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Research article

Evaluating explanatory factors of the acceptance of blockchain-based loyalty programs with neural networks

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Abstract: This study examined the factors influencing the adoption of loyalty programs powered by blockchain (BBLPs) among older adult consumers in the United States. Drawing on established technology acceptance models—such as the Unified Theory of Acceptance and Use of Technology (UTAUT), the Technology Acceptance Model 3 (TAM3), and the Cognitive–Affective–Normative (CAN) framework—a conceptual model is proposed that integrates six explanatory variables: perceived usefulness (PU), perceived ease of use (PEoU), perceived external control (PEC), positive emotions (PEM), negative emotions (NEM), and subjective norm (SN). To assess the model's explanatory power and predictive accuracy regarding the intention to use BBLPs, five multilayer perceptron neural networks with different architectures were implemented. The study pursues two main objectives: (1) to evaluate the explanatory and predictive capabilities of the proposed model using deep learning techniques, and (2) to determine the relative importance of each explanatory variable using the permutation feature importance method. The results show that all neural network (NN) models achieved high explanatory power and strong predictive performance under Monte Carlo cross-validation. A single-hidden-layer network based on Kolmogorov's theorem (13 neurons) offered the best balance between fit and predictive ability. PU consistently emerged as the most influential predictor of usage intention, whereas NEM and SN were the least relevant factors across all configurations. The relative importance of PEoU, PEC, and PEM varied across architectures. These findings confirm the primacy of cognitive variables over affective and normative factors in explaining the acceptance of BBLPs and highlight the usefulness of NNs for modeling technology adoption in marketing research. They also demonstrate that explainable NNs can simultaneously enhance prediction and provide transparent, ranked insights for managerial prioritization in consumers' loyalty settings.

Keywords: blockchain-based loyalty programs (BBLPS); technology adoption models; deep learning; neural networks (NNs); permutation feature importance (PFI)

JEL Codes: C45, M15, M38, O32

1. Introduction

Loyalty programs (LPs) represent a key tool in consumer relationship management, as they incentivize repeat purchases and strengthen brand attachment (Thomas et al., 2023). However, prior research highlights persistent constraints, most notably low user engagement, limited transparency in points and rewards management, and perceptions of unfair or unattractive rewards (Steinhoff & Palmatier, 2016). They ultimately weaken program effectiveness and long-term loyalty outcomes (Kim et al., 2021).

In this context, blockchain (BLC) has risen as one of the most relevant innovations of this century. BLC is commonly associated with cryptocurrency markets and their novel developments. Thus, one relevant application of BLC within this mainstream use is green cryptocurrencies, which are increasingly assuming the role of functional and economically mature instruments in contexts of inflation and uncertainty (Dimitriadis et al., 2025a). By contrast, BLC-based assets such as DeFi and NFTs operate primarily as complementary and hedging mechanisms vis-à-vis traditional currencies, rather than as full substitutes for fiat money (Dimitriadis et al., 2024). Moreover, in environments of high uncertainty, evidence shows that agents' preferences are reconfigured according to the perceived capacity of cryptocurrencies to reduce systemic risk, highlighting the importance of alternative assets over traditional solutions, regardless of their average returns (Dimitriadis et al., 2025b). However, the application of BLC has expanded to a wide range of domains, from human resource management to finance (Dong et al., 2023), and more recently, digital marketing (Wasiq et al., 2023), enabling organizations to optimize operations and improve decision-making processes. This study focuses on this latter field, particularly on the implementation of blockchain-based loyalty programs (BBLPs).

Blockchain (BLC) offers a set of technical features—such as decentralization, immutability, traceability, transparency, and cryptographic security—that make it a promising solution to address several of the shortcomings observed in traditional loyalty programs (Rejeb et al., 2020). These properties allow for the design of more reliable systems with clearly defined and visible operational rules for all participants, and with rewards that can be managed in a fairer and more flexible manner (Tu et al., 2022). Consequently, BBLPs have the potential to generate higher levels of trust, engagement, and satisfaction among users (Utz et al., 2023).

Nonetheless, despite the transformative potential of BLC, adoption beyond cryptocurrency-related applications has progressed more slowly than expected (Treiblmaier & Petrozhitskaya, 2023). This slow uptake is commonly attributed to limited public understanding, perceived technological complexity, a scarcity of widely recognized everyday use cases, and uneven familiarity with decentralized digital environments across population segments (Gschnaidtner et al., 2024). Against this backdrop, the present study examines the determinants of blockchain-based loyalty program (BBLP) acceptance, with the aim of identifying the cognitive, affective, and normative drivers that shape older consumers' intention to use BBLPs. Accordingly, we address the following research question: What cognitive, affective, and normative factors explain and predict digital immigrants' intention to use BBLPs?

The motivation to focus on digital immigrant cohorts (Generation X, Baby Boomers, and the Silent Generation) is that these generations are gaining visibility and purchasing power, yet both marketing practice and scholarship continue to underprioritize their strategic relevance. As Bui (2022) noted, the growing ageing population—together with their increasing participation in digital platforms—creates substantial opportunities to engage that grey market.

Empirical evidence on the determinants of BBLP acceptance, particularly among digital immigrants, remains limited. Moreover, prior work has largely relied on linear modeling approaches that may miss nonlinear relationships between acceptance drivers and intention to use. Addressing this gap is important because BBLPs are frequently proposed as a means to enhance transparency and engagement in traditional loyalty programs, while adoption may be especially demanding for older consumers who tend to report lower familiarity with digital environments and higher perceived complexity (Palfrey & Gasser, 2011).

Generational differences in technology use and attitudes have been widely documented, especially between those who grew up in digital environments—so-called digital natives—and those who were introduced to such environments later in life. While digital natives typically develop technological competencies from an early age, digital immigrants tend to have a more instrumental and gradual relationship with technology (Akçayır et al., 2016). These generational differences also extend to behavior toward loyalty programs. The literature suggests that Baby Boomers, for example, show higher levels of commitment to such programs, driven by more stable consumption patterns and stronger brand identification (Ferguson & Brohaugh, 2010). In contrast, Millennials and Generation Z tend to prioritize immediate rewards, personalized experiences, and corporate social responsibility in their brand relationships (Moisescu & Gică, 2020). Understanding these differences is essential for designing more effective loyalty programs tailored to the preferences of each generational cohort.

The theoretical foundation of this study is based on extensions of the Technology Acceptance Model (TAM) (Davis, 1989), specifically TAM3 (Venkatesh & Bala, 2008), the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), and the Cognitive–Affective–Normative (CAN) model (Pelegrín-Borondo et al., 2017). These theories have been widely used to analyze the acceptance of emerging technologies, including BLC applications in areas such as cryptocurrencies (Bommer et al., 2023), supply chains (Taherdoost, 2022), and BBLPs (Arias-Oliva et al., 2024).

