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Fuzzy Set Qualitative Comparative Analysis of Loyalty Programmes Powered with Blockchain via an UTAUT2 Framework

Mario Arias-Oliva [1], Jaume Gené-Albesa [2], Jorge de Andrés-Sánchez [3,*] and Miguel Llorens-Marín [1]

[1] Marketing Department, Faculty of Business and Economy, University Complutense of Madrid, Campus de Somosaguas, 28223 Madrid, Spain; mario.arias@ucm.es (M.A.-O.); mllorens@ucm.es (M.L.-M.)
[2] Department of Business Administration, University Rovira i Virgili, Campus de Bellissens, 43204 Reus, Spain; jaume.gene@urv.cat
[3] Social and Business Research Laboratory, University Rovira i Virgili, Campus de Bellissens, 43204 Reus, Spain
* Correspondence: jorge.deandres@urv.cat

Abstract: (1) Background: Loyalty programmes are business strategies aimed at increasing customer fidelity to brands. One of the most promising technologies of the 21st century is blockchain, whose application to the management of loyalty programmes can increase transparency and reliability, enable interoperability, and facilitate centralised management. (2) Methods: This study evaluates the antecedents of the acceptance of blockchain-based loyalty programmes (BBLPs) using a model grounded in the technology acceptance model UTAUT2. The four basic constructs of UTAUT, which we call the UTAUT-baseline, are considered explanatory factors: performance expectancy (PER), effort expectancy (EFF), social influence (SOC), and facilitating conditions (FAC). Additionally, we consider the constructs introduced in UTAUT2: hedonic motivation (HED) and perceived price value (PRI), to which we add innovativeness (INN) and trust (TRU), and we refer to these as UTAUT-extended, along with the moderating variables of UTAUT and UTAUT2: gender, age, and experience. The analytical approach used is complexity theory, which aims to capture the configurations that lead to both acceptance and rejection positions regarding BBLPs. This analysis is performed via fuzzy set qualitative comparative analysis (fsQCA). (3) Results: Eight explanatory configurations of the acceptance of BBLPs have been obtained, in which the presence of all UTAUT-baseline and UTAUT-extended constructs is a condition in at least three prime implicates. The constructs with the greatest presence as core conditions are PER, EFF, and TRU. On the other hand, nine configurations leading to the rejection of BBLPs have been identified. The absence of all UTAUT-baseline and UTAUT-extended variables is a condition in at least three configurations. The core conditions with the greatest presence in the rejection of BBLPs are the lack of FAC, HED, and PRI. (4) Practical implications: The results obtained are of great interest to business owners, as they allow for the characterisation of different profiles of people potentially engaged with BBLPs, as well as the profiles of consumers reluctant to adopt them.

Keywords: blockchain technology; loyalty programmes; blockchain-based loyalty programmes; UTAUT2; technology acceptance models; complexity theory; configurational analysis; fuzzy set qualitative comparative analysis

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1. Introduction

Loyalty programmes (LPs) are strategies designed by companies to induce customers to make repeat purchases or interact continuously with the brand. These strategies aim to foster customer loyalty through rewards, discounts, point accumulation, or other incentives that offer additional value to the consumer for their preference [1]. Most LPs are based on a point accumulation system, where they are earned for each purchase or specific action and can later be redeemed for products, services, or discounts [2]. LPs not only increase customer retention rates but also help companies gather data on their consumption habits and preferences, allowing for more effective and personalised marketing strategies [3].

One of the most significant technologies to emerge in the 21st century is blockchain [4]. It can be defined as a distributed ledger technology that allows information to be stored securely, transparently, and immutably. It consists of a chain of linked blocks containing records of transactions or data. Each block is connected to the previous and subsequent blocks through a unique identifier called a hash, which ensures the integrity and sequence of the information [5]. The primary characteristic of blockchain is its decentralisation. Unlike traditional systems that rely on a central authority to validate and store transactions, blockchain transactions are collectively validated by network participants. This ensures that the data are resistant to tampering, as any alteration to one block would modify all subsequent blocks and be immediately detected [4].

The use of blockchain extends far beyond cryptocurrencies [6]. Other promising applications include smart contracts, supply chain management, digital identity, electronic voting, and the provision of financial services [7]. In this work, we are particularly interested in its vast potential to transform digital marketing by offering greater transparency, security, and trust between brands and consumers [8]. This includes, for example, transparency in digital advertising, ensuring that each publicity reaches the correct target audience [9], and giving users full control over their personal information [10]. The present study focuses on the use of blockchain as a technology to support loyalty programmes, specifically blockchain-based loyalty programmes (BBLPs).

Loyalty and reward programmes can be made more efficient and personalised with blockchain, allowing consumers to accumulate points that can be redeemed across different brands in a transparent and secure manner [11]. Furthermore, blockchain technology eliminates the fragmentation of LPs, creating a universal point system that is easy to manage and more attractive to customers [12]. Blockchain technology enables the tokenisation of assets and rewards in BBLPs, which can be exchanged for discounts, products, or even other cryptocurrencies [13], increasing the appeal of BBLPs. Additionally, the use of smart contracts in the implementation of BBLPs simplifies the process of applying rewards for customers, increasing their satisfaction with the LP [14].

Although blockchain technology has enormous potential across various fields, its adoption has been relatively slow and modest [11]. This can be attributed to the initial effort required for its adoption, uncertainty regarding its lack of regulation, and a general lack of awareness of the technology [15]. While there are numerous studies in the field of cryptocurrency acceptance [16], studies in other blockchain applications, excluding supply chains, are practically nonexistent, as highlighted in the review [17]. This observation includes BBLPs.

The purpose of this paper is to evaluate the antecedents leading to the acceptance and rejection of BBLPs and analyse these drivers via the extended unified theory of acceptance and use of technology (UTAUT) [18] and UTAUT2 [19]. Concretely, we suppose that attitudes toward the use of BBLPs can be explained by factors such as gender, user experience, performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, perceived price value, innovativeness and trust. This conceptual framework is reflected in Figure 1.

The analytical approach adopted is not conventional structural equation modelling and multiple regression, which is variable-oriented, but complexity theory, which is case-oriented [20]. This approach assumes that there are multiple paths that lead to either supporting or inhibiting a particular behavioural intention [20,21]. This view is consistent with the fact that users of an information system [22] and those who reject it can also be classified into different typologies [23].

Complexity theory also assumes that the explanations for the presence and absence of a particular outcome in business phenomena are not symmetrical [24]. This also applies to the field of technology acceptance, as while the unacceptability of a technology leads to its rejection, acceptability does not necessarily imply the intention to use it [23].

