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Assessing acceptance of blockchain-based loyalty programs using correlational and configurational methods and a cognitive–affective–normative framework

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Abstract

Purpose – Blockchain-based loyalty programs (BBLPs) offer several benefits over traditional loyalty programs (LPs), such as tokenization, adding value to noncash points and real-time reward redemption. However, successful adoption of BBLPs relies on the acceptance of potential users. This study aimed to assess BBLP acceptance by surveying 661 participants from the Western United States.

Design/methodology/approach – The analysis employed partial least squares structural equation modeling (PLS-SEM) and fuzzy set qualitative comparative analysis (fsQCA) using the cognitive-affective-normative (CAN) model for technology acceptance.

Findings – The results of PLS-SEM showed that perceived usefulness (PU) has the greatest impact on BBLP acceptance, followed by perceived ease of use (PEoU) and affective variables, albeit with smaller effect sizes. The use of fsQCA allows for the identification of various configurations that explain acceptance and rejection. Acceptance is most commonly associated with the presence of PU, PEoU, positive emotions (PEM) and the absence of negative emotions (NEM). In contrast, rejection is primarily explained by the absence of PU alongside the absence of PEoU, trust (TR), social influence (SI) and the presence of NEM.

Research limitations/implications – From a methodological perspective, it has been demonstrated that the sequential use of correlational and configurational methods can be useful for understanding how behavioral intention toward a new technology is formed. This study shows that the combined use of PLS-SEM and fsQCA provides a deeper explanation of BBLP acceptance than using a single analytical tool.

Practical implications – The configurations obtained with fsQCA allow the visualization of different profiles of potential BBLP users, facilitating the design of various market penetration strategies based on the user profile the seller seeks to reach and/or the type of technology they intend to commercialize.

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Originality/value – While studies on the acceptance of cryptocurrencies are abundant, research on the acceptance of blockchain in other areas, such as marketing, is scarce, and its application in the implementation of LPs is nonexistent. This study pioneered the analysis of the acceptance of BBLPs. The complementary use of fsQCA alongside regression findings allows for more insightful conclusions than those obtained using PLS-SEM alone.

Keywords Behavior, Consumer behavior, Digital systems, ICT, Management information systems

Paper type Research article

1. Introduction

Loyalty programs (LPs) are marketing tools used by firms to incentivize customer loyalty. The fundamental objective of LPs is to create, maintain and strengthen the relationships between brands and their customers (Chen *et al.*, 2021). LPs reward customers for their repeated loyalty, and often offer points, discounts or other incentives that can be redeemed for future purchases or special benefits (Breugelmans *et al.*, 2015). In addition, some LPs have tiered levels, allowing customers to reach higher levels of benefit as they spend more time or participate more frequently (Belli *et al.*, 2022). These programs also often include personalized, exclusive offers or early access to sales to keep customers engaged and encourage them to return (Septianto *et al.*, 2019). LPs collect valuable data on customer preferences and behaviors to help companies personalize their marketing efforts and improve customer retention (Chen *et al.*, 2021).

Blockchain has gained increased visibility in the past few years. As the world heads toward a new era in which information and communications technologies are driving Industry 4.0, organizations are paying increased attention to the significant potential to transform businesses in multiple ways (Ghosal *et al.*, 2024). Therefore, blockchain applications go far beyond cryptocurrencies. We can mention improving the traceability of products in a supply chain (Ma *et al.*, 2024), integrating quality trust in the supply of products to consumers (Jiang *et al.*, 2024) and helping with strategic financial decision-making (Wang *et al.*, 2023).

The use of blockchain can be particularly beneficial for small firms that enhance their productivity. By adopting blockchain, businesses can address inefficiencies in supply chain management, enhance data security and foster trust among stakeholders (Jain *et al.*, 2024; Ran *et al.*, 2024). Similarly, the decentralization of blockchain and its low operating costs can benefit small businesses in obtaining financing, as they often face various barriers to accessing credit through traditional banking and credit markets (Kumar *et al.*, 2023). The applications in healthcare also have enormous potential. These include the secure management of medical records, clinical trials and pharmaceutical supply chains. Blockchain also facilitates patient consent management and decentralized data governance. With advanced architectures such as lightweight blockchain and cloud-based hybrid systems, this technology enhances operational efficiency, reduces fraud and strengthens trust in healthcare systems, promoting safer patient care (Dandotiya and Ghosal, 2024; Dandotiya *et al.*, 2025).

This study focuses on the application of blockchain technology in marketing. It can be summarized into four points: new forms of interaction between consumers and companies, new types of data that allow advanced analytical methods, the creation of marketing innovations, and the need to develop new strategic frameworks in the field of marketing (Hoffman *et al.*, 2022). Within these areas, our study focused on the promising use of blockchain in power LPs (Rejeb *et al.*, 2020). Specifically, we refer to blockchain-based loyalty programs (BBLPs).

BBLPs differ from conventional LPs in several respects. First, blockchain technology offers advantages such as greater transparency, decentralization and distribution, which can solve credibility issues and the lack of interoperability between platforms present in traditional LPs (Shaikh *et al.*, 2023). Additionally, BBLPs allow innovative services similar to a shared economy, facilitating customers to accumulate, use, transfer and benefit more flexibly (Treiblmaier and Petrozhitskaya, 2023). If the BBLPs of two brands, A and B, share the same platform, a consumer of products from both brands will be able to use the rewards earned from one brand to benefit from, for example, discounts on the other. They may even transfer the accumulated rewards to third parties as if they were financial assets such as bonds or stocks.

Consequently, BBLPs provide a potentially more efficient, transparent and user-friendly approach to improving customer loyalty and engagement than traditional programs (Wu *et al.*, 2022). Blockchain technology enables the development of new types of LPs that are difficult to execute using traditional systems. For example, customers can earn rewards not only by making purchases but also by engaging in community activities, contributing content or sharing their experiences on social media. Additionally, by tokenizing these rewards, they become more flexible, attractive and better adapted to the diverse motivations of LP participants (Treiblmaier and Petrozhitskaya, 2023). For example, rewards often include cryptocurrencies (Abooleet and Kinnett, 2023), but they can also consist of personalized works of art, such as non-fungible tokens (Fortagne and Lis, 2024), or participation in challenges that add value to the brand by gamifying the LP (Arias-Oliva *et al.*, 2024). Likewise, the use of smart contracts makes the execution of rights acquired through an LP more transparent and effective (Alqarni, 2024).

The issues raised in the previous paragraphs motivate this study, which aims to expand the literature on the factors influencing consumer acceptance of BBLPs. In emerging technologies that are not widely used, such as blockchain, it is important to understand the reasons for their acceptance or rejection (Perdana *et al.*, 2021). There is a wide range of literature on the factors affecting blockchain application acceptance in the fields of cryptocurrencies (Bommer *et al.*, 2023) and supply chain management (AlShamsi *et al.*, 2022). However, in other areas of business management and marketing, analyses are scarce (AlShamsi *et al.*, 2022).

Analyzing the acceptance of a new technology requires a theoretical framework that provides a solid foundation for comprehensively explaining its adoption. For blockchain applications, Taherdoost (2022) identified the Technology Acceptance Model (TAM) by Davis (1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh *et al.* (2003) as the most commonly used conceptual frameworks. The mainstream contributions to blockchain application acceptance emphasize are placed on instrumental variables typical of TAM and UTAUT, such as perceived usefulness (PU), ease of use and factors linked to social influence (SI) (e.g. Knauer and Mann, 2019). Additionally, the potential significance of perceived trust as a key variable is often highlighted (Albayati *et al.*, 2020; Gan and Lau, 2024).

The approach adopted in this study is based on the cognitive–affective–normative (CAN) framework by Reinares-Lara *et al.* (2016) and Pelegrín-Borondo *et al.* (2016). These factors include two explanatory cognitive baseline variables of TAM: PU and perceived ease of use (PEoU), with the addition of trust (TR) and a normative component, subjective norms (SN). These variables are common to theoretical frameworks such as the TAM and UTAUT. The distinguishing feature of CAN, which has not yet been applied to blockchain acceptance, is its incorporation of emotional variables into the analysis. Following Pelegrín-Borondo *et al.* (2016), CAN differentiates between positive and negative emotions (NEM). This is particularly relevant to the proposed blockchain application, as engagement with LPs depends not only on instrumental factors but also on emotional ones (Septianto *et al.*, 2019). The research objectives (RO) were as follows:

- *RO1.* Measure the average impact of each explanatory variable on intention to use (IU) BBLPs. This variable-oriented assessment was developed with the help of partial least squares structural equation modeling (PLS-SEM).