The proposed theoretical framework (see Figure 1) posits that the intention to use BBLPs is explained by six variables categorized following the CAN groundwork. From the six, three are cognitive factors [perceived usefulness (PU), perceived ease of use (PEoU), and perceived external control (PEC)], two are affective [positive emotions (PEM) and negative emotions (NEM)], and one is normative [subjective norm (SN)]. With this conceptual scheme, the study aims to achieve two main research objectives:

RO1: Develop a theoretical framework capable of explaining and predicting the acceptance of BBLPs and implementing and validating it through deep learning techniques.

RO2: Determine the relative importance hierarchy of explanatory factors in predicting the intention to use BBLPs using deep learning tools.

Accordingly, this paper contributes (i) by extending and integrating UTAUT, TAM3, and the CAN framework to explain BBLP acceptance in an under-studied cohort; (ii) by modeling intention to use with a type of neural network (NN) so-called multilayer perceptron (MLP) and assessing both explanatory (fit) and predictive performance; and (iii) by providing interpretable, actionable insights through permutation feature importance (PFI) to support managerial prioritization.

Methodologically, we rely on a quantitative, survey-based design conducted among US adults aged 45 and older and estimate the proposed model with deep learning (MLP), complemented with PFI for explainability. This design strengthens internal consistency and allows robust out-of-sample assessment via Monte Carlo cross-validation and a comparison of multiple MLP architectures under a consistent training configuration, enabling a transparent assessment of generalization and robustness.

In contrast to conventional empirical approaches based on linear models, such as partial least squares structural equation modeling (PLS-SEM), this study adopts a nonlinear approach based on deep neural networks, specifically multilayer perceptrons (MLPs). The use of NNs to analyze the determinants of technology acceptance is justified by their ability to model complex nonlinear relationships among multiple variables, capturing hidden patterns that traditional statistical methods—such as structural equation models—may overlook (Legesse et al., 2024). Unlike these models, which assume linear and compensatory relationships, NNs can identify non-additive interactions, threshold effects, and more flexible dependency structures that better reflect the dynamics of technology adoption (Alwabel & Zeng, 2021; Rad et al., 2022). This capability is particularly valuable when working with theoretical models such as TAM, UTAUT, or CAN, which integrate cognitive, affective, and social constructs. Moreover, the application of NNs significantly enhances model predictive accuracy, as demonstrated in studies on the acceptance of emerging technologies such as mobile money (Gbongli et al., 2019), the use of educational technologies like ChatGPT (Salifu et al., 2024), and BLC in public infrastructure management (Legesse et al., 2024).

Specifically, TAM3 posits that the influence of subjective norm on intention to use is mediated by perceived usefulness, and that perceived external control affects intention indirectly through perceived ease of use. While TAM3 assumes indirect effects of affective variables, models such as UTAUT2 and CAN allow for the possibility of direct effects. NNs can capture such complex and emergent patterns directly from the data (Legesse et al., 2024).

Although deep learning models are often considered opaque in terms of interpretability, there are techniques that allow for the evaluation of the relevance of each explanatory variable. In this study, we use the PFI (Fisher et al., 2019), which ranks variables based on the performance loss incurred when each predictor is individually perturbed. This approach allows the study not only to improve prediction but also to generate a clear ranking of adoption drivers, thereby strengthening the managerial interpretability of the proposed framework.

The remainder of the paper is organized as follows: Section 2 develops a literature review on the acceptance and use of BLC applications. Section 3 presents the theoretical groundwork and hypotheses. Section 4 describes the materials and methods, including sampling, measurement, and the NN modeling procedure. Section 5 reports the empirical results for the measurement assessment and the two research objectives. Section 6 discusses the findings and implications, and Section 7 concludes with limitations and future research directions.

2. Literature review

Table 1 provides a comprehensive review of studies on the acceptance of BLC-based applications that rely on technology adoption and diffusion theories. Regarding application domains, cryptocurrencies constitute the most frequently examined context (Albayati et al., 2020; Almuraqab, 2020; Arias-Oliva et al., 2019; Jegerson et al., 2023). However, prior research has also consistently addressed other relevant BLC settings, such as supply-chain applications (Alazab et al., 2021; Sharma et al., 2023), banking/finance/accounting (Chen, 2023; Gan & Lau, 2024), academy and learning (Al-Hattami, 2024; Gao & Li, 2021), tourism and travel (Anbari et al., 2024; Nuryyev et al., 2020), and food traceability (Nudin et al., 2024; Ornelas Herrera et al., 2025). In addition, more specific applications have recently gained attention, including BBLPs (Arias-Oliva et al., 2024; Souto-Romero et al., 2025) and sector-focused use cases such as BLC-enabled infrastructure management (Legesse et al., 2024).

Table 1. Review of the literature on blockchain technology acceptance.

Author(s) and year	Key influences in this paper	Methodology	Major findings (relevant constructs in blockchain context)
Albayati et al. (2020)	PU, PEoU and SN → IU	PLS-SEM	Supports the effects of PU, PEoU, and SN on intention to use in cryptocurrencies.
Almuraqab (2020)	PU, PEoU and SN → IU	PLS-SEM	Confirms the influence of PU, PEoU, and SN on intention to use in cryptocurrencies.
Arias-Oliva et al. (2019)	PU, PEoU and PEC → IU	PLS-SEM	Shows the role of PU, PEoU, and PEC in shaping intention to use in cryptocurrencies.
Jegerson et al. (2023)	PU, PEoU and SN → IU	CB-SEM	Supports the effects of PU, PEoU, and SN on intention to use in cryptocurrencies.
Alazab et al. (2021)	PU, PEoU, PEC and SN → IU	PLS-SEM	Reports positive links of PU, PEoU, PEC, and SN with intention to use in supply-chain BLC applications.
Bandinelli et al. (2023)	PU and PEoU → IU	CB-SEM	Confirms the effects of PU and PEoU on intention to use in supply-chain contexts.
Sharma et al. (2023)	PU, PEoU, PEC and SN → IU	PLS-SEM	Shows that PU, PEoU, PEC, and SN contribute to intention to use in supply-chain BLC settings.
Khalil & Ahmed (2024)	PEoU → IU	PLS-SEM	Provides evidence for PEoU → intention to use in supply-chain BLC applications.
Khelil et al. (2024)	PEoU → IU	PLS-SEM	Supports the relationship between PEoU and intention to use in supply-chain BLC settings.
Bouebdallah et al. (2025)	PU → IU	PLS-SEM	Confirms PU → intention to use in banking/finance/accounting BLC contexts.
Chen (2023)	PU, PEoU and SN → IU	PLS-SEM	Supports the effects of PU, PEoU, and SN on intention to use in banking/finance/accounting.
Gan & Lau (2024)	PU and PEoU → IU	CB-SEM	Provides evidence of PU and PEoU effects on intention to use in banking/finance/accounting BLC applications.
Gil-Cordero et al. (2024)	PU and PEoU → IU	PLS-SEM and fsQCA	Confirms the influence of PU and PEoU on intention to use in banking/finance/accounting settings.
Afifa et al. (2023)	SN → IU	PLS-SEM	Shows that SN influences intention to use in banking/finance/accounting BLC contexts.
Al-Hattami (2024)	PU and PEoU → IU	PLS-SEM	Supports the effects of PU and PEoU on intention to use in academy/learning BLC-related applications.