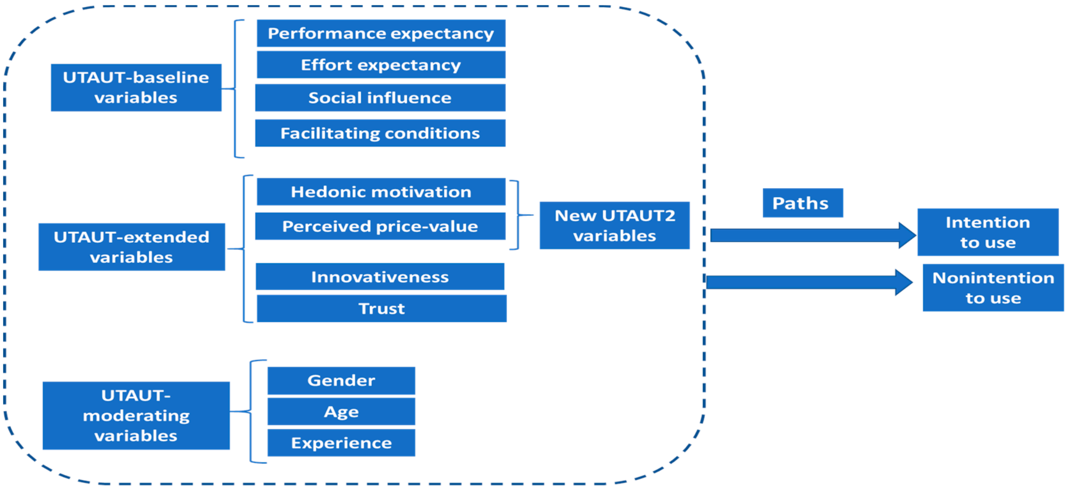

Figure 1. Analytical groundwork in our paper.

An analytical tool particularly suited to adopting the perspective of complexity theory is fuzzy set qualitative comparative analysis (fsQCA), which has been applied in the analysis of technology acceptance across various information systems, contexts, and different conceptual frameworks [25–28]. These applications include the analysis of blockchain technology acceptance for cryptocurrencies [29] and crypto-wallets [30].

Thus, the research questions (RQs) that address the acceptance of BBLPs are as follows:

- RQ1: What are the paths that lead to the acceptance and rejection of the use of BBLPs?
- RQ2: Is the explanation for the acceptance and rejection of the use of BBLPs symmetrical?

The successful implementation of any technology in a given field requires an understanding of the factors that influence the intention to use it. In this context, this paper sheds light on the acceptance of blockchain use in loyalty programmes. This topic remains underexplored in the limited literature on the acceptance of blockchain-powered information systems. Understanding this may be valuable for brands considering the use of blockchain to implement LPs and, more broadly, for enhancing comprehension of blockchain's role in firms' relationships with their stakeholders.

The approach used, fsQCA, which is case-oriented, is innovative in studies on blockchain technology acceptance, which typically employs variable-oriented techniques. With fsQCA, we can capture the pathways leading to both the acceptance and rejection of BBLPs. These pathways emerge from the interaction of the presence or absence of UTAUT factors and can be associated with different consumer profiles, both willing and unwilling to adopt BBLPs. Furthermore, we find that the profiles of those who accept BBLPs and those who reject BBLPs are not mirror opposites.

To address these research questions and achieve these results, we develop the work as follows. In the second section, we propose a theoretical model for the acceptance of BBLPs on the basis of UTAUT2, which explains their acceptance, and we formulate hypotheses that can be tested via complexity theory instruments. In the third section, we describe the survey used and the methods employed for its analysis. In the fourth section, we present the results obtained, which are the configurations that explain both the acceptance and rejection of BBLPs. We conclude by discussing the results obtained, highlighting the theoretical and practical implications, and summarising the main conclusions drawn from the work undertaken.

2. Theoretical Groundwork

2.1. A Configurational UTAUT2 Framework to Explain the Acceptance of Blockchain-Based Loyalty Programmes

The literature reviews on the acceptance of blockchain [7,17] indicate that the most commonly used conceptual models are the Technology Acceptance Model (TAM) [31] and its extension, TAM2 [32], as well as UTAUT and its extension, UTAUT2. This observation can also be seen in the literature reviewed in Table 1. The present work is based on the approach of UTAUT2 [19], which extends the UTAUT model [18], adding hedonic motivation and perceived price value as explanatory variables for the use of new technologies and considering the moderator variables recognised in UTAUT and UTAUT2: gender, age, and experience. UTAUT2 is not a closed analytical framework but rather one that must be adjusted to the technology being evaluated [33,34]. Thus, as shown in Figure 1, the theoretical framework used in this study also includes trust and innovativeness as additional explanatory variables.

In this way, we can differentiate three groups of variables that precede the acceptance or rejection of BBLPs. The first type of factor is the original variable of the UTAUT model, which we refer to as the UTAUT-baseline. These are performance expectancy, effort expectancy, social influence, and facilitating conditions. The second type of variables will be those we refer to as UTAUT-extended, which include two variables introduced in UTAUT2: hedonic motivation and perceived price value, to which we add innovativeness and trust. The third type of variables are those considered moderators in previous works [18,19], which we refer to as UTAUT-moderating variables: gender, age, and experience (EXP).

The outcome explained in this work is behavioural intention, which refers to a person's willingness to perform a specific behaviour [35]. In this case, the outcome is the intention to use BBLPs (INT). The intention to use is the most common construct used to measure acceptance in UTAUT-based models [18,19], and it is also the case in studies on the acceptance of BBLPs mentioned in Table 1. Importantly, the development of blockchain applications has not yet reached a mature phase [11], meaning that it is not an easily accessible technology for everyone. Therefore, issues related to acceptance, framed in terms of intention to use, can be addressed on an equal basis among potential respondents, which would not be the case if actual usage were measured.

Table 1. Papers about the acceptance of blockchain-based applications.

Setting	UTAUT-Based	TAM-Based	Others
Cryptocurrencies	[28,36–38]	[39–42]	[43]
Supply chain	[44–47]	[48–50]	
Academic applications	[51]	[52–54]	
Internal processes of organisations	[55]	[56,57]	
Financial and accounting applications	[58]		[30]
Miscellanea		[59,60]	[61]

The UTAUT model extension analysed, as shown in Figure 1, does not present relationships between variables, as this study employs a configurational approach from complexity theory [20]. In this study, the aim is to identify the different paths that emerge from the combination of conditions related to the presence or absence of factors leading to the explained outcome, which can be either intention to use (acceptance) or absence of intention or no intention (rejection). The set of paths that explains an outcome is referred to as the solution.

Generally, the paths of a solution that precedes an outcome (e.g., acceptance) and its negation (rejection) are not the mirror opposite [24]. Furthermore, in fsQCA, the differentiation between different types of explanatory variables loses relevance as being a condition of a path neutralising this heterogeneity [62]. In other words, in the proposed UTAUT2-based model, explanatory and moderator variables are placed on the same level and are relevant for explaining the acceptance or rejection of BBLPs depending on their presence or absence as a condition in the paths that precede the evaluated outcome.

Importantly, establishing correlational hypotheses about the relationship between explanatory variables and the outcome remains useful. In configurational studies, obtaining the so-called intermediate solution, which is commonly reported in fsQCA-based studies [20], requires the use of simplifying assumptions that must be theoretically well-founded regarding how a given condition is causally related to the outcome [63]. Additionally, this approach will be useful in formulating propositions about the structure of the explanatory paths for the intention and no intention to use.

