). Conducting online surveys. Journal of Human Lactation, 35(3), 413–417. https://doi.org/10.1177/0890334419848734

Bourne, V. (2016). Embracing a Digital Future: Transforming to leap ahead. Dell Technologies.

Borges-Tiago, M. T., Almeida, A., Tiago, F. G. B., & Avelar, S. M. M. (2024). *Bridging the innovative attitude–behavior gap: A dual-level analysis. Journal of Innovation & Knowledge, 9*(4), 100561. https://doi.org/10.1016/j.jik.2024.100561

Burgess, C., & Burgess, M. (2020). The new marketing: How to Win in the Digital Age. SAGE.

Dalmaijer, E. S., Nord, C. L., & Astle, D. E. (2022). Statistical power for cluster analysis. BMC Bioinformatics, 23(1), 205. https://doi.org/10.1186/s12859-022-04675-1

Eg, R., Tønnesen, Ö. D., & Tennfjord, M. K. (2023). A scoping review of personalized user experiences on social media: The interplay between algorithms and human factors. Computers in Human Behavior Reports, 9, 100253. https://www.sciencedirect.com/science/article/pii/S2451958822000872?via%3Dihub

Faroukhi, A. Z., Alaoui, I. E., Gahi, Y., & Amine, A. (2020). Big data monetization throughout Big Data Value Chain: a comprehensive review. Journal of Big Data, 7(1). https://doi.org/10.1186/s40537-019-0281-5

Frow, P., McColl-Kennedy, J. R., Hilton, T., Davidson, A., Payne, A., & Brozovic, D. (2014). Value propositions. Marketing Theory, 14(3), 327–351. https://doi.org/10.1177/1470593114534346

Hooper, D. (2012). Exploratory factor analysis. In M. M. Seawright (Ed.), Practical Assessment, Research & Evaluation, 18(6), 1–7. https://doi.org/10.7275/qv2q-rk76

Garcia-Rivadulla, S. (2016). Personalization vs. privacy: An inevitable trade-off? IFLA Journal, 42(3), 227–238. https://doi.org/10.1177/0340035216662890

Gerring, J. (2017). Qualitative methods. Annual Review of Political Science, 20, 15–36. https://www.annualreviews.org/content/journals/10.1146/annurev-polisci-092415-024158

Gerber, N., Gerber, P., & Volkamer, M. (2018). Explaining the privacy paradox: A systematic review of literature investigating privacy attitude and behavior. Computers & Security, 77, 226–261. https://www.sciencedirect.com/science/article/abs/pii/S0167404818303031?via%3Dihub

Gomes, J. , & Cesário, F. (2014). *Investigação em gestão de recursos humanos*. Escolar Editora

Hajarian, M., Diaz, P., Aedo, I., & Minaei-Bidgoli, B. (2025). A gamified nudging method for privacy personalization in social networks and its effects on online hostility and user engagement. Electronic Commerce Research and Applications, 74, 101554. https://doi.org/10.1016/j.elerap.2025.101554

Hemker, S., Herrando, C., & Constantinides, E. (2021). The transformation of data marketing: How an ethical lens on consumer data collection shapes the future of marketing. Sustainability, 13(20), 11208. https://www.mdpi.com/2071-1050/13/20/11208

Hollebeek, L. D., & Macky, K. (2018). Digital content Marketing's role in fostering consumer engagement, trust, and value: framework, fundamental propositions, and implications. Journal of Interactive Marketing, 45(1), 27–41. https://doi.org/10.1016/j.intmar.2018.07.003

Kokolakis, S. (2017). Privacy attitudes and privacy behaviour: A review of current research on the privacy paradox phenomenon. Computers & Security, 64, 122–134. https://www.sciencedirect.com/science/article/abs/pii/S0167404815001017?via%3Dihub

Kotler, P., Kartajaya, H., & Setiawan, I. (2021). Marketing 5.0: Technology for Humanity. John Wiley & Sons.

Lambillotte, L., Bart, Y., & Poncin, I. (2022). *When does information transparency reduce the downside of personalization? The role of need for cognition and perceived control. Journal of Interactive Marketing, 57*(3), 393–420. https://doi.org/10.1177/10949968221095557

Marsh, D., & Stoker, G. (Eds.). (2010). Theory and methods in political science (3rd ed.). Palgrave Macmillan. ISBN 978-0-230-57627-8 https://www.biknotes.com/_files/ugd/b8b6dc_8ec08f3deed84f9ca0067138fc4a19a7.pdf#page=284

Martí, P., Serrano-Estrada, L., & Nolasco-Cirugeda, A. (2019). Social media data: Challenges, opportunities and limitations in urban studies. Computers, Environment and Urban Systems, 74, 161–174. https://www.sciencedirect.com/science/article/pii/S0198971518302333?via%3Dihub

Martin, K. D., & Murphy, P. E. (2016). The role of data privacy in marketing. Journal of the Academy of Marketing Science, 45(2), 135–155. https://doi.org/10.1007/s11747-016-0495-4

Mosteller, J., & Poddar, A. (2017). To Share and protect: Using Regulatory focus Theory to examine the privacy paradox of consumers' social media engagement and online privacy protection behaviors. Journal of Interactive Marketing, 39(1), 27–38. https://doi.org/10.1016/j.intmar.2017.02.003

Müller, E., Hopf, H. (2017). Competence Center for the Digital Transformation in Small and Medium-Sized Enterprises. Procedia Manufacturing 11, 1495–1500. doi:10.1016/j.promfg.2017.07.281

Quach, S., Thaichon, P., Martin, K. D., Weaven, S., & Palmatier, R. W. (2022). Digital technologies: tensions in privacy and data. Journal of the Academy of Marketing Science, 50(6), 1299–1323. https://doi.org/10.1007/s11747-022-00845-y