Continued on next page

Author(s) and year	Key influences in this paper	Methodology	Major findings (relevant constructs in blockchain context)
Chawla et al. (2024)	PU and PEoU → IU	PLS-SEM	Confirms the influence of PU and PEoU on intention to use in academic/learning contexts.
Gao & Li (2021)	PU, PEoU and SN → IU	CB-SEM	Provides evidence for the effects of PU, PEoU, and SN on intention to use in academic/learning settings.
Shrestha & Vassileva (2019)	PU → IU	PLS-SEM	Supports PU → intention to use in academy/learning BLC-related contexts.
Anbari et al. (2024)	PU, PEoU, PEC and SN → IU	PLS-SEM	Shows that PU, PEoU, PEC, and SN affect intention to use in tourism/travel BLC applications.
Li et al. (2021)	PU → IU	CB-SEM	Confirms PU → intention to use in tourism/travel BLC contexts.
Nuryyev et al. (2020)	PU, PEoU and SN → IU	CB-SEM	Supports the effects of PU, PEoU, and SN on intention to use in tourism/travel BLC settings.
Li et al. (2025)	PU and PEoU → IU	HR	Provides evidence of PU and PEoU effects on intention to use in food traceability (also listed under tourism/travel).
Nudin et al. (2024)	PU, PEoU and PEC → IU	PLS-SEM	Shows the influence of PU, PEoU, and PEC on intention to use in food traceability BLC applications.
Ornelas Herrera et al. (2025)	PU and PEoU → IU	PLS-SEM	Confirms the effects of PU and PEoU on intention to use in food traceability contexts.
Arias-Oliva et al. (2024)	PU, PEoU, SN, PEC and PEM → IU	fsQCA	Supports that there are several combinations of PU, PEOU, SN, PEC, and PEM shaping intention to use in BBLPs.
Souto-Romero et al. (2025)	PU and PEoU → IU	PLS-SEM and QR	Provides evidence that PU and PEoU shape intention to use in BBLPs.
Legesse et al. (2024)	PU and PEC → IU	PLS-SEM and ANN	Supports the effects of PU and PEC on intention to use BLC to manage infrastructure.
Mannonov & Myeong (2024)	PU and PEoU → IU	PLS-SEM	Confirms the influence of PU and PEoU on intention to use in other BLC contexts.
Present contribution	A CAN framework influences IU	ANN	ANN is used not as a complementary method for predictive purposes but to provide a comprehensive explanation of IU.

Note: (a) PU = perceived usefulness; PEoU = perceived ease of use; SN = subjective norm; PEC = perceived external control; PEM = positive emotions; IU = intention to use. (b) PLS-SEM = partial least squares structural equation modeling; CB-SEM = covariance-based structural equation modeling; fsQCA = fuzzy-set qualitative comparative analysis; QR = quantile regression; HR = hierarchical regression.

From a theoretical perspective, most contributions are grounded in TAM/UTAUT (and their extensions). Thus, although several studies incorporate complementary constructs (e.g., compatibility, trust, trialability) depending on the specific domain, the most recurrent determinants explaining intention to use are perceived usefulness, followed by perceived ease of use, subjective norm, and perceived external control (see, for example, Albayati et al., 2020; Alazab et al., 2021; Chen, 2023; Anbari et al., 2024). Methodologically, the literature is clearly dominated by PLS-SEM (e.g., Albayati et al., 2020; Alazab et al., 2021; Chen, 2023; Nudin et al., 2024), although alternative approaches are also observed, such as covariance based-structural equation modeling (Jegerson et al., 2023; Bandinelli et al., 2023; Gan & Lau, 2024), fuzzy set qualitative comparative analysis (Gil-Cordero et al., 2024; Arias-Oliva et al., 2024), quantile regression (Souto-Romero et al., 2025), and hierarchical regression (Li et al., 2025).

The use of NNs remains very limited in technology acceptance literature. Based on Table 1, NNs have been used in only one study (Legesse et al., 2024) and primarily as a complementary tool to enhance the predictive performance of PLS-SEM. Yet, prior research has not fully leveraged NNs' explanatory potential through modern interpretability techniques, such as PFI (Fisher et al., 2019) or Shapley Additive Explanations (SHAP) (Lundberg & Lee, 2017), which allow researchers to weigh and rank the relative importance of explanatory factors. Therefore, the relevance of this study lies in showing that ANN architectures not only offer strong predictive capabilities but also enable a clear visualization and prioritization of the key determinants underlying the acceptance of BBLPs, thereby supporting more actionable managerial decision-making.

3. Proposed model and hypothesis development

3.1. General overview of proposed model

The study of the factors that drive the acceptance of a given technology requires framing the problem within a theoretical model that enables the application of analytical tools to assess the explanatory and predictive capacity of the model against empirical evidence (Figure 1). Following the CAN model approach (Pelegrín-Borondo et al., 2017), we classify the variables used into three dimensions: cognitive (PU, PEoU, and PEC), affective (PEM and NEM), and normative (SN). While PU and PEoU are core components of the TAM model, both PEC and SN are present in TAM3 and UTAUT, although their influence on acceptance operates through different mechanisms that affect usage intention. PEM and NEM, on the other hand, are variables from the CAN model but can conceptually be associated with constructs found in TAM3 and UTAUT2, such as hedonic motivation—defined as the pursuit of pleasurable experiences through technology use (Venkatesh et al., 2012)—and computer anxiety, referring to negative feelings commonly experienced when using technology (Venkatesh & Bala, 2008), respectively.