2.2. Development of the Correlational Hypothesis

2.2.1. Influence of UTAUT-Baseline Variables on Intention to Use

Performance expectancy (PER) in the UTAUT model is conceptualised as the extent to which a person believes that using a technology can help improve their performance in a task [18]. It is often the most significant latent variable in analyses of new technology adoption [18]. Blockchain technology enables the creation of a universal customer loyalty programme that promotes transparency, accountability, fairness, and ethics, addressing the limitations of traditional programmes, such as being restricted to specific merchants, offering unfair rewards, and lacking transparency in operational mechanisms [64].

Effort expectancy (EFF) refers to the level of ease associated with using the evaluated technology [18]. Authors such as Grover et al. [65] emphasise that, along with PER, EFF is a critical variable for understanding the acceptance of blockchain applications. Making blockchain-based applications user-friendly is crucial to increasing their adoption, especially among users unfamiliar with this technology. Research highlights the importance of user-centered design in addressing usability challenges in decentralised applications [66].

The usability and quality of the web interfaces with which users interact significantly influence the acceptance of blockchain-based systems [30], confirming the need for intuitive designs in blockchain application workspaces [52].

Social influence (SOC) is the degree to which a person perceives those important others believe that they should use the new system being evaluated [18]. New products and services in the early stages of development may require social influence for adoption, especially when they require greater technological knowledge than available alternatives do, as is the case with blockchain-based developments [38]. Furthermore, the social influence on the intention to adopt blockchain technology is limited by the widespread lack of knowledge about its potential [11]. The influence exerted by the business sector directly impacts blockchain adoption, making strong corporate support essential for promoting the use of BBLPs so that customers will adopt them [55]. In this context, social media platforms such as Twitter, Facebook, and YouTube can play a key role in promoting BBLPs [8].

Facilitating conditions (FACs) can be conceptualised as the extent to which a person perceives that organisational and technical resources are sufficient to support the use of the evaluated technology [18]. In the context of BBLPs, they refer to users' perceptions of the availability of resources and assistance that enable them to use blockchain technology effectively [67]. Therefore, if users perceive an adequate level of technological, organisational, network, and human support when blockchain is used, they are more likely to have a smoother and more satisfying experience with the technology, which in turn increases their engagement with it [46,47].

Therefore, we state the following correlational hypothesis:

Hypothesis 1 (H1). *Performance expectancy is positively correlated with the intention to use BBLPs.*

Hypothesis 2 (H2). *Effort expectancy is positively correlated with the intention to use BBLPs.*

Hypothesis 3 (H3). *Social influence is positively correlated with the intention to use BBLPs.*

Hypothesis 4 (H4). *Facilitating conditions are positively correlated with the intention to use BBLPs.*

2.2.2. Influence of UTAUT-Extended Variables on Intention to Use

Hedonic motivation (HED) is defined as the enjoyment or pleasure derived from using a technology [19]. Beyond the individual user's predisposition to experience pleasure when using any technology, blockchain enables the gamification of applications through elements such as points and challenges, which enhance user motivation [68]. Gamification in blockchain-based loyalty programmes increases customer engagement by allowing them to participate in consensus processes, rewarding them with tokens, and influencing their behaviour through rewards for system participation [69].

The perceived price value (PRI) is defined as the cognitive trade-off that consumers make between the perceived benefits of applications and the monetary cost of their use [19]. BBLPs offer services with characteristics of a shared economy, providing advantages in terms of use, accumulation, relevance, expiration, and transferability [11]. Moreover, blockchain technology allows the creation of a decentralised point alliance, eliminating data interaction barriers between platforms and enhancing the value of loyalty points through a point trading mechanism, which in many programs can be converted into cryptocurrencies [70].

Innovativeness (INN) refers to an individual's predisposition toward the use of new technologies [71]. Innovativeness encourages the adoption of emerging technologies such as blockchain, which many consumers and businesses are still unaware of in terms of its applications and potential benefits [11]. The significance of this variable has been demonstrated in both contexts where the use of blockchain applications is mandatory, such as in the business environment [55], and where its use is voluntary, such as in cryptocurrency investment [38].

With respect to trust (TRU) in new technologies, two dimensions are distinguished: cognitive and relational [72]. The cognitive dimension is associated with the perception that the technology is suitable for its intended purposes. The main features of blockchain, such as decentralisation, immutability, and transparency, offer great potential for improving the security, reliability, and privacy of transactions, which can foster cognitive trust among users [4,50,67].

On the other hand, regarding the relational dimension of trust, Nakamoto [5] highlighted that the primary goal of blockchain technology is to create a decentralised electronic payment system. Therefore, in blockchain applications, there is no reliable reference authority [7], and the question of "who" trust is placed in becomes diluted [73]. Furthermore, it is a technology with relatively weak regulation by government authorities [67]. As a result, blockchain technology may generate lower relational trust among certain users than centralised information systems do.

Therefore, we state the following correlational hypothesis:

Hypothesis 5 (H5). *Hedonic motivation is positively correlated with the intention to use BBLPs.*

Hypothesis 6 (H6). *Perceived price value is positively correlated with the intention to use BBLPs.*

Hypothesis 7 (H7). *Innovativeness is positively correlated with the intention to use BBLPs.*

Hypothesis 8 (H8). *Trust is positively correlated with the intention to use BBLPs.*

2.2.3. Influence of UTAUT-Moderating Variables on Intention to Use

In the UTAUT and UTAUT2 models, gender (GEN), age (AGE), and experience (EXP) act as moderating variables that influence the impact of the explanatory variables on acceptance [18,19]. The direction of moderation for gender and age, as postulated in UTAUT and UTAUT2, depends on the moderated variable. For gender, being male strengthens the impact of performance expectancy, hedonic motivation, and perceived price value on acceptance, whereas being female strengthens it in the case of effort expectancy, social influence, and facilitating conditions. Similarly, being younger may increase the influence of PER, HED, and PRI, whereas being older may enhance the effects of EFF, SOC, and FAC [18,19].

Experience may negatively influence the strength of the relationship between EFF and SOC with acceptance but may have a positive effect on the intensity of the relationship between FAC and usage [18].

Therefore, while it can be assumed that GEN, AGE, and EXP interact with the UTAUT-baseline and UTAUT-extended variables to influence the intention to use, we cannot hypothesise the precise direction of that impact. Thus, for this group of variables, we will neither make hypotheses regarding the sign of their link with INT nor their relationships with the other explanatory factors to explain the outcome. However, they will be considered in determining the configurations that lead to the acceptance or rejection of BBLPs, given their potential moderating capacity on the influence of the rest of the explanatory variables.

2.3. Development of Configurational Laws About the Acceptance of BBLPs

The attitudes of individuals towards information technologies are influenced by their personalities [74]. Thus, two users with different personalities may arrive at the same judgment through completely different pathways. Among users of an information system, several profiles can be distinguished: enthusiasts, practicalists, socialisers, traditionalists, and guardians [22]. On the other hand, among nonusers, it can be differentiated between resistors, rejecters, expelled individuals, and excluded individuals [23].