Payne, A., Frow, P., & Eggert, A. (2017). The customer value proposition: evolution, development, and application in marketing. Journal of the Academy of Marketing Science, 45(4), 467–489. https://doi.org/10.1007/s11747-017-0523-z

Piepponen, A., Ritala, P., Keränen, J., & Maijanen, P. (2022). Digital transformation of the value proposition: A single case study in the media industry. Journal of Business Research, 150, 311–325.

https://www.sciencedirect.com/science/article/pii/S0148296322004404?via%3Dihub

Raj, N. S., & Renumol, V. G. (2021). A systematic literature review on adaptive content recommenders in personalized learning environments from 2015 to 2020. Journal of Computers in Education, 9(1), 113–148. https://doi.org/10.1007/s40692-021-00199-4

Rattray, J., & Jones, M. (2007). Essential elements of questionnaire design and development. *Journal of Clinical Nursing*, *16*(2), 234–243. https://doi.org/10.1111/j.1365-2702.2006.01573.x

Roberts, C. (2007). Mixing modes of data collection in surveys: A methodological review [Discussion paper]. National Centre for Research Methods. NCRM EPrints Repository. https://eprints.ncrm.ac.uk/id/eprint/418/

Rosário, A. T., & Dias, J. C. (2023). How has data-driven marketing evolved: Challenges and opportunities with emerging technologies. International Journal of Information Management Data Insights, 3, 100203. https://www.sciencedirect.com/science/article/pii/S2667096823000496?via%3Dihub

Saura, J. R. (2021). Using data sciences in digital marketing: Framework, methods, and performance metrics. Journal of Innovation & Knowledge, 6(2), 92–102 https://www.sciencedirect.com/science/article/pii/S2444569X20300329?via%3Dihub

Spiller, L. (2020). Direct, Digital & Data-Driven marketing. SAGE.

Waldman, A. E. (2020). Cognitive biases, dark patterns, and the 'privacy paradox'. Current Opinion in Psychology, 31, 105–109. https://www.sciencedirect.com/science/article/abs/pii/S2352250X19301484?via%3Dihub

Stevenson, D., & Pasek, J. (2015). *Privacy concern, trust, and desire for content personalization.* University of Michigan & Stanford Law School. SSRN. https://doi.org/10.2139/ssrn.2587541

Appendices

A1. Survey questionnaire

1. Aceito participar voluntariamente neste estudo, compreendendo que as minhas respostas são anónimas e usadas apenas para fins académicos.
    - Sim, aceito participar.
    - Não, não aceito participar. *(termina o questionário se selecionado)*
2. Utiliza redes sociais?
    - Sim.
    - Não. *(termina o questionário se selecionado)*
3. Idade (anos) _____
4. Sexo:
    - Feminino
    - Masculino
    - Outro
5. Qual o nível mais elevado de instrução que completou?
    - 2º ciclo do ensino básico (6º ano)
    - 3º ciclo do ensino básico (9º ano)
    - Ensino secundário (12º ano)
    - Bacharelato/Licenciatura
    - Mestrado ou superior
6. Como descreve o seu nível de consumo habitual? (escala de intensidade, não relacionada com rendimento)
    - Muito reduzido (consumo apenas o essencial)
    - Reduzido (consumo limitado)
    - Moderado (consumo equilibrado)
    - Elevado (consumo frequente)
    - Muito elevado (consumo intenso)
7. Com que frequência utiliza redes sociais?
    - Várias vezes por dia
    - Uma vez por dia

- Algumas vezes por semana
- Uma vez por semana
- Menos de uma vez por semana

8. Quais destas plataformas utiliza com mais frequência? *(Pode selecionar várias)*
    - Instagram
    - TikTok
    - Facebook
    - LinkedIn
    - YouTube
    - Snapchat
    - Twitter/X
    - Outra(s): _____
9. Em qual destas plataformas sente mais confiança para partilhar os seus dados pessoais?
    - Instagram
    - TikTok
    - Facebook
    - LinkedIn
    - YouTube
    - Snapchat
    - Twitter/X
    - Outra(s): _____
10. Costuma partilhar os seus dados pessoais com marcas nas redes sociais (ex: localização, preferências, gostos, cliques em anúncios, preenchimento de formulários, participação em passatempos, uso de filtros ou quizzes, histórico de navegação, permissões em apps conectadas às redes sociais)?
    - Sim, frequentemente
    - Sim, ocasionalmente
    - Raramente
    - Nunca
    - Não sei / Não tenho a certeza
11. Pense na forma como habitualmente interage com marcas nas redes sociais. Indique em que medida as seguintes afirmações correspondem ao que costuma fazer:

(1 = Não corresponde de todo | 5 = Corresponde totalmente)

	1	2	3	4	5
A personalização de ofertas e conteúdos faz com que considere justa a partilha dos meus dados pessoais					
Estou mais disponível para partilhar os meus dados pessoais quando uma marca me oferece benefícios personalizados.					
Prefiro marcas que comunicam de forma clara a forma como utilizam os meus dados.					
Compreender exatamente como os meus dados serão utilizados deixa-me mais confortável em partilhá-los.					