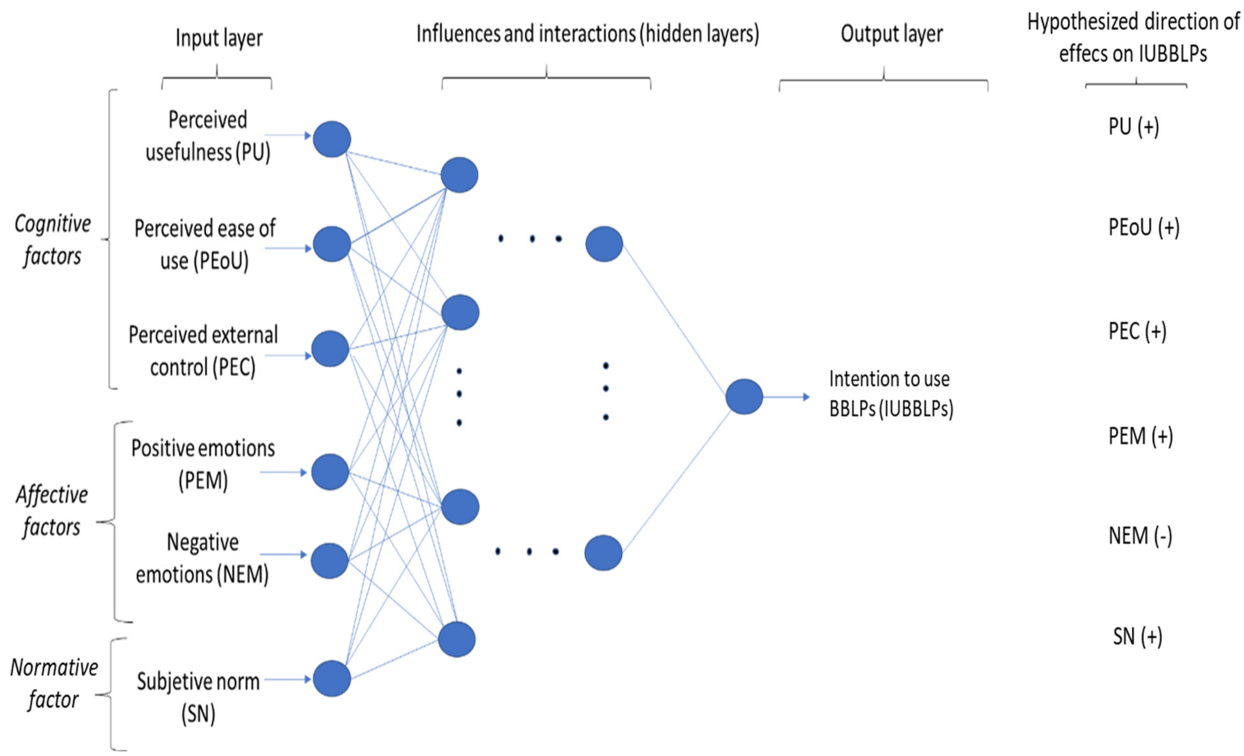

Figure 1. Proposed research model and hypothesized relationships.

The dependent variable corresponds to acceptance, measured through intention to use, understood as an individual's willingness to adopt a specific behavior (Ajzen, 2002). This variable is widely used in the main technology acceptance models upon which this work is based, including TAM3, UTAUT, and CAN. In our specific case, intention to use refers to the intention to use BBLPs (IUBBLPs). We consider it justified not to analyze actual use, given that BLC applications have not yet reached a level of technological maturity that allows for widespread adoption (Gschnaidtner et al., 2024), which also applies to BBLPs (Souto-Romero et al., 2025).

3.2. Cognitive variables

Perceived usefulness (PU) is equivalent to performance expectancy in the UTAUT model and is one of the most influential variables in the study of technology adoption (Venkatesh et al., 2003). It has proven especially relevant in research on the acceptance of BLC-based applications (Arias-Oliva et al., 2024).

One of the main advantages of BLC over centralized systems lies in its ability to implement more innovative loyalty programs, offering benefits in terms such as personalization, aggregation, significance, expiration, and portability (Utz et al., 2023). Additionally, BLC enables decentralized alliances between different platforms, overcoming interoperability barriers and allowing greater accumulated value for the end user (Santos et al., 2023).

Perceived ease of use (PEoU), another central component of TAM and equivalent to effort expectancy in UTAUT, refers to the degree to which a person perceives a technology as easy to use (Davis, 1989). Along with PU, PEoU is a key variable in explaining the adoption of BLC-based solutions (Taherdoost, 2022). Ensuring simplicity in BLC applications is essential, particularly for users lacking experience with BLC. This underscores the need for architectures with the user as the focus to overcome usability issues in decentralized environments (Jang et al., 2020).

Several studies have shown that ease of use, perceived usability, and system quality significantly affect the intention to use BLC-based applications, underscoring the importance of intuitive designs that promote sustained adoption (Shrestha & Vassileva, 2019). For example, the use of middlewares that abstract the technical complexity of BLC allows users to interact through familiar interfaces, reducing entry barriers in solutions such as BBLPs (Teruel & Trujillo, 2020).

Perceived external control (PEC) is equivalent to facilitating conditions in UTAUT (Venkatesh & Bala, 2008) and can be defined as the feeling of having the necessary technical and organizational resources to effectively use a technology (Venkatesh et al., 2003). In the context of BBLPs, PEC reflects the user's perception of the availability of adequate means to fully leverage a BLC-powered program (Norbu et al., 2024). PEC encompasses both material resources (e.g., connectivity and devices like smartphones or tablets) and the skills required to complete tasks successfully (Jegerson et al., 2023). When users perceive a sufficient level of technical, organizational, human, and infrastructure support, their experience with the technology tends to be smoother and more satisfying, leading to greater engagement (Alazab et al., 2021; Sharma et al., 2023). In particular, the integration of BLC platforms demands solid technical infrastructure. For instance, in the transport sector, both digital service quality and technological infrastructure are decisive factors in accepting these solutions, directly affecting ease of use (Anbari et al., 2024).

As summarized in Table 1, existing literature extensively documents the influence of PU and PEoU on the intention to use (IU) BLC in various contexts, including cryptocurrencies, supply chain management, food traceability, and BBLPs. The positive effect of PEC on IU has also been established, particularly in cryptocurrency and logistics domains, which account for the majority of empirical studies. So, this paper postulates:

Hypothesis 1 (H1): PU positively influences IUBBLPs.

Hypothesis 2 (H2): PEoU positively influences IUBBLPs.

Hypothesis 3 (H3): PEC positively influences IUBBLPs.

3.3. Affective factors

Psychology and consumer behavior literature consistently demonstrate that emotions play a decisive role in individual evaluation and decision-making (Lerner et al., 2015). In the field of loyalty programs, Treiblmaier and Petrozhitskaya (2023) analyzed Twitter posts about two types of loyalty programs—one traditional and one BLC-based—and identified both positive emotions (e.g., joy and anticipation) and negative ones (e.g., sadness). Based on this approach and aligned with the CAN model, this study includes two broad emotional dimensions: positive emotions (PEM) and negative emotions (NEM).

Among positive emotions, feelings like pride and happiness have been associated with more effective loyalty program structures (Septianto et al., 2019). Consumers value emotionally gratifying experiences, prompting organizations to develop strategies that foster pleasant emotional states, with loyalty programs being a widely used tool for this purpose (Agarwal et al., 2022).