Therefore, the acceptance and rejection of BBLPs, similar to other technologies, can be achieved through various equifinal causal configurations. In explaining acceptance, a practical user is likely to emphasise factors such as utility and ease of use. In contrast, for a social user, a key condition may be social influence and the opportunity to interact with other users, especially if the platform is gamified. An enthusiastic user may show a strong inclination towards personal innovation and hedonistic motivation in using BBLPs despite perceiving other advantages, such as utility and usability. Additionally, the positive or negative attitude towards a technology tends to be asymmetric, as while the acceptability of a technology does not always guarantee its adoption, unacceptability can drive resistance or rejection of the technology [23].

Complexity theory posits that in social phenomena, there are multiple paths leading to the same outcome, and the relationships that characterise them are asymmetric [20,24]. An appropriate analytical tool for this purpose is fuzzy set qualitative comparative analysis (fsQCA), which allows the identification, within a sample, of the different combinations of variables that lead to the evaluated outcome. It also detects asymmetric relationships between variables, although it has no limitations in its application in the presence of symmetry [75].

Although the application of fsQCA in studies of technological acceptance is not as common as structural equation modelling is, it is not unusual. It has been used to characterise users of banking applications [26] and health applications [76]. In the field of blockchain technologies, [29] applied fsQCA to analyse the propensity for and rejection of cryptocurrency investment, and [30] used it as a complementary tool to PLS-SEM in analysing the acceptance of crypto wallet acceptance.

In the fsQCA setting, there are "strong" hypotheses, such as those enunciated in Section 2.2, which are tested via correlational methods. Rather, "soft" propositions or laws are suggested [63], which are often labelled propositions or principles. However, this requires the use of theoretical reflections on the relationships between the variables, similar to those made during the development of Section 2.2. These principles do not identify factors associated positively or negatively with an outcome; instead, they outline the possible conditions relative to an input factor (the presence or absence of input variables) that must interact with the other variables to precede the desired outcome, which in our work is the presence or absence of acceptance of BBLPs [63].

Thus, we propose the following propositions regarding how the paths that lead to the acceptance and rejection of BBLPs are configured:

Proposition 1 (P1). *The paths leading to the intention to use BBLPs involve a combination of some of the following conditions: the presence of some of the UTAUT-baseline variables and the presence of some of the UTAUT-extended variables, as well as the presence or absence of some of the UTAUT-moderating variables.*

Proposition 2 (P2). *The paths leading to the no intention to use BBLPs involve a combination of some of the following conditions: the absence of some of the UTAUT-baseline variables and the absence of some of the UTAUT-extended variables, as well as the presence or absence of some of the UTAUT-moderating variables.*

Proposition 3 (P3). *The paths preceding the intention and no intention to use BBLPs are not symmetrical.*

Thus, while assessing P1 and P2 allows us to answer RQ1, evaluating P3 enables us to address RQ2.

3. Materials and Methods

3.1. Sampling

This study employs a structured, self-administered online survey, which was completed by individuals aged at least 18 residing in southern states of the United States (Alabama, Arkansas, Delaware, the District of Columbia, Florida, Georgia, Kentucky, Louisiana, Maryland, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, Virginia, and West Virginia) in the spring of 2024.

Invitations were sent to individuals from a customer panel managed by a leading research and data platform, resulting in an initial sample of 644 responses. After reviewing two attention checks and one check applied to filter out hastily completed responses, a final sample of 419 observations was ultimately used.

While the implementation of fsQCA does not require a specific sample size, we establish a minimum sample variable. Given that the fsQCA implementation protocol [75] employs methodologies typical of structural equation modelling in intermediate steps, we used criteria from regression analysis. With GPower 3.1 software [77], we established a minimum sample size of 336 observations, which provided a test power of 80% and the ability to detect small effect sizes (0.05) at conventional significance levels (5%). Therefore, the sample size used in our work meets this criterion.

3.2. Sample Profile

The profile of the respondents is detailed in Table 2. A total of 46.65% of the individuals reported being female, and 51.67% were male. Among the respondents, 59.32% were aged under 55 years. The highest levels of education reported were a high school diploma or equivalent (111, 26.56%), a college degree (118, 28.23%), and a bachelor's degree (109, 26.08%). Among the respondents, 148 (35.87%) reported an annual income of $75,000 or more. The majority of the ethnic groups reported were White or Caucasian (46.65%), followed by Latino (20.87%) and Asian or Pacific Islander (14.11%).

Table 2. Sample profile.

Variable	Number	Percentage
Gender		
Woman	195	46.65%
Man	216	51.67%
Other/non answered	7	1.67%
Age		
From 18 to 24 years	63	15.07%
From 25 to 34 years	98	23.44%
From 35 to 44 years	87	20.81%
From 44 to 54 years	83	19.86%

Table 2. *Cont.*

Variable	Number	Percentage
55 years or more	87	20.81%
Academic degree		
Less than high school	17	4.07%
High school	111	26.56%
College degree	118	28.23%
Bachelor's degree	109	26.08%
Professional degree	12	2.87%
Postgraduate	51	12.20%
Annual income		
Less than $25,000	73	17.46%
Between $25,000 and $49,999	107	25.60%
Between $50,000 and $74,999	91	21.77%
Between $75,000 and $99,999	45	10.77%
$100,000 and more	95	22.73%
No answered	7	1.67%
Racial or ethnic group		
White or Caucasian	195	46.65%
Latinx, Spanish or Latino	87	20.81%
Black/African American	23	5.50%
Asian/Pacific Islander	59	14.11%
Other/no answered	54	12.92%

3.3. Variable Measurement

With respect to the moderating variables in the UTAUT2 model, the variables gender and age are observed through the groups indicated in Table 2, which consists of 3 in the former case and 5 in the latter.

For the experience variable, we constructed a scale with two items, as indicated in Table 3. The items INT, PER, EFF, SOC, and FAC, which are part of the basic UTAUT model, were constructed on the basis of the proposals in [18]. The items for HED, TRI, and INN were derived from those proposed in [19]. Finally, the trust scale is based on the scale by Morgan and Hunt [78]. All these latent variables are considered reflective types. The items from all these scales are presented in Table 3.

Table 3. Scales used in this paper.

Intention to use (INT)
INT1: Assuming my favourite brand has a blockchain-based loyalty programme, I would sign up for it
INT2: Assuming my favourite brand has a blockchain-based loyalty programme, I would use it regularly
Experience (EXP)
EXP1: I often use conventional loyalty programmes
EXP2: I often use blockchain-based loyalty programmes
Performance expectancy (PER)
PER1: A blockchain-based loyalty programme will be useful for me
PER2: Blockchain will provide me with more control over my interactions
PER3: Blockchain will provide more options to take advantage of the loyalty program
Effort expectancy (EFF)
EFF1: It will be easy for me to learn how to use rewards and tokens in a blockchain-based loyalty programme
EFF2: I will find blockchain easy to use
Social influence (SOC)
SOC1: The people who are important to me will think that I should use my brands' blockchain-based loyalty programmes
SOC2: People whose opinions I value would like me to use my brands' blockchain-based loyalty programmes

