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How Blockchain technology impacts loyalty programs and the willingness of consumers to adopt them

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Master in Marketing

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During the two years of my master's degree, I have acquired a wealth of knowledge about the field of marketing. However, I have also gained a deeper understanding of myself, as it has enabled me to more fully challenge myself and have faith in my abilities. I am extremely proud to have completed my dissertation, which marks the conclusion of another chapter in my life. Therefore, I can’t help but thank all the people who were part of this journey.

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Abstract

The rapidly evolving business landscape has garnered significant attention for blockchain technology, which is an innovative technology capable of changing businesses' structure and approaches to customers. The purpose of this study is to determine and comprehend the factors that influence customers' acceptance and adoption of this technology, considering its potential to transform traditional loyalty programs.

To achieve the objective, a conceptual model is developed, based on Technology Acceptance Model (TAM), extending it to the external variables of Informational Social Influence, Psychological Value, Economic Value, Perceived Security and Trust Propensity. This results in a conceptual model that can explain and comprehend the relationship between these variables and the desire to use or accept Blockchain technology. To validate the model, a quantitative approached is used, through an online questionnaire, which was split into Scenario 1 – a group with questions related to blockchain technology's application in loyalty programs, and Scenario 2 – a group with questions related to traditional loyalty programs. This led to a comparison between two samples. IBM SPSS Statistics is used to examine the relationship between independent variables and a dependent variable using a multiple linear regression model.

The results of the study demonstrate that Psychological Value is a predictor of both perceived usefulness and ease of use, while Economic Value and Trust Propensity positively influence perceived ease of use of a program.

This research aims to bring developments yet to be explored within the literature and offer practical implications for marketers and companies that intend to adopt blockchain technology in their loyalty programs by analyzing the consumer acceptance and behaviour.

Keywords: Technology Acceptance Model, blockchain, loyalty program, acceptance, trust, value

JEL Classification System: M30 General (M300 Marketing and Advertising: General); M31 Marketing (M310 Marketing)

Resumo

A rápida evolução do panorama empresarial tem atraído uma atenção significativa para a tecnologia blockchain, que é inovadora e capaz de alterar a estrutura das empresas e as suas abordagens aos clientes. O objetivo deste estudo é determinar e compreender os fatores que influenciam a aceitação e a adoção desta tecnologia pelos clientes, considerando o seu potencial para transformar os programas de fidelidade tradicionais.

Para atingir o objetivo, é desenvolvido um modelo conceptual, baseado no Modelo de Aceitação de Tecnologia (TAM), alargando-o às variáveis externas Informational Social Influence, Psychological Value, Economic Value, Perceived Security e Trust Propensity. Isto resulta num modelo concetpual que permite explicar e compreender a relação entre estas variáveis e o desejo de utilizar ou aceitar a tecnologia Blockchain. Para validar o modelo, é utilizada uma abordagem quantitativa, através de um questionário online, que foi dividido pelo Cenário 1 - um grupo com questões relacionadas com a aplicação da tecnologia blockchain em programas de fidelidade, e Cenário 2 - um grupo com questões relacionadas com programas de fidelidade tradicionais. Isto levou a uma comparação entre duas amostras. O IBM SPSS Statistics é usado para examinar a relação entre variáveis independentes e uma variável dependente usando um modelo de regressão linear múltipla.

Os resultados do estudo demonstram que Psychological Value é um preditor da utilidade e da facilidade de uso percebida, enquanto Economic Value e Trust Propensity influenciam positivamente a facilidade de uso percebida de um programa.

Esta pesquisa tem como objetivo trazer desenvolvimentos ainda não explorados na literatura e oferecer implicações práticas para profissionais de marketing e empresas que pretendem adotar a tecnologia blockchain nos seus programas de fidelidade, analisando a aceitação e o comportamento do consumidor.

Palavras-chave: *Technology Acceptance Model*, Blockchain, programa de fidelidade, aceitação, confiança, valor

Sistema de Classificação JEL: M30 General (M300 Marketing and Advertising: General); M31 Marketing (M310 Marketing)

Index

Index of Figures

Index of Tables

Introduction

Context and Relevance

Digital transformation has urged the increased adoption of several technologies, including loyalty programs. According to *MarketsandMarkets*, the global market for loyalty management is predicted to nearly double, rising from $8.6 billion in 2021 to an estimated $18.2 billion by 2026 (Kecsmar, 2022).

In an increasingly competitive market, brands aim to increase customer loyalty to their products and services. Therefore, brands have started collecting and maintaining customer data systematically, typically through the introduction of loyalty programs to improve customer retention (Rejeb et al., 2020). However, these traditional loyalty programs have experienced significant challenges. Typically, they give customers rewards in a specific industry, and users must remain in the loyalty system for an extended period and collect points to obtain benefits that are not always attractive to them. Moreover, due to privacy concerns, consumers frequently are not willing to give their personal information to join these programs. As a result, the number of customers in loyalty systems is dropping daily (Sonmezturk et al., 2020).

Blockchain technology has attracted a lot of attention in the quickly changing world of modern business, due to its potential to transform several industries and to revolutionize data security, transparency, and trust (Gad et al., 2022; Palmer, 2023). This growing relevance has increased demand for blockchain development companies, who are crucial actors in the progress of this technology. In this evolving context, Portugal has positioned itself as an appealing hotspot for blockchain innovation. Several companies and start-ups are working to harness the power of blockchain in the country's growing ecosystem (Palmer, 2023). Consequently, blockchain technology presents a promising solution to the challenges faced by loyalty programs, providing a secure and transparent platform for managing them.

Research Aim

The purpose of the present study is to assess the impact of blockchain-based loyalty programs on consumers decision-making and their willingness to adopt this kind of program. Several investigations have focused on the implementation of this technology and studied its possible impacts on both a social and economic level. However, the current literature lacks an analysis from the consumer’s perspective. Therefore, this dissertation aims to fill this gap and analyse the consumer perception and their willingness to accept blockchain technology, using for this purpose the model developed by Davis (1989), the Technology Acceptance Model (TAM).

One of the objectives of this dissertation is to delve deeper into blockchain technology's potential as a solution to the limitations faced by conventional loyalty programs. Therefore, this investigation focused on analysing two different samples for one of the scenarios: a blockchain-based loyalty program situation and a traditional loyalty program situation.

Also, the purpose of the current dissertation is to guide marketers and managers to define future user-oriented strategies based on the analysis of consumer perception in different aspects and situations. At the same time, this research seeks to reveal the potential of blockchain technology as a tool for marketing and businesses.

Three main research questions will serve as a guide as this investigation continues:

RQ1 - How does the integration of blockchain technology enhance the efficiency and effectiveness of loyalty programs in terms of customer engagement?

This research question seeks to explore how incorporating blockchain can improve both operational efficiency and consumer engagement within loyalty programs, potentially increasing the participation and satisfaction of customers.

RQ2 - How does blockchain impact the level of trust perceived by consumers in loyalty programs?

This research question focuses on examining how blockchain technology influences consumers' trust levels in loyalty programs, particularly regarding transparency, security and overall reliability.

RQ3 - In what ways can blockchain-enabled decentralized identity solutions be leveraged to enhance data privacy within loyalty programs, and how does this affect consumers' willingness to participate and share personal information?

Finally, this research question investigates how decentralized identity solutions, enabled by blockchain, can enhance data privacy in loyalty programs and how this increased privacy might affect consumers' willingness to engage and share their personal information.

Dissertation Structure

The present Master Thesis is presented as a dissertation and is divided into six major chapters: Introduction, Literature Review, Conceptual Model and Research Hypotheses, Methodology, Results and Conclusion and Limitations. The first chapter introduces the topic under study, the context and highlights its relevance. The second chapter, which is the literature review, places the foundation for understanding the key concepts under study. The third, presents the proposed conceptual model and as well as the research hypotheses. The methodology's chapter describes the research design, the methods used for data collection, analysis and the data treatment process. The fifth chapter presents the results and discussion of the findings. And the final chapter, which is the conclusion, summarizes the main theoretical insights, managerial implications, limitations and suggests areas for future research.

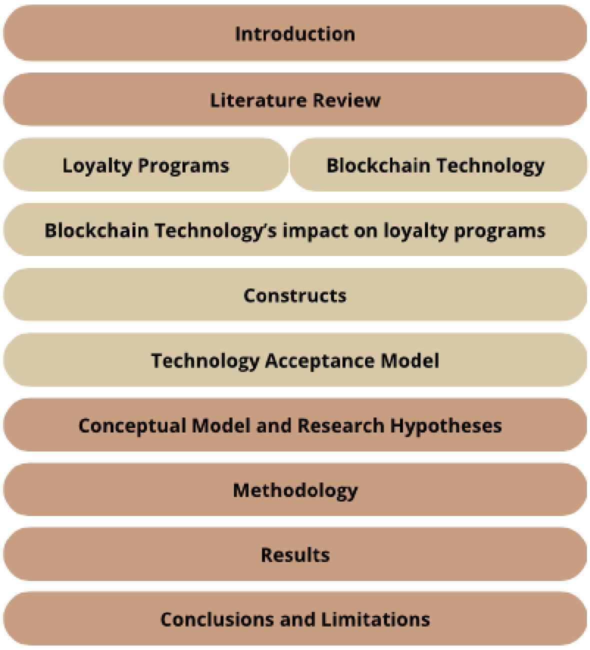

Figure 3.1 – Dissertation's Structure

Source: Own elaboration

1. Literature Review

This literature review aims to contextualise and get a global vision of the current research problem primarily by examining traditional loyalty programs, its relevance and characteristics. Then blockchain technology is introduced, containing its main features and applications and impact, especially on loyalty programs. The constructs under analysis are also explained, as well as the theoretical model TAM, a tool of prediction and acceptance of technology.

1.1 Loyalty programs

Since the late nineteenth century, manufacturers and marketplaces have been creating and implementing loyalty systems that motivate customers to purchase their products. Punch cards, points, tiered, fee-based, cash-back, and coalition loyalty programs are the six traditional forms of loyalty programs (Sonmezturk et al., 2020).

Recent research by Treiblmaier & Petrozhitskaya (2023) state that loyalty programs "*comprise all those measures that companies take to create, strengthen, and maintain customer loyalty*" (p.2), mainly by providing incentives that are gathered and saved as points that may subsequently be used for benefits. More precisely, these programs are frequently constructed in such a way that users earn rewards by making transactions, which can then be redeemed as discounts, free products, rebates, or promotions to a higher tier in the system (Treiblmaier & Petrozhitskaya, 2023). Associated with the term and characteristics of loyalty programs created by companies, is customer loyalty, "*the strength of the relationship between an individual's relative attitude and repeat patronage*" (Dick & Basu, 1994, p.99).

Several researchers have described loyalty programs in their own terms, highlighting the differences between them since different variants of these programs have been created. Blattberg et al. (2008) distinguish between frequency reward programs, where incentives are exclusively based on accumulated points, and customer tier programs, where different benefits are offered to different customer groups. The first provides short-term rewards, whilst the latter are intended to foster long-term relationships. They can also vary in the number of places where someone can earn and spend points. Generally, the more partners a program has, the more appealing it becomes. The type of reward can be differentiated into monetary or non-monetary and direct, meaning rewards that are closely related to a firm's offering, versus indirect, other rewards such as cash (McCall & Voorhees, 2010).

Regarding the application of these programs in industries, Chen et al. (2021) demonstrate that most of the research is done in the retail, hospitality and airline industries. This is because hospitality services tend to give experiential advantages, so the efficacy of certain loyalty program design characteristics differs from other industries that focus a primary emphasis on functional benefits, such as discount retailing. Although it was originated in the airline industry, the retail industry rapidly adopted these systems, probably because retailer scanner data and consumer panel data are more easily available in the retail sector. As a result, non-monetary awards, such as improvements and additional services that improve program members' service experience, play an important role in increasing customer loyalty. Another reason why loyalty programs are so prevalent in the airline and hospitality industries is that services, such as hotel rooms and airplane seats, are highly perishable. This critical characteristic makes it appealing for loyalty program operators to reward loyal clients (Chen et al., 2021).

The development of effective loyalty programs and the collection of consumer data, including purchase trends, transaction history, and preferences, have been facilitated by technological advancement. For instance, the introduction of database management software has enabled thorough and customized customer tracking, bringing in a new era in loyalty marketing. Marketers are increasingly using loyalty programs in a wide range of companies (Rejeb et al., 2020).

1.1.1 Relevance of loyalty programs

Loyalty programs are a crucial tool in marketing used to promote repeat purchases and customer relationships (Chen et al., 2021). According to Accenture, more than 90% of the companies have loyalty programs (Morgan, 2020). By implementing these programs, businesses improve long-term customer engagement and foster emotional ties with the brand, profiting continuously from this relationship. Additionally, it keeps customers from switching to the competition by demonstrating to them that the relationship is worthwhile and will be compensated in some way. It also boosts sales of the company's other products as well as the quantity of the same product sold, being financially advantageous for businesses (cross-selling). Loyalty programs can offer different types of rewards to customers such as financial benefits, service benefits with a positive shopping experience, gifts and exclusive events. Moreover, they provide customers with a psychological sense of acceptance and belonging (Kaizen Institute Consulting Group, 2023).

With digitalization and new technologies significant opportunities for the development of loyalty programs are presented and draw attention to new concepts for further study (Agarwal et al., 2010). Some of the developments are that loyalty programs are expected to move from plastic cards to intangible and virtual accounts that are managed only through mobile applications. Moreover, companies have enhanced analytical tools that enable them to gain insights from large amounts of data they collect every day, enabling managers to estimate product preferences and price sensitivities. It has been concluded that the digitalization of these programs is more cost-efficient and reduce the problem of data input errors (Chen et al., 2021).

The downside identified by Chen et al. (2021) is that there are ethical issues related to privacy and data security because of the volume of data that loyalty programs gather. The risks are associated to the consequences of privacy concerns, loss of control and risks from hackers, that might inhibit loyalty program adoption and usage. In the marketing literature, personalization-privacy issues are gaining importance, but very few studies examine the privacy aspects of loyalty programs.

1.1.2 Limitations and challenges of traditional loyalty programs

As we have established, loyalty programs have been developed to be more efficient and effective, but they are still limited in terms of program components. Many companies are using loyalty programs to retain their current member base rather than expanding the features of reward programs to draw in new potential customers. According to Rejeb et al. (2020), consumers value participating in appealing and flexible loyalty programs. Some companies tend to retain their customers creating situations where customers feel restricted or bound to their services, which is an issue that becomes more challenging when loyalty points remain unused (Rejeb et al., 2020).

Moreover, Treiblmaier & Petrozhitskaya (2023) discovered that prevalent limits in existing loyalty programs frequently confine customers to a limited set of offerings, many of which merely mirror a company's standard products and services, but at discounted rates. Besides, traditional loyalty programs frequently deal with complex background operations which results in delays in crediting points to the customer's account, particularly in tiered programs where points are accumulated depending on spending but are not promptly reflected. Previous research has highlighted the negative perception of loyalty programs when they compel customers to redeem rewards. Although companies may have a rational reason to encourage customers to use their points as quickly as possible, either through consumption or removal to update their balance sheets, this approach may not be in line with consumers' preferences. From the standpoint of the consumer, it would be preferable to have the opportunity to maintain loyalty points in a cash-like way with no set expiration date.

1.2 Blockchain technology overview

A group of researchers who wanted to develop a mechanism to timestamp digital documents so they couldn't be altered or backdated initially introduced the term “blockchain” in 1991 (Yadav et al., 2023). However, it remained dormant until Satoshi Nakamoto created and put forward a virtual currency named Bitcoin in 2008. To enable direct online payments between parties, Nakamoto came up with the concept of an entirely peer-to-peer version of electronic cash, presenting a new paradigm for making transactions and exchanging value in an online setting (Clohessy et al., 2019; Nakamoto, 2008). Nowadays, blockchain has been present in many areas besides cryptocurrencies, such as supply chain management, healthcare, finance, real estate, tourism, and marketing (Rejeb et al., 2020).

Treiblmaier (2018) proposes the following definition of blockchain: ‘‘*digital, decentralized, and distributed ledger in which transactions are logged and added in chronological order with the goal of creating permanent and tamperproof records*” (p. 547). The idea behind blockchain is that it is a "chain of blocks," where each new "block" is appended to an earlier block and connected by a cryptographic hash, forming a "chain" that is used to create the bitcoin (Ali et al., 2023).

Many authors present how a blockchain is structured. Peres et al. (2023) give a very detailed and understandable explanation: a block stores coded transaction data with information such as date, time, money transferred, buyer’s and seller’s identity, or other important and private information. Each transaction in a block has the same time stamp, and each block has its own fingerprint, known as a hash. Once a block is created, any change within the block will modify the hash. As a result, the hash creates a cryptographic signature that protects the block and is difficult to change or attack. Another important characteristic is that blockchain is part of the Distributed Ledger Technology (DLT), which is a decentralized, permissionless distributed database, that allows the recording of data and transactions via a dispersed network on synchronized and shared ledgers (Peres et al., 2023). This means that a replicated database is kept up to date and that its operation is independent of a single entity or an intermediary (Yadav et al., 2023). The transactions take place within a peer-to-peer network of globally distributed computers known as nodes. Every node keeps a copy of the blockchain and contributes to the network's functionality and security. When a node wants to incorporate a new block into an existing chain, all the other nodes must verify the block to confirm that it has not been altered. Each node adds this block to its blockchain once it has been confirmed (Peres et al., 2023). Finally, a block is generated, and the transaction is completed when all nodes in the network reach a consensus (Zheng et al., 2017).

1.2.1 Blockchain technology characteristics

To understand how blockchain technology can be leveraged and used in several industries, it’s important to explore the key features that distinguish it from other technologies. Zheng et al. (2017) identify four characteristics: decentralization, persistency, anonymity, and auditability.

In traditional centralized transaction systems, the central trusted agency must validate each transaction. In contrast of this centralized mode, blockchain doesn’t need a third party. Moreover, once a transaction is added to the blockchain, it is nearly impossible to remove it and blocks that contain invalid transactions can be found very quickly. Regarding its anonymity, each user can connect to the blockchain with a generated address, and it can preserve some privacy through the public and private keys, allowing transactions without any real identity exposure. Lastly, since every transaction on the blockchain is timestamped and validated, people can simply consult any node in the distributed network to verify and trace earlier records, which improves the transparency of the data stored (Zheng et al., 2018). According to research conducted by Ali et al. (2023) on the characteristics of blockchain and its relationship with trust, it was concluded that blockchain is a functionally versatile, tamper-proof, immutable, trustworthy asset and has reliable technical features that ensure the data integrity and provides a transparent, privacy-protected environment, allowing users to create value.

1.2.2 Blockchain technology applications

Blockchain technology has caught tremendous attention from businesses. Its applications can be found in numerous areas such as finance, marketing, healthcare, and supply chain (Nigam et al., 2022). Gad et al. (2022) also conducted a comprehensive study investigating the applications of blockchain technology across several sectors. Their research encompassed the exploration of blockchain in financial services, the energy sector, education, healthcare management, and governance, fostering a transparent government-citizen relationship and improving government services.

The application of blockchain in marketing have become present and Stallone et al. (2021) illustrate a broad spectrum of use cases, encompassing the field of programmatic advertising, incorporating supply chain transparency, payment transparency, fraud prevention, and consumer reward. However, Parssinen et al. (2018) in their research concluded that "*blockchain is not yet ready to be widely implemented in online advertising*" (p. 54897) at least on a large scale without compromising transparency, the inability to modify blocks, quality of information, and energy efficiency.

A frequent issue in the world of content delivery is that original authors of digital assets such as books, documents, and audible content may not receive a fair portion of sales or royalties. This disparity arises because intermediaries such as publishers, retailers, and digital asset providers might contribute to authors obtaining only a fraction of their rightful royalty share. Since authors are not directly involved in the sales process, there is an inherent lack of trust between authors and publishers when it comes to payment settlements. By providing the appropriate incentives, blockchain can aid in the verifiability, authenticity, and transferability of digital assets as content (Stallone et al., 2021).