- *RO2.* Determine how the factors of the CAN model combine in the analyzed sample to produce adoption and resistance to BBLPs. The approach of this second research objective was case oriented. Fuzzy set qualitative comparative analysis (fsQCA) is an appropriate instrument for this purpose and is commonly used in knowledge management studies (Woodside, 2014).

2. Theoretical groundwork

2.1 General considerations

This study used the CAN framework proposed by Reinares-Lara *et al.* (2016) and Pelegrín-Borondo *et al.* (2016). The formulation shown in Figure 1 models cognitive and normative variables based on TAM (Davis, 1989) and its extensions, such as TAM2 (Venkatesh and Davis, 2000) as well as UTAUT (Venkatesh *et al.*, 2003). While TAM and UTAUT, in their basic formulations, are essentially focused on instrumental explanatory constructs, the CAN model acknowledges that affective variables can also be relevant in explaining the acceptance of new information systems (Reinares-Lara *et al.*, 2016). In this study, these emotional factors were measured using the conceptual framework of Mohammad and Turney (2013), which was used in the sentiment analysis of LPs by Treiblmaier and Petrozhitskaya (2023).

The measures of the CAN model include, within the cognitive factors, efficiency concepts associated with TAM and UTAUT, such as PU (or performance expectancy in UTAUT modeling) and PEoU (or effort expectancy in UTAUT modeling). Additionally, among the cognitive variables, this study included trust, as it is a key factor in blockchain-powered relationships (Albayati *et al.*, 2020). In the blockchain context, trust is divided into algorithmic trust in the blockchain protocol, trust toward peers and service providers, and trust in decentralized applications (Gan and Lau, 2024). This second aspect is particularly relevant because the trustee is no longer a clearly defined central authority. Instead, it is dispersed among a set of blockchain community participants, such as miners or algorithmic authorities (Teng, 2021).

The CAN model also recognizes the relevance of subjective norms to users' perceptions of a new technology. To explain how users perceive a particular technology, it must be compatible with the beliefs and norms of the group or the social groups to which they belong (Venkatesh and Davis, 2000; Venkatesh *et al.*, 2003). In this study, the normative variable is SI.

The main contribution of CAN compared with TAM and UTAUT lies in its emphasis on the emotional-affective dimension in shaping perceptions and the adoption of information systems. Emotions significantly influence human decision-making and judgment (Lerner *et al.*, 2015) as well as the adoption of blockchain applications (Perdana *et al.*, 2021). In the context of analyzing the acceptance of blockchain for configuring LPs, the emotional aspect encompasses both the technological component and rewards and incentives associated with any LP.

Positive emotions (PEM), like satisfaction and joy, can foster the LP engagement rate (Septianto *et al.*, 2019). Conversely, NEM stemming from service failures or unmet expectations may discourage customers from enrolling in programs that fail to meet their needs (Nguyen *et al.*, 2022).

From a technological perspective, feelings of enjoyment and satisfaction in using the system positively influence a user's intention to engage in activities that require its use (Subero-Navarro *et al.*, 2022). However, technology can also have a detrimental impact, as

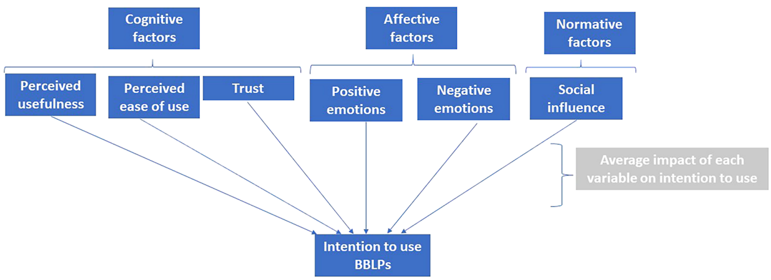

Figure 1. Proposed cognitive-affective-normative model. Source: Authors' own work

difficulties, frustrations or phobias associated with its use may negatively affect psychological wellbeing (Di Giacomo *et al.*, 2020).

The outcome explored in this study is behavioral intention, defined as an individual's willingness to perform a certain behavior (Ajzen, 2002). Here, we refer to the IU BBLPs. This outcome is considered in the UTAUT model and its extensions, such as UTAUT2 and CAN as precursors to the effective use of technology (Venkatesh *et al.*, 2003, 2012; Pelegrín-Borondo *et al.*, 2016). Moreover, IU can be evaluated under consistent conditions across individuals, which is not the case with its effective use (Andrés-Sánchez *et al.*, 2024).

Figure 1 shows the approach we followed to justify the acceptance model of the BBLPs. Its development will lead to the proposal of a hypothesis for each path that can be tested using a regression technique. This analysis allows us to fulfil RO1, as it poses a variable-oriented research question. However, this does not allow for the implementation of RO2, which inquires into the different configurations of explanatory factors that precede the acceptance and rejection of BBLPs. For this second objective, we used the theoretical framework shown in Figure 1, on which we applied fsQCA.

2.2 Model development

2.2.1 Cognitive variables. The first cognitive construct considered is PU, defined by Davis (1989) as "the extent to which an individual believes that the use of a specific system would enhance their performance." In our context, we refer to the differential utility of participating in a BBLP compared with a conventional program.

BBLPs offer several advantages over traditional programs in terms of their usefulness. First, they provide innovative services to customers through shared economic properties, offering advantages in use, accumulation, relevance, expiration and transferability (Treiblmaier and Petrozhitskaya, 2023). Moreover, blockchain permits the establishment of decentralized point partnerships, avoiding data transmission constraints between LP systems (Santos *et al.*, 2023).

PU was the most relevant variable for the evaluated blockchain-based applications (Table 1). Thus, we propose the following:

H1. PU has a positive link with IU BBLPs.

A widely acknowledged definition of PEoU is "the extent to which an individual believes that using a particular system would require minimal effort" (Davis, 1989). In the context of BBLPs, we refer to the increased (or diminution) of usability of the LP attributable to the fact that its operation relies on blockchain.

The importance of PEoU, perceived usability, and system quality in shaping the user adoption of blockchain-based systems has been widely highlighted (Norbu *et al.*, 2024). When individuals recognize an adequate degree of technological infrastructure, organizational frameworks, interconnected systems and personal assistance in the context of blockchain utilization, their inclination to adopt and interact with the technology increases significantly (Alazab *et al.*, 2021).

The literature reviewed in Table 1 confirms that PEoU is a key variable in explaining the approval of applications powered by blockchain. Therefore, we propose:

H2. PEoU has a positive link with IU BBLPs.

Trust (TR) can be conceptualized as a multidimensional factor that embeds issues such as privacy, transparency, regulatory rules and security (Norbu *et al.*, 2024). In this study, this construct refers to the influence of blockchain technology on the incremental perception of trust generated by a LP.

The principal traits of this technology, such as decentralization, inherent inability to alter records and transparency, foster significant opportunities for enhancing the safeguarding of transactions and the protection of sensitive information. The transparent and auditable nature

Table 1. Findings from the literature about the influence of cognitive variables (perceived usefulness, perceived ease of use and trust) and normative variables (trust) on acceptance of blockchain applications

	Setting
Papers supporting that perceived usefulness (or performance expectancy) positively influences the acceptance of BBLPs	
Arias-Oliva *et al.* (2019), Almuraqab (2020), Albayati *et al.* (2020), Gil-Cordero *et al.* (2020), Jegerson *et al.* (2023)	Cryptocurrencies
Kamble *et al.* (2019), Alazab *et al.* (2021), Sharma *et al.* (2023)	Supply chain
Shrestha and Vassileva (2019), Gao and Li (2021), Chawla *et al.* (2024)	Academic applications
Singh *et al.* (2019), Lian *et al.* (2020), Bandinelli *et al.* (2023), Chen (2023)	Processes of organizations
Gan and Lau (2024), Gil-Cordero *et al.* (2024)	Financial and accounting applications
Knauer and Mann (2019), Nuryyev *et al.* (2020), Li *et al.* (2021)	Miscelanea
Papers supporting that PEoU (or effort expectancy) positively influences acceptance of BBLPs	
Almuraqab (2020), Albayati *et al.* (2020), Gil-Cordero *et al.* (2020)	Cryptocurrencies
Kamble *et al.* (2019), Alazab *et al.* (2021), Sharma *et al.* (2023)	Supply chain
Shrestha and Vassileva (2019), Gao and Li (2021), Chawla *et al.* (2024)	Academic applications
Singh *et al.* (2019), Lian *et al.* (2020), Bandinelli *et al.* (2023), Chen (2023)	Internal processes of organizations
Afifa *et al.* (2023), Gan and Lau (2024)	Financial and accounting applications
Knauer and Mann (2019), Nuryyev *et al.* (2020), Li *et al.* (2021)	Miscellanea
Papers supporting that trust positively influences acceptance of BBLPs	
Almuraqab (2020), Albayati *et al.* (2020), Gil-Cordero *et al.* (2020)	Cryptocurrencies
Kamble *et al.* (2019), Wamba *et al.* (2020), Wong *et al.* (2020), Alazab *et al.* (2021), Sharma *et al.* (2023)	Supply chain
Gao and Li (2021)	Academic applications
Bandinelli *et al.* (2023)	Processes of organizations
Afifa *et al.* (2023), Gan and Lau (2024), Gil-Cordero *et al.* (2024)	Financial and accounting applications
Nuryyev *et al.* (2020)	Miscelanea
Papers supporting that social influence (or subjective norm) positively influences the acceptance of BBLPs	
Almuraqab (2020), Albayati *et al.* (2020), Jegerson *et al.* (2023), Gil-Cordero *et al.* (2020, 2024)	Cryptocurrencies
Kamble *et al.* (2019), Wamba *et al.* (2020), Alazab *et al.* (2021), Sharma *et al.* (2023)	Supply chain
Gao and Li (2021)	Academic applications
Chen (2023)	Organizational applications
Afifa *et al.* (2023)	Financial and accounting applications
Nuryyev *et al.* (2020)	Miscelanea