Table 3. *Cont.*

Facilitating conditions (FAC)
FAC1: I have the necessary knowledge to use a blockchain-based loyalty programmes
FAC2: A blockchain-based loyalty programme is compatible with other technologies I use
FAC3: The ease of use of the interface will increase my intention to use the blockchain-based loyalty programme
FAC4: Availability of tutorials and support material will increase my intention to use the blockchain-based loyalty programme
Hedonic motivation (HED)
HED1: I would enjoy being a member of a blockchain-based loyalty programme
HED2: The blockchain-based loyalty programme would give me pleasure when I exchange tokens
HED3: I feel like belonging to a blockchain-based loyalty programme makes me special compared to other customers
Price-value (PRI)
PRI1: It would be beneficial for me to become a member of a blockchain-based loyalty programme
PRI2: A blockchain-based loyalty programme would give me economic advantages
PRI3: A blockchain-based loyalty programme would offer me additional value for my money
Innovativeness (INN)
INN1: When I hear about a new innovative product or service aligned with my needs, I try to test it as soon as I can
INN2: Among my friends or family, I am usually the first to try out new innovative products and services
Trust (TRU)
TRU1: I am confident that the blockchain-based loyalty programme system will make the correct decisions
TRU2: I believe that the blockchain-based loyalty programmes are designed with user needs in mind.
TRU3: I trust the security of the blockchain-based loyalty programme

All questions related to the measurement of latent variables were answered via an 11-point Likert scale ranging from 0 (‘strongly disagree’) to 10 (‘strongly agree’), with a neutral position corresponding to a score of 5.

3.4. Data Analysis

The application of fsQCA is carried out following the protocol in [75] for its application with latent variables observed from scales. Thus, we differentiate between two distinct analyses. First, an assessment of the internal consistency of the scales and their discriminant validity is conducted. Second, the explanatory solutions for intention and no intention to use are determined.

The first analysis is performed using SmartPLS 4.0, and the steps followed are as follows:

Step 1: Evaluate the reliability of the construct scales (i.e., all variables except gender and age) by analysing internal consistency, convergent validity, and discriminant validity. Internal consistency is measured via Cronbach’s alpha (CA) and compounded reliability (CR). Convergent validity is assessed with the average variance extracted (AVE) and factor loadings [79].

Step 2: The latent variables are quantified through standardised factor loading. The variable gender is defined as a variable taking a value of 0 for females, 1 for males, and 0.5 in other cases. The age variable is defined by scaling the intervals shown in Table 2 on a [0,1] continuum, increasing progressively. Thus:

$$AGE = \begin{cases} 1 \text{ for ages } 55+ \text{ years} \\ 0.8 \text{ for ages between 45–54 years} \\ 0.5 \text{ for ages between 35–44 years} \\ 0.2 \text{ for ages between 25–34 years} \\ 0 \text{ for ages between 18–24 years} \end{cases}$$

Step 3: The discriminant validity of the factors is evaluated via the Fornell–Larcker criterion [79].

Step 4: The analysis of correlations between intention to use and the explanatory factors allows for the assessment of the hypotheses made regarding the sign of the correlation between the variables.

Subsequently, we determine the solutions known as parsimonious and intermediate for intention and no intention to use employing the fsQCA 3.1 software [80]. This is done by implementing the following steps:

Step 1: We calibrate the membership functions of the explanatory variables and the outcomes. In the case of gender and age, the membership function is simply their value considered in Step 2 of the previous analysis.

To determine the membership functions for the latent variables, we consider the standardised factor loadings used in the analysis of convergent validity and discriminant capacity as the baseline measurement. This approach was used in [27,29]. To adjust the membership functions, we define total membership as the 90th percentile of the factor loading, nonmembership as the 10th percentile, and the crossover point as the 50th percentile. The membership levels for intermediate factor loadings are determined via linear interpolation.

Step 2: An analysis is conducted on the necessary condition status of the presence and absence of the explanatory factors in both the acceptance of the BBLPs (INT) and their rejection, which corresponds to the negation of the outcome intention to use (¬INT).

Step 3: We obtain the prime implicates (also known as paths, recipes or configurations) that contain the intermediate and parsimonious solutions for INT and ¬INT. These prime implicates can be interpreted as the profiles or paths associated with the acceptance and rejection of the BBLPs.

Step 4: We present the intermediate solution, which contains the parsimonious solution. Within the configurations of the intermediate solution, we differentiate between core conditions, which are present in both the prime implicates of the intermediate solution and those of the parsimonious solution, and peripheral conditions, which are present only in the configuration shown in the intermediate condition. The former can be considered strong causes, whereas the latter can be viewed as weak causes [20]. Importantly, obtaining the prime implications of the intermediate solution requires formulating hypotheses regarding the presence or absence of the explanatory factors in the recipes for INT and ¬INT, which are based on hypotheses regarding the sign of the relationship between the input variables and INT developed in Section 2.2.

Step 5: To evaluate the explanatory power of a recipe, its consistency and coverage are used. While consistency measures the significance of a particular configuration, coverage indicates empirical relevance [28], which could be likened to effect size in statistical analyses.

4. Results

4.1. Results of the Statistical Analysis

The results presented in Table 4 allow us to infer, first, that the average valuation of the sample regarding the BBLPs is slightly above 5, indicating a valuation that is marginally higher than the neutral value.

Table 4. Descriptive statistics of the latent variables used in this paper.

	Mean	DE	Factor Loading	CA	CR	AVE
Intention to use (INT)				0.898	0.952	0.908
INT1	5.62	3.19	0.95			
INT2	5.75	3.05	0.95			
Experience (EXP)				0.678	0.861	0.756
EXP1	3.92	3.07	0.85			
EXP2	1.90	2.81	0.89			

Table 4. *Cont.*

	Mean	DE	Factor Loading	CA	CR	AVE
Performance Expectancy (PER)				0.946	0.965	0.902
PER1	5.84	2.90	0.95			
PER2	5.91	2.88	0.95			
PER3	6.02	2.86	0.95			
Effort Expectancy (EFF)				0.907	0.956	0.915
EFF1	5.93	2.71	0.96			
EFF2	5.87	2.84	0.96			
Social Influence (SOC)				0.931	0.967	0.935
SOC1	4.79	2.99	0.96			
SOC2	4.81	2.89	0.97			
Facilitating Conditions (FAC)				0.913	0.939	0.795
FAC1	5.13	3.02	0.82			
FAC2	5.64	2.76	0.92			
FAC3	5.78	2.76	0.93			
FAC4	6.06	2.82	0.89			
Hedonism (HED)				0.928	0.954	0.874
HED1	5.82	2.85	0.95			
HED2	5.72	2.88	0.95			
HED3	5.21	2.90	0.91			
Price-value (PRI)				0.942	0.963	0.896
PRI1	5.79	2.86	0.95			
PRI2	5.75	2.79	0.94			
PRI3	5.88	2.75	0.95			
Innovativeness (INN)				0.889	0.947	0.899
INN1	5.53	2.84	0.96			
INN2	5.23	3.00	0.94			
Trust (TRU)				0.939	0.961	0.892
TRU1	5.65	2.87	0.95			
TRU2	5.77	2.79	0.94			
TRU3	5.53	2.91	0.94			

Table 4 also shows that all the factors demonstrate internal consistency. With the exception of EXP, all the factors have CA and CR values greater than 0.7. In the case of EXP, CA = 0.678; however, CR = 0.861, allowing us to assume that EXP does not have significant issues regarding its internal consistency. Furthermore, all scales exhibit convergent validity, as the AVE is greater than 0.5 and the factor loadings exceed 0.7. Therefore, we can conclude that all scales are valid, including the experience scale.