In technology contexts, pleasant emotions can favorably influence users' willingness to adopt digital products. Enjoyment and pleasure from using a system can significantly increase intention to use (Purwanto et al., 2019; Subero-Navarro et al., 2022).

However, these programs also face limitations. Operational errors, perceived unfairness in rewards, or unmet expectations may trigger negative emotions such as anger, disappointment, or frustration (Choi et al., 2007). These adverse affective responses reduce user satisfaction and active participation (Hwang & Kwon, 2016). When users feel their expectations are not met, the perceived value of the program declines, and their willingness to continue engaging decreases (Nguyen et al., 2022). Nonetheless, recent research suggests that negative emotions can have a catalytic effect: when customers perceive that their complaints are effectively addressed, these emotions may present opportunities to strengthen loyalty (Maduku et al., 2024).

Technology can significantly affect psychological well-being, and not all users adapt to it easily; some experience frustration or difficulty when using new technologies (Di Giacomo et al., 2020). This psychological dimension is particularly relevant in BLC applications for food traceability. In this context, W. Li et al. (2025) found that emotions such as optimism, insecurity, and discomfort act as moderating variables in the link between PU, PEoU, and acceptance of BLC systems. Additionally, Nudin et al. (2024) highlighted that perceived risk has a significant negative influence on usage intention. Based on this evidence, we propose:

Hypothesis 4 (H4): PEM positively influences IUBBLPs.

Hypothesis 5 (H5): NEM negatively influences IUBBLPs.

3.4. Subjective norms

Subjective norm (SN) refers to the perceived social pressure to perform or avoid a particular behavior (Ajzen, 1991). This concept was incorporated into TAM2 (Venkatesh, 2000) and later into

UTAUT as social influence (Venkatesh et al., 2003). Numerous studies highlight the importance of opinions from connected persons as key determinants of technology acceptance, making SN a cornerstone of the CAN model as well (Pelegrín-Borondo et al., 2017). In this study, SN is understood as the perceived social pressure concerning the appropriateness of using BLC to empower loyalty programs.

This variable is particularly relevant in the early stages of innovation adoption, especially when the technology requires more technical skills than conventional alternatives—such as BLC applications (Jegerson et al., 2023). However, the need for specialized knowledge may limit SN's effect on BBLP usage intention: widespread unfamiliarity with how the technology works and its benefits restricts its influence (Treiblmaier & Petrozhitskaya, 2023). In this context, support from institutions and companies becomes crucial; their active involvement can be a key catalyst for promoting the adoption of BLC-based applications (Chen, 2023). Likewise, digital media—especially platforms like Twitter, Facebook, or YouTube—can play an important role in increasing visibility, generating trust, and normalizing the use of these programs (Rejeb et al., 2020).

Ultimately, subjective norms influence individual decisions to adopt BLC technologies. Motivations for adopting such technologies may be tied to moral or personal values deemed desirable by the social environment, such as privacy, security, decentralization, minimal regulatory intervention, and anonymity (Teng, 2021). However, ethical concerns also exist around BLC use: some applications, like cryptocurrencies, have been associated with illicit activities such as money laundering (Ishmaev, 2021). Other concerns include high energy consumption (Tripathi et al., 2023) and regulatory challenges stemming from legal loopholes (Zwitter & Hazenberg, 2021).

As shown in Table 1, subjective norm has been confirmed as an explanatory variable for BLC technology acceptance in contexts including cryptocurrencies, supply chains, banking, finance, accounting, and academia. Therefore, we propose:

Hypothesis 6 (H6): SN positively influences IUBBLPs.

4. Materials and methods

4.1. Sampling

This study is based on a structured, self-administered online survey conducted from May 1, 2024, to July 30, 2024. The survey targeted individuals aged 45 and older residing in the United States. A stratified sampling approach was employed, with minimum quota requirements established: at least 45% male and 45% female, and at least 35% representation for each of the two age groups considered (45–54 years and 55 years or older). A minimum geographic representation of 15% was also ensured for each of the country's four traditional regions (Northeast, Midwest, South, and West). These quota thresholds were set to ensure minimum coverage of key demographic strata (gender, age group, and US region), thereby reducing the risk of unbalanced samples that are common in online surveys. At the same time, because data were collected via an online quota-based design rather than probability sampling, the findings should be interpreted as generalizable primarily to the target population of US online consumers aged 45+ rather than as fully population-representative estimates.

This research has been approved by the corresponding author's institution (CEIPSA-2024-PRD-0030), and informed consent was provided from all the subjects involved in the study.

4.2. Sample

A total of 946 responses were collected, of which 811 were retained after applying quality filters that excluded responses deemed suspicious due to excessively fast completion or lack of attention. Table 2 summarizes their sociodemographic profile, with a balanced gender distribution: 50.68% male, 48.71% female, 0.37% identified with another gender, and 0.25% did not respond. In terms of age, 39.21% were between 45 and 54 years old, and 60.79% were 55 or older. Geographically, most participants resided in the West (40.81%), followed by the Northeast (21.45%), the South (20.72%), and the Midwest (16.77%).

Regarding educational attainment, 5.80% had not completed high school, 25.52% had completed high school, 29.84% had some college education or held a technical degree, and 38.84% held a bachelor's degree or higher. In terms of annual household income, 64.24% reported earnings below $75,000, while 33.17% reported incomes of $75,000 or more; 2.59% did not respond. As for racial or ethnic background, 73.12% identified as white or Caucasian, with the remainder identifying as Hispanic or Latino (7.40%), African American (6.41%), Asian or Pacific Islander (5.43%), other ethnicities (1.48%), or did not respond (6.17%).

To assess the adequacy of the sample size, we conducted a power analysis using G*Power 3.1 (Faul et al., 2009). Assuming the model depicted in Figure 1 is estimated via linear regression with six explanatory variables—as is commonly done with PLS-SEM in this type of study—we evaluated the statistical power for detecting global model effects. For a 5% significance level, the power to detect small effect sizes ($f^2 = 0.025$) reaches 80%, which would require a coefficient of determination of at least 2.44%. As an additional benchmark, a Cochran worst-case approximation for proportions (95% confidence; $p = 0.5$) yields an indicative margin of error of approximately ±3.4 percentage points for $n = 811$.

Table 2. Sociodemographic profile of the sample (n = 811).