Stallone et al. (2021) also suggest the concept of "content & experience," which focuses on encouraging valuable content, ensuring authenticity and verifiability, preventing censorship, and removing single points of failure. Furthermore, the research also presents a practical example of a platform using blockchain technology that emphasizes human interconnectivity, adding sub-categories such as loyalty, referral, and advocacy programs. This platform strives to improve the consumer experience, increasing loyalty, referrals, and advocacy. From the consumer's perspective, the use of blockchain technology provides benefits such as greater brand interaction, streamlined redemption of loyalty points, and real-time recognition for loyalty, all of which contribute to increased customer satisfaction. So, customers can use blockchain to combine their loyalty points into a single wallet, making redemption quicker and rewarding loyalty more immediately and transparently.

Moreover, blockchain enables e-commerce platforms to provide an efficient payment system, decentralized control to prevent the control of big companies, an anti-fraud system, lower transaction processing fees, and overall efficient e-commerce platforms. It fosters trust and credibility in business transactions since it tracks and shares customer records and allows everyone to see the progress of transactions (Stallone et al., 2021).

Lastly, Stallone et al. (2021) highlight the importance of a blockchain-based data market, particularly for people who seek to sell information securely and anonymously in a trustworthy setting. As a solution, the blockchain-based platform allows the transaction of information between buyers and sellers anonymously. Individuals acquire access to data sources like Facebook, Amazon, and Google, have the opportunity to monitor offers from possible buyers and sell efficiently their data. Through this system, companies can directly purchase personal data from consumers using a business-specific currency or tokens. This strategy not only facilitates frictionless transactions but also acts as a solution for compensating consumers for sharing access to their data, with the payments handled only when the transaction is confirmed.

Many of the suggested applications of blockchain technology in marketing are related to loyalty programs, according to Peres et al. (2023) in their study of the potential impact of blockchain on several core marketing areas.

1.3 Blockchain technology's impact on loyalty programs

As we established in a previous topic, traditional loyalty programs face some challenges and limitations. Blockchain has been identified as a technology that will transform loyalty systems (Treiblmaier & Petrozhitskaya, 2023). This perspective is reinforced by previous survey research, such as the one conducted by Lemos et al. (2022), with marketing professionals anticipating a positive impact of blockchain on loyalty programs. Early investigations into the matter have already demonstrated that programs based on blockchain can enhance customer perceptions of economic value and fulfil their intrinsic motivations (Treiblmaier & Petrozhitskaya, 2023).

Treiblmaier & Petrozhitskaya (2023) give examples of how blockchain technology can improve the properties of existing loyalty programs, such as allowing for immediate transaction settlement and facilitating the transferability of redeemed points between hitherto separated programs. Moreover, recent industry loyalty program implementations demonstrate the practicality of the blockchain concept and how it can be used to improve customer loyalty. An example is "Dish", which established a backend token-based loyalty system on the Cardano blockchain in 2022, allowing users to manage their coins while maintaining their privacy through a decentralized identification (Treiblmaier & Petrozhitskaya, 2023).

1.3.1 Blockchain-based loyalty program's impact on consumers

This present study aims to evaluate the impact of blockchain-based loyalty programs on consumers. Research state that blockchain-based loyalty programs represent a paradigm shift in customer engagement and reward systems. The adoption of this technology allows companies to use digital currency, such as tokens, for a more effective redemption of loyalty points, hence improving the entire consumer experience. Customers get the advantage of exchanging their loyalty tokens with others using blockchain-enabled loyalty programs, breaking away from standardized loyalty programs, and accessing a greater range of benefits (Boukis, 2019). The impact of blockchain extends to encourage customers to cash in their points for products and services in other industries, or to exchange them for cash if the value rises.

Also, expanding the range of redemption alternatives may significantly raise the perceived value of digital currencies for users, which would motivate them to engage in blockchain-based loyalty programs. Taking advantage of blockchain capabilities, since its transactions are visible to all network users, brands may eventually be able to provide more personalized reward products and bundles to their clients based on their preferences and past redemption activity. Loyalty programs like these may have an impact on consumers' perceptions of the brand and lead to more favorable user-generated content regarding the company's goods and services. This development could be highly attractive for new brands (Boukis, 2019). Boukis (2019) gives an example of a start-up, called Loyyal, that demonstrates the potential of blockchain-based loyalty incentives, offering exchangeable tokens across diverse markets.

Also, Utz et al. (2023) discuss how blockchain might be applied to create a customer loyalty program for electricity suppliers, concluding that customer agency, sufficient and verifiable information, acceptable levels of usability, and unrestricted data access may all improve customer loyalty. The discovery that the immutable and transparent storage of data on the blockchain can have a major positive impact on the dimensions of trust is particularly remarkable.

1.3.2 Relevance of blockchain-based programs for marketing

On the application and relevance of blockchain in the marketing field, Rejeb et al. (2020) illustrate how blockchain technology can empower consumer-centric paradigm and foster disintermediation, combat click fraud, reinforce trust and transparency, enable privacy protection, empower security, and enable creative loyalty programs.

Focusing on privacy issues, research has shown that customers worry about their transaction anonymity, because there is a greater chance that their personal identifiable information will be illegally obtained, misused, and exposed. Ever since website cookies began collecting and storing personal data in information systems, privacy concerns have risen. Information security is also becoming a critical component as brands take on the role of protectors of customer personal information. In order to close security gaps and boost consumer trust in the field of digital advertising, brands need to build a strong technological basis (Rejeb et al., 2020).

In this respect, blockchain technology can be a solution to these problems and benefit both brands and consumers, ensuring an unbeatable level of security. Asymmetric encryption, digital signatures, and access control are just a few of the security measures that can be used to ensure that an extensive amount of customer data is stored, transferred, and retrieved securely in blockchain-based platforms. In order to give customers an accurate picture of a brand's features and values, it can also aid in the synchronization and integration of marketing-related data among network participants. Additionally, since transactions are not linked to actual identities once they are routed to a random set of points in the network, they would retain more control over their personally information and entrust it on a blockchain platform (Jesus et al., 2018). While transactions have the option to remain completely private, they are nevertheless subject to consensus verification by other members of the shared network.

Peres et al. (2023) on the research of the blockchain applications in marketing, they identify its potential to improve customer equity measurement and management while also addressing some important privacy-related issues. Among the examples are the ability to create and exchange customer-specific currencies, which enables the computation of customer value from the totality of user transactions, and the possibility of compensating customers based on their worth (Stallone et al., 2021). Additionally, participants may trade their loyalty points and receive cryptocurrency loyalty rewards (Peres et al., 2023).

Giving the analysis above on some relevant research areas, the present study aims to focus its analysis on the potential use of blockchain technology as a useful tool for ensuring privacy and enable the creation more appealing and customer-centric loyalty programs.

1.4 Constructs

In this section, the constructs chosen for this research's conceptual model are explored in detail.

1.4.1 Informational Social Influence

Informational Social Influence (ISI) refers to the impact that information or opinions from others has on a person's decisions, particularly in uncertain situations or new learnings. Deutsch & Gerard (1955) distinguish between two types of social influence: normative and informational. The last one, occurs when someone accept information from others as evidence of reality, particularly when they lack confidence in their own knowledge. In the context of technology adoption, ISI have a crucial role in shaping user's confidence in exploring and using new technologies (Jang et al., 2024).

When studying technology acceptance, mainly in the field of senior technology adoption, ISI helps reducing difficulties because it provides people the necessary information and support to overcome the fears towards new technologies. When analysing the context of this study, social information provided by others not only reduces the perceived complexity of the new program or system but also increases user's perceived benefits, such as ease of use and usefulness. As Jang et al. (2024) highlight, ISI can alter the user's perception of difficulties, making it easier for people to engage with new systems and adopt them for a long term.

1.4.2 Economic Value

In marketing, economic value is commonly defined as the observable advantages and cost savings that customers see when they buy a good or service. The broader literature on economic value also emphasizes how important it is to client loyalty and satisfaction. Research indicates that consumers who believe a brand has great economic value are more likely to form lasting relationships with it (Bolton & Drew, 1991). This is especially important in highly competitive markets because consumers are continuously weighing the advantages and disadvantages of options and have a high price sensitivity.

According to Treiblmaier & Petrozhitskaya (2023), blockchain technology can significantly increase the economic value of business-to-consumer connections. Blockchain technology makes it possible for customers and companies to communicate directly, frequently avoiding the need for middlemen. This lowers expenses for companies and may result in lower prices for customers. Furthermore, blockchain can lower perceived purchasing risks, increasing confidence through transparency, which strengthens the economic value proposition. The incorporation of blockchain technology into loyalty programs facilitates the development of increasingly customized and adaptable rewards, thereby augmenting the advantages that customers obtain and strengthening their assessment of financial worth. Consumers who perceive higher economic benefits from loyalty programs are more likely to participate actively, which in turn increases the perceived value of loyalty points (Treiblmaier & Petrozhitskaya, 2023).

1.4.3 Psychological Value

Psychological value includes the emotional and cognitive benefits that consumers get from interacting with a brand, like feelings of trust, security and emotional satisfaction. Additionally, there is a strong correlation between it and brand loyalty, since consumers who feel emotionally connected to a brand are more likely to engage in repeat purchases and advocate for the brand (Oliver, 1999).

The potential of blockchain technology to improve psychological value by fostering greater trust and transparency in brand-consumer relationships is highlighted by Treiblmaier & Petrozhitskaya (2023). Customers might feel more secure in their transactions since they have more control over their personal data and can trust that the information provided by businesses is truthful and impenetrable due to the immutable nature of blockchain records. This is consistent with research conducted by (Aaker et al., 2004), who highlight the importance of trust as a foundational element of strong relationships with brands. Customers are more likely to feel positive about a brand when they think it is trustworthy, which raises the brand's psychological worth overall.

1.4.4 Perceived security

Perceived security plays a critical role in influencing consumers' intentions to engage in online transactions, as it directly impacts their trust in the platform and their willingness to share personal information or complete purchases. Salisbury et al. (2001) found that perceived security significantly influences consumers' purchase intentions on the World Wide Web, where the assurance of data protection and secure transactions is predominant.

This concept of perceived security is particularly relevant in the context of blockchain technology, which offers a decentralized and cryptographically secured platform that enhances consumer confidence in digital transactions. Blockchain’s inherent characteristics, such as immutability and transparency, provide a heightened sense of security, as transactions recorded on the blockchain cannot be altered or tampered with after they have been validated. This reassurance reduces the perceived risk associated with online transactions, making consumers more likely to engage in e-commerce and digital interactions. Furthermore, blockchain technology's ability to allow consumers to control their personal data - granting access only when necessary and verifying transactions without revealing sensitive information- enhances their sense of security (Treiblmaier & Petrozhitskaya, 2023). By addressing common concerns related to data breaches and identity theft, blockchain can significantly improve perceived security, leading to increased consumer trust and higher engagement in online purchasing activities. This alignment with the findings of Salisbury et al. (2001) suggests that as perceived security improves, so too does the likelihood of consumer participation in digital economies facilitated by blockchain technology.

1.4.5 Trust Propensity

Following Perceived Security, the construct Trust Propensity is defined by McKnight et al. (2002) as someone's willingness to trust others, including systems or technologies, shaped by personal experiences and external influences, such as media and societal norms. This construct is often associated to early opinions about the technology, which can affect the decision to engage with and adopt new systems (Venkatesh et al., 2003).

Trust propensity has been found to significantly impact user's acceptance of intelligent programs specifically, where the decision-making processes are often perceived as complex or opaque. In those contexts, trust is critical to mitigate perceived risks. According to research, it acts as an important factor in overcoming barriers to accept a new system, especially when there is no transparency of the system. Moreover, Venkatesh et al. (2003) emphasize that trust propensity is closely linked to behavioural intention, which is a core construct of the Unified Theory of Acceptance and Use of Technology (UTAUT), explained in section 1.5 in detail. This relationship is important because people with higher trust propensity are more likely to form positive intentions to use the program, even when there are uncertainties about its performance (Venkatesh et al., 2003). Research has shown that improving transparency and demonstrating system reliability can enhance trust propensity, leading to higher adoption rates (Wanner et al., 2022).

1.4.6 Perceived Usefulness

This construct refers to the degree to which an individual believes that using a particular system or technology will enhance their job performance, according to Davis (1989).

Research has shown that when people perceive a system as useful, they are more likely to develop positive attitudes toward using it, which increases the likelihood of adoption and continued use (Venkatesh & Bala, 2008). Perceived Usefulness has a significant impact on continuous usage throughout time, instead of just being relevant during the early phases of technology adoption. Some studies have also reported it as a major predictor of user acceptability in a variety of situations, including e-learning (Lee et al., 2005), mobile banking (Riquelme & Rios, 2010) and healthcare technology (Holden & Karsh, 2010).

1.4.7 Perceived ease of use

According to Davis (1989), perceived ease of use is the extent to which someone believes that using a particular technology or system will be effortless. It plays a crucial role in determining user's acceptance and adoption of new technologies, since that if a system is easy to use it reduces the cognitive strain associated with learning and utilizing new tools. Therefore, users are more likely to consider a system helpful if they find it easy to use, as it will take them less time and effort to complete their activities (Venkatesh & Davis, 2000).

Furthermore, it is demonstrated that perceived ease of use directly affects users' behavioural intentions to utilize a system, frequently acting as a mediator in the relationship between users' perceptions of the system's utility and their actual usage (Venkatesh & Davis, 2000).

1.4.8 Intention to use and Actual Usage

A key construct in the Technology Acceptance Model is intention to use, which describes the motivational elements that influence a person's propensity to use a certain system or technology. It is seen as the direct precursor of actual system usage in the context of the model. It is shaped by users' attitudes and behavioural intentions toward adopting a technology, which are influenced by perceived usefulness and perceived ease of use.

Actual usage refers to the real-world application or implementation of a technology by users, representing the end behaviour that the Technology Acceptance Model seeks to predict (Davis, 1989).

1.5 Technology Acceptance Model

Since this research is studying the impact of blockchain-based loyalty programs on the consumers decision-making, it's important to consider the model that explores the attitude of consumer towards the adoption of technology. Several models have emerged to try to explain the intention to use a technology, to understand and predict user behaviour. Among these models, the Technology Acceptance Model (TAM) is a widely used and accepted paradigm that investigates consumers' desire to use a certain technology.

TAM is a theoretical framework that aims to explain the acceptance and use of new technologies by individuals and organizations. It is based on the premise that the user's intention to use a technology is a strong indicator of the actual usage of it (Davis, 1989; Davis et al., 1989; Venkatesh & Davis, 1996). The Theory of Reasoned Action (TRA) presented by Fishbein & Ajzen (1975) served as a foundation for TAM. TRA is a model that can forecast and explain behaviour in general and relies its conclusions on intents and attitudes.

The Technology Acceptance Model was proposed by Fred Davis in 1985, formulated to explain the adoption of a computational technology in the organisational context. It then suffered several modifications, but the final version of TAM suggests that the main determinants of technology acceptance are Perceived Usefulness and Perceived Ease-of-Use (Davis, 1989). Besides, the model also incorporates other factors that influence user acceptance and adoption of new technologies. More specifically, Behavioural intention, which refers to the user's intention to use the technology and is influenced by Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), and Actual Usage, which refers to the actual use of the technology, influenced by Behavioural Intention. Although not studied in detail in the base model, it is assumed that external variables can contribute to influencing the user behaviour (Venkatesh & Davis, 1996).

Several adaptations and extensions of the model arose. In 2000, Venkatesh and Davis suggested a revised version of TAM, known as TAM2. This model attempts to explain Perceived Usefulness and Intention to Use through Social Influence and Cognitive Instrumental Processes (Job relevance, Output quality, Result Demonstrability, Perceived Ease of Use), and it was concluded that these significantly influence user acceptance (Venkatesh & Davis, 2000). Subsequently, the Unified Theory of Acceptance and Use of Technology (UTAUT) was proposed by Venkatesh, Morris, Davis and Davis 2003, which incorporated eight models already studied into a single framework to understand technology adoption. A new model, TAM3, was proposed and tested in the IT context, encompassing four different types of PU and PEOU determinants – Individual Differences, System Characteristics, Social Influence and Facilitating conditions (Venkatesh & Bala, 2008).

2. Conceptual Model and Research Hypotheses

Blockchain technology, while widely recognized for its application in the financial sector, has gained adhesion in the marketing area due to its ability to address issues such as transparency and data security. Research has highlighted how blockchain can revolutionize digital advertising, because it can verify engagements and ensure ad fraud prevention using smart contracts. Specific to the present study, blockchain can also transform loyalty programs, as traditional loyalty programs suffer from inefficiencies.

These developments in the application of blockchain within marketing reflect a shift towards creating more consumer-centric approaches, where transparency and trust constitute the foundation of customer-brand relationships. The development of a model to study the consumer's perspective and behaviour is based on the idea of continuing this approach and filling a gap in the existing literature, using significant data to validate the model. Therefore, the purpose of this dissertation is to clarify the consumer's perspective on the acceptance and use of Blockchain technology as a beneficial tool in traditional loyalty programs. Thus, the TAM model was used as a way of understanding consumer behaviour in relation to the problem under study. As presented above, the topic will be investigated based on the following constructs: Informational Social Influence, Economic Value, Psychological Value, Perceived Security and Trust Propensity.

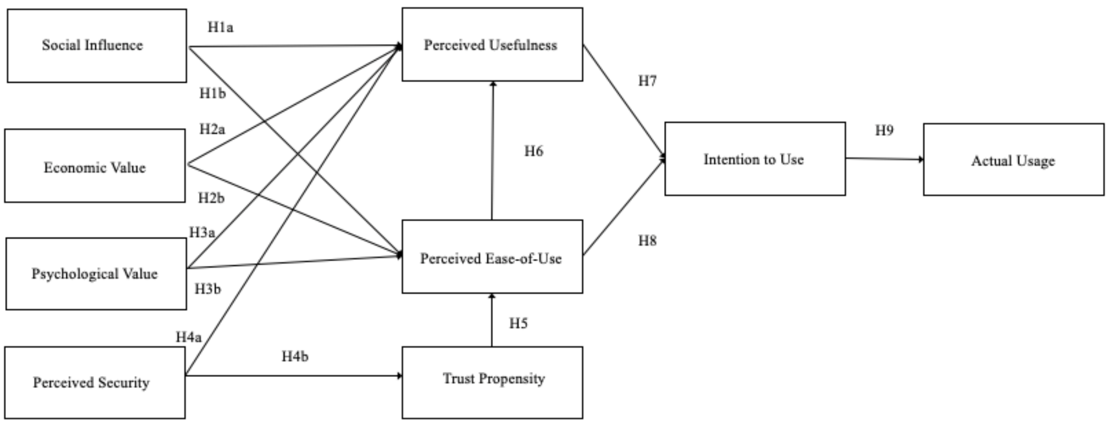

Figure 3.2 – Conceptual model of investigation - adapted from Technology Acceptance Model

Source: Own elaboration

Based on the literature review presented above, the following hypotheses are presented in the conceptual model shown in Figure 3.2.

H1a – Informational Social Influence positively affects Perceived Usefulness.

It is expected that when people receive recommendations or opinions from others they trust, they are more likely to find a loyalty program useful.

H2a – Economic Value positively influences Perceived Usefulness.

If users perceive that a loyalty program offers financial benefits, it is expected that they find the program more useful.

H3a – Psychological Value positively influences Perceived Usefulness.

It is anticipated that emotional benefits provided by participating in the program, increase how useful the program appears to users.

H4a – Perceived Security positively affects Perceived Usefulness.

When users feel secure and that the program can protect their personal information, they are more likely to perceive the program as valuable and beneficial to use.

H1b – Informational Social Influence positively affects Perceived Ease-of-Use.

If people receive guidance or support from others, they are more likely to find the loyalty program easy to use.

H2b - Economic Value positively influences Perceived Ease-of-Use.

People who feel they are getting financial benefits from a program are more likely to find it easy to use, because they perceived the effort as worth the reward.

H3b - Psychological Value positively influences Perceived Ease-of-Use.