Source(s): Authors' own work

of blockchain allows end-to-end visibility into processes supported by the blockchain. This enables customers and firms to verify the origin and authenticity of transactions (Jain *et al.*, 2024). These features can be key factors in fostering cognitive trust between users and customers (Dandotiya and Ghosal, 2024). On the other hand, blockchain technology may generate less relational trust compared to centralized systems. There are two reasons for this phenomenon: lack of a reliable central authority (Taherdoost, 2022) and absence of robust regulation by government authorities (Norbu *et al.*, 2024).

In blockchain applications, regulations essentially stem from computer codes. Desirable or undesirable behavior is not regulated ex-post by third parties, as is the case with legal regulations but is instead enforced *ex ante* with the help of technological tools. This eliminates the need for judicial arbitration and leaves no room for ambiguity (Ishmaev, 2020). However, the downside is that the criteria underpinning the evaluation of these behaviors may be opaque to an average user.

Nevertheless, rather than viewing this as a loss of trust, it may be more accurate to interpret the "absence of trust" enabled by blockchain. This is because of a shift in trust from centralized authorities to the technology itself and the individuals associated with it, such as developers and miners, or algorithmic authority (Teng, 2021).

Treiblmaier and Petrozhitskaya (2023) conducted sentiment analysis of the two LPs. The first was powered by a blockchain and the other was not. The study showed that the main judgment used by users to determine which is preferable is based on the feeling of trust. As indicated in Table 1, numerous studies have found that trust is a relevant variable in understanding the adoption of technologies powered by blockchain, including cryptocurrencies and educational applications. Therefore, we propose the following:

H3. TR is linked positively with IU BBLPs.

2.2.2 Affective factors. The consideration of emotions is not common in studies on the acceptance of blockchain technologies, likely because these studies often focus on applications with a utilitarian focus and limited emotional engagement, such as supply chain management (Jain *et al.*, 2024) or the security of health records for anonymous patients (Dandotiya *et al.*, 2025). However, the psychology and consumer research literature has established that emotion is a significant factor influencing judgment and decision-making (Lerner *et al.*, 2015).

In the case of LPs, emotions play a particularly important role. Positive feelings like pride or exclusivity can significantly enhance their effectiveness (Agarwal *et al.*, 2022). On the other hand, NEM such as frustration caused by system failures or unmet expectations can have counterproductive effects (Choi *et al.*, 2007). Therefore, this aspect receives special attention in the proposed model. Treiblmaier and Petrozhitskaya (2023) show that tweets judging two LPs argue for pleasant emotions, such as happiness, as well as unfavorable feelings, such as disappointment. Thus, following the CAN model, this study states two great sets of feelings as input factors: positive and negative feelings.

Customers consider the pursuit of PEM fundamental to their shopping experiences. They can be defined as feelings that stimulate a given action (Pelegrín-Borondo *et al.*, 2016), which, in our case, would be engaging with a LP if it relies on blockchain.

Companies are increasingly seeking opportunities to produce joy for their clients, and LPs are commonly employed to generate favorable emotions (Agarwal *et al.*, 2022). PEMs can increase the effectiveness and engagement of LPs by enhancing repurchase intentions, with pride showing the strongest impact on customer-ranking programs (Septianto *et al.*, 2019). LPs can be strategic tools to foster emotional commitment, which partially mediates the relationship between LP benefits and loyalty behaviors such as repeat purchases (Baloglu *et al.*, 2017).

On the other hand, several studies have confirmed the influence of pleasure in the decision to use technological products (Purwanto *et al.*, 2019). PEM are highly predictive of the intention to engage in activities supported by novel technologies (Subero-Navarro *et al.*, 2022). Thus, we propose the following:

H4. PEM has a positive link with IU BBLPs.

NEM can be defined as inhibitory feelings that prevent action (Pelegrín-Borondo *et al.*, 2016), which in our case is engaging with a LP powered by blockchain. LPs can fail due to rejection, reduction or postponement of rewards, which may lead to NEM, such as anger, regret and resignation (Choi *et al.*, 2007). As a result, LPs can generate NEM that significantly impact customer behavior and brand loyalty. Research shows that degradation within these programs intensifies NEM, which in turn increases customers' intentions to switch to competitors. This effect is moderated by factors such as an individual's internal locus of control and prior satisfaction with the company, suggesting that emotional responses are complex and context dependent (Hwang and Kwon, 2016). In general, while LPs aim to foster customer retention, they can unintentionally trigger NEM that undermine loyalty, underscoring the need for careful management of customer experience (Kurtoğlu *et al.*, 2021).

Furthermore, it is well known that in a significant group of consumers, an action on which there is no negative attitude can cause rejection if mediated by a novel technology. The literature has reported a negative influence on the behavioral intention of constructs, such as technostress or cyberphobia (Koul and Eydgahi, 2020). Thus, we propose:

H5. NEM has a negative link with IU BBLPs.

2.2.3 Social influence. SI can be defined as a person's perception that significant others think the evaluated technology should be used and that they themselves should adopt the new system (Venkatesh *et al.*, 2003). In our case, this refers to LPs powered by the blockchain. Literature underscores the importance of close persons' perspectives, like parents, siblings or peers, as relevant factors in a CAN model (Pelegrín-Borondo *et al.*, 2016).

Products and services that are in the initial phases of development, such as those utilizing blockchain, may need a strong flow of supportive feedback to gain acceptance, especially if they demand a certain level of technological understanding (Jegerson *et al.*, 2023). This explains why SI is relevant to consumer services mediated by internet platforms. SI stimulates users to interact with a platform or application for a sufficiently long period to gain proficiency, affecting loyalty to the evaluated technology (Albayati *et al.*, 2020). Furthermore, the use of blockchain technology in SI is hampered by a widespread lack of understanding of its possibilities (Treiblmaier and Petrozhitskaya, 2023).

Blockchain applications are regulated by code. Given the low barriers to entry and malleability of codes, these new regulatory regimes in the digital environment pave the way for regulation by private actors (Ishmaev, 2020). Although countries adopt comprehensive regulations regarding data privacy, they frequently do not have a solid implementation plan for blockchain, leading to concerns regarding data management, privacy, security and crypto regulation of cryptos (Norbu *et al.*, 2024). This may hinder the adoption of BBLP applications by individuals ideologically distant from liberalism.

These arguments explain why Table 1 presents several contributions, outlining the relevance of SI and subjective norms in the acceptance of blockchain applications.

H6. Favorable SI is positively linked with the IU BBLPs.

2.3 Configurational tennets about the adoption and resistance to BBLPs

Users' personal traits, such as openness, neuroticism and self-affectivity, significantly influence their judgment of information technologies (Barnett *et al.*, 2015). Thus, two persons with divergent temperaments can have the same opinion about a technology that is induced by different arguments. Among the users of a given technology, Birkland (2019) differentiates between practicalists, enthusiasts, traditionalists, socializers and guardians. Gauttier (2019) distinguishes four types of nonusers: resisters, expelled, excluded and rejecters.

Thus, the adoption of and resistance to BBLPs can be achieved through different paths that arise under various combinations of conditions. In the case of BBLP acceptance, the path associated with a practicalist is linked to conditions, such as usefulness and usability. By contrast, for a socializer, a necessary condition is likely to be social induction, for example, through word-of-mouth or electronic-word-of-mouth (Gil-Cordero *et al.*, 2024). In this context, the fsQCA is a powerful tool for evaluating the acceptance of new technologies, allowing us to capture nuances that correlational analysis cannot. It can capture a variety of paths in the sample, leading to the same response (Woodside, 2014).