Item	Profile
Gender	Men 411 (50.68%); Women 395 (48.71%); Other 3 (0.37%) Non-answer 2 (0.25%)
Age	Between 45 and 54 years 318 (39.21%); 55 years or more 493 (60.79%)
Region	Northeast 174 (21.45%); Midwest 136 (16.77%); West 331 (40.81%); South 168 (20.72%); Non-answer 2 (0.25%)
Education	Less than high school 47 (5.80%); High school 207 (25.52%); Some college or associate degree 242 (29.84%); Bachelor's degree or beyond 315 (38.84%)
Annual household income	Less than $25000 165 (20.35%); $25000–$49999 195 (24.04%); $50000–$74999 161 (19.85%); $75000–$99999 105 (12.95%); $100000 or more 164 (20.22%); Non-answer 21 (2.59%)
Racial or ethnic group	White or Caucasian 593 (73.12%); Latinx, Hispanic, Latino, or Spanish origin 60 (7.40%); Black or African American 52 (6.41%); Asian/Pacific Islander 44 (5.43%); Another race or ethnicity not listed 12 (1.48%); Non-answer 50 (6.17%)

4.3. Measurement of variables

The scales used to measure both the dependent variable (behavioral intention) and the independent variables (PU, PEoU, PEC, and SN) are based on the extended Technology Acceptance Model, TAM3 (Venkatesh & Bala, 2008). Items related to positive and negative emotions were adapted from Mohammad and Turney (2013), taking into account the findings of Treiblmaier and

Petrozhitskaya (2023) in the context of loyalty program (LP) evaluations. Table 3 presents the variables considered, their source, and the exact wording of the items.

Table 3. Items of the scales used in this paper and their source.

Item	Source
Intention to use (IUBBLPs)	
IUBBLPs1: Should a brand I regularly use implement a BBLP, I would actively participate in it.	Venkatesh and Bala (2008) and Arias-Oliva et al. (2024)
IUBBLPs2: If a brand I regularly use adopts a BBLP, I would engage with it on a frequent and consistent basis.	
Perceived usefulness (PU)	
PU1: The BBLP is useful to me.	Venkatesh and Bala (2008) and Arias-Oliva et al. (2024)
PU2: This technology empowers me to exert greater control over how I manage and navigate my interactions.	
PU3: The BBLP delivers a broader and more versatile range of functionalities than conventional loyalty programs, enabling enhanced value extraction from loyalty schemes	
Perceived ease of use (PEoU)	
PEoU1: Learning to use rewards in a BBLP requires no effort.	Venkatesh and Bala (2008) and Arias-Oliva et al. (2024)
PEoU2: This blockchain-based technology is easy to use.	
Perceived external control (PEC)	
PEC1: I have sufficient knowledge to use blockchain technology.	Venkatesh and Bala (2008) and Arias-Oliva et al. (2024)
PEC2: BBLPs are compatible with other technologies I frequently use.	
PEC3: An easy-to-use interface enhances the perception of BBLPs.	
PEC4: Tutorials and support materials will enhance the value of BBLPs.	
Positive emotions (PEM)	
PEM1: Trust	Mohammad and Turney (2013) and Treiblmaier and Petrozhitskaya (2023)
PEM2: Anticipation	
PEM3: Surprise	
PEM4: Joy	
Negative emotions (NEM)	
NEM1: Anger	Mohammad and Turney (2013) and Treiblmaier and Petrozhitskaya (2023)
NEM2: Fear	
NEM3: Sadness	
Subjective norms (SN)	
SN1: Persons who are relevant to me think that I have to engage BBLPs.	Venkatesh & Bala (2008) and Arias-Oliva et al. (2024)
SN2: Persons whose thoughts I appreciate feel that I ought to use the BBLPs of brands.	

All responses were collected using an 11-point Likert scale, varying from 0 to 10. This broader scale, compared to the more traditional 4-, 5-, or 7-point scales, has been recommended by several authors due to its advantages. It allows for greater precision in capturing nuances in respondents' perceptions and offers higher psychometric sensitivity, facilitating approximations to interval-level measurement and normal distribution. Additionally, its 0–10 format is intuitive and easy for most people to interpret (Leung, 2011).

4.4. Data analysis using multilayer perceptron neural networks

Although NNs were applied in this study, because the variables were measured using scales, it was necessary to assess internal consistency, convergent validity, and discriminant validity (Gbongli et al., 2019; Legesse et al., 2024; Salifu et al., 2024). To construct variable scores, standardized extraction of the first principal component of each scale was performed. Using these scores, discriminant validity and the correlations between IUBBLPs and the input factors were analyzed. These correlations also serve as a preliminary empirical test of the hypotheses proposed in Section 2. These analyses were conducted using the semTools package in R.

To address research objectives (RO1 and RO2), five NN models were trained. Denoting a network architecture as XE → X1 → ... → Xn → XS, where XE is the number of input neurons, X1–Xn represent the number of neurons in the hidden layers, and XS is the number of output neurons, we used XE = 6 and XS = 1 in this study.

Of the five networks trained, three had a single hidden layer (6→X1→1), and two had two hidden layers (6→X1→X2→1). The number of neurons in the hidden layers of the first three networks was determined using well-known heuristics:

- Network 1 (NN1), architecture (6→5→1): Based on Hecht-Nielsen's heuristic, which suggests the hidden layer should have 2/3*XE + XS neurons. For our case, X1 = 5.
- Network 2 (NN2), architecture (6→13→1): According to Kolmogorov's theorem, a single hidden layer with 2*XE + 1 neurons can approximate any continuous function. For 6 inputs: 2 ×6 + 1 = 13.
- Network 3 (NN3), architecture (6→2→1): Based on Widrow's rule, the optimal number of hidden neurons is approximately the square root of the product of input and output neurons, √(6×1) ≈ 2.45, thus X1 = 2.

The two networks with two hidden layers were designed using a funnel-shaped structure to allow progressive feature extraction. A common heuristic is to assign X1 ≈ 2×XE and X2 ≈ X1/2 (Zhang, 2000):

- Network 4 (NN4), architecture (6→12→6→1): Strictly follows this heuristic.
- Network 5 (NN5), architecture (6→10→5→1): Slightly reduces the number of neurons to mitigate overfitting, adhering to recommended ranges. Given the dataset of 811 observations and 6 predictors, narrower architectures are preferred over excessively wide ones. Thus, this network uses slightly fewer neurons in the first hidden layer, while ensuring even symmetry (Goodfellow et al., 2016).

All NNs were trained in R using the torch library under a consistent configuration. The scores of the input variables (PU, PEoU, PEC, PEM, NEM, and SN) as well as the output variable (IUBBLPs) correspond to standardized values derived from the first principal component of their respective measurement items. The first principal component was adopted as a benchmark over simpler aggregation methods, such as arithmetic averages, because it maximizes the variance explained by the indicators and assigns empirically derived weights to each item. Consequently, this approach provides a more informative and efficient composite measure than unweighted mean scores (DiStefano et al., 2009). While mean-scale scores are more directly interpretable in the original 0–10 metric, principal component–based scores trade off some of that simplicity for a variance-maximizing, empirically weighted composite. Therefore, we will report descriptive statistics at the item level (Table 4) to preserve interpretability.