If a program provides emotional benefits, such as enjoyment, users may find it easier to engage with.

H4b – Perceived Security positively affects Trust Propensity.

When people perceive the program as secure, they are more likely to develop an inherent tendency to trust the system.

H5 – Trust Propensity positively affects Perceived Ease-of-Use.

People who are more inclined to trust programs or technologies, it is expected that they will find the program easier to use.

H6 – Perceived Ease-of-Use is positively related with Perceived Usefulness.

If people find a loyalty program easy to use, they are more likely to see it as beneficial or useful to their needs.

H7 – Perceived Usefulness positively affects Intention to Use.

When people believe a loyalty program is useful, it is expected that they will intend to use it regularly.

H8 – Perceived Ease-of-Use positively affects Intention to Use.

If users find the program easy to navigate and understand, they are more likely to develop the intention to use regularly.

H9 – Intention to Use positively affects Actual Usage.

When users have a strong intention to use the program, they are more likely to be motivated into using it in real life.

3. Methodology

In this chapter are highlighted the methods used for the research of the dissertation. The primary data collection method is presented as well as the study's population. To conclude, the design of the research and how the data collected was processed is presented.

3.1 Primary Data Collection

The present research employed a quantitative approach to test the research hypotheses and validate the proposed conceptual model. It involved conducting an online questionnaire and using a randomizer where, at a certain point of the questionnaire, people were redirected to one of two scenarios randomly: a group with questions related to the use of blockchain in loyalty programs and another related to the use of traditional loyalty programs. The survey approach is by far the most common method of primary data collection in marketing research, representing 72% of all marketing research spending. It is based upon the use of structured questionnaires administered to a sample of a target population. Participants are asked a variety of questions regarding their behaviour, intentions, attitudes, awareness, motivations and demographic and lifestyle characteristics. This method has several advantages: it is simple to administer, and the data obtained are consistent because the responses are limited to the alternatives stated. The use of fixed- response questions reduce the variability in the results that may be caused by differences in interviewers. Finaly, coding, analysis and interpretation of the data are simple. There are various types of survey methods, but the one used for this study was the online survey. Given the broader trends in technology adoption, it has now become the dominant means of delivering surveys (Malhotra et al., 2017).

3.2 Research Design

The questionnaire used to collect the data from the present study was developed in Qualtrics platform, which is an online tool of easy access and use, that makes it possible to create and share surveys using a link. The present survey was entirely anonymous, simply requesting verification of the respondents' age of majority, to safeguard the participants' privacy.

The purpose of this survey was to gather opinions and behaviours from participants on using a loyalty program, to evaluate the possibility of integrating blockchain technology into the program. To do that, using Qualtrics platform tools, a sample asked to a group of questions related to the use of blockchain in loyalty programs and another answered to questions related to the use of traditional loyalty programs, to allow the comparison between these two samples. Prior to being disseminated, the survey was piloted with around ten individuals to ensure that it was generally understood and to make any necessary adjustments based on the responses received.

The questionnaire involved a total of 33 questions, where respondents had to answer 29 questions on a 7 points Likert-type scale and 4 demographic questions. During the survey's preparation and design, Likert scales that have been statistically examined and validated by other authors were employed as validated scales. This allowed for the standardization of the collected responses to enable easier comparison between them (Appendix A). Each question was derived from the items in previously researched constructs, as shown in Table 3.1. The structure of the questionnaire is split by three blocks:

In the first block, the objectives of the study were presented as well as the security of the data collected.

Before entering the second block, respondents were randomly distributed by one of two scenarios: a block with questions regarding the use of blockchain technology in loyalty programs and a block with questions about the use of a traditional loyalty program. Both blocks analysed the same constructs, but in different scenarios. So, in the beginning, there was a brief explanation of the scenario: for the first, integrating blockchain technology, it was presented some characteristics and benefits of using this technology in a loyalty program; for the second, regarding a traditional loyalty program, it was shown some characteristics and limitations of the program that could be solved by the integration of blockchain. Respondents were also asked to think of a brand for which they had signed up to its loyalty program. Regarding the questions of these blocks, the following constructs were analysed, based on the likert scale:

- Firstly, Perceived Security was evaluated with 4 items on a 7-point Likert scale (1=Strongly Disagree, 7=Strongly Agree), based on an adaptation of the scale developed and studied by Salisbury et al. (2001).
- Trust Propensity was analysed with 3 items on a 7-point Likert scale (1=Strongly Disagree, 7=Strongly Agree), based on an adaptation of the scale developed and studied by (Wanner et al., 2022).

- Economic Value and Psychological Value, both with 3 items, were evaluated on a 7-point Likert scale (1=Strongly Disagree, 7=Strongly Agree), supported by Treiblmaier & Petrozhitskaya (2023).
- Informational Social Influence was assessed with 2 items on a 7-point Likert scale (1=Strongly Disagree, 7=Strongly Agree), based on Jang et al. (2024).
- Perceived Usefulness and Perceived Ease-of-Use were both supported by the study from Davis (1989) with 6 items each. They were evaluated on a 7-point Likert scale, but Perceived Usefulness from 1=Extremely unlikely to 7=Extremely likely and Perceived Ease of Use from 1=Strongly Disagree to 7=Strongly Agree.
- Lastly, Intention to Use was assessed with 2 items on a 7-point Likert scale (1=Strongly Disagree, 7=Strongly Agree), supported by research from Venkatesh & Davis (2000). For the final construct, Actual Usage, was evaluated with 3 items on a 7-point Likert scale (1=Strongly Disagree, 7=Strongly Agree) and measured using the scale studied by Moon & Kim (2001).

In the last block of the questionnaire, respondents were asked to answer four demographic questions about their age, gender, level of education and occupation.

Table 3.1 – Constructs' literature

Constructs	Source
Informational Social Influence	Adapted from Jang et al. (2024)
Economic Value	Adapted from Treiblmaier and Petrozhitskaya (2023)
Psychological Value	Adapted from Treiblmaier and Petrozhitskaya (2023)
Perceived Security	Adapted from Salisbury et al. (2001)
Trust Propensity	Adapted from Wanner et al. (2022)
Perceived Ease-of-Use	Adapted from Davis (1989)
Perceived Usefulness	Adapted from Davis (1989)
Intention to Use	Adapted from Venkatesh & Davis (2000)
Actual Usage	Adapted from Moon & Kim (2001)

Source: Own elaboration

3.3 Data Treatment and Processing

The first step of data treatment was to cleanse the data on Qualtrics platform. Respondents that were aged under 18 years old were excluded as well as the ones that didn't complete the questionnaire. Thus, a total of 310 valid responses were obtained. The data was then imported into the IBM SPSS Statistics Version 28 software. An important step was to split the data in two groups, creating new variables blockgroup 1 and blockgroup 2, to differentiate the respondents from Scenario 1 and Scenario 2. In addition to simple descriptive statistics, exploratory analyses and models of simple regression and multiple regression were developed using the SPSS software. There are two categories of statistical data (all the information gathered on a variable) in this questionnaire: qualitative and quantitative. Data that can only have categorical values is considered qualitative data. Due to the fact that the categories are limited to establishing relationships of equality or difference, gender is a nominal qualitative data. As the categories can create ordered relationships, education level and occupation is an example of ordinal qualitative data. On the other hand, only numerical values are possible for quantitative data. This is the case for Likert scale data, which has a finite set of values and is therefore categorized as discrete quantitative data. Contrarily, since age is a continuous quantitative variable with an infinite range of values, it cannot be quantified.

4. Results

4.1 Sample Characterization

The survey was conducted with data being collected between 9th July and 11th September. SPSS software was used to analyse results in order to provide more in-depth conclusions. From the total of 310 answers, 144 answered to the group on the application of blockchain technology in loyalty programs (Group 1) and 166 answered to the group on traditional loyalty programs (Group 2). After the sample was characterized and a preliminary exploratory analysis of the data was done, simple and multiple regression models were developed to test the hypothesis proposed between the different constructs and adequately test the proposed conceptual model.

4.1.1 Socio-Demographic Characteristics

Regarding respondents' socio-demographic characteristics, the pie chart Figure 3.1 related to the Group 1 shows the percentage of 70% women, 29% men and 1% non-binary.

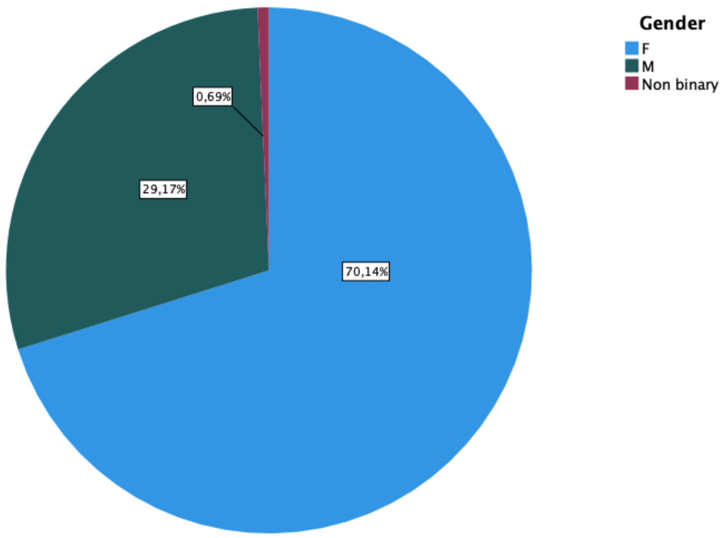

Figure 3.1 – Pie chart Gender: Group 1

Source: Own elaboration using SPSS data

The pie chart (Figure 1.2) related to the Group 2 shows the percentage of 55% women, 45% men and 1% preferred not to mention their gender. It can therefore be considered that there is a balance with regard to the gender variable on this group.

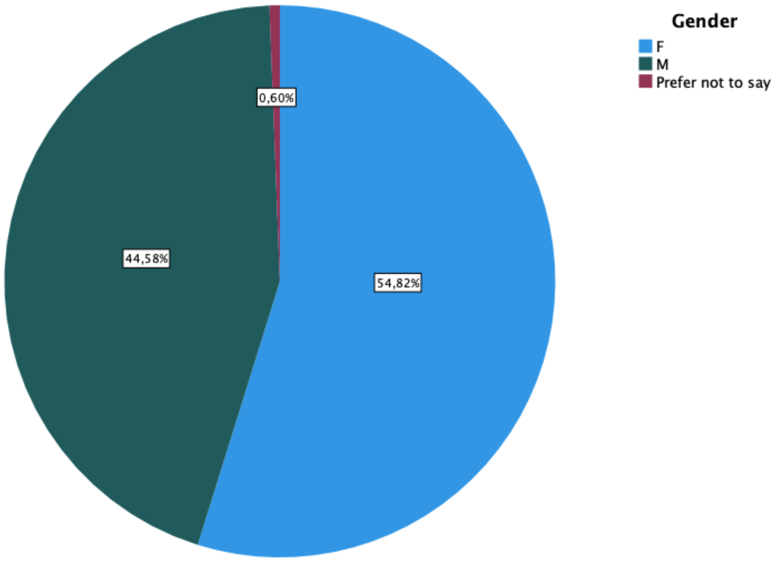

Figure 1.2 – Pie chart Gender: Group 2

Source: Own elaboration using SPSS data

Regarding the age, two age groups were formed to obtain a more accurate representation of the respondents' age range: 18-35 years old and >35 years old. For both scenarios 1 and 2, the group 18-35 years old is most figurative, representing the majority of all participants, as both pie charts show.

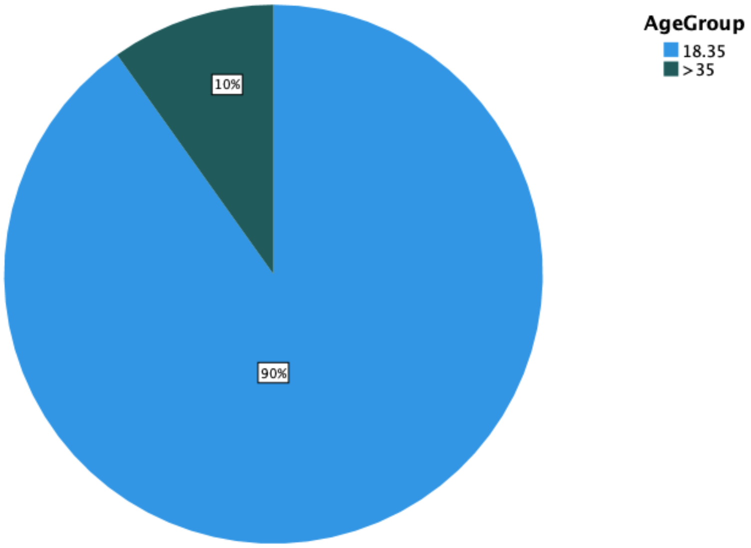

Figure 1.3 – Pie chart Age: Group 1

Source: Own elaboration using SPSS data

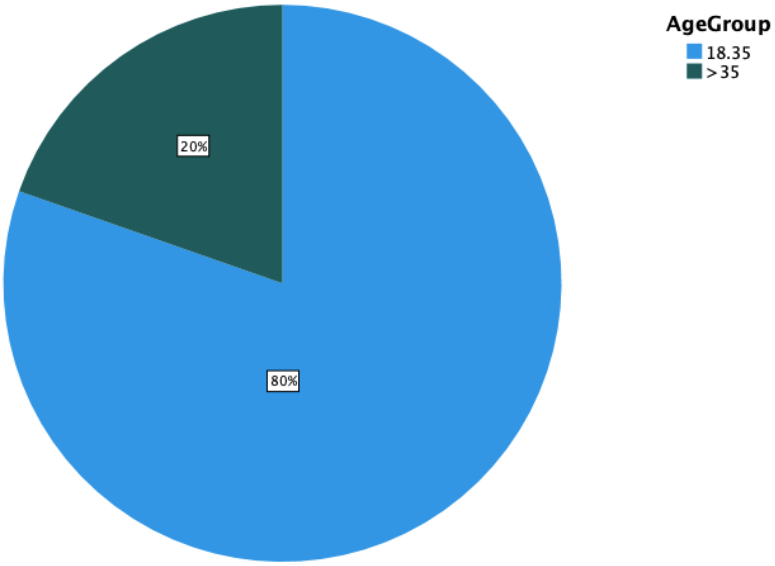

Figure 1.4 – Pie chart Age: Group 2

Source: Own elaboration using SPSS data

Five alternatives were developed in relation to education level: “High School”; “Bachelor degree”; “Masters degree”; “Pos-graduation” and “Doctorate”. For both scenarios, around 50% of the respondents have a master’s degree. It can thus be inferred from the bar graph in Figure 1.5 and Figure 1.6 that the sample has a fairly high level of education.

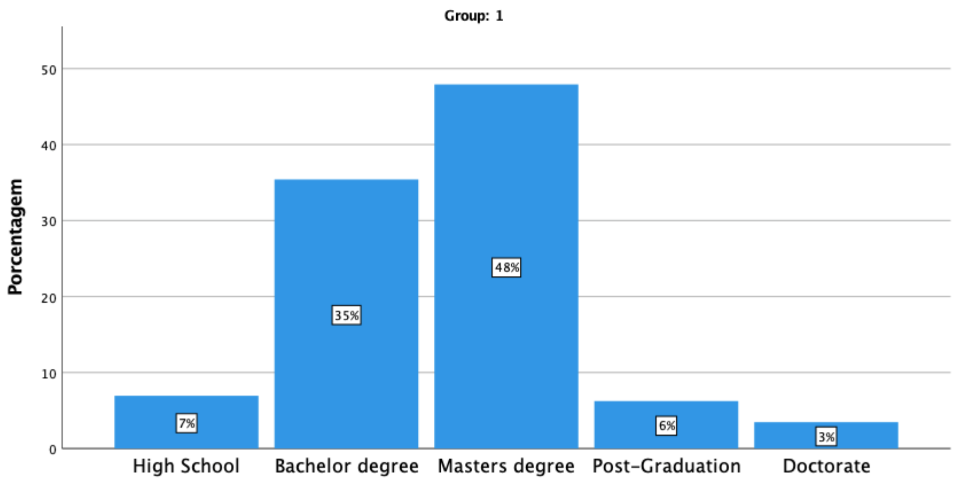

Figure 1.5 – Bar chart Level of Education: Group 1

Source: Own elaboration using SPSS data

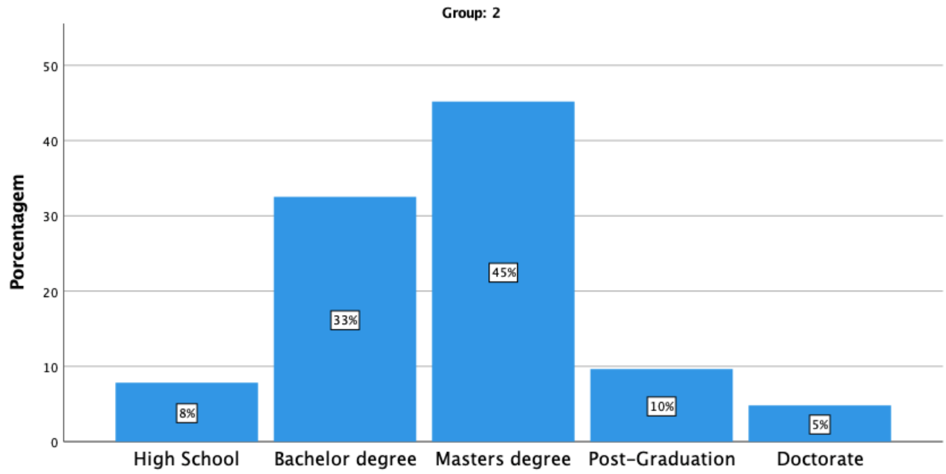

Figure 1.6 – Bar chart Level of Education: Group 2

Source: Own elaboration using SPSS data

Related to the occupation, there were also five options: "Student"; "Working student"; "Employed"; "Self-employed" and "Unemployed". In both groups, students, whether full-time or working students represent the largest portion, though their presence is more significant in Group 1. Group 2, on the other hand, has a higher proportion of employed respondents (36% compared to 22% in Group 1).