Positive and negative attitudes toward technology are asymmetrical. While acceptability may not generate acceptance, unacceptability can stimulate resistance and nonacceptance of technology (Gauttier, 2019). The fsQCA is suitable for dealing with nonsymmetrical relationships between variables. However, this technique can be employed when relationships are symmetrical (Pappas and Woodside, 2021).

Thus, despite the use of fsQCA in the field of technology adoption studies not being as widespread as that of structural equation modeling, it is not extraordinary. It has been used to characterize the adoption of financial apps (Veríssimo, 2016) and health apps (Veríssimo, 2018). In the blockchain acceptance setting, Arias-Oliva *et al.* (2021) used fsQCA to analyze the acceptance of cryptocurrency investments, and Gil-Cordero *et al.* (2024) analyzed cryptocurrency wallet acceptance.

With fsQCA, strong hypotheses are not established, as typically formulated in correlational methods and justified in section 2.2. Instead, "soft laws" are proposed, often referred to as propositions or principles (Rutten and Rubinson, 2022). They are supported by the considerations made in the conceptual development of subsections 2.1 and 2.2. Furthermore, fsQCA does not refer to factors that are positively or negatively related to the outcomes. This focus refers to conditions (presence or absence of income) that combine with other conditions preceding the desired outcome (Rutten and Rubinson, 2022).

Therefore, we present the following propositions on how the paths toward adoption and resistance to BBLPs are structured, as illustrated in Figure 2.

P1. The configurations that precede the behavioral IU BBLPs include a mix of the following conditions: the presence of PU, PEoU, TR, PEM, and SI, and the absence of NEM.

P2. The configurations that precede behavioral non-IU BBLPs include a mix of the following conditions: absence of PU, PEoU, TR, PEM and SI, and presence of NEM.

P3. The configurations for favorable and unfavorable judgments regarding the IU BBLPs are not symmetrical.

3. Materials and analytical methods

3.1 Sample and sampling

This study employed a survey that was answered online and completed by persons aged 18+ years residing in the western states of the United States. We refer to Arkansas, Arizona, California, Colorado, Hawaii, Idaho, Montana, New Mexico, Nevada, Oregon, Utah, Washington and Wyoming. Invitations were sent in February 2024 to a consumer panel operated by a prominent data-investigation platform, and responses were collected at the end of March 2024. The sample had advanced stratification objectives according to sex and age.

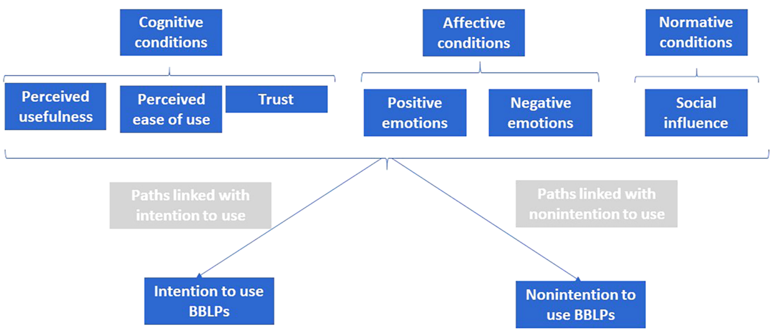

Figure 2. Configurational formulation of a CAN model to explain acceptance and rejection of BBLPs. Source: Authors' own work

The first criterion was to obtain at least 40% of the responses from both females and males. The second criterion was to secure at least 45% of the responses from Generation X members or baby boomers, as they often have higher income levels and, therefore, greater purchasing power. The data investigation platform maintains profiles of potential participants, allowing invitations to be sent in alignment with the stratification objectives.

The questionnaire was initially tested by two blockchain technology practitioners and three marketing specialists to ensure the proper formulation of the questions. It was also subjected to linguistic review. To ensure that the respondents provided well-considered answers, we included two attention-check questions and monitored their responses.

We obtained an initial sample of 1,016 respondents. After careful review and application of attention and time checks to avoid careless answers, the final sample of 661 responses was deemed valid. The sample size was considered adequate for the power of contrast in the regression presented in Figure 1. Using software GPower 3.1 (Faul *et al*., 2009), we verified that the rejection of the null hypothesis of significance for the overall model at a 5% level has a contrast power of 99% for very small effect sizes (0.05).

Respondents' profiles are listed in Table 2. This shows that 53% of the individuals were women and 46% were men. Among the respondents, 50.08% were aged 44 years or older. Therefore, a predefined objective regarding composition according to sex and age was met.

The majority of the participants had a high school diploma or equivalent (188, 28%) and a university degree (153, 23%). The majority reported ethnicity as White or Caucasian (386, 58%), followed by black or African American (11%). The majority of annual income levels were \$25,000 to \$49,999 (179, 27.08%), followed by less than \$25,000 (141, 21.33%) and \$50,000 to \$74,999 (132, 19.97%).

3.2 Variable measurement

The questionnaire began with an introductory text on the BBLPs. Participants were asked to provide sociodemographic information and questions about their perception of BBLPs. This is presented in the Appendix.

Table 3 presents only the items considered for measuring the variables embedded in Figure 1. The scales used to measure the dependent variables IU and PU, PEoU and SI are based on the TAM2 model (Venkatesh and Davis, 2000), which is commonly used in CAN modeling (Alesanco-Llorente *et al.*, 2023). The TR scale was developed for the items in Morgan and Hunt (1994). These scales were modelled as reflective.

The questions for PEM and NEM were taken from Mohammad and Turney (2013), considering the results of Treiblmaier and Petrozhitskaya (2023) in the context of LPs. It is important to note that to measure both PEM and NEM, the questions do not inquire about symptoms of a specific emotional state, but about feelings that are not necessarily linked. For example, a person may experience a sense of disappointment when observing that the LP does not meet their expectations but may not feel anger. Therefore, constructs related to emotions were considered formative.

The items were responded to using an eleven-point Likert scale that varied from ranging from 0 ("strongly disagree") to 10 ("strongly agree"). Detailed linguistic labels of the items are presented in Table 3.

3.3 Data analysis

RO1, inquiries about the relationship between CAN explanatory factors and acceptance require using a correlational method, making PLS-SEM an appropriate method. It does not require difficult requirements for data normality. Additionally, PLS-SEM allows for working with formative latent variables, as positive and NEM have been conceptualized (Hair *et al*., 2019). By contrast, RO2 inquired about the configurations observed in the sample of people who showed an IU BBLPs and those who rejected such LPs.

Table 2. Sample profile

Item	Responses
Sex	
Women	350 (52.95%)
Man	303 (45.84%)
Other/non answered	8 (1.21%)
Age	
Between 18 and 24 years	76 (11.50%)
Between 25 and 34 years	124 (18.76%)
Between 35 and 44 years	130 (19.67%)
Between 44 and 54 years	138 (20.88%)
More than 55+ years	193 (29.20%)
Academic degree	
Less than a high school	61 (9.23%)
High school	188 (28.44%)
College degree	188 (28.44%)
Bachelor's	153 (23.15%)
Professional	19 (2.87%)
Post-graduate	52 (7.87%)
Ethnicity	
White or Caucasian	386 (58.40%)
Latinx, Hispanic etc.	71 (10.74%)
Black/African American	95 (14.37%)
Asian/Oceanic	36 (5.45%)
Native (American, Native)	6 (0.91%)
Another ethnicity/mestizo	58 (8.77%)
Prefer not to answer	9 (1.36%)
Annual income	
Less than $25,000	141 (21.33%)
$25,000 to $49,999	179 (27.08%)
$50,000 to $74,999	132 (19.97%)
$75,000 to $99,999	83 (12.56%)
$100,000 or more	117 (17.70%)
Prefer not to answer	9 (1.36%)

Source(s): Authors' own work

PLS-SEM analysis was conducted using SmartPLS 4.0. This procedure was performed according to the protocol proposed by Hair *et al*. (2019). We detailed the steps to estimate the model in Figure 1 using PLS-SEM.

Step 1: Evaluate the reliability of the reflective construct scales by analyzing their internal consistency with Cronbach's alpha (CA), composite reliability (CR) and convergent validity with the average variance extracted (AVE) and factor loadings. Discriminant validity was examined using the Fornell-Larcker criterion and by assessing Pearson's correlations between the factor scores (Cheung *et al*., 2023). Additionally, collinearity in the outer model was assessed using variance inflation factors (VIF).