All hidden layers used the Rectified Linear Unit (ReLU) activation function, with mean squared error (MSE) as the loss function and the Adam optimizer with a fixed learning rate of 0.01. Training was performed over 100 full epochs (full batch), and random seeds [set.seed(123) and torch_manual_seed(123)] were set for reproducibility.

Although the sigmoid activation function was widely used in early NNs, ReLU is now the preferred choice, especially in regression tasks and models with multiple hidden layerre-s. This is because ReLU avoids the vanishing gradient problem, as its derivative remains non-zero for positive values, allowing more efficient error propagation during training (Glorot & Bengio, 2010). ReLU also enables faster and more stable convergence, improves computational efficiency by avoiding exponential operations, and reduces the likelihood of suboptimal local minima (Goodfellow et al., 2016).

To reduce the risk of overfitting, the set of architectures was defined to cover increasing levels of complexity while constraining the number of hidden units to recommended ranges given the sample size (n = 811) and the number of predictors (XE = 6). In particular, in addition to the funnel-shaped two-layer design, a more parsimonious two-hidden-layer network (6→10→5→1) was intentionally specified to mitigate potential over-parameterization. Overfitting was further assessed by contrasting in-sample fit with R^2, root mean squared error (RMSE), and mean absolute error (MAE) with out-of-sample predictive performance (Q^2, RMSE, MAE) under Monte Carlo cross-validation (1,000 random 70/30 splits), thereby evaluating generalization stability across repeated resamples under a fixed training configuration and reproducible seeds.

RO1 aims to assess the models' ability to explain adherence to BBLPs. This was done by analyzing the fit of the NNs to the observed IUBBLPs values and their predictive performance. Model fit was evaluated using R^2, RMSE, and MAE across the full sample. Predictive performance was assessed via Monte Carlo cross-validation by randomly splitting the sample into 70% training and 30% validation sets, repeated 1,000 times. Predictive metrics included the average Q^2, RMSE, and MAE. ANOVA and paired t-tests were applied to these metrics to determine whether differences in predictive performance between models were statistically significant. This analysis enables ranking the networks by their generalization capability.

RO2 focuses on evaluating the relative importance of the explanatory variables in predicting IUBBLPs. To this end, the permutation feature importance (PFI) method (Fisher et al., 2019) was applied to all five NN models. PFI results were compared across the different neural architectures. Additionally, we compared the PFI results with the average absolute Shapley additive explanations (SHAP) values, following Lundberg and Lee (2017), obtained from the NN with the highest predictive performance in RO1. This step was also implemented in R using the fastshap package.

5. Results

Three findings summarize our results. First, the proposed acceptance model explains and predicts IUBBLPs with high accuracy across all evaluated MLP architectures. Second, the single-hidden-layer network NN2 (6→13→1) delivers the best out-of-sample predictive performance, whereas NN5 (6→10→5→1) provides the best in-sample fit. Third, importance analyses consistently indicate that cognitive variables and, especially, PU, are the dominant drivers of IUBBLPs; SN and NEM remain among the least influential predictors. In this regard, Figure 2 shows the results regarding 6→13→1.

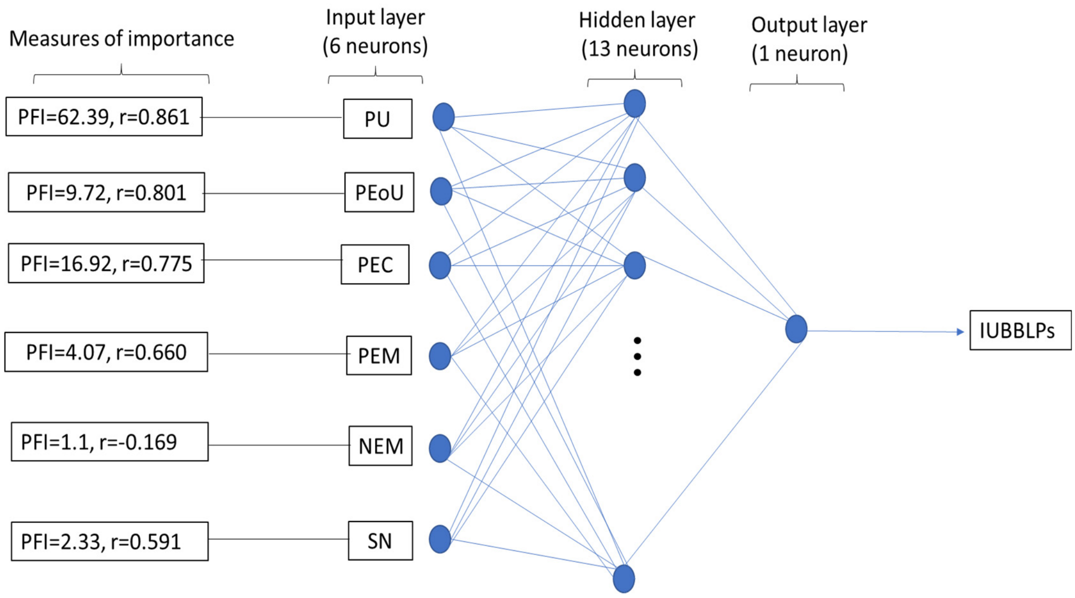

Figure 2. Shape of the optimal multilayer perceptron (6→13→1). (Note: PFI = permutation feature importance and r = Pearson correlation of explanatory variables with IUBBLPs.)

5.1. Evaluation of the measurement model and descriptive statistics

Table 4 indicates that IUBBLPs is, on average, close to the neutral point, with PU and PEoU slightly above neutrality, PEC around neutrality, and PEM below neutrality. NEM items display low values (i.e., weak negative emotional reactions), whereas SN is clearly below neutrality.

Regarding distributional assumptions, the Cramér–von Mises test rejects normality for all items; however, this does not pose a concern in our neural-network setting.

Table 4. Descriptive statistics of items.

Item	Mean	SD	CVM	Factor loading
Intention to use (IUBBLPs)				
IUBBLPs1	5.062	3.268	1.902	0.971
IUBBLPs2	5.052	3.282	1.91	0.971
Perceived usefulness (PU)				
PU1	5.189	3.198	1.889	0.958
PU2	5.17	3.101	1.828	0.959
PU3	5.432	3.12	1.682	0.959
Perceived ease of use (PEoU)				
PEoU1	5.23	3.086	1.733	0.974
PEoU2	5.104	3.042	1.923	0.971
Perceived external control (PEC)				
PEC1	4.351	3.18	1.924	0.862
PEC2	4.836	2.939	2.048	0.937
PEC3	5.074	3.15	1.735	0.954
PEC4	5.257	3.141	1.719	0.928
Positive emotions (PEM)				
PEM1	4.403	3.132	2.207	0.914

Continued on next page

Item	Mean	SD	CVM	Factor loading
PEM2	4.321	3.229	2.76	0.938
PEM3	3.998	3.042	2.968	0.898
PEM4	4.06	3.166	3.123	0.945
Negative emotions (NEM)				
NEM1	1.77	2.397	13.556	0.874
NEM2	2.6	2.837	7.542	0.916
NEM3	1.947	2.57	14.07	0.837
Subjective norms (SN)				
SN1	3.691	3.077	3.001	0.973
SN2	3.815	3.092	2.703	0.973

Note: (a) SD stands for standard deviation, CVM is the Cramér–von Mises statistic. (b) In all cases, the CVM test rejects normality for all items ($p < 0.001$).