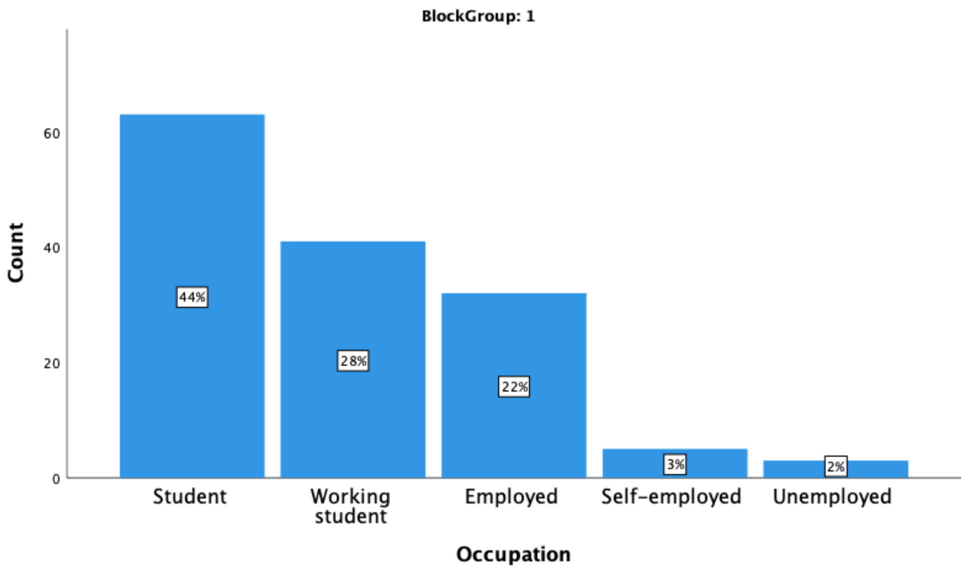

Figure 1.7 – Bar chart Occupation: Group 1

Source: Own elaboration using SPSS data

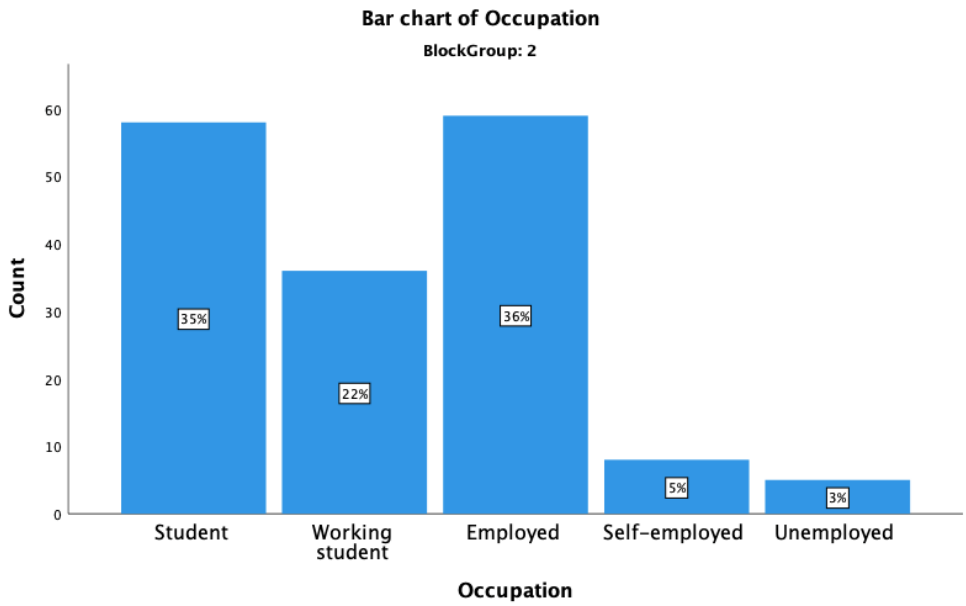

Figure 1.8 – Bar chart Occupation: Group 2

Source: Own elaboration using SPSS data

4.2 Result presentation

To analyse the results, the measures of each construct were aggregated. The aggregate construct's value is calculated by averaging the individual values that constitute it, with no weighting applied. Therefore, new variables were created for group 1 and group 2 in separate. For group 1: Score1_PS; Score1_TP; Score1_EV; Score1_PV; Score1_ISI; Score1_PU; Score1_PEOU; Score1_ITU; Score1_AU.

For group 2: Score2_PS; Score2_TP; Score2_EV; Score2_PV; Score2_ISI; Score2_PU; Score2_PEOU; Score2_ITU; Score2_AU. From this point onwards, whenever the name of a construct is used, it refers to its aggregate value. Regarding the scale used, all constructs were based on items measured on 7-point likert-type scales.

The construct Perceived Security, representing the average PS across all four items has a mean value of 4,27 and 4,37 for scenario 1 (blockchain-based loyalty program) and scenario 2 (traditional loyalty program), respectively. The value of the mean shows that respondents feel somewhat secure in providing information and have a moderate perceived security in the system, since the values of both scenarios are higher than the average of the 1-7 Likert-type scale.

Trust Propensity, representing the average of TP across six items, has a mean value of 4,03 for scenario 1 and 4,39 for scenario 2. These values show that both blockchain-based and traditional loyalty programs have a moderate level of trust. However, blockchain programs are slightly behind, while traditional programs are trusted more.

Economic Value, representing the average economic value across three items, is a construct which the mean values are 5,04 and 5,41 for scenario 1 and 2, respectively. According to the high mean values, both types of programs are seen as economical valuable, but traditional programs are still seen as more economically advantageous, probably because they are more familiar to respondents.

Psychological value, representing the average psychological value across three items, has high mean values of 4,92 for scenario 1 and 4,88 for scenario 2. Although the difference is small, blockchain-based programs are perceived slightly more favourably in terms of psychological value. This might be due to the novelty of blockchain, which could create a feeling of exclusivity.

Informational Social Influence, representing the average social influence across three items has a mean value of 4,33 for scenario 1 and 3,89 for scenario 2. The higher mean for blockchain-based programs suggests that respondents lean more on others for advice and information when using these programs compared to traditional loyalty programs.

Perceived Usefulness, representing the average perceived usefulness across six items has a mean value of 4,22 for scenario 1 and 4,18 for scenario 2. This indicates that respondents tend to moderately perceive utility when making decisions, especially on blockchain-based programs where the mean value is higher. Moreover, Perceived Ease-of-Use is a construct representing the average perceived ease-of-use across six items too. It has a mean value of 5,52 for scenario 1 and 5,32 for scenario 2, which indicates that respondents tendo to take the perceived ease of use of a program into account when making decisions. Like the case before, they value more the ease of use of a blockchain-based program.

Intention to Use, representing the average intention to use across two items, has a mean value of 5,23 for scenario 1 and 5,56 for scenario 2. This suggests that people have a high intention of using the programs. However, the intention is higher for traditional programs, since the mean value is superior. Finaly, Actual Usage, representing the average actual usage across three items, follows the same pattern as intention to use. It has a mean value of 2,91 for scenario 1 and 2,99 for scenario 2, indicating that respondents are somewhat willing to use the programs, but the willingness is more evident for traditional ones.

4.3 Preliminary Exploratory Analysis

The primary goal of exploratory data analysis, which occurs early in the research process, is to examine and characterize the data in order to find and emphasize elements or patterns that are of greater interest. More precisely, using the suggested conceptual model as a basis, a reliability and validity study as well as a multiple linear regression analysis will be conducted.

4.3.1 Data Reliability

Analysing the reliability and validity of the items used is important to understand the quality of the study being carried out. Reliability is responsible to demonstrate how consistent the measurement is, while validity aims to demonstrate how accurate the results are (Malhotra et al., 2017).

To examine the reliability of the analysis, Cronbach's alpha test was conducted. The items of each construct were analysed, as well as their totality, in order to understand the degree of consistency (Malhotra et al., 2017). The values obtained are between 0 and 1. The closer the values are to 1, the better the internal consistency between the constructs. Values between 0,8 and 0,9 indicate excellent consistency, between 0,7 and 0,8 good consistency and between 0,6 and 0,7 acceptable. However, values below 0,6 show lack of consistency between construct items or between constructs, which could mean lack of reliability.

Table 1.1 – Group 1: Cronbach's Alpha of each Construct

Main Construct	Cronbach´s Alpha
Perceived Security	0.945
Trust Propensity	0.941
Economic Value	0.869
Psychological Value	0.794
Informational Social Influence	0.860
Perceived Usefulness	0.916
Perceived Ease of Use	0.919
Intention to Use	0.901
Actual Usage	0.745

Source: Own elaboration

A Cronbach's alpha value of 0,887 was obtained for group 1, which indicates a very high level of consistency between the items on the scale, as shown in Table 1.2.

Table 1.2 – Group 1: Cronbach's Alpha of all Constructs

Chronbach's Alpha	Nº of items
0,887	9

Source: Own elaboration

Table 1.3 – Group 2: Cronbach's Alpha of each Construct

Main Construct	Cronbach´s Alpha
Perceived Security	0.950
Trust Propensity	0.920
Economic Value	0.929
Psychological Value	0.803
Informational Social Influence	0.832
Perceived Usefulness	0.916
Perceived Ease of Use	0.911
Intention to Use	0.930
Actual Usage	0.730

Source: Own elaboration

A Cronbach's alpha value of 0,865 was obtained for group 2, which indicates a very high level of consistency between the items on the scale, as shown in Table 1.4.

Table 1.4 – Group 2: Cronbach's Alpha of each Construct

Chronbach's Alpha	Nº of items
0,865	9

Source: Own elaboration

4.4 Simple and Multiple Linear Regression Models

In order to understand the relationships between the various constructs and to suitably test the conceptual model, simple and multiple linear regression analyses were performed. The simple linear regression analysis aims to understand the mathematical relationship between and independent and a dependent variable, while the multiple involves two or more independent variables (Malhotra et al., 2017).

4.4.1 MLRM Assumptions

The multiple linear regression model (MLRM) is a statistical method that allows us to investigate the presence of a relationship between independent variables and a dependent variable. For an MRLM to be used for inference, the following requirements must be met (Gauss-Markov theorem): 1) Linearity of the relationship between each X and Y; 2) The mean of the residual component of the model is zero; 3) The independent variables are not correlated with the residual terms; 4) There is no correlation among the residual terms; 5) The variance of the random term is constant; 6) Normality of the residuals and 7) There is no correlation among the explanatory variables. If all assumptions hold it is possible to generalize conclusions for the entire population, if not, it is only possible to characterize the sample. For the three MLRMs that were conducted for each group (1 and 2), all the assumptions are held (Appendix D).

4.4.2 Discussion of Results

4.4.2.1 Multiple Linear Regression - ISI, EV, PV and PS as independent variables and PU as dependent variable:

Group 1 – Blockchain-based loyalty program

To evaluate the influence of Informational Social Influence, Economic Value, Psychological Value and Perceived Security on the Perceived Usefulness of a blockchain-based loyalty program, a multiple linear regression model was used, considering the three constructs as independent variables and PU as dependent variable. From SPSS the following values were obtained:

Table 1.5 – Group 1: Multiple Regression, PU as the dependent variable

Model	Unstandardized Coefficients		Standardized Coefficients	Sig	Adjusted R Square	ANOVA Sig
	B	STD. ERROR	B			
(Constant)	0,848	0,406		0,039	0,37	<0,001
ISI	0,205	0,061	0,251	0,001		
EV	0,034	0,100	0,032	0,341		
PV	0,362	0,106	0,339	<0,001		
PS	0,123	0,069	0,153	0,076		

*Note: the confidence interval used is 95%
Source: Own elaboration

The equation of the fitted regression model is:

$$fittedPU = 0{,}848 + 0{,}205 * ISI + 0{,}034 * EV + 0{,}362 * PV + 0{,}123 * PS + \varepsilon$$

Group 2 – Traditional Loyalty Programs

To evaluate the influence of Informational Social Influence, Economic Value, Psychological Value and Perceived Security on the Perceived Usefulness of a loyalty program, a multiple linear regression model was used, considering the three constructs as independent variables and PU as dependent variable. From SPSS the following values were obtained:

Table 1.6 – Group 2: Multiple Regression, PU as the dependent variable

Model	Unstandardized Coefficients		Standardized Coefficients	Sig	Adjusted R Square	ANOVA Sig
	B	STD. ERROR	B			
(Constant)	0,989	0,405		0,016	0,338	<0,001
ISI	0,298	0,063	0,341	<0,001		
EV	0,065	0,087	0,065	0,456		
PV	0,280	0,099	0,269	0,005		
PS	0,072	0,070	0,086	0,303		

*Note: the confidence interval used is 95%
Source: Own elaboration

The equation of the fitted regression model is:

$$fittedPU = 0{,}989 + 0{,}298 * ISI + 0{,}065 * EV + 0{,}280 * PV + 0{,}072 * PS + \varepsilon$$

- The two samples present very similar low R Square values, although the higher is for blockchain-based loyalty program scenario, 0,37. It can be said that ISI, EV and PV explain more of the variation of PU in this scenario than in a traditional loyalty program scenario, in which the value of R Square is 0,34.

- Informational Social Influence has a standardized coefficient of 0,34 in group 2, which is higher than in group 1, 0,251, meaning that this construct has a higher impact on Perceived Usefulness of traditional loyalty programs than it has on a blockchain-based program.
- Economic Value present very low and similar values of coefficients in both groups which indicates that there is not a significant difference between the effect of EV on PU for the two samples.
- For the variable Psychological Value, the coefficient's value is higher for group 1 than it is for group 2, 0,339 and 0,269, respectively. It means that PV has more impact on the Perceived Usefulness of a blockchain-based program, which is a new technology.
- For both samples, there is statistical evidence that ISI and PV significantly influence PU, since the significance value is lower than 0,001, but EV and PS do not, since Sig > 0,05.
- So, H1a and H3a can be confirmed, but H2a and H4a are rejected:
  - H1a: Informational Social Influence positively affects Perceived Usefulness.
  - H2a: Economic Value positively influences Perceived Usefulness.
  - H3a: Psychological value positively influences Perceived Usefulness.
  - H4a: Perceived Security positively affects Perceived Usefulness.

4.4.2.2 Multiple Linear Regression - ISI, EV, PV as independent variables and PEOU as dependent variable:

Group 1 – Blockchain-based loyalty program

To evaluate the influence of Informational Social Influence, Economic Value and Psychological Value on the Perceived Ease of Use of a blockchain-based loyalty program, a multiple linear regression model was used, considering the three constructs as independent variables and PEOU as dependent variable. From SPSS the following values were obtained:

Table 1.7 – Group 1: Multiple Regression, PEOU as the dependent variable

Model	Unstandardized Coefficients		Standardized Coefficients	Sig	Adjusted R Square	ANOVA Sig
	B	STD. ERROR	B			
(Constant)	2,514	0,361		<0,001	0,354	<0,001
ISI	-0,065	0,055	-0,091	0,234		
EV	0,352	0,085	0,373	<0,001		
PV	0,308	0,090	0,327	<0,001		

*Note: the confidence interval used is 95%
Source: Own elaboration

The equation of the fitted regression model is:

$$fittedPEOU = 2{,}514 - 0{,}065 * ISI + 0{,}352 * EV + 0{,}308 * PV + \varepsilon$$

Group 2 –Traditional loyalty program

To evaluate the influence of Informational Social Influence, Economic Value and Psychological Value on the Perceived Ease of Use of a loyalty program, a multiple linear regression model was used, considering the three constructs as independent variables and PEOU as dependent variable. From SPSS the following values were obtained:

Table 1.8 – Group 2: Multiple Regression, PEOU as the dependent variable

Model	Unstandardized Coefficients		Standardized Coefficients	Sig	Adjusted R Square	ANOVA Sig
	B	STD. ERROR	B			
(Constant)	2,064	0,323		<0,001	0,389	<0,001
ISI	0,118	0,049	0,162	0,018		
EV	0,373	0,067	0,443	<0,001		
PV	0,161	0,075	0,187	0,033		

*Note: the confidence interval used is 95%
Source: Own elaboration

The equation of the fitted regression model is:

$$fittedPEOU = 2{,}064 + 0{,}118 * ISI + 0{,}373 * EV + 0{,}161 * PV + \varepsilon$$

- Like the previous regression, the R square for the two samples is similar, although it’s higher for group 2, 0,389, than for group 1, 0,354. This means that ISI, EV and PV explain more of the variation of Perceived Ease of Use of a traditional loyalty program.

- Informational Social Influence proved not to be a significant variable to explain the Perceived Ease of Use of a blockchain-based loyalty program since the significance value is 0,234>0,05. It also impacts negatively PEOU, as the coefficient value is negative. For group 2, this construct is significant and positively impacts the PEOU of a traditional loyalty program.
- The variable Economic Value has a higher coefficient in group 2 than in group 1 – 0,443 and 0,373, respectively. It means that Economic Value has a higher and positive impact on the perceived ease of use of a traditional loyalty program than it has on blockchain-based program.
- Psychological Value has a higher coefficient in group 1 than it has on group 2 - 0,327 and 0,187, respectively. It can be concluded that Psychological Value has a higher impact on the Perceived Ease of Use of blockchain-based loyalty programs than it has on traditional ones.
- As it said above, for group 1, EV and PV have Sig <0,001 and ISI has Sig>0,05, so ISI is not significant to explain the model. For group 2, as the *p-values* are 0.018, 0.001 and 0.033 for Informational Social Influence, Economic Value and Psychological Value, respectively, which are <0.05, indicates that all constructs are significant and suitable for explaining the model.
- So, for group 1, H1b is rejected and, H2b and H2c are accepted. For group 2, H1b, H2b and H3b are accepted:
    - H1b: Informational Social Influence positively affects Perceived Ease of Use.
    - H2b: Economic Value positively influences Perceived Ease of Use.
    - H3b: Psychological value positively influences Perceived Ease of Use.

4.4.2.3 Simple Linear Regression – PS as independent variable and TP as dependent variable

Group 1 - Blockchain-based loyalty program

To assess the influence of the Perceived Security on Trust Propensity of a blockchain-based program, a Simple Linear Regression was used, with the PS construct as the independent variable and TP as the dependent variable. From SPSS the following values were obtained:

Table 1.9 – Group 1: Simple Regression, TP as the dependent variable

Model	Unstandardized Coefficients		Standardized Coefficients	Sig	Adjusted R Square
	B	STD. ERROR	B		
(Constant)	0,06	0,201		0,764	0,756
PS	0,931	0,044	0,871	<0,001	

*Note: the confidence interval used is 95%
Source: Own elaboration

The equation of the fitted regression model is:

$$fittedTP = 0{,}06 + 0{,}931 * PS + \varepsilon$$

Group 2 –Traditional loyalty program

To assess the influence of the Perceived Security on Trust Propensity of a loyalty program, a Simple Linear Regression was used, with the PS construct as the independent variable and TP as the dependent variable. From SPSS the following values were obtained:

Table 1.10 – Group 2: Simple Regression, TP as the dependent variable

Model	Unstandardized Coefficients		Standardized Coefficients	Sig	Adjusted R Square
	B	STD. ERROR	B		
(Constant)	0,543	0,198		0,007	0,721
PS	0,882	0,043	0,850	<0,001	

*Note: the confidence interval used is 95%
Source: Own elaboration

The equation of the fitted regression model is:

$$fittedTP = 0{,}543 + 0{,}882 * PS + \varepsilon$$

- The R Square for the two samples is considerably high and similar, being 0,756 for group 1 and 0,721 for group 2. It can be concluded that Perceived Security explains more of Trust Propensity in the blockchain scenario than in a traditional loyalty program scenario.
- For group 1, the construct Perceived Security has a coefficient of 0,871, meaning that an increase of 1 unit in Perceived Security is associated with an average

change of 0,871 in Trust Propensity. This value is higher than for group 2, 0,85, meaning that Perceived Security impacts more the Trust Propensity on a blockchain-based loyalty program than on a traditional one.

- The p-value, as shown in both tables is less than 0.05 (*Sig*=0.001), indicating that PS is significant, and adequate to explain the model. Thus, **hypothesis H4b can be confirmed**:
    - H4b: Perceived security positively affects Trust Propensity.

4.4.2.4 Simple Linear Regression – TP as independent variable and PEOU as dependent variable

Group 1 - Blockchain-based loyalty program

To determine the effect of Trust Propensity on Perceived Ease of Use of a blockchain-based program, a Simple Linear Regression was used, with the TP construct as the independent variable and PEOU as the dependent variable. From SPSS the following values were obtained:

Table 1.11 – Group 1: Simple Regression, PEOU as the dependent variable

Model	Unstandardized Coefficients		Standardized Coefficients	Sig	Adjusted R Square
	B	STD. ERROR	B		
(Constant)	4,242	0,214		<0,001	0,222
TP	0,317	0,049	0,477	<0,001	

*Note: the confidence interval used is 95%
Source: Own elaboration

The equation of the fitted regression model is:

$$fittedPEOU = \ 4{,}242 + 0{,}317 * TP + \varepsilon$$

Group 2 –Traditional loyalty program

To determine the effect of Trust Propensity on Perceived Ease of Use of a loyalty program, a Simple Linear Regression was used, with the TP construct as the independent variable and PEOU as the dependent variable. From SPSS the following values were obtained:

Table 1.12 – Group 2: Simple Regression, PEOU as the dependent variable

Model	Unstandardized Coefficients		Standardized Coefficients	Sig	Adjusted R Square
	B	STD. ERROR	B		
(Constant)	4,023	0,219		<0,001	0,193
TP	0,297	0,047	0,444	<0,001	

*Note: the confidence interval used is 95%
Source: Own elaboration

The equation of the fitted regression model is:

$$fittedPEOU = 4{,}023 + 0{,}297 * TP + \varepsilon$$

- The value of the adjusted R Square is higher in group 1 than it is in group 2 – 0,222 and 0,193, respectively. Although both values are low, Trust Propensity explains more the variation of Perceived Ease of Use of a blockchain-based loyalty program than of a traditional one.
- The variable Trust Propensity impacts more the Perceived Ease of Use of a blockchain-based program than a traditional one, since the coefficient's value is higher for group 1 than it is for group 2, 0,477 and 0,444, respectively.
- The p-value, as shown in both tables is less than 0.05 (*Sig*=0.001), indicating that TP is significant and adequate to explain the model. Thus, **hypothesis H5 can be confirmed**:
  - H5: Trust Propensity positively affects Perceived Ease of Use.