Step 2: Evaluate the viability of formative constructs with convergent validity (CV), absence of collinearity (VIF) and significance and relevance of the external loadings of the items constituting the formative constructs (Ramayah *et al*., 2018).

Step 3: Adjust the paths in Figure 1 using percentile bootstrap and 10,000 subsamples. Collinearity in the structural model was assessed by analyzing the VIF. Additionally,

Table 3. Descriptive statistics, factor loadings and VIF of the outer model

Item	Mean	SD	Factor loading	VIF
Intention to use (IU): reflective construct				
IU1: Assuming my favourite brand has a BBLP, I would enrol in it	5.310	3.188	0.958	3.289
IU2: Assuming my favourite brand has a BBLP, I would use it regularly	5.306	3.187	0.957	3.289
Perceived usefulness (PU): reflective construct				
PU1: A BBLP will be useful to me	5.726	2.981	0.932	3.364
PU2: This technology will give me more control over my interactions	5.555	2.887	0.941	4.109
PU3: This technology will provide more options to leverage loyalty programs	5.828	2.909	0.93	3.607
Perceived ease of use (PEoU): reflective construct				
PEoU1: It will be easy for me to learn how to use rewards and tokens in a BBLP	5.741	2.837	0.963	3.656
PEoU2: I will find this technology easy to use	5.740	2.885	0.961	3.656
Trust (TR): reflective construct				
TR1: I trust that the BBLP system will make the right decisions	5.174	2.941	0.964	3.836
TR2: I trust the security of the BBLP	5.218	3.047	0.965	3.836
Positive emotions (PEM): formative construct				
PEM1: Anticipation	4.871	3.133	0.938	3.116
PEM2: Surprise	4.607	3.016	0.825	3.211
PEM3: Joy	4.826	3.133	0.947	3.156
Negative emotions (NEM): formative construct				
NEM1: Anger	2.171	2.640	0.996	1.838
NEM2: Disappointment	2.389	2.827	0.608	1.838
Social influence (SI): reflective construct				
SI1: People who are important to me will think I should use my brand's BBLP	4.418	3.051	0.965	3.821
SI2: People whose opinions I value will want me to use my brand's BBLP	4.585	3.096	0.963	3.821

Note(s): (1) The responses are responded from 0 = strongly disagree to 10 = strongly agree. (2) SD = Standard deviation; VIF = Variance inflation factor (3) IU = Intention to use, PU = Perceived usefulness; PEoU = Perceived ease of use; TR = Trust; PEM = Positive emotions; NEM = Negative emotions; SI=Social influence

Source(s): Authors' own work

goodness-of-fit measures such as R^2 were calculated. In this step, the reliability of the hypotheses formulated in section 2.2 and the effect size of the paths using Cohen's effect size (f^2) can be tested.

Subsequently, we applied fsQCA with the assistance of the software by Ragin (2018) fsqca 3.1. We followed the protocol of Pappas and Woodside (2021), which involves using some of the results from the PLS-SEM analysis. The phases followed in the implementation of fsQCA are as follows.

Step 1: For factors composed of multiple items, regardless of whether they are reflective or formative, it is advisable to conduct a reliability analysis of the scales. This step was conducted in the first and second stages of PLS-SEM analysis.

Step 2: The membership functions of the variables were calibrated. As the factors were measured through scales whose items needed to be aggregated, we considered the standardized factor loadings used in the PLS-SEM adjustment as the base measurement. This approach was used in the fsQCA proposed by Arias-Oliva *et al*. (2021). To fit the membership functions, we stated full membership in the percentile 90 of the factor loading, nonmembership in the percentile 10, and percentile 50 as the crossover value. The membership levels of the intermediate factor loadings were determined using linear interpolation.

Step 3: An assessment is developed to determine the necessity of the presence or absence of conditions for IU. It was also run for its negation, represented as ¬IU, which corresponds to the rejection of the evaluated technology.

Step 4: We fit the so-called prime implicates (configurations or recipes) that precede the output results by executing a Boolean minimization algorithm. These prime implicates are understood as profiles linked with IU or non-IU BBLPs.

Step 5: To determine how these factors impact the outcome, we consider the intermediate solution. It embeds configurations that include core conditions, which are present in both intermediate and parsimonious solutions, and peripheral conditions, which are only present in the intermediate solution (Fiss, 2011). These last conditions can be considered weak causes (Fiss, 2011). Note that the construction of the recipes of the intermediate solution is based on the use of the hypotheses described in Section 2.2.

To assess the explanatory capability of the recipe, consistency (CONS) and coverage (COV) indicators must be calculated. While CONS informs about the significance of a particular prime implicate, COV measures empirical importance.

4. Results

4.1 Descriptive measures of items and assessment of the measurement model

The descriptive statistics for the items are shown in Table 3. There is a favorable mainstream for the IU BBLPs, as the averages of IU1 and IU2 are slightly above 5 and significantly different from 5 ($p < 0.01$).

Table 4 indicates that the reflective scales are reliable, since CA and CR were above 0.7, AVE was above 0.5, and the factor loadings were at least 0.702 for all items. Table 3 shows that the formation of latent variables does not present serious collinearity problems because the VIFs, although often above 3.3, never exceed 5.

Convergent validity of PEM and NEM measures was above 0.7. Moreover, the VIF of the indicators is below 3.3, so there are no collinearity problems in the formation of latent variables. Likewise, the factor loadings are above 0.6 and statistically significant. This result suggests that the indicators used in the construction of the constructs are relevant.

Table 4. Analysis of internal consistency and convergence validity of scales

Construct	CA	CR	CV	AVE
IU	0.91	0.957	–	0.917
PU	0.927	0.954	–	0.873
PEoU	0.92	0.962	–	0.926
TR	0.925	0.964	–	0.93
PEM	–	–	0.981	0.829
NEM	–	–	0.888	0.681
SI	0.924	0.964	–	0.93

Note(s): (1) CA = Cronbach's alpha; CR = composite reliability; CV = convergent validity; AVE = Average variance extracted

Source(s): Authors' own work

Findings in Table 5 suggest that the scales also had adequate discriminant capacity. The Fornell–Larcker criterion was met, as the squared AVEs of the factors were greater than their Pearson correlations. Similarly, the Pearson correlations did not exceed 0.85.

4.2 Results of PLS-SEM adjustment

The quality of the model's fit was satisfactory. As shown in Figure 3, the coefficient of determination was close to 75% ($R^2 = 71\%$).

Table 6 displays fitted values of path coefficients (β). Regarding the cognitive variables, were significant PU ($\beta = 0.619$, $p < 0.001$) and PEoU ($\beta = 0.175$, $p = 0.002$) but TR was not. Therefore, H1 and H2 were supported. However, hypothesis H3 was not supported.

Latent variables related to emotions had a significant relationship with IU. We observed that for PEM, $\beta = 0.123$, $p = 0.002$ and for NEM, $\beta = -0.078$, $p = 0.015$. However, the SI was not statistically significant. It is also observed that while the effect size of Cohen for PU can be considered medium ($f^2 = 0.341$), in the case of PEoU, PEM and NEM, it is small ($f^2 < 0.2$). Finally, SI and trust were practically null.

4.3 Results of the fuzzy set qualitative comparative analysis

The first step of the fsQCA involved verifying the internal consistency of the scales used, as has already been discussed. Second, we adjust the membership functions of the factors involved in the analysis. The points of full membership, nonmembership and crossover, adjusted based on the factor loadings of the constructs, are provided in Table 7.

For example, in the case of PU, the membership function was constructed based on an evaluation of the three items that constitute this latent variable. The aggregation value of these items is considered the factor score, with the 10th percentile being -1.476, the median being –0.017, and the 90th percentile being 1.447. Thus, full acceptance of the technology occurred with a factor score of 1.447 (membership in PU = 1) and full rejection occurred below -1.476 (membership in IU = 0). The crossover point implied a neutral position, and was at the 50th percentile (membership = 0.5). Based on these values, the degree of acceptance (between zero and one) of any observation was rated based on the IU factor score.

The necessity analysis in Table 8 shows that there was no factor whose presence or absence was a necessary condition for acceptance or nonacceptance. PU, PEoU, TR, SI, PEM and SI obtained a consistency ≥0.8, but did not reach the recommended threshold of 0.9. Similarly, when the outcome was resistance to use, the absence of PE, PEoU and TR presented a consistency ≥0.8, but did not reach 0.9.