Table 5 shows that according to the Fornell–Larcker criterion, the variables possess discriminant validity. The square root of the AVE for all factors is greater than their correlation with other variables.

Note that the correlations of the UTAUT-baseline and UTAUT-extended variables with INT are positive, with $p < 0.001$. Thus, the hypotheses regarding the positive relationship between these variables and INT, developed in Section 2.2 (H1–H8), are supported by the correlations observed in our sample.

Table 5. Matrix for assessing the discriminant validity of the constructs.

	INT	GENDER	AGE	EXP	PER	EFF	SOC	FAC	HED	TRI	INN	TRU
INT	0.95											
GENDER	0.08	1										
AGE	−0.02	0.09	1									
EXP	0.39	0.08	−0.14	0.87								
PER	0.82	0.1	−0.07	0.38	0.95							
EFF	0.73	0.05	−0.11	0.34	0.82	0.96						
SOC	0.63	0.1	−0.2	0.39	0.7	0.65	0.97					
FAC	0.75	0.11	−0.12	0.37	0.82	0.8	0.72	0.89				
HED	0.76	0.05	−0.16	0.4	0.85	0.81	0.77	0.85	0.93			
PRI	0.76	0.08	−0.13	0.34	0.85	0.8	0.76	0.85	0.89	0.95		
INN	0.5	0.14	−0.25	0.35	0.6	0.57	0.62	0.65	0.63	0.64	0.95	
TRU	0.72	0.1	−0.17	0.35	0.83	0.77	0.78	0.83	0.85	0.85	0.64	0.94

Note: The principal diagonal shows the squared AVEs. Under the principal diagonal are the correlations between the factors.

4.2. Results of Configurational Analysis

Table 6 displays the factor loading values of the latent variables that have been used in constructing the membership functions. The variables for age and gender have already been defined in the data analysis section.

Table 6. Values of factor loadings used to construct the membership functions of latent variables.

Percentile	INT	EXP	PER	EFF	SOC	FAC	HED	PRI	INN	TRU
10th	−1.576	−1.102	−1.600	−1.298	−1.692	−1.531	−1.533	−1.565	−1.374	−1.480
50th	−0.061	−0.275	0.028	0.038	0.071	0.066	0.011	−0.048	0.001	0.006
90th	1.453	1.61	1.369	1.353	1.359	1.291	1.279	1.215	1.39	1.363

Table 7 presents the results of the necessary condition analysis for the factors examined. The consistency of the presence of PER, EFF, SOC, FAC, HED, TRI, INN, and TRU is substantially greater in explaining INT (ranging from 0.790 for HED to 0.889 for PER) than in explaining ¬INT (ranging from 0.477 for HED and TRI to 0.515 for SOC). Similarly, the absence of these latent variables shows greater consistency in explaining INT than in explaining ¬INT. This finding aligns with the fact that the correlation of these factors with INT is positive.

Table 7 also indicates that the presence of EXP is more consistently a necessary condition for explaining INT (consistency = 0.764) than for ¬INT (consistency = 0.528), whereas its absence is more consistent in explaining ¬INT (consistency = 0.681) than INT (consistency = 0.580). With respect to GENDER, its absence shows greater consistency than its presence as a necessary condition for both INT and ¬INT. Finally, AGE and ¬AGE exhibit similar consistency as conditions for intention and no intention to use. In any case, neither the presence nor the absence of any explanatory factor reaches the status of a necessary condition, as the consistency observed, both as antecedents of INT and ¬INT, never reaches 0.9.

Figure 2 presents the intermediate solution for the intention to use. Both coverage (0.802) and consistency (0.824) are satisfactory, and it consists of eight configurations. In five of these configurations, the presence of at least one of the UTAUT-baseline variables—PER, EFF, and SOC—emerges as a core condition. Among the UTAUT-extended variables, INN is a core condition in two of the recipes, while TRU appears as a core condition in five. The remaining variables (FAC, HED, and PRI), despite not being core conditions, serve as peripheral conditions in various recipes.

Table 7. Necessity analysis.

	IU		~IU	
	Consistency	**Coverage**	**Consistency**	**Coverage**
AGE	0.554	0.549	0.446	0.498
GENDER	0.649	0.750	0.593	0.777
EXP	0.764	0.681	0.528	0.529
PER	0.889	0.883	0.483	0.540
EFF	0.862	0.825	0.481	0.519
SOC	0.832	0.791	0.515	0.552
FAC	0.859	0.840	0.480	0.529
HED	0.860	0.857	0.477	0.535
PRI	0.853	0.878	0.477	0.553
INN	0.790	0.748	0.508	0.541
TRU	0.852	0.836	0.484	0.535
¬AGE	0.502	0.450	0.498	0.502
¬GENDER	0.726	0.526	0.656	0.534
¬EXP	0.580	0.579	0.681	0.763
¬PER	0.542	0.485	0.871	0.876
¬EFF	0.536	0.500	0.815	0.855
¬SOC	0.573	0.536	0.778	0.818
¬FAC	0.534	0.491	0.825	0.845
¬HED	0.537	0.479	0.840	0.844
¬PRI	0.538	0.461	0.858	0.829
¬INN	0.567	0.534	0.732	0.776
¬TRU	0.545	0.494	0.819	0.837

	1	2	3	4	5	6	7	8
GENDER	⨂		⊗		•	⊗		
AGE		⨂	⊗		•			
EXP	●	●		●	⨂		●	
PER				●	●	●	●	●
EFF			●		●	●	●	●
SOC				●		•	●	●
FAC					•	•	•	•
HED						•	•	•
PRI						•	•	•
INN				●	•			●
TRU				●	●	●	●	●
Coverage	0.303	0.419	0.214	0.488	0.180	0.289	0.486	0.572
Consistency	0.759	0.845	0.868	0.959	0.944	0.960	0.974	0.952

Note: (a) Circle • indicates the presence of a factor as a condition, circle ⊗ indicates the absence of a factor, and a blank indicates no relevance in the prime implication. (b) Large circles represent core conditions, and small circles represent peripheral conditions. (c) The coverage of the solution is 0.802, and the consistency is 0.824.

Figure 2. Intermediate solution for intention to use.

Notably, in seven of the eight configurations, UTAUT-moderating variables appear. In fact, two configurations consist solely of moderating variables: ¬AGE • EXP and ¬GENDER • EXP. Therefore, proposition P1 is supported by the results.

Figure 3 displays the intermediate solution for ¬INT. Its coverage (0.717) is slightly lower than the value for INT, whereas its consistency (0.894) is greater. This solution comprises nine recipes. In all the prime implicates the absence of at least one UTAUT-baseline variable manifests as a core condition. Additionally, in seven prime implicates (from the third to the ninth), the absence of at least two of the UTAUT-extended variables is a core condition. In eight of the nine recipes, at least two moderating variables are included, albeit as peripheral conditions, which aligns with proposition P2.