4.4.2.5 Simple Linear Regression – PEOU as independent variable and PU as dependent variable

Group 1 - Blockchain-based loyalty program

To assess the influence of the Perceived Ease of Use on the Perceived Usefulness of a blockchain-based program, a Simple Linear Regression was used, with the PEOU construct as the independent variable and PU as the dependent variable. From SPSS the following values were obtained:

Table 1.13 – Group 1: Simple Regression, PU as the dependent variable

Model	Unstandardized Coefficients		Standardized Coefficients	Sig	Adjusted R Square
	B	STD. ERROR	B		
(Constant)	1,305	0,475		0,007	0,211
PEOU	0,529	0,084	0,465	<0,001	

*Note: the confidence interval used is 95%
Source: Own elaboration

The equation of the fitted regression model is:

$$fittedPU = 1{,}305 + 0{,}529 * PEOU + \varepsilon$$

Group 2 –Traditional loyalty program

To assess the influence of the Perceived Ease of Use on the Perceived Usefulness of a traditional loyalty program, a Simple Linear Regression was used, with the PEOU construct as the independent variable and PU as the dependent variable. From SPSS the following values were obtained:

Table 1.14 – Group 2: Simple Regression, PU as the dependent variable

Model	Unstandardized Coefficients		Standardized Coefficients	Sig	Adjusted R Square
	B	STD. ERROR	B		
(Constant)	1,332	0,458		0,004	0,193
PEOU	0,535	0,084	0,445	<0,001	

*Note: the confidence interval used is 95%
Source: Own elaboration

The equation of the fitted regression model is:

$$fittedPU = 1{,}332 + 0{,}535 * PEOU + \varepsilon$$

- The Adjusted R Square is similar and low for both groups. So, there is no difference between scenario 1 and 2.
- Perceived Ease of Use, as independent variable, has a positive coefficient value for both groups, being higher in group 1. It can be concluded that

Perceived Ease of Use impacts more the Perceived Usefulness of blockchain-based loyalty programs.

- The *p-value* for both groups is less than 0.05 (S*ig*=0.001), indicating that PEOU is significant, and adequate to explain the model. **Hypothesis H6 can be confirmed:**
    - H6: Perceived Ease of use is positively related with Perceived Usefulness.

4.4.2.6 Multiple Linear Regression – PU and PEOU as independent variables and ITU as dependent variable:

Group 1 - Blockchain-based loyalty program

To evaluate the influence of Perceived Usefulness and Perceived Ease of Use on the Intention to Use of a blockchain-based loyalty program, a multiple linear regression model was used, considering the two constructs as independent variables and Intention to Use as dependent variable. From SPSS the following values were obtained:

Table 1.15 – Group 1: Multiple Regression, ITU as the dependent variable

Model	Unstandardized Coefficients		Standardized Coefficients	Sig	Adjusted R Square	ANOVA Sig
	B	STD. ERROR	B			
(Constant)	0,333	0,358		0,354	0,574	<0,001
PU	0,226	0,062	0,226	<0,001		
PEOU	0,714	0,07	0,629	<0,001		

*Note: the confidence interval used is 95%
Source: Own elaboration

The equation of the fitted regression model is:

$$fittedITU = 0{,}333 + 0{,}226 * PU + 0{,}714 * PEOU + \varepsilon$$

Group 2 –Traditional loyalty program

To evaluate the influence of Perceived Usefulness and Perceived Ease of Use on the Intention to Use of a loyalty program, a multiple linear regression model was used, considering the two constructs as independent variables and Intention to Use as dependent variable. From SPSS the following values were obtained:

Table 1.16 – Group 2: Multiple Regression, ITU as the dependent variable

Model	Unstandardized Coefficients		Standardized Coefficients	Sig	Adjusted R Square	ANOVA Sig
	B	STD. ERROR	B			
(Constant)	1,721	0,387		<0,001	0,384	<0,001
PU	0,052	0,064	0,055	0,418		
PEOU	0,681	0,078	0,599	<0,001		

*Note: the confidence interval used is 95%
Source: Own elaboration

The equation of the fitted regression model is:

$$fittedITU = 1{,}721 + 0{,}052 * PU + 0{,}681 * PEOU + \varepsilon$$

- Contrary to previous regressions, the adjusted R Square is much higher for group 1 than it is for group 2, 0,574 and 0,384, respectively. Therefore, for the same model and variables, but for different scenarios, the explanatory variables Perceived Usefulness and Perceived Ease of Use explain considerably more of the variation of Intention to Use of a blockchain-based loyalty program than it does for a traditional program.
- However, for group 2, as Perceived Usefulness has a Sig>0,05: 0,418, it can be concluded that is not significant for explaining the model. On the other hand, for group 1, it is significant and positively influences the Intention to Use of a blockchain-based loyalty program, having a coefficient value of 0,226.
- PEOU significantly and positively impacts Intention to Use for both groups, since sig<0,001 and the values of coefficients are positive and high. On group 1, it is concluded that Perceived Ease of Use has more impact on the Intention to Use of a program, since the coefficient value is higher, 0,629.
- Thus, for group 1 the hypotheses H7 and H8 are accepted. For group 2, H7 is rejected and H8 is accepted:
  - H7: Perceived Usefulness positively affects Intention to Use.
  - H8: Perceived Ease of Use positively affects Intention to Use.

4.4.2.7 Simple Linear Regression – ITU as independent variable and AU as dependent variable

Group 1 - Blockchain-based loyalty program

To determine the effect of Intention to Use on Actual Usage of a blockchain-based program, a Simple Linear Regression was used, with ITU construct as the independent variable and AU as the dependent variable. From SPSS the following values were obtained:

Table 1.17 – Group 1: Simple Regression, AU as the dependent variable

Model	Unstandardized Coefficients		Standardized Coefficients	Sig	Adjusted R Square
	B	STD. ERROR	B		
(Constant)	0,854	0,336		<0,012	0,212
ITU	0,393	0,062	0,467	<0,001	

*Note: the confidence interval used is 95%
Source: Own elaboration

The equation of the fitted regression model is:

$$fittedAU = 0{,}854 + 0{,}393 * ITU + \varepsilon$$

Group 2 –Traditional loyalty program

To determine the effect of Intention to Use on Actual Usage of a traditional loyalty program, a Simple Linear Regression was used, with ITU construct as the independent variable and AU as the dependent variable. From SPSS the following values were obtained:

Table 1.18 – Group 2: Simple Regression, AU as the dependent variable

Model	Unstandardized Coefficients		Standardized Coefficients	Sig	Adjusted R Square
	B	STD. ERROR	B		
(Constant)	1,608	0,358		<0,001	0,082
ITU	0,249	0,063	0,296	<0,001	

*Note: the confidence interval used is 95%
Source: Own elaboration

The equation of the fitted regression model is:

$$fittedAU = 1{,}608 + 0{,}249 * ITU + \varepsilon$$

- The value of the adjusted R Square even though is low for both samples, it his higher in group 1, 0,212, than it is in group 2, 0,082. It means Intention to Use explains more the variation of the Actual Usage of a blockchain-based loyalty program than of a traditional one.
- By observing both tables, it can be said that Intention to Use positively and significantly influences Intention to Use, since sig<0,001 and the coefficient values are positive. However, Intention to Use has more impact on the Actual Usage of a blockchain-based program than on a traditional one, since the coefficient value is higher for group 1 than it is for group 2 – 0,467 and 0,296, respectively.
- Thus, hypothesis H9 can be confirmed:
    - H9: Intention to Use positively affects Actual Usage.

In conclusion, Table 1.19 and

Table 1.20 show the hypotheses under analysis and the extent to which each study contributed to validate them:

Table 1.19 – Validation of hypotheses for group 1

Hypotheses for Group 1	Validation
H1a - Informational Social Influence positively affects Perceived Usefulness	Accepted
H2a - Economic Value positively influences Perceived Usefulness	Rejected
H3a - Psychological Value positively influences Perceived Usefulness	Accepted
H4a - Perceived Security positively affects Perceived Usefulness	Rejected
H1b- Informational Social Influence positively affects Perceived Ease-of-Use	Rejected
H2b - Economic Value positively influences Perceived Ease-of-Use	Accepted
H3b - Psychological Value positively Influences Perceived Ease of Use	Accepted
H4b - Perceived security positively affects Trust Propensity	Accepted
H5 - Trust Propensity positively affects Perceived Ease of Use	Accepted
H6 - Perceived Ease of use is positively related with Perceived Usefulness	Accepted
H7 - Perceived Usefulness positively affects Intention to Use	Accepted
H8 - Perceived Ease-of-Use positively affects Intention to Use	Accepted
H9 - Intention to Use positively affects Actual Usage	Accepted

Source: Own elaboration

Table 1.20 – Validation of hypotheses for group 2

Hypotheses for Group 2	Validation
H1a - Informational Social Influence positively affects Perceived Usefulness	Accepted
H2a - Economic Value positively influences Perceived Usefulness	Rejected
H3a - Psychological Value positively influences Perceived Usefulness	Accepted
H4a - Perceived Security positively affects Perceived Usefulness	Rejected
H1b- Informational Social Influence positively affects Perceived Ease-of-Use	Accepted
H2b - Economic Value positively influences Perceived Ease-of-Use	Accepted
H3b - Psychological Value positively Influences Perceived Ease of Use	Accepted
H4b - Perceived security positively affects Trust Propensity	Accepted
H5 - Trust Propensity positively affects Perceived Ease of Use	Accepted
H6 - Perceived Ease of use is positively related with Perceived Usefulness	Accepted
H7 - Perceived Usefulness positively affects Intention to Use	Rejected
H8 - Perceived Ease-of-Use positively affects Intention to Use	Accepted
H9 - Intention to Use positively affects Actual Usage	Accepted

Source: Own elaboration

Conclusions and Limitations

This present chapter summarizes and accesses the objectives defined for the study through theoretical implications and managerial contributions. The purpose of theoretical implications is to make inferences about how consumers view the application of blockchain technology in loyalty programs, as well as traditional loyalty programs, comparing the two scenarios. This is regarding the variables informational social influence, economic value, psychological value, perceived security, trust propensity, perceived usefulness, perceived ease of use, intention to use and actual usage. Comparing the results with previous research is another aspect of theoretical implications. The study's managerial contributions intend to assist managers and marketeers in comprehending the potential repercussions of the research, which tries to explain the findings of using blockchain technology in loyalty programs.

Theoretical Implications

The present study can validate the proposed conceptual model, although it does not support all the previously established hypotheses. Analysing the questionnaire's results, it shows that Informational Social Influence has a positive influence in the Perceived Usefulness of both types of programs, blockchain-based loyalty programs and traditional loyalty programs. This is aligned with the research by (Jang et al., 2024), that developed a scale to measure the impact that informational social influence has on someone's intention to adopt new technologies. It shows that Informational Social Influence helps people gain confidence in using new programs, providing them the necessary information and support from their family and friends. Jang et al. (2024) also supports that ISI has a positive impact on Perceived Ease of Use, but on the contrary, in the present study, for the adoption of blockchain-based loyalty programs, ISI is not a significant construct, meaning that people do not need external influence to find a new system easy to use.

Regarding the factors that affect someone's perception in terms of ease of use and usefulness, the importance of the economic value was considered. This effect is validated by the results of Treiblmaier & Petrozhitskaya (2023) in which they analyzed the influence of economic value on the use of loyalty programs. Economic Value refers to the financial and efficiency advantages that a person perceives from using a particular program or technology. The study stated that there are economic advantages provided by a program, such as cost savings and efficiency, that then influence positively the perceived ease-of-use and usefulness of a program. Analysing this study's questionnaire, Economic Value is not significant to explain the Perceived Usefulness of a program, meaning that people consider that these economic benefits don't determine if either a blockchain-based or a traditional loyalty program is useful. On the other hand, it has a positive impact on the perceived ease-of-use of a program, so it can be concluded that a person is more likely to view the program as easy to use if he/she perceives financial rewards. Furthermore, it was demonstrated by the samples that the impact was higher on traditional loyalty program than it was on blockchain-based program's sample, which could suggest that people are more familiar with traditional loyalty programs and may find blockchain-based programs more complex and unfamiliar.

Treiblmaier & Petrozhitskaya (2023) also studied the impact that psychological value has on the perceived ease-of-use and perceived usefulness. They considered it as an important variable because it captures the emotional benefits like pleasure, enjoyment and sense of being special a person develops from participating in loyalty programs. They offer customers a deeper connection to the brand, transcending just economic benefits.

This relationship was considered for the present research, being that psychological value proved to be a significant variable in explaining the perceived ease-of-use and usefulness of a loyalty program, aligning with Treiblmaier & Petrozhitskaya (2023). Looking into the obtained results, psychological value has a greater impact on the perceived ease-of-use and perceived usefulness of a blockchain-based loyalty program than in a traditional one, which suggests that the emotional and psychological benefits provided by blockchain-based programs are more important drivers of engagement and satisfaction compared to traditional loyalty programs. It can also be inferred that, as a new technology, blockchain offer a sense of exclusivity and innovation, and people may feel advanced and forward-thinking participating in these programs. This also supports the research on the growing role of emotional factors in technology acceptance, where it's suggested that people are drawn to new technologies because they offer engaging and stimulating experiences compared to established systems.

Nowadays, as there have been security concerns and consequently, difficulties in trusting programs and unknown systems, the relationship between perceived security and trust propensity was integrated in this study. Perceived Security as described in Salisbury et al. (2001) article, refers to someone's belief that a system is safe to transmit sensitive information, like credit card information or personal data. According to the results, there is a very positive impact of perceived security in trust propensity, which means that if someone has the perception that a program is secure, the tendency to trust increases significantly, even if he/she has no experience with the program. Comparing the two scenarios, perceived security proved to have more impact on the trust propensity for blockchain-based programs than for traditional ones, which implies that possibly people view security as more critical in establishing trust in a new technology as blockchain. Moreover, this analysis is important because trust propensity relates to the perceived ease-of-use of a program, as studied by Wanner et al. (2022) that uses Technology Acceptance Model as a base. The research emphasizes that integrating trust propensity in the model is essential, particularly because many AI systems have a “black box”, where transparency is limited, and people rely heavily on their own and innate trust to engage with the technology effectively. The results of this present study align with the positive impact of trust propensity on the perceive ease-of-use of a program, especially on the PEOU of a blockchain-based loyalty program, since the impact is higher than on the PEOU of a traditional loyalty program. This may be due to the novelty of blockchain technology, many people could lack a deep understanding of its characteristics. As a result, people with higher trust propensity are more likely to accept a blockchain-based program, despite potential uncertainties and complexities. On the other hand, in traditional programs, as people are more familiar with how the system operates, their baseline inclination to trust is less critical in shaping perceived ease of use of a program.

Regarding the constructs and correlations of the Technology Acceptance Model tested by Davis (1989), Moon & Kim (2001) and Venkatesh & Davis (2000) they are all confirmed. Davis (1989) validated that Perceived Ease of Use is a significant antecedent of Perceived Usefulness defending that the easier a system is to use the more useful people perceive it to be. So, if a system is simple to navigate and operate, people are more likely to see its benefits and effectiveness to improve their performance. This proved to be more relevant for the perceived usefulness of blockchain-based loyalty programs than of traditional ones, because since people may not know this new technology, the perceived ease of use has a greater influence on whether they find the new program beneficial or useful, rather than a traditional program that they already use. Furthermore, the same studies concluded that Intention to Use is determined by Perceived Ease of Use and Perceived Usefulness. However, Perceived Usefulness has a more direct and stronger impact on Intention to Use than Perceived Ease of Use. This cannot be corroborated with the present research, because Perceived Ease of Use is the one that has more impact on the Intention to Use of both types of programs, traditional and blockchain-based. Besides, Perceived Usefulness proved not to be significant in explaining the Intention to Use of a traditional loyalty program. The conclusion that can be inferred is that for blockchain programs, people consider the program useful, but ease of use is more important and critical in deciding the intention to use. This is due to the complexity of this technology, where making the system user-friendly is the key, even if the program offers additional benefits. For traditional loyalty programs, Perceived Usefulness is not significant, likely because they are already familiar with the benefits, focusing on the ease of interaction.

Lastly, the final hypothesis that leads to the actual use of technology, was also corroborated by Moon & Kim (2001). The impact of intention to use on actual usage proved to be greater on blockchain based programs, meaning that people's intentions are more likely to translate into real behaviour in these programs compared to traditional ones. This can imply that blockchain typically appeal to people who are more engaged and committed to innovation or new technologies. As a result, once they decide to use it, they are more likely to actively do so. On the other hand, with traditional loyalty programs, people may have formed the intention to use, but due to daily usage, low engagement or less novelty, this intention doesn't translate into actual behaviour as consistently as it does with a blockchain-based program.

To conclude, this study validates the main aspects of TAM, and at the same time provides new insights from consumers on how to adopt blockchain-based programs. It also demonstrates that ease of use is essential to drive engagement in this type of program, while emotional and psychological benefits play an important role in influencing people's perceptions of these programs. Furthermore, security concerns proved to be very critical in establishing trust in the new technology, being perceived security and trust propensity essential variables for an user acceptance.

Managerial Contributions

This study provides practical implications for companies and brands that want to implement blockchain technology in their loyalty programs and enable them to develop effective marketing strategies to promote their products and services, retain and delight customers. This investigation focused on two separate samples, leading to a comparison between the two. According to the model developed, people are influenced by internal, external factors, and their own environment.

Chitturi et al. (2008) show that psychological value can be a stronger motivator for technology adoption than purely functional benefits, which aligns with the results obtained, since psychological value has more impact on the perceived usefulness of a program than economic value. As Treiblmaier & Petrozhitskaya (2023) highlighted, people who feel exclusivity, enjoyment and who perceive the innovation of the loyalty program are more likely to adopt this kind of program. This supports the finding that psychological value has a higher impact on blockchain-based programs than traditional ones. So, managers should focus on creating unique experiences provided by blockchain in their programs, like offer personalized rewards or premium features, that can answer these emotional drivers. This will make people more willing to participate in the program. Associated to the psychological value, managers must concentrate their efforts on educating people of all economic benefits that come with blockchain technology, since the results obtained showed unfamiliarity and the perception of complexity of this technology. Consequently, economic value didn't show great impact on perceived usefulness of a program in this study.

In today's digital landscape, Perceived Security is critical for both companies and customers. Without this element, customers are unlikely to trust the platform enough to buy and share their personal information. On the other hand, managers who recognize the value of security are better positioned to guide their businesses toward becoming trusted companies (S. Kim & Park, 2013). Kim & Malhotra (2005) suggest that participants of innovative technologies are drawn to systems that are positioned as advanced and secure. Results show that perceived security has a high impact in driving trust propensity, especially in new technologies, as Salisbury et al. (2001) showed in their research: higher perceptions of security lead to stronger trust in systems.

According to this study, there is a positive impact of trust propensity on the perceive ease-of-use of a program, more on blockchain-based loyalty programs than on traditional ones, which means that people with higher trust propensity are more likely to accept a blockchain-based program, despite potential uncertainties and complexities. McKnight et al. (2002) further support this by emphasizing the role of trust propensity in shaping people's perceptions of ease of use and security. So, managers need to have some strategies like making security measures clear and transparent, highlighting the features like encryption and decentralized data storing; implement automated reward systems, where points are issued instantly, and transactions can be seen transparently and in real-time. More importantly, these programs need to be a source of information to enhance trust, especially in new technologies where people lack familiarity.