The determination of sufficient conditions is presented in Tables 9 and 10. Table 9 lists the sufficient conditions for IU. We obtained six configurations with a consistency of 0.85 and coverage of 0.88. All explanatory factors appear to be core conditions in at least one prime

Table 5. Discriminant validity assessment

	IU	PU	PEoU	TR	PEM	NEM	SI
IU	0.958						
PU	0.828	0.934					
PEoU	0.749	0.826	0.962				
TR	0.675	0.771	0.772	0.964			
PEM	0.595	0.639	0.617	0.712	0.910		
NEM	−0.076	−0.026	−0.036	0.058	0.211	0.825	
SI	0.598	0.689	0.657	0.775	0.684	0.142	0.964

Note(s): The principal diagonal displays the AVEs, with Pearson correlations shown below
Source(s): Authors' own work

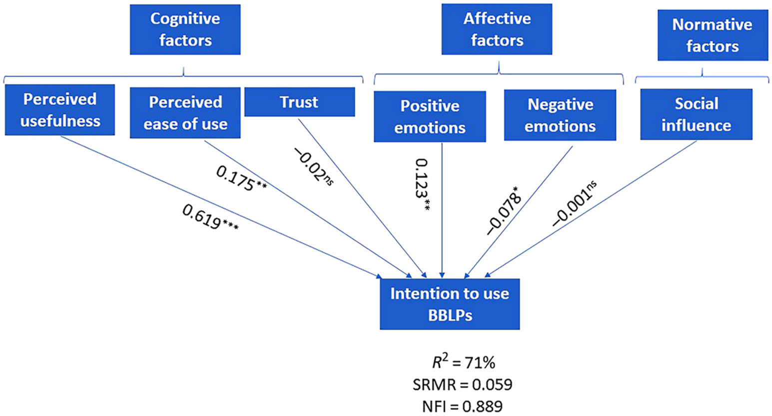

Figure 3. Results of fitting the CAN model developed in Section 2.2. Note: (1) R^2 = determination coefficient, SRMR = standardized root mean square residual, and NFI = normed fit index (2) With "***" we denote significance at 0.1% level, "**" significance at 1% level, "*" significance at 5% level and "ns" is not significant.
Source: Authors' own work

Table 6. Results of the estimation of path coefficients and decision on hypothesis

Relation	β	VIF	f^2	SD	t-ratio	p-values	Decision
PU → BI	0.619	3.86	0.341	0.055	11.255	<0.001	Supported
PEoU → BI	0.175	3.707	0.028	0.058	3.033	0.002	Supported
TR → BI	−0.02	4.081	<0.001	0.045	0.444	0.657	Not supported
PEM → BI	0.123	2.416	0.021	0.039	3.162	0.002	Supported
NEM → BI	−0.078	1.124	0.019	0.032	2.445	0.015	Supported
SI → BI	−0.001	2.884	<0.001	0.04	0.017	0.987	Not supported

Source(s): Authors' own work

Table 7. Points of standardized loadings used to define membership in the assessed latent variables

	IU	PU	PEoU	TR	PEM	NEM	SI
Nonmembership	−1.576	−1.476	−1.538	−1.626	−1.641	−0.785	−1.52
Crossover point	−0.101	−0.017	−0.083	−0.065	0.05	−0.419	0.169
Full-membership	1.538	1.447	1.371	1.319	1.248	1.41	1.514

Source(s): Authors' own work

implicate of IU. Similarly, they participate in the sign assumed in the hypotheses in Section 2.2. Therefore, Proposition 1 is satisfied.

However, there is no necessary factor to produce IU, as no variable participates in all prime implicates. The most common conditions were the presence of PU (core condition in four prime implicates), the presence of PEoU and PEM, and the absence of NEM (core condition in three prime implicates). Less common conditions are the presence of SI (core condition in one prime implicate and peripheral condition in one prime implicate) and trust (core condition in one prime implicate).

Table 10 lists the sufficient conditions for ¬IU. We obtained seven configurations with an overall consistency of 0.82 and coverage of 0.89. Explanatory factors appeared to be core

Table 8. Necessity analysis of the conditions for IU and nonintention to use

	IU cons	cov	¬IU cons	cov
PU	0.88	0.85	0.47	0.49
PEoU	0.84	0.84	0.48	0.52
TR	0.82	0.83	0.49	0.54
PEM	0.80	0.79	0.50	0.54
NEM	0.55	0.42	0.59	0.49
SI	0.84	0.75	0.53	0.50
¬PU	0.50	0.48	0.84	0.87
¬PEoU	0.52	0.48	0.83	0.82
¬TR	0.53	0.48	0.82	0.80
¬PEM	0.54	0.51	0.78	0.78
¬NEM	0.59	0.69	0.50	0.62
¬SI	0.55	0.57	0.76	0.84

Source(s): Authors' own work

Table 9. Intermediate solution for intention to use insideables

	1	2	3	4	5	6
PU	•			•	•	•
PEoU			•			•
TR		•		•		
PEM			•	•	•	
NEM	⊗	⊗	⊗			
SI					•	•
cov	0.59	0.58	0.47	0.67	0.62	0.62
cons	0.90	0.86	0.91	0.92	0.92	0.92
cov	0.88					
cons	0.85					

Note(s): 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 implicate. Big circles symbolize core conditions, and small circles symbolize peripheral conditions

Source(s): Authors' own work

conditions in at least one prime implicate of nonuse. The exception is PEM. Similarly, the factors that are conditions in at least one configuration participate, as established in proposition 2: PU, PEoU, TR and SI are negated in the recipe, and NEM is present. The fact that neither the presence nor the absence of PEM in ¬IU leads us to conclude that proposition 2 is partially fulfilled.

In Table 10, it is also noteworthy that no factor is necessary to produce rejection, as no variable participates in all prime implicates. The most common conditions are ¬PU (core condition in four prime implicates), ¬PEoU, ¬TR and NEM, which are the core conditions in three prime implicates.

A comparison of Tables 9 and 10 confirms that the explanations of IU and its negation are asymmetrical. The presence of PU, PEoU and the negation of NEM participated as core conditions in the same number of IU configurations as the negation of PU and PEoU and the presence of NEM in ¬IU configurations. However, this behavior did not occur for other CAN factors. The clearest case is the PEM, whose presence is a condition in three IU configurations. However, its negation is not necessary in any ¬IU configuration. Therefore, Proposition 3 is satisfied.

Table 10. Intermediate solution of nonintention to use insideables

	1	2	3	4	5	6	7
PU	⊗	⊗	⊗		⊗		
PEoU			⊗	⊗		⊗	
TR		⊗				⊗	⊗
PEM							
NEM				•	•		•
SI	⊗					⊗	⊗
cov	0.79	0.76	0.79	0.41	0.43	0.70	0.37
cons	0.90	0.91	0.89	0.87	0.88	0.92	0.90
cov	0.89						
cons	0.82						

Note(s): Circle • indicates the presence of a factor as a condition, circle ⊗ indicates the absence of a factor, and blank indicates no relevance in the prime implicate. Large circles represent core conditions, and small circles represent peripheral conditions

Source(s): Authors' own work

5. Discussion

5.1 Primary insights

This study analyzes the adequacy of a model based on the CAN model to understand the adoption of BBLPs. The evaluation was conducted using a survey with a sample size of 661 people in the western United States. The response to research objective 1 (RO1) inquired about the statistical significance of CAN exogenous variables. PU and PEoU, PEM and NEM are significant in explaining IU. In contrast, trust (TR) and SI are not.

Research objective 2 (RO2) inquired about how the CAN model factors combined in the analyzed sample embraced and rejected BBLPs. The acceptance of LPs powered by blockchain can result from six paths that combine the presence of PU, PEoU, TR, PEM and SI, and the absence of NEM. Non-IU combines the absence of PU, PEoU, TR and SI and the presence of NEM in seven configurations. However, neither the presence nor the absence of a PEM is a condition in any of the paths causing rejection. Likewise, the configurations associated with intention are not symmetrical to those associated with nonintention.

PU is the variable with the greatest impact on IU. In PLS-SEM estimation, we observed a higher value for the path coefficient and the greatest effect size. The fsQCA indicates that PU participated in the greatest number of prime implicates, explaining both intention and non-IU. This finding is consistent with the fact that this variable is the most important to the acceptance of instrumental new technologies (Venkatesh *et al.*, 2012). Its relevance is also in accordance with mainstream reports on blockchain applications in all evaluated areas, including cryptocurrencies (Arias-Oliva *et al.*, 2019; Almuraqab, 2020; Albayati *et al.*, 2020; Jegerson *et al.*, 2023), supply chain management (Sharma *et al.*, 2023) and finance and banking (Gil-Cordero *et al.*, 2024).