12. Pense no nível de confiança que sente quando utiliza redes sociais e contacta com marcas nesses espaços. Indique em que medida as seguintes afirmações refletem o seu comportamento ou perceção habitual:
(1 = Não corresponde de todo | 5 = Corresponde totalmente)

	1	2	3	4	5
Confio nas plataformas de redes sociais que utilizo regularmente					
Confio em marcas que conheço bem, mesmo quando pedem dados pessoais					
Quando confio numa marca, aceito mais facilmente que os conteúdos sejam personalizados com base nos meus dados					
A confiança que tenho numa plataforma influencia a minha decisão de partilhar dados					

13. Pense nas situações em que desconfia de marcas ou plataformas nas redes sociais. Indique em que medida as seguintes afirmações refletem a sua perceção habitual:

(1 = Não corresponde de todo | 5 = Corresponde totalmente)

	1	2	3	4	5
Já tive más experiências anteriores que me tornaram mais cauteloso(a)					
Desconfio quando não é clara a origem da página ou do conteúdo					
Fico reticente quando sinto que a informação fornecida pela marca é insuficiente					
Acredito que muitas marcas usam os dados para fins que não são comunicados de forma transparente					

14. Pense nas experiências que já teve com marcas nas redes sociais — como campanhas, passatempos, conteúdos exclusivos ou interações com influenciadores. Indique em que medida as seguintes afirmações correspondem ao que costuma sentir ou fazer:
(1 = Não corresponde de todo | 5 = Corresponde totalmente)

	1	2	3	4	5
Aceder a conteúdos exclusivos faz com que esteja mais disposto(a) a partilhar dados					
Quando participo em passatempos ou campanhas interativas, aceito partilhar mais dados pessoais					
A relação com influenciadores digitais influencia a minha perceção de justiça na troca de dados com uma marca					

Sinto que a troca de dados é justa quando recebo experiências únicas em troca					

15. Pense na forma como as marcas comunicam sobre a recolha e utilização dos seus dados pessoais. Indique em que medida concorda com as seguintes afirmações com base na sua experiência nas redes sociais:
    (1 = Não corresponde de todo | 5 = Corresponde totalmente)

	1	2	3	4	5
Quanto mais transparente for uma marca sobre os dados que recolhe, mais valor reconheço na proposta apresentada					
A transparência na recolha de dados torna-me mais recetivo(a) às vantagens oferecidas					
Sinto que a falta de clareza sobre a recolha de dados reduz o valor de uma proposta de marca					
Mesmo que uma proposta pareça vantajosa, se não for transparente, hesito em partilhar os meus dados					

16. Considera os seus dados pessoais (ex: nome, localização, histórico de navegação, preferências) como algo:
    1 – Pouco valioso 2 3 4 5 – Muito valioso

17. Pense de forma geral na sua atitude perante a partilha de dados pessoais com marcas nas redes sociais. Indique em que medida concorda com as seguintes afirmações.
    (1 = Discordo totalmente | 5 = Concordo totalmente)

	1	2	3	4	5
Estou disposto(a) a partilhar os meus dados pessoais em troca de benefícios reais					

Acredito que a partilha de dados nas redes sociais pode ser vantajosa para mim					
A decisão de partilhar dados depende da relação que tenho com a marca					

18. Está disposto(a) a partilhar os seus dados pessoais com marcas nas redes sociais?
    - Sim
    - Não
19. [Se respondeu "Não" à questão 18] Quais são as principais razões para não estar disposto(a) a partilhar os seus dados pessoais? (pode selecionar várias opções)
    - Falta de confiança nas marcas
    - Preocupações com privacidade e segurança
    - Más experiências anteriores
    - Falta de clareza sobre a utilização dos dados
    - Não vejo benefícios suficientes
    - Outra: _____
20. Até que ponto estaria disposto(a) a ceder diferentes tipos de dados pessoais às marcas nas redes sociais?
    (1 = Nunca partilharia | 5 = Partilharia sem problema)

	1	2	3	4	5
Dados de contacto (*e-mail*, telefone)					
Localização em tempo real					
Preferências de consumo e interesses					
Histórico de navegação *online*					
Interações nas redes sociais (*likes*, comentários, partilhas)					
Fotografias e conteúdos multimédia					
Permissões em *apps* conectadas às redes sociais					

A2. Additional results

Suplementary table 1. Descriptive statistics for the main variables.

The table summarizes the number of valid cases (N), minimum and maximum values, means, standard deviations, and distribution parameters (skewness and kurtosis) for each variable.

Variable	Minimum	Maximum	Mean	Standard deviation	Skewness	Kurtosis
Age	18	78	36,40	15,263	0,845	-0,502
Gender	0	1	0,67	0,470	-0,741	-1,464
Education level	1	3	2,16	0,694	-0,224	-0,912
Consumption level	1	5	3,30	0,736	0,074	0,468
Frequency of SM use	1	4	3,61	0,760	-1,920	2,784
Most used platforms						
Instagram	0	1	0,90	0,295	-2,772	5,738
Facebook	0	1	0,28	0,449	1,002	-1,005
TikTok	0	1	0,41	0,493	0,372	-1,879
LinkedIn	0	1	0,40	0,490	0,431	-1,831
YouTube	0	1	0,54	0,500	-0,147	-1,997
Snapchat	0	1	0,04	0,199	4,667	19,965
Whatsapp	0	1	0,03	0,176	5,372	27,101
Twitter/X	0	1	0,05	0,228	3,950	13,728

Suplementary table 2. Descriptive statistics and reliability for the main constructs.

This table summarizes the descriptive statistics and reliability coefficients (Cronbach's alpha) for each construct included in the study. For each variable, the corresponding survey question and individual items are presented along with their mean and standard deviation values. The results indicate that all constructs demonstrate satisfactory internal consistency (α > 0.77) and average mean scores ranging between 3.1 and 4.4 on a five-point Likert scale, suggesting generally positive perceptions of personalization, transparency, and trust.