In traditional loyalty programs, that people use nowadays, perceived ease-of use was found to be a significant variable in this study, while perceived usefulness was not. This is highly supported by Gefen & Straub (2000), which suggests that ease of use plays a more significant role when the program is already familiar to people. Also, since perceived ease-of-use has a greater impact on the intention to use of blockchain-based programs, managers should prioritize usability, the easier a system is to use, the more likely people will engage with it. This is very relevant in the case of blockchain, that can be perceived as complex.

To conclude, marketing should focus on emphasizing the newness, security, and exclusivity of the programs, especially when integrating a new technology as blockchain. And businesses should rethink how they engage and reward customers in an era where consumers are highly informed and have access to various digital platforms.

Limitations

Although this study has provided significant insights into the understanding of the topic, it is important to recognize that, as all research studies, there are some inherent limitations to the study that may affect its applicability in real world. These limitations are the type of study, time, cost, sample size and questionnaire construction and may have implications for the results obtained.

One of the limitations of this study is related to the sample used. It is quite hard to accurately evaluate the behaviour and feelings of the respondents, because it is a quantitative survey, and the results are based on numeric responses. In addition, the survey was spread through some online platforms, like Instagram, so there was no control and verification of the accuracy and honesty of the respondent's answers, which may have caused a lack of context in certain questions. Although the size of the sample was 310 respondents and the quality of the sample are not a limiting factor, the results obtained do not permit expansion to larger or more demographically diverse groups.

Due to the novelty of this topic, changes and new research may have emerged that presents different results or affects the relevance of the conclusions obtained. Another factor that can influence the validity of the conclusions and their relevance is the inability to compare the results obtained with real-world examples. Therefore, the study's ability to validate its findings is eliminated due to the absence of well-documented comparable circumstances.

Lastly, it should be acknowledged that there are inherent limits and that all study has been conducted based on assumptions. These restrictions might have affected the validity and reliability of the reached conclusions. To improve the approach and ensure more reliable results, future research could concentrate on addressing these limitations.

Future Research

Given the limitations presented above, several directions could be taken in future research. Firstly, it could be chosen to evaluate other constructs and their influence on blockchain's technology acceptance. In addition, the application of other more recent and complex models to TAM could be relevant to the study, such as the Unified Theory of Acceptance and Use of Technology (UTAUT). Moreover, it would also be crucial to approach the brands in this sector and find out if they have consumer profiles that would allow for a more accurate and detailed definition of the variables to be examined. Consequently, better outcomes could be achieved when understanding what motivates the adoption of this new technology.

In terms of methodology, other research techniques, such as qualitative, could be applied. Structured interviews or focus groups would yield greater details regarding the attitudes, opinions and feelings of participants on this matter. Future research could also replicate the study with a different group of people, altering the age groups, geographic setting. While this research focused on blockchain in loyalty programs, future studies could explore cross-industry applications and conduct comparative studies between different sectors, such as supply chain management and the energy sector to assess the different impacts of blockchain's characteristics on these.

Concluding, the study in this area is still limited and unrepresentative of the prediction and acceptance of blockchain-based loyalty programs. It's necessary a more extensive study to consolidate the theme. It is therefore hoped that this dissertation would encourage more research and the development of new theoretical models to assist brands in improving their approach to consumers and their own.

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Appendices

Appendix A – Online Survey

Hello, my name is Matilde Lima and I'm on my 2nd year of Msc in Marketing at ISCTE. This questionnaire is part of my dissertation development.

This research aims to investigate the impact of blockchain technology in loyalty programs, and consequently, the willingness to adopt this blockchain-based program. Don't worry, throughout the questionnaire the different topics that I need you to answer will be explained in detail.

In order to protect your privacy, the results will be kept anonymous.
It takes less than 5 minutes.
Thank you for your participation!

→

Introduction of Scenario 2: Traditional loyalty programs

Now, think about a brand that you have signed up to its loyalty program (Continente card, Sephora, Starbucks, etc).

Loyalty programs offer various benefits and incentives for customers, like rewards and discounts, free products or special offers. Also, they typically collect and retain personal information about their members, which can raise important privacy concerns.

Consider the following characteristics of a loyalty program:

- Managed by an organization or a group of companies
- Data and transactions are stored in a centralized database
- Points and rewards are generally limited to the issuing brand
- Users have limited control over their points and rewards

Consider "program" as the loyalty program that you have signed up for.

Introduction of Scenario 1: Blockchain-based loyalty program

Now, think about a brand that you have signed up to its loyalty program (Continente card, Sephora, Starbucks, etc).

Loyalty programs offer various benefits and incentives for customers, like rewards and discounts, free products or special offers. Also, they typically collect and retain personal information about their members, which raises important privacy concerns.

Introducing blockchain technology revolutionizes this type of programs, both in security and functionality:

- Security: Transactions recorded on the blockchain are transparent and cannot be altered, providing a secure and trustworthy record of loyalty points and transactions. It also allows customers to control their data, sharing only the necessary information with brands.

-Functionality: Blockchain can enable the exchange of loyalty points between different brands and platforms, increasing the utility and value of the points.

Imagine these two scenarios that you could enjoy by being part of a program like this:

Scenario 1:

You purchase something at some store. The transaction is recorded on the blockchain, and points are automatically credited to your digital wallet.

Scenario 2:

You can transfer points to another user via the blockchain network. The transfer is recorded and verified on the blockchain, ensuring transparency and security.

Consider "program" as the new loyalty program using blockchain technology introduced before.

PS1. I would feel secure sending personal information to the program.

1 = Strongly disagree	Moderately Disagree	Somewhat disagree	4 = Neither agree or disagree	Somewhat agree	Moderately agree	7 = Strongly agree
○	○	○	○	○	○	○

PS2. The program is a secure means through which to send sensitive information.

1 = Strongly disagree	Moderately Disagree	Somewhat disagree	4 = Neither agree or disagree	Somewhat agree	Moderately agree	7 = Strongly agree
○	○	○	○	○	○	○

PS3. I would feel totally safe providing sensitive information to the program about myself over the program.

1 = Strongly disagree	Moderately Disagree	Somewhat disagree	4 = Neither agree or disagree	Somewhat agree	Moderately agree	7 = Strongly agree
○	○	○	○	○	○	○

PS4. Overall, the program is a safe place to transmit sensitive information.

1 = Strongly disagree	Moderately Disagree	Somewhat disagree	4 = Neither agree or disagree	Somewhat agree	Moderately agree	7 = Strongly agree
○	○	○	○	○	○	○

TP1. It would be easy for me to trust this program.

1 = Strongly disagree	Moderately Disagree	Somewhat disagree	4 = Neither agree or disagree	Somewhat agree	Moderately agree	7 = Strongly agree
○	○	○	○	○	○	○

TP2. My tendency to trust this program would be high.

1 = Strongly disagree	Moderately Disagree	Somewhat disagree	4 = Neither agree or disagree	Somewhat agree	Moderately agree	7 = Strongly agree
○	○	○	○	○	○	○

TP3. I would tend to trust this program, even though I have little or no knowledge of it.

1 = Strongly disagree	Moderately Disagree	Somewhat disagree	4 = Neither agree or disagree	Somewhat agree	Moderately agree	7 = Strongly agree
○	○	○	○	○	○	○

EV1. It would be economically reasonable for me to become member of this new program.

1 = Strongly disagree	Moderately Disagree	Somewhat disagree	4 = Neither agree or disagree	Somewhat agree	Moderately agree	7 = Strongly agree
○	○	○	○	○	○	○

EV2. The loyalty program would give me monetary advantages.

1 = Strongly disagree	Moderately Disagree	Somewhat disagree	4 = Neither agree or disagree	Somewhat agree	Moderately agree	7 = Strongly agree
○	○	○	○	○	○	○

EV3. The loyalty program would offer me additional value for my money.

1 = Strongly disagree	Moderately Disagree	Somewhat disagree	4 = Neither agree or disagree	Somewhat agree	Moderately agree	7 = Strongly agree
○	○	○	○	○	○	○

PV1. I would enjoy being a member of the loyalty program.

1 = Strongly disagree	Moderately Disagree	Somewhat disagree	4 = Neither agree or disagree	Somewhat agree	Moderately agree	7 = Strongly agree
○	○	○	○	○	○	○

PV2. The loyalty program would give pleasure when I exchange loyalty points.

1 = Strongly disagree	Moderately Disagree	Somewhat disagree	4 = Neither agree or disagree	Somewhat agree	Moderately agree	7 = Strongly agree
○	○	○	○	○	○	○

PV3. I feel like the program would make me feel special compared to other costumers.

1 = Strongly disagree	Moderately Disagree	Somewhat disagree	4 = Neither agree or disagree	Somewhat agree	Moderately agree	7 = Strongly agree
○	○	○	○	○	○	○

ISI1. When I need to use a new program, I often ask my family or friends for useful information.

1 = Strongly disagree	Moderately Disagree	Somewhat disagree	4 = Neither agree or disagree	Somewhat agree	Moderately agree	7 = Strongly agree
○	○	○	○	○	○	○

ISI2. I often ask friends or family for useful information to help use digital technology.

1 = Strongly disagree	Moderately Disagree	Somewhat disagree	4 = Neither agree or disagree	Somewhat agree	Moderately agree	7 = Strongly agree
○	○	○	○	○	○	○

ISI3. When I need to use a new technology, I often obtain useful information from others.

1 = Strongly disagree	Moderately Disagree	Somewhat disagree	4 = Neither agree or disagree	Somewhat agree	Moderately agree	7 = Strongly agree
○	○	○	○	○	○	○

PU. Using the program...

	1 = Extremely unlikely	Quite unlikely	Slightly unlikely	4 = Neither likely or unlikely	Slightly likely	Quite likely	7 = Extremely likely
PU1. Would address my daily needs	○	○	○	○	○	○	○
PU2. Would enable me to accomplish tasks more quickly	○	○	○	○	○	○	○
PU3. Would increase my productivity	○	○	○	○	○	○	○
PU4. Would improve my shopping performance	○	○	○	○	○	○	○
PU5. Would enhance my effectiveness on daily activities	○	○	○	○	○	○	○

PU6. I would find the program useful on my daily activities.

1 = Extremely unlikely	Quite unlikely	Slightly unlikely	4 = Neither likely or unlikely	Slightly likely	Quite likely	7 = Extremely likely
○	○	○	○	○	○	○

PEOU1. Learning to operate with the program should be easy.

1 = Extremely unlikely	Quite unlikely	Slightly unlikely	4 = Neither likely or unlikely	Slightly likely	Quite likely	7 = Extremely likely
○	○	○	○	○	○	○

PEOU2. Interacting with the program should not require a lot of my mental effort.

1 = Extremely unlikely	Quite unlikely	Slightly unlikely	4 = Neither likely or unlikely	Slightly likely	Quite likely	7 = Extremely likely
○	○	○	○	○	○	○

PEOU3. I should find the program flexible to use.

1 = Extremely unlikely	Quite unlikely	Slightly unlikely	4 = Neither likely or unlikely	Slightly likely	Quite likely	7 = Extremely likely
○	○	○	○	○	○	○

PEOU4. The program should provide helpful guidance in performing tasks.

1 = Extremely unlikely	Quite unlikely	Slightly unlilkely	4 = Neither likely or unlikely	Slightly likely	Quite likely	7 = Extremely likely
○	○	○	○	○	○	○

PEOU5. I should find it easy to get the program to do what I want it to do.

1 = Extremely unlikely	Quite unlikely	Slightly unlilkely	4 = Neither likely or unlikely	Slightly likely	Quite likely	7 = Extremely likely
○	○	○	○	○	○	○

PEOU6. I should find the program easy to use.

1 = Extremely unlikely	Quite unlikely	Slightly unlilkely	4 = Neither likely or unlikely	Slightly likely	Quite likely	7 = Extremely likely
○	○	○	○	○	○	○

ITU1. Assuming I have access to the program, I intend to use it.

1 = Strongly disagree	Moderately Disagree	Somewhat disagree	4 = Neither agree or disagree	Somewhat agree	Moderately agree	7 = Strongly agree
○	○	○	○	○	○	○

ITU2. Given that I have access to the program, I predict that I would use it.

1 = Strongly disagree	Moderately Disagree	Somewhat disagree	4 = Neither agree or disagree	Somewhat agree	Moderately agree	7 = Strongly agree
○	○	○	○	○	○	○

AU1. How many times would you use the program during a week?

1 = Never	Less than once a week	About once a week	4= 2 or 3 times a week	Several times a week	Once a day	7 = Several times each days
○	○	○	○	○	○	○

AU2. How many hours would you use the program every week?

1 = <1h	1-5h	5-10h	4= 10h-15h	15h-20h	20h-25h	7 => 25h
◯	◯	◯	◯	◯	◯	◯

AU3. How frequently would you use the program?

1 = Never	Quite infrequent	Slightly infrequent	4 = Neither frequent or inefrequent	Slightly frequent	Quite frequent	7 = Extremely frequent
◯	◯	◯	◯	◯	◯	◯

→

Please indicate your age:

Please indicate your gender:

Please indicate the highest degree or level of education you have completed or are completing:

- ◯ High School
- ◯ Bachelor degree
- ◯ Masters degree
- ◯ Post-Graduation
- ◯ Doctorate

Please indicate your ocupation.

- ◯ Student
- ◯ Working student
- ◯ Employed
- ◯ Self-employed
- ◯ Unemployed

Appendix B – Constructs, Scales and Authors

Variables	Q	Items	Fount
Perceived Usefulness	PU1	A blockchain-based program would address my daily needs.	(Davis, 1989)
	PU2	Using the program would enable me to accomplish tasks more quickly.	
	PU3	Using the program would increase my productivity.	
	PU4	Using the program would improve my shopping performance.	
	PU5	Using the program would enhance my effectiveness on daily activities.	
	PU6	I would find the program useful on my daily activities.	
Perceived Ease of Use	PEOU1	Learning to operate with the program should be easy.	(Davis, 1989)
	PEOU2	Interacting with the program should not require a lot of my mental effort.	
	PEOU3	I should find the program flexible to use.	
	PEOU4	The program provides helpful guidance in performing tasks.	
	PEOU5	I should find it easy to get the program to do what I want it to do.	
	PEOU6	I should find the program easy to use.	
Intention to use	ITU1	Assuming I have access to the program, I intend to use it.	(Venkatesh & Davis, 2000)
	ITU2	Given that I have access to the program, I predict that I would use it.	
Actual Usage	AU1	How many times would you use the program during a week?	(Moon & Kim, 2001)
	AU2	How frequently would you use the program?	
Trust Propensity	TP1	It would be easy for me to trust this program.	(Wanner et al., 2022)
	TP2	My tendency to trust this program would be high.	
	TP3	I would tend to trust this program, even though I have little or no knowledge of it.	
Informational Social Influence	ISI1	When I need to use a new program, I often ask my family or friends for useful information.	(Jang et al., 2023)
	ISI2	I often ask friends or family for useful information to help use digital technology.	
	IS3	When I need to use a new technology, I often obtain useful information from others.	
Perceived Security	PS1	I would feel secure sending information to the program	(Salisbury et al., 2001)
	PS2	The program is a secure means through which to send sensitive information	
	PS3	I would feel totally safe providing sensitive information about myself over the program	
	PS4	Overall, the program is a safe place to transmit sensitive information	
Economic Value	EV1	It would be economically reasonable for me to become member of this new program	(Treiblmaier & Petrozhitskaya, 2023)
	EV2	The loyalty program would give me monetary advantages.	
	EV3	The loyalty program would offer me additional value for my money.	
Psychological Value	PV1	I would enjoy being a member of the loyalty program.	(Treiblmaier & Petrozhitskaya, 2023)
	PV2	The loyalty program would give me pleasure when I exchange miles.	
	PV3	I feel like the loyalty program makes me special compared to other customers.	

Appendix C – Descriptive Statistics of the constructs

Perceived Security

Descriptive Statistics[a]

	N	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
PS1. I would feel secure sending personal information to the program.	144	4,63	1,595	-,331	,202	-,676	,401
PS2. The program is a secure means through which to send sensitive information.	144	4,35	1,661	-,178	,202	-,838	,401
PS3. I would feel totally safe providing sensitive information to the program about myself over the program.	144	3,92	1,782	,162	,202	-1,104	,401
PS4. Overall, the program is a safe place to transmit sensitive information.	144	4,19	1,746	-,124	,202	-,974	,401
Score1_PS	144	4,2708	1,57352	-,026	,202	-,836	,401
Valid N (listwise)	144						

a. BlockGroup = 1,00

Descriptive Statistics[a]

	N	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
PS1. I feel secure sending personal information to the program.	166	4,63	1,664	-,572	,188	-,375	,375
PS2. The program is a secure means through which to send sensitive information.	166	4,51	1,625	-,513	,188	-,439	,375
PS3. I feel totally safe providing sensitive information to the program about myself over the program.	166	4,05	1,805	-,129	,188	-,930	,375
PS4. Overall, the program is a safe place to transmit sensitive information.	166	4,29	1,688	-,296	,188	-,705	,375
Score2_PS	166	4,3675	1,58322	-,374	,188	-,522	,375
Valid N (listwise)	166						

a. BlockGroup = 2,00

Trust Propensity

Descriptive Statistics[a]

	N	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
TP1. It would be easy for me to trust this program.	144	4,24	1,711	-,241	,202	-,837	,401
TP2. My tendency to trust this program would be high.	144	4,20	1,732	-,127	,202	-,957	,401
TP3. I would tend to trust this program, even though I have little or no knowledge of it.	144	3,66	1,885	,154	,202	-1,086	,401
Score1_TP	144	4,0347	1,68162	-,013	,202	-,883	,401
Valid N (listwise)	144						

a. BlockGroup = 1,00

Descriptive Statistics[a]

	N	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
TP1. It's easy for me to trust this program.	166	4,57	1,682	-,425	,188	-,506	,375
TP2. My tendency to trust this program is high.	166	4,44	1,780	-,282	,188	-,779	,375
TP3. I tend to trust this program, even though I have little or no knowledge of it.	166	4,17	1,842	-,272	,188	-,903	,375
Score2_TP	166	4,3956	1,64311	-,351	,188	-,596	,375
Valid N (listwise)	166						

a. BlockGroup = 2,00

Economic Value

Descriptive Statistics[a]

	N	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
EV1. It would be economically reasonable for me to become member of this new program.	144	4,82	1,485	-,529	,202	-,043	,401
EV2. The loyalty program would give me monetary advantages.	144	5,17	1,219	-,995	,202	2,381	,401
EV3. The loyalty program would offer me additional value for my money.	144	5,15	1,275	-1,029	,202	1,905	,401
Score1_EV	144	5,0486	1,18523	-,807	,202	1,645	,401
Valid N (listwise)	144						

a. BlockGroup = 1,00

Descriptive Statistics[a]

	N	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
EV1. It's economically reasonable for me to be a member of this program.	166	5,34	1,391	-1,116	,188	1,358	,375
EV2. The loyalty program gives me monetary advantages.	166	5,49	1,404	-1,317	,188	2,132	,375
EV3. The loyalty program offers me additional value for my money.	166	5,40	1,388	-1,126	,188	1,525	,375
Score2_EV	166	5,4096	1,30508	-1,210	,188	2,051	,375
Valid N (listwise)	166						

a. BlockGroup = 2,00

Psychological Value

Descriptive Statistics[a]

	N	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
PV1. I would enjoy being a member of the loyalty program.	144	5,04	1,337	-,611	,202	,766	,401
PV2. The loyalty program would give pleasure when I exchange loyalty points.	144	5,34	1,307	-1,016	,202	1,695	,401
PV3. I feel like the program would make me feel special compared to other costumers.	144	4,40	1,583	-,471	,202	-,262	,401
Score1_PV	144	4,9259	1,19012	-,666	,202	1,113	,401
Valid N (listwise)	144						

a. BlockGroup = 1,00

Descriptive Statistics[a]