	1	2	3	4	5	6	7	8	9
GENDER	⨂	⨂	•			⨂	⨂	⊗	⊗
AGE	●	•	•	●		●		●	⊗
EXP	•	•	⨂	•		•	⨂		⨂
PER					⊗		⊗	⊗	⊗
EFF	⨂			⊗	⨂		⨂	⨂	
SOC			⨂		⨂	⨂	⨂	⨂	⨂
FAC		⨂		⨂	⨂	⨂	⨂	⨂	⨂
HED			⨂	⨂	⨂	⨂	⨂	⨂	⨂
PRI			⨂	⨂	⨂	⨂	⨂	⨂	⨂
INN		⊗			⊗			⊗	⊗
TRU					⊗	⊗	⊗	⊗	⊗
coverage	0.19	0.17	0.27	0.35	0.59	0.16	0.29	0.27	0.17
consistency	0.85	0.87	0.92	0.93	0.95	0.93	0.98	0.94	0.98

Note: (a) Circle • indicates the presence of a factor as a condition, circle ⊗ indicates the absence of a factor, and a blank indicates no relevance in the prime implication. (b) Large circles represent core conditions, and small circles represent peripheral conditions. (c) The coverage of the solution is 0.717, and the consistency is 0.894.

Figure 3. Intermediate solution for nonintention to use.

A comparison of Figures 2 and 3 demonstrates that the explanations for INT and ¬INT are far from symmetrical. This assertion includes, first, the number of configurations, which are eight for INT and nine for ¬INT. Furthermore, it is evident that none of the configurations for INT have a mirror opposite in ¬INT. For example, since we observed ¬AGE • EXP in INT, there should be a configuration such as AGE • ¬EXP for ¬INT, which does not occur.

Third, there are factors that serve as symmetrical conditions in both INT and ¬INT, such as EFF, which must be present as a core condition in five configurations of INT and negated as a core condition in four configurations of ¬INT. Conversely, other factors exhibit asymmetric participation in the configurations of acceptance and rejection. Thus, the presence of PER and TRU is a core condition in the five configurations of INT; however, their absence is not a core condition in the paths of ¬INT. Moreover, while the presence of FAC, HED, and PRI is not a core condition in the configurations of INT, their absence (¬FAC, ¬HED, and ¬PRI) is a core condition in seven prime implicates of ¬INT. Hence, P3 is supported.

5. Discussion

5.1. General Considerations

This study develops an explanatory model for the adoption of blockchain-based loyalty programmes (BBLPs) using the UTAUT2 model as a foundation and complexity theory implemented through fsQCA. The results of the preliminary correlation analysis between the four UTAUT-baseline variables and the four UTAUT-extended variables with the intention to use BBLPs supported the eight hypotheses regarding the sign of these correlations, which were developed in Section 2.2. The direction of these correlations was considered in the subsequent configurational analysis of the paths leading to the acceptance and rejection of BBLPs.

The configurations obtained to explain both the intention to use (INT) and the no intention to use (¬INT) present a high degree of consistency (>0.8) and adequate coverage (>0.7). The paths constituting the acceptance solution allow for the identification of different profiles associated with individuals willing to adopt BBLPs, while those associated with ¬INT are linked to those who tend to reject their use.

Regarding the first research question (RQ1), the paths explaining acceptance include the presence of various variables from both UTAUT-baseline and UTAUT-extended type, whereas those associated with rejection are characterised by the absence of these same variables. The configurations also incorporate UTAUT-moderating factors. However, for this type of variable, we cannot unequivocally state their direction in relation to the intention to use, given how they can be present or absent, depending on the configuration.

Concerning the second research question (RQ2), we have observed that the configurations preceding the acceptance and rejection of BBLPs are not symmetrical.

In terms of the UTAUT-baseline variables, the presence of performance expectancy (PER), effort expectancy (EFF), social influence (SOC), and facilitating conditions (FAC) is a condition in several of the main paths leading to INT, whereas their absence characterises the paths leading to ¬INT. A similar analysis can be made regarding the variables we refer to as UTAUT-extended: the presence of hedonic motivation (HED), perceived price value (PRI), innovativeness (INN), and trust (TRU) is a condition in the paths leading to the intention to use, whereas their absence is a condition in those leading to no intention.

The influence of PER, INN, and TRU with INT is more intense in the intention to use than in the no intention. The presence of these three variables is a core condition in various configurations of INT, while their absence is always peripheral in the configurations of ¬INT. The literature on blockchain applications strongly supports the positive relationship of these variables with acceptance. In the case of performance expectancy, this positive relationship has been reported in areas such as cryptocurrencies [36,38], supply chain management [47], academic applications [51], and travel-related industries such as aviation and tourism [60]. The significant relationship between innovativeness and the acceptance of blockchain applications has been documented in organisational management [55], the use of cryptocurrencies [38], and supply chain management [45,81]. Additionally, the positive relationship between trust and the intention to use has been reported in several blockchain applications [37,40,42,50,58].

On the other hand, the positive relationships of FAC, HED, and PRI with the intention to use are manifested primarily when their absence is a core condition in various configurations of ¬INT. The presence of these variables is also a condition, albeit peripheral, in some configurations of INT. In the case of FAC, this positive relationship with acceptance has been demonstrated in the application of blockchain technology in contexts such as cryptocurrency investment [36] or supply chain management [46,47]. The positive relationship of HED with the intention to use HED aligns with the findings within the cryptocurrency domain [38], in gamification blockchain applications [54,61], and in academic uses [52]. The relevance of the positive relationship between price value and the intention to use has been reported in the literature across various fields of blockchain technology applications [16,38,49,50].

The positive relationship of EFF and SOC with the intention to use is manifested both as a core condition of their presence in several paths towards INT and because their absence is a core condition in various configurations of ¬INT. The literature consistently shows that EFF is a relevant factor in explaining the acceptance of blockchain technology applications. This assertion applies to areas including cryptocurrency investment [36,40], supply chain management [47,50], finance and banking [58], educational applications [51], and internal organisational processes [57]. There is also a substantial amount of research reporting that social influence is a relevant variable in explaining the acceptance of blockchain technology applications [37,38,41,42,46].

The fact that, at times, the presence and, at other times, the absence of gender, age, and experience is a condition in seven of the eight configurations of INT and in eight of the nine configurations of ¬INT is consistent with [18,19]. These studies suggest that, within a correlational analytical framework, such variables should act as moderators of the impact of UTAUT-basic factors and UTAUT-extended variables on the intention to use BBLPs.

5.2. Theoretical and Practical Implications

From a theoretical standpoint, we have demonstrated that the application of a UTAUT2 model within the context of complexity theory provides a satisfactory explanation of the antecedents leading to the acceptance and rejection of blockchain in loyalty programmes. We established that the solutions obtained with fsQCA for both intention and no intention to use exhibited high coverage (above 0.7), and the configurations showed adequate consistency (above 0.8).