Variable	Question	Mean (Cronbach's alpha)	Item	Mean	Standard Deviation
Personalization	11. Think about how you usually interact with brands on social media. Indicate the extent to which the following statements correspond to your usual behavior:	3,874 (α = 0,778)	The personalization of offers and content makes me consider the sharing of my personal data fair.	3,186	± 1,208
			I am more willing to share my personal data when a brand offers me personalized benefits.	3,486	± 1,277
			I prefer brands that clearly communicate how they use my data.	4,591	± 0,786
			Understanding exactly how my data will be used makes me feel more comfortable sharing it.	4,232	± 1,000
Trust	12. Think about the level of trust you feel when using social media and interacting with brands in those spaces. Indicate the extent to which the following statements reflect your usual perception or behavior:	3,555 (α = 0,832)	I trust the social media platforms I use regularly.	2,955	± 0,945
			I trust brands I already know, even when they ask for personal data.	3,623	± 1,002
			When I trust a brand, I more easily accept that content is personalized based on my data.	3,673	± 1,115
			The trust I have in a platform influences my decision to share personal data.	3,968	± 1,116
Discomfort with Data Sharing	13. Think about situations in which you distrust brands or platforms on social media. Indicate the extent to which the following statements reflect your usual perception:	3,906 (α = 0,778)	I have had previous negative experiences that made me more cautious.	2,536	± 1,156
			I become suspicious when the origin of a page or content is unclear.	4,468	± 0,851
			I feel hesitant when the information provided by the brand is insufficient.	4,286	± 0,878
			I believe many brands use data for purposes that are not clearly communicated.	4,332	± 0,846
Experiential Mechanisms	14. Think about experiences you have had with brands on social media — such as campaigns, contests, exclusive content, or interactions with influencers. Indicate the extent to which the following statements correspond to what you usually feel or do:	3,117 (α = 0,925)	Accessing exclusive content makes me more willing to share data.	3,414	± 1,245
			When I take part in contests or interactive campaigns, I agree to share more personal data.	3,109	± 1,350
			My interaction with digital influencers affects my perception of fairness in exchanging data with a brand.	2,736	± 1,262
			I feel that data exchange is fair when I receive unique experiences in return.	3,209	± 1,311
Transparency	15. Think about how brands communicate about the collection and use of your personal data. Indicate the extent to which you agree with the following statements based on your experience on social media:	4,405 (α = 0,830)	The more transparent a brand is about the data it collects, the more value I recognize in its proposal.	4,536	± 0,749
			Transparency in data collection makes me more receptive to the benefits offered.	4,282	± 0,861
			I feel that a lack of clarity about data collection reduces the perceived value of a brand's proposal.	4,495	± 0,755
			Even if a proposal seems advantageous, if it is not transparent, I hesitate to share my data.	4,305	± 0,908

Suplementary table 3. Pearson bivariate correlations between all study items

This table displays the Pearson correlation coefficients (r) and corresponding significance levels (p) for all items included in the study. The results show consistent positive associations among personalization, trust, transparency, and willingness-to-share measures, while discomfort-related items exhibit negative correlations with these constructs.