	N	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
PV1. I enjoy being a member of the loyalty program.	166	5,16	1,354	-,759	,188	1,098	,375
PV2. The loyalty program gives me pleasure when I exchange loyalty points.	166	5,40	1,435	-,988	,188	1,131	,375
PV3. I feel like the program makes me feel special compared to other costumers.	166	4,10	1,690	-,239	,188	-,657	,375
Score2_PV	166	4,8876	1,26999	-,643	,188	,988	,375
Valid N (listwise)	166						

a. BlockGroup = 2,00

Informational Social Influence

Descriptive Statistics[a]

	N	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
ISI1. When I need to use a new program, I often ask my family or friends for useful information.	144	4,34	1,794	-,318	,202	-,866	,401
ISI2. I often ask friends or family for useful information to help use digital technology.	144	3,94	1,900	-,188	,202	-1,177	,401
ISI3. When I need to use a new technology, I often obtain useful information from others.	144	4,74	1,542	-,697	,202	,104	,401
Score1_ISI	144	4,3380	1,54899	-,217	,202	-,853	,401
Valid N (listwise)	144						

a. BlockGroup = 1,00

Descriptive Statistics[a]

	N	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
ISI1. When I need to use a new program, I often ask my family or friends for useful information.	166	4,03	1,827	-,148	,188	-1,038	,375
ISI2. I often ask friends or family for useful information to help use digital technology.	166	3,42	1,773	,312	,188	-,899	,375
ISI3. When I need to use a new technology, I often obtain useful information from others.	166	4,23	1,643	-,365	,188	-,661	,375
Score2_ISI	166	3,8936	1,51315	-,026	,188	-,682	,375
Valid N (listwise)	166						

a. BlockGroup = 2,00

Perceived Usefulness

Descriptive Statistics[a]

	N	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
PU. Using the program... - PU1. Would address my daily needs	144	4,15	1,584	-,298	,202	-,803	,401
PU. Using the program... - PU2. Would enable me to accomplish tasks more quickly	144	4,18	1,540	-,378	,202	-,626	,401
PU. Using the program... - PU3. Would increase my productivity	144	3,95	1,552	-,157	,202	-,563	,401
PU. Using the program... - PU4. Would improve my shopping performance	144	4,88	1,309	-,860	,202	1,026	,401
PU. Using the program... - PU5. Would enhance my effectiveness on daily activities	144	3,96	1,599	,006	,202	-,760	,401
PU6. I would find the program useful on my daily activities.	144	4,22	1,473	-,485	,202	-,557	,401
Score1_PU	144	4,2234	1,27024	-,280	,202	-,140	,401
Valid N (listwise)	144						

a. BlockGroup = 1,00

Descriptive Statistics[a]

	N	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
PU. Using the program... – PU1. addresses my daily needs	166	4,40	1,549	–,491	,188	–,546	,375
PU. Using the program... – PU2. enables me to accomplish tasks more quickly	166	4,11	1,673	–,283	,188	–,980	,375
PU. Using the program... – PU3. increases my productivity	166	3,83	1,613	–,082	,188	–,939	,375
PU. Using the program... – PU4. improves my shopping performance	166	4,69	1,504	–,707	,188	–,145	,375
PU. Using the program... – PU5. enhances my effectiveness on daily activities	166	3,82	1,570	–,096	,188	–,819	,375
PU6. I find the program useful on my daily activities.	166	4,25	1,532	–,373	,188	–,631	,375
Score2_PU	166	4,1847	1,32116	–,293	,188	–,609	,375
Valid N (listwise)	166						

a. BlockGroup = 2,00

Perceived Ease-of-Use

Descriptive Statistics[a]

	N	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
PEOU1. Learning to operate with the program should be easy.	144	5,49	1,257	–1,350	,202	2,633	,401
PEOU2. Interacting with the program should not require a lot of my mental effort.	144	5,57	1,372	–1,341	,202	1,628	,401
PEOU3. I should find the program flexible to use.	144	5,60	1,313	–1,304	,202	1,856	,401
PEOU4. The program should provide helpful guidance in performing tasks.	144	5,30	1,410	–1,335	,202	2,000	,401
PEOU5. I should find it easy to get the program to do what I want it to do.	144	5,51	1,327	–1,179	,202	1,350	,401
PEOU6. I should find the program easy to use.	144	5,67	1,257	–1,423	,202	2,478	,401
Score1_PEOU	144	5,5208	1,11793	–1,539	,202	3,498	,401
Valid N (listwise)	144						

a. BlockGroup = 1,00

Descriptive Statistics[a]

	N	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
PEOU1. Learning to operate with the program is easy.	166	5,53	1,296	-1,249	,188	1,919	,375
PEOU2. Interacting with the program does not require a lot of my mental effort.	166	5,60	1,303	-1,330	,188	2,052	,375
PEOU3. I find the program flexible to use.	166	5,27	1,270	-,744	,188	,671	,375
PEOU4. The program provides helpful guidance in performing tasks.	166	4,75	1,491	-,534	,188	-,227	,375
PEOU5. I find it easy to get the program to do what I want it to do.	166	5,17	1,339	-,845	,188	,880	,375
PEOU6. I find the program easy to use.	166	5,65	1,205	-1,253	,188	2,381	,375
Score2_PEOU	166	5,3283	1,09812	-1,193	,188	2,634	,375
Valid N (listwise)	166						

a. BlockGroup = 2,00

Intention to Use

Descriptive Statistics[a]

	N	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
ITU1. Assuming I have access to the program, I intend to use it.	144	5,29	1,300	-,907	,202	1,288	,401
ITU2. Given that I have access to the program, I predict that I would use it.	144	5,17	1,360	-,928	,202	1,062	,401
Score1_ITU	144	5,2326	1,26948	-,862	,202	1,269	,401
Valid N (listwise)	144						

a. BlockGroup = 1,00

Descriptive Statistics[a]

	N	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
ITU1. Assuming I have access to the program, I intend to use it.	166	5,64	1,265	-1,230	,188	2,210	,375
ITU2. Given that I have access to the program, I predict that I would use it.	166	5,49	1,315	-1,090	,188	1,481	,375
Score2_ITU	166	5,5663	1,24747	-1,162	,188	1,925	,375
Valid N (listwise)	166						

a. BlockGroup = 2,00

Actual Usage

Descriptive Statistics[a]

	N	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
AU1. How many times would you use the program during a week?	144	3,35	1,319	,414	,202	-,361	,401
AU2. How many hours would you use the program every week?	144	1,67	1,147	2,547	,202	7,698	,401
AU3. How frequently would you use the program?	144	3,71	1,453	,036	,202	-,828	,401
Score1_AU	144	2,9097	1,06817	,720	,202	,949	,401
Valid N (listwise)	144						

a. BlockGroup = 1,00

Descriptive Statistics[a]

	N	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
AU1. How many times do you use the program during a week?	166	3,39	1,302	,475	,188	-,602	,375
AU2. How many hours do you use the program every week?	166	1,57	1,075	2,582	,188	7,512	,375
AU3. How frequently do you use the program?	166	4,02	1,501	-,074	,188	-,944	,375
Score2_AU	166	2,9960	1,05089	,755	,188	1,031	,375
Valid N (listwise)	166						

a. BlockGroup = 2,00

Appendix D – Linear Regression Assumptions

Checking the Assumptions - Multiple Linear Regression Models – GROUP 1

Estimating a multiple linear regression model by OLS (Ordinary Least Squares) – ISI, EV, PV, PS as independent variables and PU as dependent variable:

1) Linearity of the relationship between each X and Y

By construction, the theoretical model assumes linearity:

Perceived Usefulness = $\beta 0 + \beta 1$ * Informational Social Influence + $\beta 2$ *Economic Value + $\beta 3$ * Psychological Value + $\beta 4$ * Perceived Security + ε

2) The mean of the residual component of the model is zero

Residuals Statistics[a,b]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1,5734	5,9252	4,2234	,79049	144
Residual	-4,09183	1,81663	,00000	,99430	144
Std. Predicted Value	-3,352	2,153	,000	1,000	144
Std. Residual	-4,057	1,801	,000	,986	144

a. BlockGroup = 1,00

b. Dependent Variable: Score1_PU

3) The independent variables are not correlated with the residual terms:

Correlations[a]

		Unstandardized Residual	Score1_ISI	Score1_EV	Score1_PV	Score1_PS
Unstandardized Residual	Pearson Correlation	1	,000	,000	,000	,000
	Sig. (2-tailed)		1,000	1,000	1,000	1,000
	N	144	144	144	144	144
Score1_ISI	Pearson Correlation	,000	1	,322**	,461**	,281**
	Sig. (2-tailed)	1,000		<,001	<,001	<,001
	N	144	144	144	144	144
Score1_EV	Pearson Correlation	,000	,322**	1	,664**	,572**
	Sig. (2-tailed)	1,000	<,001		<,001	<,001
	N	144	144	144	144	144
Score1_PV	Pearson Correlation	,000	,461**	,664**	1	,577**
	Sig. (2-tailed)	1,000	<,001	<,001		<,001
	N	144	144	144	144	144
Score1_PS	Pearson Correlation	,000	,281**	,572**	,577**	1
	Sig. (2-tailed)	1,000	<,001	<,001	<,001	
	N	144	144	144	144	144

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

a. BlockGroup = 1,00

4) There is no correlation among the residual terms:

Since the value of the Durbin-Watson is close to 2, residuals are assumed to be independent.

Model Summary[a,c]

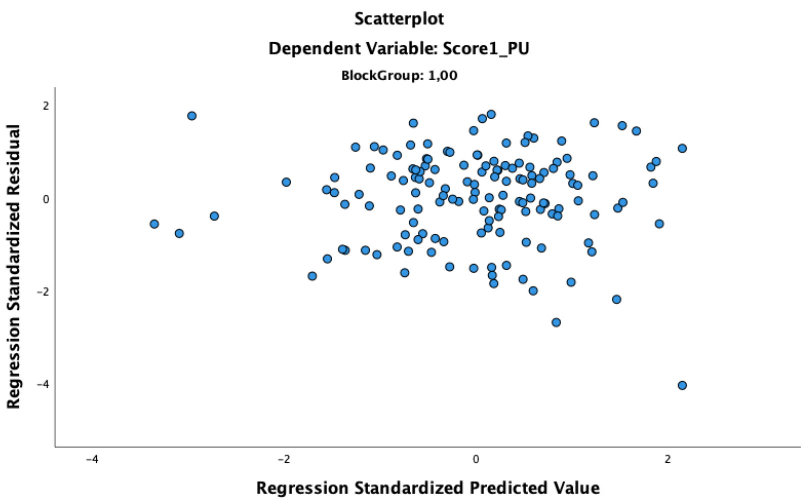
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,622[b]	,387	,370	1,00851	2,390

a. BlockGroup = 1,00

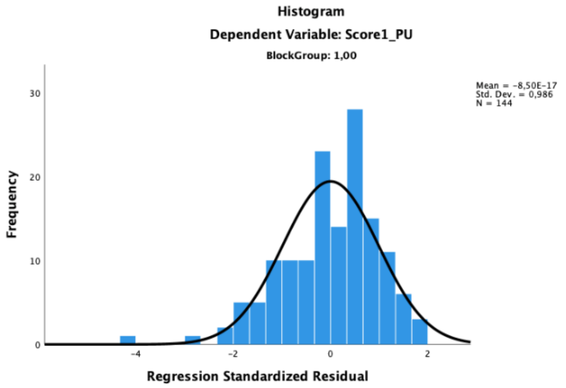
b. Predictors: (Constant), Score1_PS, Score1_ISI, Score1_EV, Score1_PV

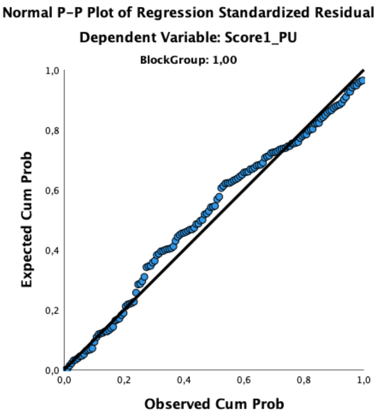
c. Dependent Variable: Score1_PU

5) The variance of the random term is constant



6) Normality of the residuals





7) There is no correlation among the explanatory variables

Coefficients[a,b]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	,848	,406		2,088	,039		
	Score1_ISI	,205	,061	,251	3,346	,001	,787	1,271
	Score1_EV	,034	,100	,032	,341	,734	,505	1,979
	Score1_PV	,362	,106	,339	3,419	<,001	,447	2,237
	Score1_PS	,123	,069	,153	1,789	,076	,604	1,657

a. BlockGroup = 1,00

b. Dependent Variable: Score1_PU

Conclusion:

- Since TOL > 0.1 for all independent variables, the conclusion is that they are not correlated among themselves, and the assumption holds.
- Since VIF < 10 for all explanatory variables, conclude that there is no serious correlation among themselves and therefore the assumption holds.

Estimating a multiple linear regression model by OLS (Ordinary Least Squares) – ISI, EV and PV as independent variables and PEOU as dependent variable:

1) Linearity of the relationship between each X and Y

By construction, the theoretical model assumes linearity:

Perceived Ease-of-Use = $\beta 0 + \beta 1 * \text{ISI} + \beta 2 * \text{EV} + \beta 3 * \text{PV} + \varepsilon$

2) The mean of the residual component of the model is zero:

Residuals Statistics[a,b]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	3,0427	6,7580	5,5208	,67758	144
Residual	-3,97312	1,95567	,00000	,88918	144
Std. Predicted Value	-3,657	1,826	,000	1,000	144
Std. Residual	-4,421	2,176	,000	,989	144

a. BlockGroup = 1,00

b. Dependent Variable: Score1_PEOU

3) The independent variables are not correlated with the residual terms:

Correlations[a]

		Unstandardized Residual	Score1_ISI	Score1_EV	Score1_PV
Unstandardized Residual	Pearson Correlation	1	,000	,000	,000
	Sig. (2-tailed)		1,000	1,000	1,000
	N	144	144	144	144
Score1_ISI	Pearson Correlation	,000	1	,322**	,461**
	Sig. (2-tailed)	1,000		<,001	<,001
	N	144	144	144	144
Score1_EV	Pearson Correlation	,000	,322**	1	,664**
	Sig. (2-tailed)	1,000	<,001		<,001
	N	144	144	144	144
Score1_PV	Pearson Correlation	,000	,461**	,664**	1
	Sig. (2-tailed)	1,000	<,001	<,001	
	N	144	144	144	144

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

a. BlockGroup = 1,00

4) There is no correlation among the residual terms:

Model Summary[a,c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,606[b]	,367	,354	,89866	1,926

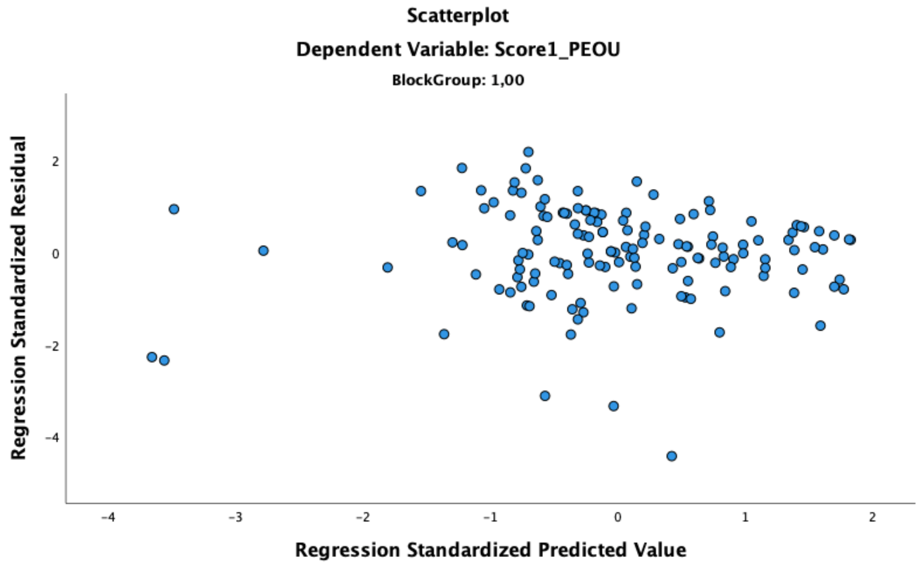
a. BlockGroup = 1,00

b. Predictors: (Constant), Score1_PV, Score1_ISI, Score1_EV

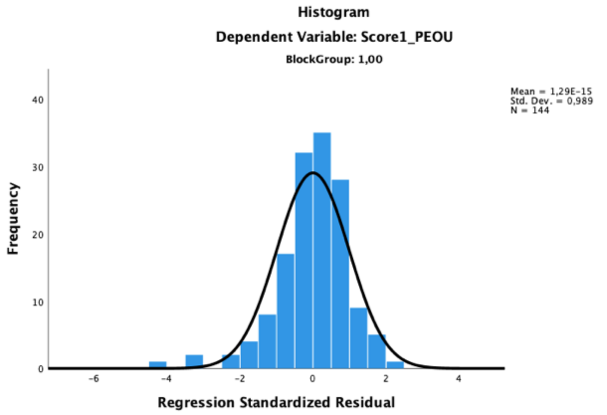
c. Dependent Variable: Score1_PEOU

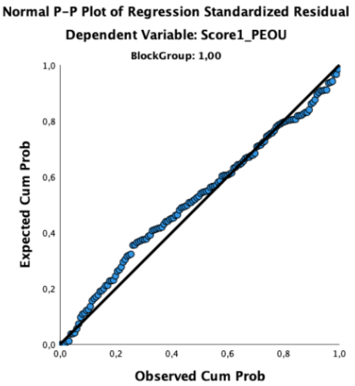
Since the value of the Durbin-Watson is close to 2, residuals are assumed to be independent.