PLS-SEM analysis revealed a significantly positive statistical influence of PEoU on IU. This result is supported by the literature on the acceptance of blockchain technology in various contexts (Almuraqab, 2020; Albayati *et al.*, 2020; Gao and Li, 2021; Afifa *et al.*, 2023; Bandinelli *et al.*, 2023; Gan and Lau, 2024; Chawla *et al.*, 2024). We found that its presence was a condition in three configurations explaining use and in three others explaining nonintention. Therefore, we can infer that like PU, its relationship with the acceptance and rejection of BBLPs is somewhat symmetrical.

It may seem surprising that TR was not significant in the PLS-SEM adjustment. This can be explained by the fact that the application of blockchain does not affect the core of a product offered by a brand, but rather affects a complementary aspect, such as the associated LP. Likewise, failure of the LP should not result in significant economic losses for consumers.

Moreover, it should be noted that Wong *et al.* (2020) also did not observe statistical significance in the impact of trust on the acceptance of blockchain in supply chain management applications.

However, it is also noteworthy that in configurational analysis, trust must be present in a prime implicator explaining IU, and the absence of trust is a condition in the three recipes of ¬IU. So, the fsQCA analysis revealed that trust is a condition for producing acceptance and nonacceptance of BBLPs. This is consistent with the reports indicated in Table 1, supporting the positive influence of trust on IU. The lack of statistical significance of the direct impact of TR, but its emergence in certain explanatory configurations of acceptance or rejection, is consistent with findings about the influence of TR on IU mediated by PU or PEoU (Kamble *et al*., 2019; Afifa *et al.*, 2023). It also aligns with the consideration of TR as a moderating factor (Gil-Cordero *et al*., 2020; Alazab *et al*., 2021).

The two affective variables showed significance in the PLS-SEM adjustment to explain behavioral intention toward BBLPs. This finding coincides with that of Lerner *et al*. (2015), who noted that emotion is a significant factor that influences consumer judgment and decision-making. This aligns with the study by Perdana *et al*. (2021) in the blockchain acceptance setting.

The fact that PEM is positively related to behavioral intention toward BBLPs is twofold. First, PEM are relevant to adherence to an LP (Septianto *et al*., 2019; Agarwal *et al*., 2022). Second, PEM foster engagement in activities mediated by novel technologies (Purwanto *et al*., 2019; Subero-Navarro *et al*., 2022; Alesanco-Llorente *et al*., 2023). Furthermore, fsQCA allows us to infer that the positive influence of PEM on IU is due to its presence as a condition in the three prime implicates. In contrast, PEM neither negated nor did it form part of any configuration in the explanation of nonintention.

The inverse relationship between NEM and IU is consistent with evidence that they can lead to disaffection for LPs (Hwang and Kwon, 2016; Nguyen *et al*., 2022). Additionally, negative feelings toward technologies, such as technostress or cyberphobia, manifest in various studies as barriers to explaining attitudes toward technologically mediated activities (Koul and Eydgahi, 2020; Subero-Navarro *et al*., 2022). The configurational analysis reveals that, unlike PEM, NEM is a condition that explains both IU (in three-prime implicates) and ¬IU (also in three-prime implicates).

We observed that the normative variable SI did not have a statistically significant link with the IU. Although our report contradicts the main reports indicated in Table 1, we also note that this nonsignificance is not extraordinary. Kamble *et al*. (2019) and Alazab *et al*. (2021) in a supply chain context, and Arias-Oliva *et al*. (2019) in a cryptocurrency setting, also found that SI does not have a significant link with IU blockchain applications.

By contrast, the fsQCA analysis suggests that SI is a condition in a recipe explaining IU (its presence is necessary) and is an absent factor in the three prime implicates related to nonacceptance. This finding suggests that the influence of SI on IU does indeed exist, but not directly; rather, it is mediated by variables, such as PU or PEoU. This mediation has been found to be significant in cryptocurrencies (Albayati *et al*., 2020), acceptance of nonfungible tokens (Perez *et al.*, 2023) and organizational process settings (Chen, 2023).

5.2 Implications of the study

The CAN-based model developed in this study provides a suitable framework to understand the drivers of BBLP adoption. PLS-SEM analysis revealed that the model fit was good (R^2 > 70%). Our model often surpasses most studies on the acceptance of blockchain technology, as reviewed in Table 1, where R^2 is substantially below 70%. In the configurational study, we observed that the solutions obtained with fsQCA for both acceptance and rejection had high coverage (approximately 0.9), and the configurations obtained had high consistency (>0.8).

From a methodological perspective, it has been demonstrated that the sequential use of correlational and configurational methods can be useful for understanding how behavioral intention toward a new technology is formed. Similar to Gil-Cordero *et al*. (2024), to analyze cryptowallet acceptance, this study shows that the combined use of PLS-SEM and fsQCA provides a deeper explanation of BBLP acceptance than using a single analytical tool.

The results have important implications for companies interested in implementing blockchain-powered LPs. The correlational analysis highlighted the relevance of two cognitive variables (PEoU and PU) and emotional variables. Therefore, the implementation of BBLPs requires firms to improve their perceived benefits and usability compared with conventional LPs. The aim of providing PEM to users and avoiding negative feelings (e.g. due to LP failures) is another axis that should guide the actions of firms for the implementation of BBLPs.

The fsQCA analysis allows us to determine that PU, PEoU, or NEM impact acceptance and rejection similarly, since they appear symmetrically in the paths leading to intention and nonintention. By contrast, the presence of PEM plays a greater role in the antecedent configurations of IU than its lack in ¬IU. Similarly, the absence of TR and SI tends to manifest more as conditions leading to nonintention, rather than their presence contributing to acceptance. We observed that all the configurations, IU and ¬IU, contained cognitive variables. However, they do not necessarily include affective and normative variables.

The configurations obtained with fsQCA allow for the visualization of different profiles of potential BBLP users. Identifying these profiles facilitates the design of various market penetration strategies based on the user profile that the seller seeks to reach and/or the type of product to commercialize. For example, path PU ● PEoU ● SI can be associated with a profile that essentially values the utility and usability of the BBLP. However, PEoU ● PEM ● ¬NEM can be associated with a potential user for whom the emotional components are the most important. In this profile, the presence of PEM may be associated with avoiding feelings of frustration generated by a system that fails owing to usability shortcomings.

5.3 Measures to expand the use of blockchain-based loyalty programs

PU is a key factor in understanding both intention and non-IU BBLP. Consequently, the widespread adoption of these programs depends on customers actively experiencing and recognizing their benefits. To facilitate this, brands must implement strategies to enhance the perceived value of BBLPs. So:

(1) One effective approach is monetization. Research indicates that LPs offering monetary rewards are generally preferred over nonmonetized programs (Ruzeviciute and Kamleitner, 2017). Blockchain technology provides a seamless mechanism for monetization by enabling the use of cryptocurrencies as rewards. It may make more tangible and versatile for customers.

(2) Brands should develop strategies that maximize the transferability of rewards, an inherent advantage of blockchain technology (Treiblmaier and Petrozhitskaya, 2023). To fully leverage this potential, companies must establish alliances and participate in shared platforms that integrate LPs. These platforms would ensure liquidity for rewards, allowing them to be transferred and traded, like financial assets. By doing so, they would not only increase the attractiveness of BBLPs but also add substantial value to the LP ecosystem as a whole.

The fact that PEoU is also a significant factor highlights the need for measures that simplify the use of the BBLPS. To achieve this goal, two guiding measures must be considered.

(1) First, the usability of web applications supporting BBLPs must be high to ensure that they are user-friendly and intuitive (Shrestha and Vassileva, 2019). A seamless user experience, characterized by clear navigation, minimal technical complexity and responsive design, is crucial for encouraging engagement. Simplified onboarding processes, clear reward tracking and easily accessible redemption options should be prioritized to reduce potential barriers.

(2) Second, implementing smart contracts can help mitigate low engagement in LPs, particularly when rewards are difficult to redeem. Smart contracts enable the automation, transparency and real-time execution of transactions (Jain *et al.*, 2024), ensuring that customers can claim and use their rewards effortlessly. By streamlining redemption processes and reducing friction, smart contracts enhance both PEoU and overall user satisfaction, making BBLPs more attractive and effective.

The proposed measures must also play a crucial role in enhancing the emotional aspects of LPs. They may contribute to strengthening the psychological bond between customers and brands, ultimately fostering greater loyalty. Concretely:

(1) By increasing the overall value of the program, customers are more likely to experience PEM, such as joy and excitement, reinforcing their engagement and long-term loyalty. Furthermore, the automatic execution of rewards through blockchain technology enhances the sense of anticipation because users can expect seamless and timely gratification without unnecessary delays or complications.

(2) These measures also help mitigate NEM, such as frustration, disappointment or anger. These feelings may arise when customers struggle to claim promised rewards due to inefficiencies or a lack of transparency. BBLPs create a more satisfying and frustration-free system by ensuring smooth reward transactions and eliminating common friction points.