Variables			The personalization of offers and content makes me consider the sharing of my personal data fair.	I am more willing to share my personal data when a brand offers me personalized benefits.	I prefer brands that clearly communicate how they use my data.	Understanding exactly how my data will be used makes me feel more comfortable sharing it.	I trust the social media platforms I use regularly.	I trust brands I already know, even when they ask for personal data.	When I trust a brand, I more easily accept that content is personalized based on my data.	The trust I have in a platform influences my decision to share personal data.	I have had previous negative experiences that made me more cautious.	I become suspicious when the origin of a page or content is unclear.	I feel hesitant when the information provided by the brand is insufficient.	I believe many brands use data for purposes that are not clearly communicated.	Accessing exclusive content makes me more willing to share data.	When I take part in contests or interactive campaigns, I agree to share more personal data.	My interaction with digital influencers affects my perception of fairness in exchanging data with a brand.	I feel that data exchange is fair when I receive unique experiences in return.	The more transparent a brand is about the data it collects, the more value I recognize in its proposal.	Transparency in data collection makes me more receptive to the benefits offered.	I feel that a lack of clarity about data collection reduces the perceived value of a brand's proposal.	Even if a proposal seems advantageous, if it is not transparent, I hesitate to share my data.	Are you willing to share your personal data with brands on social media?	I believe that sharing data on social media can be advantageous for me.	The decision to share data depends on the relationship I have with the brand.	Are you willing to share your personal data with brands on social media?
Personalization	The personalization of offers and content makes me consider the sharing of my personal data fair.	r																								
		Sig.																								
	I am more willing to share my personal data when a brand offers me personalized benefits.	r	.886**																							
		Sig.	0,000																							
	I prefer brands that clearly communicate how they use my data.	r	,278**	,272**																						
		Sig.	0,000	0,000																						
	Understanding exactly how my data will be used makes me feel more comfortable sharing it.	r	,372**	,376**	,592**																					
		Sig.	0,000	0,000	0,000																					
Trust	I trust the social media platforms I use regularly.	r	,532**	,473**	0,0609468	,296**																				
		Sig.	1,883E-17	0,000	0,368	0,000																				
	I trust brands I already know, even when they ask for personal data.	r	,621**	,616**	,348**	,466**	,585**																			
		Sig.	0,000	2,492E-24	0,000	0,000	0,000																			
	When I trust a brand, I more easily accept that content is personalized based on my data.	r	,707**	,747**	,284**	,506**	,627**	,715**																		
		Sig.	0,000	0,000	1,866E-05	0,000	0,000	0,000																		
	The trust I have in a platform influences my decision to share personal data.	r	,465**	,476**	,370**	,616**	,367**	,479**	,568**																	
		Sig.	0,000	0,000	0,000	2,242E-24	0,000	0,000	0,000																	
Discomfort with Data Sharing	I have had previous negative experiences that made me more cautious.	r	0	-0,087832	0,0717513	0,0815096	-0,086256	-0,064996	-0,082799	0,0415991																
		Sig.	0,3850853	0,194	0,289	0,229	0,202	0,337	0,221	0,539																
	I become suspicious when the origin of a page or content is unclear.	r	-,187**	-,202**	,356**	,317**	-,206**	0,0045998	-0,087944	,208**	,240**															
		Sig.	0,005	0,002608	0,000	0,000	0,002	0,946	0,194	0,002	0,000															
	I feel hesitant when the information provided by the brand is insufficient.	r	-,145*	-,206**	,329**	,272**	-,232**	-0,011584	-0,081016	,210**	,374**	,772**														
		Sig.	0,031	0,002	5,818E-07	0,000	0,001	0,864	0,231	0,002	0,000	0,000														
	I believe many brands use data for purposes that are not clearly communicated.	r	-0,123367	-,137*	,363**	,303**	-,198**	-0,024027	-0,077947	0,1176161	,279**	,588**	,572**													
		Sig.	0,068	0,042	0,000	4,901E-06	0,003	0,723	0,250	0,082	0,000	0,000	0,000													
Experiential Mechanisms	Accessing exclusive content makes me more willing to share data.	r	,753**	,778**	,235**	,341**	,431**	,547**	,667**	,476**	-,161*	-,218**	-,209**	-,183**												
		Sig.	1,432E-41	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,017	0,001	0,002	0,007												
	When I take part in contests or interactive campaigns, I agree to share more personal data.	r	,687**	,724**	,201**	,279**	,419**	,503**	,624**	,442**	-,254**	-,176**	-,215**	-,156*	,747**											
		Sig.	0,000	5,328E-37	0,003	0,000	0,000	0,000	0,000	0,000	0,000	0,009	0,001	0,021	0,000											
	My interaction with digital influencers affects my perception of fairness in exchanging data with a	r	,668**	,681**	0	,251**	,453**	,481**	,587**	,364**	-,288**	-,237**	-,294**	-,166*	,730**	,799**										
		Sig.	0,000	0,000	0,0537695	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,014	0,000	0,000										
	I feel that data exchange is fair when I receive unique experiences in return.	r	,745**	,831**	,230**	,259**	,465**	,568**	,672**	,332**	-0,117	-,268**	-,302**	-,207**	,783**	,727**	,751**									
		Sig.	0,000	0,000	0,001	0,000103	0,000	0,000	0,000	0,000	0,085	0,000	0,000	0,002	0,000	0,000	0,000									
Transparency	The more transparent a brand is about the data it collects, the more value I recognize in its proposal.	r	,354**	,323**	,654**	,559**	0,0798149	,356**	,359**	,430**	,157*	,335**	,349**	,403**	,280**	,177**	0,1262181	,225**								
		Sig.	7,012E-08	0,000	0,000	0,000	0,238	0,000	0,000	0,000	0,020	0,000	0,000	0,000	0,000	0,009	0,062	0,001								
	Transparency in data collection makes me more receptive to the benefits offered.	r	,445**	,394**	,535**	,470**	,195**	,431**	,391**	,389**	0,095	,193**	,189**	,228**	,419**	,335**	,283**	,360**	,735**							
		Sig.	0,000	1,416E-09	0,000	0,000	0,004	0,000	0,000	0,000	0,160	0,004	0,005	0,001	0,000	0,000	0,000	0,000	0,000							
	I feel that a lack of clarity about data collection reduces the perceived value of a brand's proposal.	r	0,0034353	-6,46E-05	,512**	,331**	-,179**	,140*	-0,012612	,154*	,170*	,589**	,570**	,535**	-0,082961	-0,124831	-,178**	-0,077413	,618**	,465**						
		Sig.	0,960	0,999	4,053E-16	0,000	0,008	0,039	0,852	0,022	0,012	0,000	0,000	0,000	0,220	0,065	0,008	0,253	0,000	0,000						
	Even if a proposal seems advantageous, if it is not transparent, I hesitate to share my data.	r	-,164*	-,191**	,387**	,218**	-,234**	-0,028731	-0,117544	0,0546598	,244**	,535**	,560**	,498**	-,245**	-,269**	-,296**	-,257**	,464**	,357**	,737**					
		Sig.	0,015	0,004	0,000	0,0011075	0,000	0,672	0,082	0,420	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000					
Willingness to share	Are you willing to share your personal data with brands on social media?	r	-,572**	-,608**	-,293**	-,318**	-,385**	-,528**	-,576**	-,394**	,189**	0,128416	0,1303678	,151*	-,579**	-,622**	-,532**	-,525**	-,277**	-,402**	-0,033	0,1109282				
		Sig.	1,69E-20	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,005	0,057	0,053	0,025	0,000	0,000	0,000	0,000	0,000	0,000	0,626	0,101				
	I believe that sharing data on social media can be advantageous for me.	Correl	,790**	,755**	,301**	,348**	,420**	,595**	,648**	,436**	-0,118	-,156*	-,142*	-,139*	,713**	,686**	,641**	,748**	,348**	,385**	0,018	-,153*	-,278**	,748**		
		Sig. (2	0,000	8,418E-42	0,000	0,000	0,000	0,000	0,000	0,000	0,080	0,021	0,036	0,040	0,000	0,000	0,000	0,000	0,000	0,000	0,790	0,024	0,000	0,000		
	The decision to share data depends on the relationship I have with the brand.	Correl	,535**	,545**	,469**	,561**	,385**	,544**	,543**	,602**	0,032	,147*	0,1312057	0,0801524	,539**	,466**	,358**	,462**	,527**	,592**	,300**	,151*	-0,011481	,547**	,601**	
		Sig. (2	0,000	0,000	1,914E-13	0,000	0,000	0,000	0,000	0,000	0,634	0,029	0,052	0,236	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,025	0,866	0,000	0,000	
	Are you willing to share your personal data with brands on social media?	Correl	-,572**	-,608**	-,293**	-,318**	-,385**	-,528**	-,576**	-,394**	,189**	0,128416	0,1303678	,151*	-,579**	-,622**	-,532**	-,525**	-,277**	-,402**	-0,033049	0,1109282	,266**	-,664**	-,605**	-,580**
		Sig. (2	0,000	0,000	0,000	1,52E-06	0,000	0,000	0,000	0,000	0,005	0,057	0,053	0,025	0,000	0,000	0,000	0,000	0,000	0,000	0,626	0,101	0,000	0,000	0,000	3,5518E-21

**.Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Suplementary table 4. Comparison of trust and actual consumption across digital platforms

This table presents the comparison between declared trust (or preference) and actual consumption for each social media platform. The metrics include Cohen's Kappa, Phi coefficient, Jaccard index, Precision, Recall, F1 score, and McNemar's test (p-value), which collectively assess the alignment between users' stated trust and their effective usage. Higher Kappa and F1 values indicate stronger consistency between intention and behaviour, while significant McNemar results suggest asymmetry between what users trust and what they actually use. The interpretation column provides a concise qualitative summary of each platform's behavioural pattern.