5) The variance of the random term is constant:



6) Normality of the residuals





7) There is no correlation among the explanatory variables

Coefficients[a,b]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	2,514	,361		6,958	<,001		
	Score1_ISI	-,065	,055	-,091	-1,196	,234	,787	1,271
	Score1_EV	,352	,085	,373	4,145	<,001	,559	1,790
	Score1_PV	,308	,090	,327	3,412	<,001	,491	2,038

a. BlockGroup = 1,00

b. Dependent Variable: Score1_PEOU

Conclusion:

- Since TOL > 0.1 for all independent variables, the conclusion is that they are not correlated among themselves, and the assumption holds.
- Since VIF < 10 for all explanatory variables, conclude that there is no serious correlation among themselves and therefore the assumption holds.
-

<u>Estimating a multiple linear regression model by OLS (Ordinary Least Squares) – PU and PEOU as independent variables and ITU as dependent variable:</u>

1) Linearity of the relationship between each X and Y

By construction, the theoretical model assumes linearity:

Intention to Use= $\beta 0 + \beta 1 * \text{PU} + \beta 2 * \text{PEOU} + \varepsilon$

2) The mean of the residual component of the model is zero:

Residuals Statistics[a,b]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1,2736	6,9175	5,2326	,96644	144
Residual	-2,64542	1,96563	,00000	,82315	144
Std. Predicted Value	-4,097	1,743	,000	1,000	144
Std. Residual	-3,191	2,371	,000	,993	144

a. BlockGroup = 1,00

b. Dependent Variable: Score1_ITU

3) The independent variables are not correlated with the residual terms:

Correlations[a]

		Unstandardized Residual	Score1_PU	Score1_PEOU
Unstandardized Residual	Pearson Correlation	1	,000	,000
	Sig. (2-tailed)		1,000	1,000
	N	144	144	144
Score1_PU	Pearson Correlation	,000	1	,465**
	Sig. (2-tailed)	1,000		<,001
	N	144	144	144
Score1_PEOU	Pearson Correlation	,000	,465**	1
	Sig. (2-tailed)	1,000	<,001	
	N	144	144	144

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

a. BlockGroup = 1,00

4) There is no correlation among the residual terms:

Model Summary[a,c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,761[b]	,580	,574	,82897	1,952

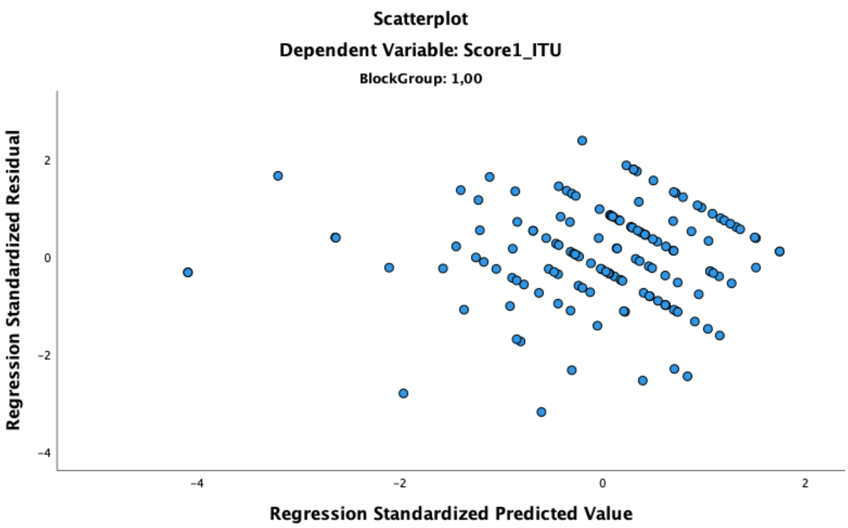
a. BlockGroup = 1,00

b. Predictors: (Constant), Score1_PEOU, Score1_PU

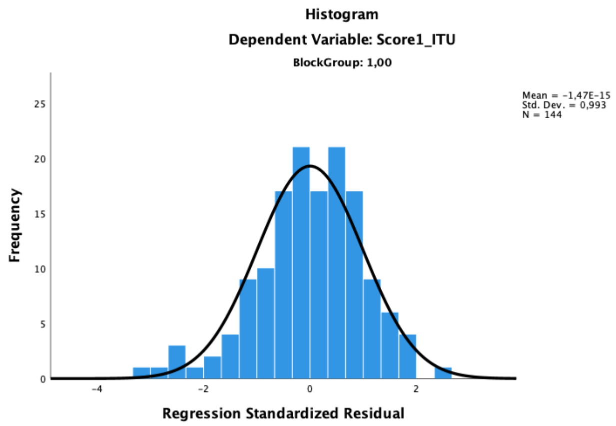
c. Dependent Variable: Score1_ITU

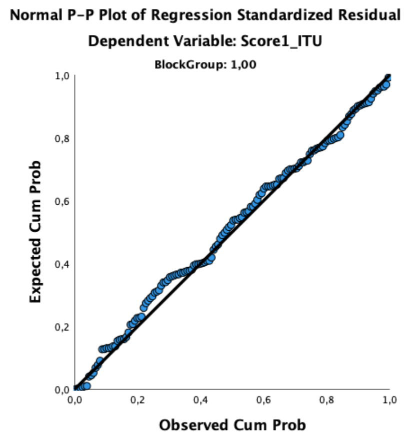
Since the value of the Durbin-Watson is close to 2, residuals are assumed to be independent.

5) The variance of the random term is constant:



6) Normality of the residuals:





7) There is no correlation among the explanatory variables

Coefficients[a,b]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	,333	,358		,929	,354		
	Score1_PU	,226	,062	,226	3,669	<,001	,784	1,276
	Score1_PEOU	,714	,070	,629	10,199	<,001	,784	1,276

a. BlockGroup = 1,00

b. Dependent Variable: Score1_ITU

Conclusion:

- Since TOL > 0.1 for all independent variables, the conclusion is that they are not correlated among themselves, and the assumption holds.
- Since VIF < 10 for all explanatory variables, conclude that there is no serious correlation among themselves and therefore the assumption holds.

Checking the Assumptions - Multiple Linear Regression Models – GROUP 2

<u>Estimating a multiple linear regression model by OLS (Ordinary Least Squares) – ISI, EV, PV, PS as independent variables and PU as dependent variable:</u>

1) Linearity of the relationship between each X and Y

By construction, the theoretical model assumes linearity:

Perceived Usefulness = $\beta 0$ + $\beta 1$ * Informational Social Influence + $\beta 2$ *Economic Value + $\beta 3$ * Psychological Value + $\beta 4$ * Perceived Security + ε

2) The mean of the residual component of the model is zero

Residuals Statistics[a,b]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1,7039	5,9944	4,1847	,78598	166
Residual	-3,09218	2,20238	,00000	1,06193	166
Std. Predicted Value	-3,156	2,302	,000	1,000	166
Std. Residual	-2,876	2,049	,000	,988	166

a. BlockGroup = 2,00

b. Dependent Variable: Score2_PU

3) The independent variables are not correlated with the residual terms:

Correlations[a]

		Unstandardized Residual	Score2_ISI	Score2_EV	Score2_PV	Score2_PS
Unstandardized Residual	Pearson Correlation	1	,000	,000	,000	,000
	Sig. (2-tailed)		1,000	1,000	1,000	1,000
	N	166	166	166	166	166
Score2_ISI	Pearson Correlation	,000	1	,104	,406**	,318**
	Sig. (2-tailed)	1,000		,182	<,001	<,001
	N	166	166	166	166	166
Score2_EV	Pearson Correlation	,000	,104	1	,624**	,535**
	Sig. (2-tailed)	1,000	,182		<,001	<,001
	N	166	166	166	166	166
Score2_PV	Pearson Correlation	,000	,406**	,624**	1	,606**
	Sig. (2-tailed)	1,000	<,001	<,001		<,001
	N	166	166	166	166	166
Score2_PS	Pearson Correlation	,000	,318**	,535**	,606**	1
	Sig. (2-tailed)	1,000	<,001	<,001	<,001	
	N	166	166	166	166	166

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

a. BlockGroup = 2,00

4) There is no correlation among the residual terms:

Since the value of the Durbin-Watson is close to 2, residuals are assumed to be independent.

Model Summary[a,c]

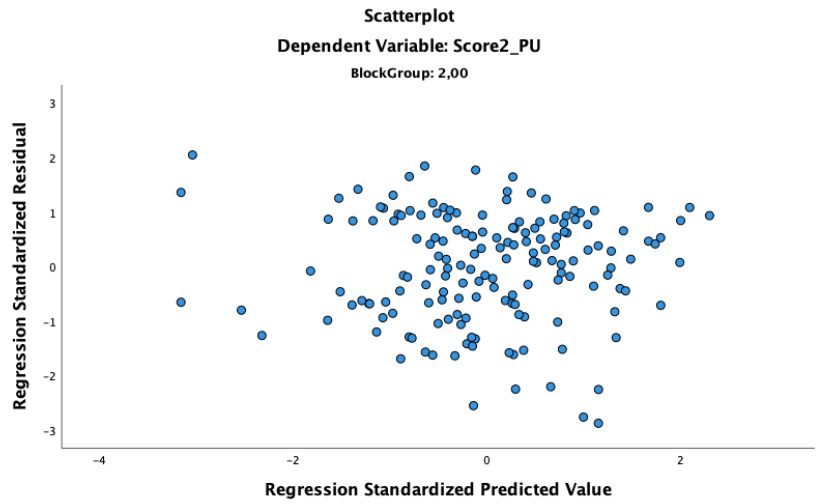
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,595[b]	,354	,338	1,07504	1,850

a. BlockGroup = 2,00

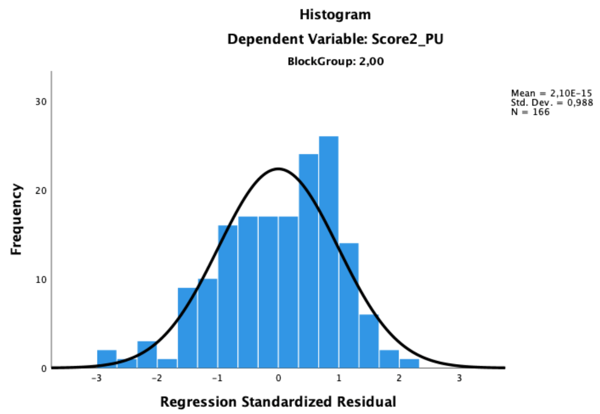
b. Predictors: (Constant), Score2_PS, Score2_ISI, Score2_EV, Score2_PV

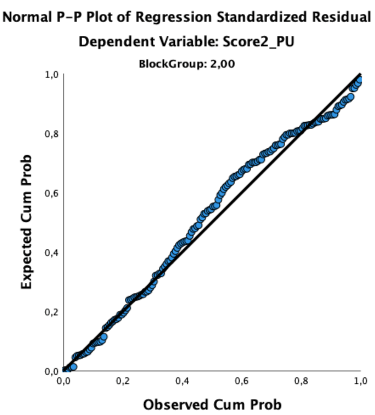
c. Dependent Variable: Score2_PU

5) The variance of the random term is constant



6) Normality of the residuals





7) There is no correlation among the explanatory variables

Coefficients[a,b]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	,989	,405		2,440	,016		
	Score2_ISI	,298	,063	,341	4,745	<,001	,778	1,285
	Score2_EV	,065	,087	,065	,748	,456	,538	1,859
	Score2_PV	,280	,099	,269	2,826	,005	,442	2,264
	Score2_PS	,072	,070	,086	1,034	,303	,578	1,731

a. BlockGroup = 2,00

b. Dependent Variable: Score2_PU

Conclusion:

- Since TOL > 0.1 for all independent variables, the conclusion is that they are not correlated among themselves, and the assumption holds.

- Since VIF < 10 for all explanatory variables, conclude that there is no serious correlation among themselves and therefore the assumption holds.

Estimating a multiple linear regression model by OLS (Ordinary Least Squares) – ISI, EV and PV as independent variables and PEOU as dependent variable:

1) Linearity of the relationship between each X and Y

By construction, the theoretical model assumes linearity:

Perceived Ease-of-Use = $\beta 0 + \beta 1 * \mathrm{ISI} + \beta 2 * \mathrm{EV} + \beta 3 * \mathrm{PV} + \varepsilon$

2) The mean of the residual component of the model is zero:

Residuals Statistics[a,b]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	2,7157	6,6281	5,3283	,69485	166
Residual	-3,03412	4,15993	,00000	,85032	166
Std. Predicted Value	-3,760	1,871	,000	1,000	166
Std. Residual	-3,536	4,848	,000	,991	166

a. BlockGroup = 2,00

b. Dependent Variable: Score2_PEOU

3) The independent variables are not correlated with the residual terms:

Correlations[a]

		Unstandardized Residual	Score2_ISI	Score2_EV	Score2_PV
Unstandardized Residual	Pearson Correlation	1	,000	,000	,000
	Sig. (2-tailed)		1,000	1,000	1,000
	N	166	166	166	166
Score2_ISI	Pearson Correlation	,000	1	,104	,406**
	Sig. (2-tailed)	1,000		,182	<,001
	N	166	166	166	166
Score2_EV	Pearson Correlation	,000	,104	1	,624**
	Sig. (2-tailed)	1,000	,182		<,001
	N	166	166	166	166
Score2_PV	Pearson Correlation	,000	,406**	,624**	1
	Sig. (2-tailed)	1,000	<,001	<,001	
	N	166	166	166	166

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

a. BlockGroup = 2,00

4) There is no correlation among the residual terms:

Model Summary[a,c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,633[b]	,400	,389	,85816	1,612

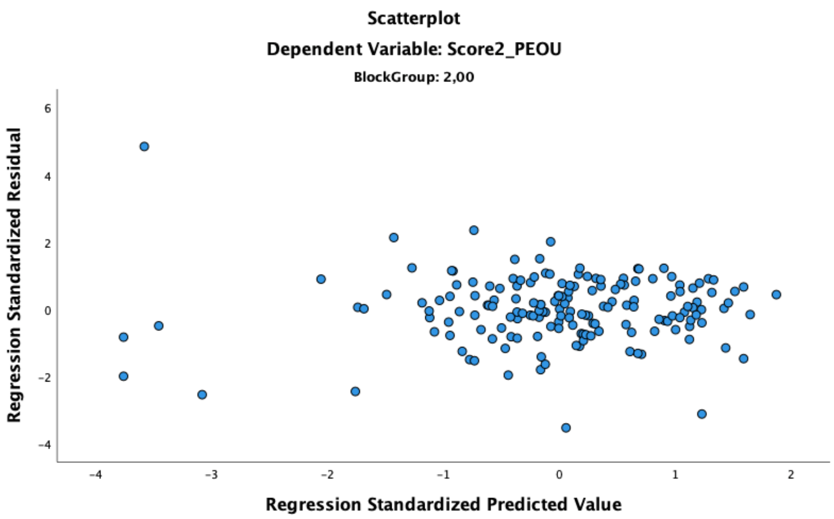
a. BlockGroup = 2,00

b. Predictors: (Constant), Score2_PV, Score2_ISI, Score2_EV

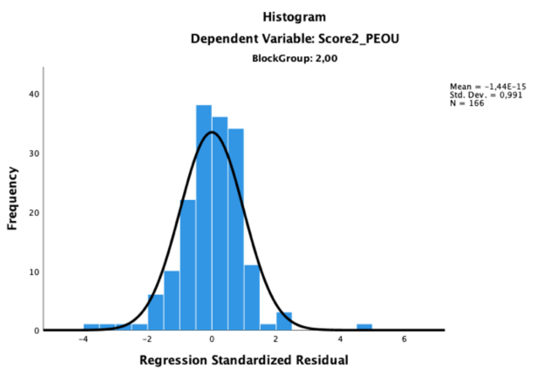
c. Dependent Variable: Score2_PEOU

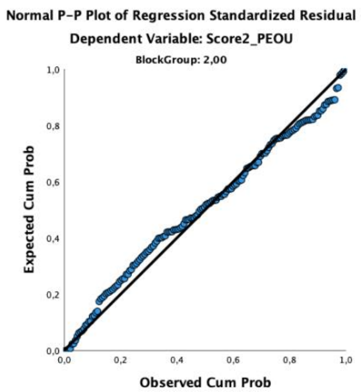
Since the value of the Durbin-Watson is close to 2, residuals are assumed to be independent.

5) The variance of the random term is constant:



6) Normality of the residuals





7) There is no correlation among the explanatory variables

Coefficients[a,b]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	VIF
1	(Constant)	2,064	,323		6,390	<,001		
	Score2_ISI	,118	,049	,162	2,384	,018	,798	1,252
	Score2_EV	,373	,067	,443	5,568	<,001	,584	1,713
	Score2_PV	,161	,075	,187	2,152	,033	,493	2,029

a. BlockGroup = 2,00

b. Dependent Variable: Score2_PEOU

Conclusion:

- Since TOL > 0.1 for all independent variables, the conclusion is that they are not correlated among themselves, and the assumption holds.
- Since VIF < 10 for all explanatory variables, conclude that there is no serious correlation among themselves and therefore the assumption holds.

Estimating a multiple linear regression model by OLS (Ordinary Least Squares) – PU and PEOU as independent variables and ITU as dependent variable:

1) Linearity of the relationship between each X and Y

By construction, the theoretical model assumes linearity:

Intention to Use= $\beta 0 + \beta 1 *$ PU+ $\beta 2 *$ PEOU + ε

2) The mean of the residual component of the model is zero:

Residuals Statistics[a,b]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	2,4542	6,8511	5,5663	,78049	166
Residual	-3,23993	3,50221	,00000	,97315	166
Std. Predicted Value	-3,987	1,646	,000	1,000	166
Std. Residual	-3,309	3,577	,000	,994	166

a. BlockGroup = 2,00

b. Dependent Variable: Score2_ITU

3) The independent variables are not correlated with the residual term

Correlations[a]

		Unstandardized Residual	Score2_PU	Score2_PEOU
Unstandardized Residual	Pearson Correlation	1	,000	,000
	Sig. (2-tailed)		1,000	1,000
	N	166	166	166
Score2_PU	Pearson Correlation	,000	1	,445**
	Sig. (2-tailed)	1,000		<,001
	N	166	166	166
Score2_PEOU	Pearson Correlation	,000	,445**	1
	Sig. (2-tailed)	1,000	<,001	
	N	166	166	166

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

a. BlockGroup = 2,00

4) There is no correlation among the residual terms:

Model Summary[a,c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,626[b]	,391	,384	,97910	1,993

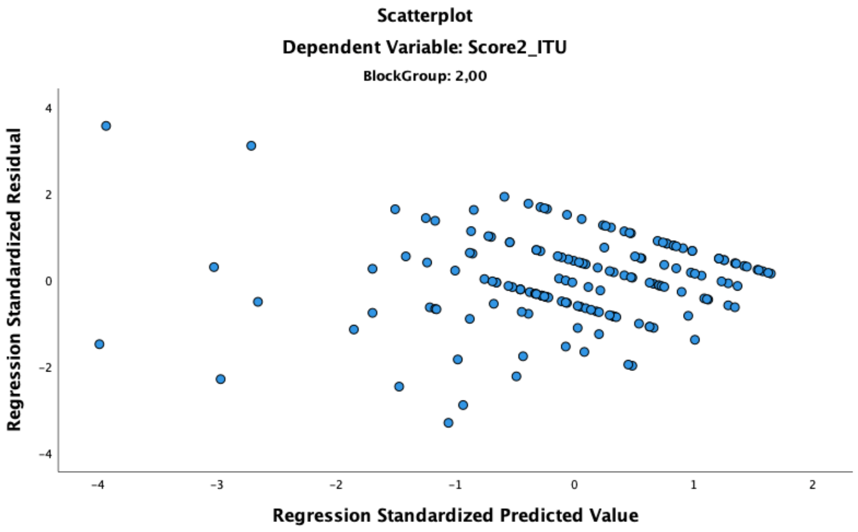
a. BlockGroup = 2,00

b. Predictors: (Constant), Score2_PEOU, Score2_PU

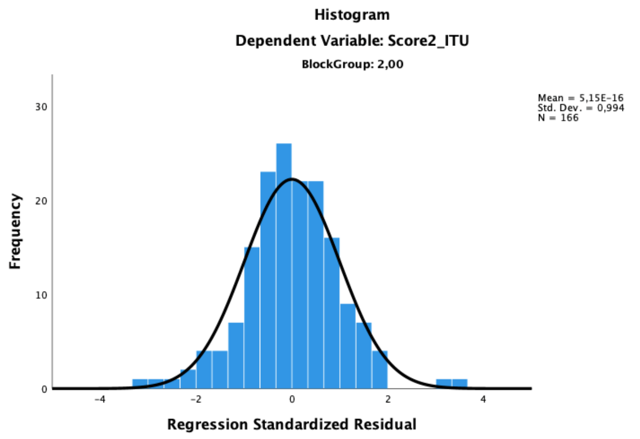
c. Dependent Variable: Score2_ITU

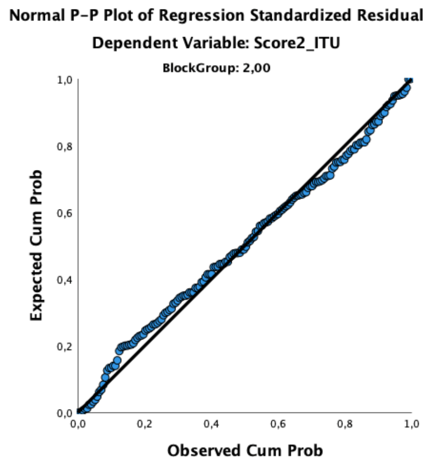
Since the value of the Durbin-Watson is close to 2, residuals are assumed to be independent.

5) The variance of the random term is constant



6) Normality of the residuals:





7) There is no correlation among the explanatory variables

Coefficients[a,b]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	1,721	,387		4,446	<,001		
	Score2_PU	,052	,064	,055	,812	,418	,802	1,247
	Score2_PEOU	,681	,078	,599	8,780	<,001	,802	1,247

a. BlockGroup = 2,00

b. Dependent Variable: Score2_ITU

Conclusion:

- Since TOL > 0.1 for all independent variables, the conclusion is that they are not correlated among themselves, and the assumption holds.
- Since VIF < 10 for all explanatory variables, conclude that there is no serious correlation among themselves and therefore the assumption holds.