(3) Blockchain technology enables new gamification strategies in LPs (Arias-Oliva *et al.*, 2024), further enhancing engagement by introducing interactive and reward elements. Features such as personalized, innovative rewards, including NFTs and exclusive digital assets (Fortagne and Lis, 2024), can evoke emotions such as surprise and delight. It may make the loyalty experience more dynamic and emotionally appealing.

5.4 Limitations and future research lines

The limitations of this study motivate further investigation. Although the sample was stratified across various states in the western region of the USA, this study was conducted exclusively on individuals from that region of the country (14 states). Consequently, conclusions drawn from this study are geographically limited.

Cultural issues can be significant in explaining behavioral intentions toward information systems. Thus, a common amplification of empirical studies on the adoption of information technologies is the application of existing models to different cultures (Zhang *et al.*, 2024). This assertion can also be extended to blockchain-based information systems. For instance, national cultural values play a crucial role in influencing the adoption and usage (Salcedo and Gupta, 2021).

The expansion of the geographical area of study can be understood both within the United States and in other regions of the world. Within the United States, cultural divergences can be modelled using both the north-south and east-west dichotomies (Louf *et al.*, 2023). On the other hand, Schwartz (2014) propose dividing the countries of the world into seven major groups based on their cultural value orientations. For instance, notable differences exist between countries with Christian and Islamic cultures and those where non-Abrahamic religions predominate. Conducting cross-cultural studies that account for these differences would provide a broader perspective of BBLP acceptance.

The sample aimed to reasonably approximate the sociodemographic composition of the western United States. The results provided an overview of the acceptance of BBLPs in this region. However, to gain an in-depth understanding of the attitudes of a specific sociodemographic group, this study would need to use a sample of individuals to fit the profile. For example, if the target group is university-educated millennials, the technological knowledge of group members is likely to be higher than the population average. It is expected that in explaining the IU, aspects such as ease of use will be less important and usefulness may be of greater importance (Venkatesh *et al.*, 2003).

The blockchain application analyzed in this study focuses on a specific aspect of marketing management. However, the technology holds vast potential with significant social implications. A particularly promising area is healthcare information management (Li and Liang, 2023; Dandotiya *et al.*, 2025), encompassing medical records, clinical trials and pharmaceutical supply chains. Other relevant contexts include the transparent enforcement of intellectual property rights (Alqarni, 2024) and the improvement of electronic voting systems, which are fundamental to democracies (El Kafhali, 2024). Notably, blockchain also fosters financial and digital inclusion, especially for underbanked and unbanked populations (Mhlanga, 2023). The literature on the acceptance of blockchain in these domains remains scarce. We believe the conceptual and analytical approach proposed in this study could serve as a valuable foundation for future research on blockchain adoption in these areas.

The findings of this study may have limited applicability over time. First, the use of blockchain applications in organizations is low (Zhang *et al.*, 2024), indicating that it is still in an early phase. Therefore, longitudinal studies would be of interest to gain a deeper understanding of the drivers that stimulate their adoption (Zhang *et al.*, 2024). It is also important to recognize that a crucial aspect of blockchain adoption involves considerable challenges associated with this technology. Some examples include high energy consumption, legal system integration and regulatory governance (Tripathi *et al.*, 2023). However, these issues require further longitudinal studies.

6. Conclusions

This study assessed behavioral intention toward BBLPs in a stratified sample from the Western states of the United States. The factors inducing BBLP acceptance were analyzed using the CAN model (Pelegrín-Borondo *et al.*, 2016).

The extension of the CAN model was suitable for explaining IU. In the analysis conducted using a correlational approach, the coefficient of determination of PLS-SEM adjustment was over 70%. In the case of the configurational approach, the solutions for acceptance and rejection have high coverage, and the prime implicates linked to both outputs have high consistency.

The PLS-SEM analysis revealed that PU had the greatest impact. PEoU and affective variables were also significant in explaining IU, but they had smaller effect sizes. Additionally, trust and SI were not relevant in explaining BBLP usage intentions. The configurational assessment shows that, in fitting acceptance, all variables are conditions of one prime implicate or more. In explaining rejection, almost all the factors were part of a configuration, with the exception of positive feelings. Notably, the profiles revealed by fsQCA for acceptance and resistance to BBLPs were not symmetrical.

Author contributions

All authors contributed equally to the paper.

Ethical compliance

With regard to ethics approval, (1) all participants were given detailed written information about the study and procedure; (2) no data directly or indirectly related to the subjects' health were collected; thus, the Declaration of Helsinki was not generally mentioned when the subjects were informed; (3) anonymity of the collected data was ensured at all times; (4) permission of the institution of the corresponding author was registered as CEIPSA-2024-PRD-0030; and (5) voluntary completion of the questionnaire was taken as consent for the data to be used in research; informed consent of the participants was implied through survey completion.

Data access statement
Research data supporting this publication are available upon request from any author.

Appendix
Questionnaire

Blockchain-based loyalty programs (BBLP) track customer purchases and activities using a blockchain ledger. When a customer purchases or completes an action, it receives the digital tokens stored in the blockchain. These tokens can then be redeemed or traded as rewards for the company.

The *improved functionalities that a BBLP provides* are as follows:

(1) A wider range of offerings to consumers, such as exclusive offers for BBLP members.

(2) The accrual of points are credited in real time

(3) Personalized offers, based on previous shopping preferences

(4) Transferability (sharing, selling or buying) of loyalty points or special/exclusive offers to other program members but also exchanges them across different loyalty programs.

(5) By exchanging and trading loyalty tokens in the BBLP ecosystem (secondary market), users can buy tokens and gain rewards and advantages or sell their tokens to gain money or other tokens.

(6) Gamification in achievement-based rewards, such as badges

(7) Security: nothing ever gets lost on a blockchain network

(8) Transparency: every transaction and its record are easily traceable

Some examples of blockchain-based loyalty programs include Starbucks Odyssey and FlyCoin.

So, first, let us know something about you:

(1) What is your gender identity?
- Female
- Male
- Nonbinary
- Prefer not to answer

(2) Which age group do you belong to?
- 18 to 24
- 25 to 34
- 35 to 44
- 45 to 54
- 55 or older

(3) What is the highest level of school you have completed?. Please select one option
- Less than a high school diploma or equivalent
- High school diploma or equivalent
- Some college or associate’s degree
- Bachelor’s degree
- Professional degree
- Post-graduate degree (Master’s, PhD)

(4) What is your annual household income?
- Less than $25,000 (1)

- $25,000 to $49,999 (2)
- $50,000 to $74,999 (3)
- $75,000 to $99,999 (4)
- $100,000 or more (5)
- Prefer not to say (7)

(5) With which racial or ethnic groups do you identify? Select all that apply.

- White or Caucasian (not Hispanic or Latino) (1)
- Latinx, Hispanic, Latino, or Spanish origin (2)
- Black or African American (3)
- Asian/Pacific Islander (4)
- Native American, Alaska Native, Aleutian (5)
- Another race or ethnicity not listed (8)
- Prefer not to answer (9)

The following statements pertain to your opinion on BBLPs: You must express your adherence to these items on a scale that oscillates between 0 (strongly disagree) and 10 (strongly agree). For example, 0 = strongly disagree, 1 = disagree very strongly, 2 = disagree strongly, 3 = disagree somewhat, 4 = slightly disagree, 5 = neutral or neither agree nor disagree, 6 = slightly agree, 7 = agree somewhat, 8 = agree strongly, 9 = agree very strongly, and 10 = strongly agree.

1: Assuming that my favorite brand has a BBLP, I would enroll in it.

2: Assuming that my favorite brand has a BBLP, I would use it regularly

3: A BBLP will be useful to me.

4: This technology will give me more control over my interactions.

5: This technology provides more options to leverage loyalty programs

6: It will be easy for me to learn how to use rewards and tokens in a BBLP.

7: I will find this technology easy to use.

8: I trust that the BBLP system will make the right decisions.

9: I trust the security of the BBLP.

10: I associate BBLPs with anticipation

11: I associate BBLPs with surprise

12: I associate BBLPs with joy

13: I associate BBLPs with anger

14: I associate BBLPs with disappointment

15: People who are important to me will think I should use my brand’s BBLP.

16: People whose opinions I value will want me to use my brand’s BBLP.

Control question between answers 2 and 3. This is a common knowledge question to ensure that one pays attention to the survey. Please choose the country where the city of Los Angeles is located (correct answer: United States).

- Germany (1)
- China (2)
- United States (3)

- Brazil

Control question between answers 10 and 11: Please check box 10 for strongly agree on a ten-point scale.

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