Platform	Trust (%)	Actual consumption (%)	Kappa[a]	McNemar_p[b]	Precision	Recall	F1[c]	Phi	Jaccard	Interpretation
Instagram	89.2	40.8	0.138	0.0	45.2	98.9	62.1	0.259	45.0	High preference and equally high usage. Moderate-to-high Kappa indicates good agreement between intention and behaviour. Non-significant McNemar test confirms balance between preference and use.
Facebook	27.4	8.5	0.397	0.0	31.1	100.0	47.5	0.497	31.1	Slightly lower preference but stable usage, reflecting a loyal user base. Moderate agreement.
TikTok	40.4	4.0	0.117	0.0	10.0	100.0	18.2	0.249	10.0	Preference exceeds usage, suggesting symbolic interest or emerging adoption. Significant McNemar test indicates an intention–action asymmetry.
LinkedIn	39.0	44.4	0.614	0.0896	82.8	72.7	77.4	0.618	63.2	Lower preference but concentrated usage among those who prefer it. Reasonable agreement (professional niche use).
YouTube	52.9	21.1	0.193	0.0	30.5	76.6	43.6	0.245	27.9	High concordance between preference and usage. High F1 and Jaccard scores identify it as the most consistent platform between liking and using.
Snapchat	4.0	2.2	0.412	0.2888	33.3	60.0	42.9	0.431	27.3	Low preference and low usage, indicating residual or generational niche relevance.
Twitter/X	5.4	1.3	0.387	0.0077	25.0	100.0	40.0	0.49	25.0	Moderate preference and relatively low usage; users tend to consume content passively rather than actively engage. Weak-to-moderate agreement.

[a] *Cohen's Kappa* (κ) - measure the degree of agreement between declared trust and actual use where p_o is the observed proportion of agreement and $p_e$is the agreement expected by chance. Interpretation: < 0.20 = poor; 0.21–0.40 = fair; 0.41–0.60 = moderate; 0.61–0.80 = substantial; > 0.81 = almost perfect. $\kappa = \frac{p_o - p_e}{1 - p_e}$

[b] McNemar test - detect significant asymmetries between the proportions of users who trust but do not use a platform and those who use but do not trust it. A significant result ($p < .05$) indicates an imbalance between intention and behaviour, i.e., an intention–action gap.

[c] *F1 Score* - harmonic mean between Precision and Recall, representing the overall balance between trust and behaviour, were $F1 = \frac{2PR}{P+R}$, and P is the Precision (proportion of trusted platforms that are actually used $P = \frac{TP}{TP+FP}$ and proportion of used platforms that were also trusted $R = \frac{TP}{TP+FN}$. Precision reflects reliability of trust, Recall reflects coverage of use, and F1 quantifies the balance between the two.

[d] Phi coefficients - measure the association between the binary variables of trust and use for each platform.

[e] Jaccard indices - estimate the proportion of shared positive responses (trust and use) out of the total number of positives observed.

Suplementary table 5. Binary logistic regression models predicting willingness to share personal data based on perceived personalization and transparency

The table summarizes five hierarchical logistic regression models examining the effects of perceived personalization, transparency, and demographic controls (age, gender, education) on consumers' willingness to share personal data. Each step represents a successive model specification, adding interaction terms or control variables to test moderating effects. Initial model: Willingness to share = $\beta_0 + \beta_1$(Perceived personalization) + β_2(Transparency)

Step	Variables	B	S.E.	Wald	df	Sig.	Exp(B)	Omnibus Test of Model Coefficients χ^2	df	Sig.	Global Percentage explained	Model
1	*Perceived personalization*	*2,296*	*0,324*	*50,146*	*1*	***0,000***	*9,932*	***93,408***	*2*	***<,000***	***79,1***	***Willingness to share = -7.02 + 2.30(Perceived personalization) - 0.27(Transparency)***
	Transparency	*-0,273*	*0,309*	*0,780*	*1*	*0,377*	*0,761*					
	Constant	*-7,022*	*1,620*	*18,787*	*1*	***0,000***	*0,001*					
2	*Perceived personalization*	*2,752*	*2,075*	*1,759*	*1*	*0,185*	*15,669*	***93,460***	*3*	***<,001***	***79,1***	*Willingness to share = -8.72 + 2.75(Perceived personalization) + 0.12(Transparency) - 0,11 (Perceived personalization by Transparency)*
	Transparency	*0,121*	*1,797*	*0,005*	*1*	*0,946*	*1,129*					
	Perceived personalization by Transparency	*-0,106*	*0,472*	*0,050*	*1*	*0,823*	*0,900*					
	Constant	*-8,715*	*7,807*	*1,246*	*1*	*0,264*	*0,000*					
3	*Perceived personalization*	2,147	0,335	41,013	1	**0,000**	8,562	**99,178**	5	**<,001**	**82,3**	*Willingness to share = -6.65 + 2.15(Perceived personalization) - 0.16(Transparency)- 0.03(Age)+0.09(Gender)+0.026(Education level)*
	Transparency	-0,158	0,329	0,231	1	0,631	0,854					
	Age	-0,026	0,013	4,095	1	**0,043**	0,975					
	Gender	0,091	0,386	0,055	1	0,814	1,095					
	Education level	0,262	0,274	0,914	1	0,339	1,300					
	Constant	-6,651	1,804	13,589	1	**0,000**	0,001					
4	*Perceived personalization*	**2,117**	**0,333**	**40,310**	**1**	**0,000**	**8,303**	**98,144**	3	**<,001**	**81,8**	***Willingness to share = -6.10 + 2.12(Perceived personalization) - 0.10(Transparency)-0.03(Age)***
	Transparency	-0,102	0,323	0,101	1	0,751	0,903					
	Age	-0,027	0,012	4,679	1	**0,031**	0,973					
	Constant	-6,100	1,703	12,837	1	**0,000**	0,002					
5	*Perceived personalization*	2,469	2,171	1,293	1	0,256	11,809	**98,171**	4	**<,001**	**81,8**	*Willingness to share = -7.42+ 2.47 (Perceived personalization) + 0.20(Transparency) - 0.02(Age) - 0,11(Perceived personalization by Transparency)*
	Transparency	0,206	1,899	0,012	1	0,914	1,228					
	Age	-0,027	0,012	4,66	1	**0,031**	0,973					
	Perceived personalization by Transparency	-0,081	0,494	0,027	1	0,869	0,922					
	Constant	-7,425	8,263	0,807	1	0,369	0,001					