The fsQCA solution for intention to use allows for the visualisation of the various profiles presented by potential users of BBLPs, which tend to be quite heterogeneous. The paths in the solution for no intention to use can also be useful in identifying profiles of individuals likely to reject BBLPs, which are not symmetrical with those who are likely to accept them [23].

However, it should also be noted that these typologies do not appear in their pure form and may manifest as hybridised, both in terms of intention and no intention. With respect to INT, the eighth recipe of its solution, PER•EFF•SOC•FAC•HED•PRI •INN•TRU, could be associated with a socialiser, as social influence is a condition in the path; however, it could also be considered a practicalist, since the user perceives utility, usability, and reliability in the blockchain (PER•EFF•TRU). They could even be characterised as enthusiast potential users, as individuals in this profile perceive that the technology has numerous properties beyond performance expectancy, effort expectancy, and trust, such as pleasurable usage and good value for money (HED•PRI), and they tend to be users inclined to try new technologies (INN). In contrast, the configuration ¬GENDER•¬AGE•EFF corresponds to a pure practicalist who is male and young and essentially values the ease of use of the loyalty programmes provided by blockchain.

Unlike correlational methods, where the correlation coefficient allows for an estimation of the strength of the relationship between explanatory variables and the intention to use, in fsQCA, that intensity is represented by the coverage of the prime implicates, whereas the strength refers to the combination of the conditions that comprise it. Therefore, correlational methods and fsQCA are not alternatives but rather complementary. Pearson correlations indicate that the variable most strongly linked to INT is performance expectancy (correlation 0.82), while the least strongly linked variable is hedonic motivation (correlation 0.5). The determination of the empirical relevance of the antecedent paths for the acceptance and rejection of BBLPs provides valuable additional information. Thus, the two antecedents with the greatest empirical relevance for explaining INT are PER•EFF•SOC•FAC•HED•PRI•INN•TRU (coverage = 0.573) and EXP•PER•SOC •INN•TRU (coverage = 0.488). In contrast, the antecedents with the highest empirical relevance for explaining rejection are ¬PER•¬EFF•¬SOC•¬FAC•¬HED•¬PRI•¬INN•¬TRU (coverage = 0.59) and ¬GENDER•¬EXP•¬EFF•¬SOC•¬FAC•¬HED•¬PRI•¬INN•¬TRU (coverage = 0.29).

The use of fsQCA allows capturing the asymmetry in the relationship between the acceptance of BBLPs and their explanatory factors, which correlational methods cannot detect. We observe that the explanatory configurations of ¬INT are not mirror opposites of those for INT. In fact, the two configurations with the highest coverage for INT and ¬INT are not symmetrical. Additionally, the participation of various variables as conditions in INT and ¬INT is also asymmetrical.

5.3. Limitations of the Study and Further Research

The study acknowledges its limitations. This research was conducted exclusively with participants from the southern region of the United States. Consequently, the results are geographically restricted. Moreover, it is important to highlight that the sample used aimed to diversify the respondents in terms of age, ethnic group, education level, and income level. The representativeness of the sample, which provides us with a general view of the pathways leading to the acceptance and rejection of BBLPs, also poses a limitation when attempting to extrapolate the results to specific industries or consumer groups, such as, for example, individuals whose professions require frequent air travel. In such cases, although the proposed methodology has proven useful for analysis, it would be desirable to use a sample restricted to the consumer group of interest, which is likely to exhibit significant sociodemographic homogeneity.

It is essential to recognise that cultural elements may play a crucial role in understanding the acceptance of information systems; therefore, a natural extension of this work would be the application of the presented model to other cultures [82]. In the context of cryptocurrencies, national cultural values related to collectivism or long-term orientation significantly influence their use [83]. Importantly, factors such as perceived utility or the emotions evoked by a loyalty programme depend on the cultural values of the region in which they are evaluated [84].

The implications of this research may not be universally applicable in the medium to long term. On the one hand, the current integration of blockchain technology has low adoption rates within organisations [82], suggesting that it is still in its early stages. Therefore, longitudinal studies would be valuable for gaining a deeper understanding of the factors that encourage its adoption [82]. Importantly, longitudinal analysis of blockchain adoption involves the notable challenges associated with this technology, such as high energy consumption, scalability, integration with legal frameworks, and governance and regulation [4].

The limitations of this study encourage future research to expand upon the findings presented. Studies on technology acceptance often depend on the cultural context in which they are conducted. Therefore, a natural extension of studies based on technology acceptance models such as UTAUT is to apply them to new cultural settings [19]. This extension could be undertaken in other regions of the United States, as its size and demographic composition make it a culturally heterogeneous country [85]. Naturally, it should also be carried out in countries on other continents with cultural, historical, and religious contexts that differ significantly from those of the United States.

It is also worth noting that the composition of the sample aimed to diversify age, ethnic group, and education level. Drawing conclusions for a homogeneous sociodemographic group of interest would require focusing observations on that particular group. Therefore, we believe that studies focused on specific consumer groups could be highly relevant to the industries involved.

As noted in the introduction, although blockchain technology has existed for over 15 years, its widespread use remains limited. Thus, it is expected that its adoption levels across various sectors—and specifically in the implementation of loyalty programmes—will evolve over time. The current stage of acceptance highlights the need for future longitudinal studies to assess the level of adoption and its explanatory factors at different stages of BBLP development, during which their adoption is expected to solidify.

6. Conclusions

This study examined perceptions within a stratified sample from southern U.S. states regarding the intention to use BBLPs. The analysis of the factors influencing the acceptance of BBLPs was based on the UTAUT2 framework [19].

The extension of UTAUT is highly suitable for analysing the adoption of BBLPs, assuming the analytical framework of complexity theory and applying fsQCA. The solutions obtained for both intention and no intention to use have coverage exceeding 0.7, and the paths associated with both outcomes show high consistency, typically approximately 0.9.

The fsQCA analysis reveals that, when explaining the intention to use, all variables are conditions in at least one configuration. However, in some cases (FAC, HED, and PRI), their presence serves exclusively as a peripheral condition. We identified eight explanatory paths for acceptance. Two of these include only conditions associated with UTAUT-moderating variables (¬GENDER•EXP and ¬AGE•EXP); one is composed of conditions linked to UTAUT-moderating factors and the presence of UTAUT-baseline variables AGE•¬GENDER•EFF); and another consists of conditions drawn from all UTAUT-baseline and UTAUT-extended factors, which must all be present. Finally, four configurations are made up of conditions that combine UTAUT-baseline and UTAUT-extended factors, which must always be present alongside UTAUT-moderating variables.

Similar considerations can be made regarding no intention, as despite the absence of all UTAUT-baseline and UTAUT-extended variables participating as conditions in recipes, performance expectancy, innovativeness, and trust only do so as peripheral conditions. Specifically, we observed nine paths leading to the no acceptance of BBLPs. All of these require the absence of at least one UTAUT-baseline variable as a condition. For example, one pathway combines UTAUT-moderating variables and UTAUT-baseline variables (¬GENDER•AGE•EXP•¬EFF), while another involves the absence of all UTAUT-baseline and UTAUT-extended variables. In seven pathways, the absence of various UTAUT-baseline and UTAUT-extended variables is combined with UTAUT-moderating variables, which may either be present or absent.

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