Suplementary table 6. Binary logistic regression models predicting willingness to share personal data based on perceived personalization and trust

The table summarizes five hierarchical logistic regression models examining the effects of perceived personalization, trust, and demographic controls (age, gender, education) on consumers' willingness to share personal data. Each step represents a successive model specification, adding interaction terms or control variables to test moderating effects. Initial model: Willingness to share = $\beta_0 + \beta_1$(Perceived personalization) + β_2(Trust)

Step	Variables	B	S.E.	Wald	df	Sig.	Exp(B)	Omnibus Test of Model Coefficients χ^2	df	Sig.	Global Percentage explained	Model
1	*Perceived personalization*	*1,501*	*0,383*	*15,386*	*1*	***0,000***	*4,488*	***102,505***	***2***	***<,000***	***81,4***	***Willingness to share = -9.04 + 1.50(Perceived personalization) + 1.09(Trust)***
	Trust	*1,090*	*0,360*	*9,144*	*1*	***0,002***	*2,974*					
	Constant	*-9,037*	*1,375*	*43,202*	*1*	***0,000***	*0,000*					
2	*Perceived personalization*	*1,619*	*1,600*	*1,024*	*1*	*0,312*	*5,049*	***102,511***	***3***	***<,001***	*81,4*	*Willingness to share = -9.47 + 1.62(Perceived personalization) + 1.12(Trust) - 0,03(Perceived personalization by Trust)*
	Trust	*1,214*	*1,679*	*0,523*	*1*	*0,470*	*3,367*					
	Perceived personalization by Trust	*-0,034*	*0,444*	*0,006*	*1*	*0,940*	*0,967*					
	Constant	*-9,465*	*5,825*	*2,641*	*1*	*0,104*	*0,000*					
3	*Perceived personalization*	1,231	0,384	10,257	1	**0,001**	3,424	**111,855**	**5**	**<,001**	**82,7**	*Willingness to share = -8.54 + 1.23(Perceived personalization) + 1.13(Trust)- 0.03(Age)+0.002(Gender)+0.44(Education level)*
	Trust	1,312	0,378	12,080	1	<,001	3,714					
	Age	-0,032	0,012	6,659	1	**0,010**	0,969					
	Gender	0,002	0,401	0,000	1	0,996	1,002					
	Education level	0,437	0,289	2,283	1	0,131	1,548					
	Constant	-8,536	1,699	25,243	1	**<,001**	0,000					
4	*Perceived personalization*	1,303	0,377	11,944	1	**0,001**	3,679	**109,498**	**3**	**<,001**	**80,5**	***Willingness to share = -7.48 + 1.30(Perceived personalization) + 1.20(Trust)-0.03(Age)***
	Trust	1,202	0,365	10,852	1	**0,001**	3,328					
	Age	-0,032	0,012	6,880	1	**0,009**	0,969					
	Constant	-7,484	1,500	24,891	1	**0,000**	0,001					
5	*Perceived personalization*	1,643	1,718	0,914	1	0,339	5,171	**109,540**	**4**	**<,001**	**90,7**	*Willingness to share = -8.72+ 1.64(Perceived personalization) + 1.56(Trust) - 0.03(Age) - 0,10(Perceived personalization by Trust)*
	Trust	1,557	1,787	0,759	1	**0,383**	4,746					
	Age	-0,032	0,012	6,912	1	**0,009**	0,969					
	Perceived personalization by Trust	-0,096	0,473	0,042	1	0,839	0,908					
	Constant	-8,716	6,28	1,926	1	0,165	0					

Annex Table 7. Binary logistic regression models predicting willingness to share personal data based on perceived personalization and experiential value

The table summarizes five hierarchical logistic regression models examining the effects of perceived personalization, experiential value, and demographic controls (age, gender, education) on consumers' willingness to share personal data. Each step represents a successive model specification, adding interaction terms or control variables to test moderating effects. Initial model: Willingness to share = $\beta_0 + \beta_1$(Perceived personalization) + β_2(Experiential value)

Step	Variables	B	S.E.	Wald	df	Sig.	Exp(B)	Omnibus Test of Model Coefficients χ^2	df	Sig.	Global Percentage explained	Model
1	*Perceived personalization*	*1,154*	*0,366*	*9,962*	*1*	***0,002***	*3,172*	***112,363***	***2***	***<,000***	***84,5***	***Willingness to share = -6.98 + 1.15(Perceived personalization) + 1.07(Experiential value)***
	Experiential value	*1,074*	*0,257*	*17,521*	*1*	***0,000***	*2,928*					
	Constant	*-6,983*	*1,195*	*34,166*	*1*	***0,000***	*0,001*					
2	*Perceived personalization*	*2,552*	*1,103*	*5,353*	*1*	***0,021***	*12,834*	***114,422***	***3***	***<,001***	***84,5***	*Willingness to share = -12.32 + 2.56(Perceived personalization) + 3.03(Experiential value) - 0,50(Perceived personalization by Experiential value)*
	Experiential value	*3,032*	*1,455*	*4,343*	*1*	***0,037***	*20,746*					
	Perceived personalization by Experiential value	*-0,500*	*0,359*	*1,938*	*1*	*0,164*	*0,606*					
	Constant	*-12,315*	*4,219*	*8,519*	*1*	***0,004***	*0,000*					
3	*Perceived personalization*	1,151	0,377	9,324	1	**0,002**	3,162	***113,546***	***5***	***<,001***	***86,4***	*Willingness to share = -7.69 + 1.15(Perceived personalization) + 1.08(Experiential value)- 0.001(Age)+0.008(Gender)+0.30(Education level)*
	Experiential value	1,082	0,296	13,321	1	**0,000**	2,949					
	Age	0,001	0,014	0,003	1	0,956	1,001					
	Gender	0,008	0,407	0,000	1	0,985	1,008					
	Education level	0,304	0,283	1,150	1	0,284	1,355					
	Constant	-7,693	1,628	22,317	1	**0,000**	0,000					
4	*Perceived personalization*	1,156	0,369	9,820	1	**0,002**	3,176	***112,364***	***3***	***<,001***	**84,5**	*Willingness to share = -6.96 + 1.57(Perceived personalization) + 1.07(Experiential value)- 0.000(Age)*
	Experiential value	1,070	0,294	13,265	1	**0,000**	2,915					
	Age	0,000	0,014	0,001	1	0,975	1,000					
	Constant	-6,959	1,422	23,947	1	**0,000**	0,001					
5	*Perceived personalization*	2,555	1,104	5,354	1	**0,021**	12,867	***114,425***	***4***	***<,001***	***84,5***	*Willingness to share = -12.28 + 2.55(Perceived personalization) + 3.02(Experiential value) - 0.001(Age) - 0,5(Perceived personalization by Experiential value)*
	Experiential value	3,024	1,463	4,273	1	**0,039**	20,571					
	Age	-0,001	0,015	0,003	1	0,960	0,999					
	Perceived personalization by Experiential value	-0,5	0,359	1,94	1	0,164	0,606					
	Constant	-12,275	4,292	8,18	1	**0,004**	0					

Annex Table 8. Binary logistic regression models predicting willingness to share personal data based on perceived transparency and experiential value

The table summarizes five hierarchical logistic regression models examining the effects of transparency, experiential value, and demographic controls (age, gender, education) on consumers' willingness to share personal data. Each step represents a successive model specification, adding interaction terms or control variables to test moderating effects. Initial model: Willingness to share = $\beta_0 + \beta_1$(Transparency) + β_2(Experiential value)

Step	Variables	B	S.E.	Wald	df	Sig.	Exp(B)	Omnibus Test of Model Coefficients χ^2	df	Sig.	Global Percentage explained	Model
1	*Transparency*	*0,695*	*0,305*	*5,210*	*1*	***0,022***	*2,004*	***106,200***	***2***	***<,001***	***84,5***	***Willingness to share = -7.21 + 0.70(Transparency) + 1.61(Experiential value)***
	Experiential value	*1,605*	*0,213*	*56,701*	*1*	***0,000***	*4,978*					
	Constant	*-7,212*	*1,572*	*21,057*	*1*	***0,000***	*0,001*					
2	*Transparency*	*1,210*	*1,405*	*0,742*	*1*	*0,389*	*3,355*	***106,278***	***3***	***<,001***	***84,5***	*Willingness to share = -6.10 + 1.21(Transparency) + 0.44(Experiential value) + 0.09(Transparency by Experiential value)*
	Experiential value	*0,440*	*0,947*	*0,216*	*1*	*0,642*	*1,553*					
	Transparency by Experiential value	*0,091*	*0,322*	*0,080*	*1*	*0,777*	*1,095*					
	Constant	*-6,100*	*4,192*	*2,117*	*1*	*0,146*	*0,002*					
3	*Transparency*	1,654	0,249	44,209	1	**0,000**	5,228	***107,409***	***5***	***<,001***	***83,6***	*Willingness to share = -7.87 + 1.65(Transparency) + 0.65(Experiential value)+0.005(Age)- 0.12(Gender)+0.29(Education level)*
	Experiential value	0,646	0,310	4,347	1	**0,037**	1,908					
	Age	0,005	0,015	0,099	1	0,753	1,005					
	Gender	-0,120	0,398	0,091	1	0,763	0,887					
	Education level	0,294	0,278	1,120	1	0,290	1,342					
	Constant	-7,868	1,874	17,634	1	**0,000**	0,000					
4	*Transparency*	1,634	0,247	43,736	1	**0,000**	5,123	***106,256***	***3***	***<,001***	**84,5**	*Willingness to share = -7.38 + 1.63(Transparency) + 0.69(Experiential value)+0.003(Age)*
	Experiential value	0,687	0,306	5,052	1	**0,025**	1,987					
	Age	0,003	0,014	0,056	1	0,814	1,003					
	Constant	-7,382	1,731	18,177	1	**0,000**	0,001					
5	*Transparency*	0,439	0,946	0,215	1	0,643	1,55	***106,330***	***4***	***<,001***	***84,1***	*Willingness to share = -6.29 + 0.44(Transparency) + 1.25(Experiential value) + 0.003(Age) + 0,09(Transparency by Experiential value)*
	Experiential value	1,247	1,416	0,776	1	0,378	3,481					
	Age	0,003	0,014	0,052	1	0,820	1,003					
	Transparency by Experiential value	0,089	0,322	0,076	1	0,783	1,093					
	Constant	-6,292	4,275	2,166	1	0,141	0,002					