Table 5 shows strong measurement quality. Internal consistency is high (Cronbach's alpha and composite reliability > 0.70), convergent validity is supported (AVE > 0.50), and item loadings exceed 0.708. Discriminant validity is also supported, as the square root of each construct's AVE exceeds its correlations with other constructs, and inter-construct correlations remain below 0.85. Finally, bivariate correlations between predictors and IUBBLPs are statistically significant and display the expected signs.

Table 5. Scale reliability measures.

	Internal consistency and convergent reliability			Matrix to assess the discriminant validity of the scales						
	Cα	Cr	AVE	IUBBLPs	PU	PEoU	PEC	PEM	NEM	SN
IUBBLPs	0.939	0.970	0.942	0.971						
PU	0.956	0.972	0.919	0.861	0.959					
PEoU	0.942	0.972	0.945	0.801	0.857	0.972				
PEC	0.940	0.957	0.848	0.775	0.838	0.838	0.921			
PEM	0.943	0.959	0.854	0.660	0.722	0.692	0.731	0.924		
NEM	0.854	0.909	0.768	−0.169	−0.107	−0.162	−0.133	0.079	0.877	
SN	0.943	0.972	0.946	0.591	0.692	0.656	0.706	0.768	0.019	0.973

Note: (a) Cα is Cronbach's alpha, CR is composite reliability, and AVE is average variance extracted. (b) In the principal diagonal comes the squared root of average variance extracted. Under the principal diagonal comes Pearson's correlation between variables. (c) All correlations of explanatory factors with IUBBLPs are significant ($p < 0.001$).

5.2. Results of research objectives 1 and 2

With regard to RO1 (fit and predictive performance), Table 6 shows that all MLP specifications achieve substantial explanatory power, with an R^2 around 75% or higher except for NN4. In-sample fit is highest for NN5, closely followed by NN2, whereas NN4 exhibits the weakest fit.

Table 6. Model fit results of the five neural networks on the full sample.

Neural network	R^2	RMSE	MAE
NN1 (6→5→1)	74.75%	0.502	0.349
NN2 (6→13→1)	77.13%	0.478	0.326
NN3 (6→2→1)	75.28%	0.497	0.347
NN4 (6→12→6→1)	64.43%	0.596	0.450
NN5 (6→10→5→1)	77.47%	0.474	0.326

Out-of-sample performance (Table 7) confirms that NN2 (6→13→1) generalizes best, achieving the highest Q^2 and the lowest prediction errors (RMSE and MAE). The ANOVA results indicate that predictive performance differs across architectures. Importantly, predictive ability remains strong across all models (Q^2 well above conventional "good prediction" heuristics), suggesting that the proposed theoretical framework is robust to architectural choices.

Table 7. Monte Carlo cross-validation results for predictive performance of the neural networks.

Neural network	Q^2	RMSE	MAE
NN1 (6→5→1)	73.90%	0.507	0.357
NN2 (6→13→1)	74.80%	0.498	0.344
NN3 (6→2→1)	67.10%	0.566	0.421
NN4 (6→12→6→1)	74.00%	0.505	0.351
NN5 (6→10→5→1)	74.10%	0.505	0.350
ANOVA	F = 11.76 (p < 0.001)	F = 11.15 (p < 0.001)	F = 9.413 (p < 0.008)

Notes: (a) F stands for Snedecor's F; in parentheses is the p-value of ANOVA.

Table 8 corroborates the previous evidence by showing that predictive differences across architectures are systematic. In particular, NN2 exhibits significantly better out-of-sample performance than the remaining specifications, whereas the two two-hidden-layer networks (NN4 and NN5) do not differ significantly from each other. Overall, the results confirm NN2 as the most reliable predictive model, while NN5 remains the best in-sample fitting alternative (Tables 6–8).

Table 8. Pairwise comparison results from Monte Carlo cross-validation of predictive performance.

	Measure = Q^2			Measure = RMSE			Measure = MAE		
	MD	t-ratio	p-value	MD	t-ratio	p-value	MD	t-ratio	p-value
NN1 vs NN2	−0.90%	−4.44	<0.001	0.009	4.68	<0.001	0.013	7.02	<0.001
NN1 vs NN3	6.80%	7.88	<0.001	−0.059	−8.31	<0.001	−0.064	−9.25	<0.001
NN1 vs NN4	−0.10%	−0.48	0.631	0.002	0.48	0.632	0.006	1.89	<0.001
NN1 vs NN5	−0.20%	−0.73	0.468	0.002	0.78	0.440	0.007	2.75	0.007
NN2 vs NN3	7.70%	9.42	<0.001	−0.068	−10.07	<0.001	−0.077	−12.03	0.000
NN2 vs NN4	0.80%	2.76	0.007	−0.007	−2.86	0.005	−0.007	−2.61	0.011
NN2 vs NN5	0.70%	3.88	<0.001	−0.007	−3.90	<0.001	−0.006	−2.93	0.004
NN3 vs NN4	−6.90%	−8.03	<0.001	0.061	8.43	<0.001	0.07	9.90	<0.001
NN3 vs NN5	−7.00%	−8.70	<0.001	0.061	9.23	<0.001	0.071	11.06	<0.001
NN4 vs NN5	−0.10%	0.07	0.945	0.000	−0.11	0.917	0.001	−0.24	0.809

Note: MD stands for mean difference.

Regarding RO2, variable importance and robustness, Table 9 shows a clear and stable importance hierarchy. Across all architectures, PU is the dominant predictor of IUBBLPs by a wide margin, typically followed by PEoU and PEC. By contrast, SN and NEM remain at the lower end of the ranking across specifications, indicating that cognitive evaluations dominate affective and normative factors in explaining IUBBLP acceptance in this cohort.

Table 10 further supports robustness: importance rankings are highly correlated across architectures and across explainability methods. In addition, SHAP values computed for NN2 produce a closely aligned pattern with PFI, confirming the primacy of PU and the limited relevance of SN. Notably, SHAP suggests that NEM may contribute modestly in specific regions of the prediction space;

however, its overall relevance remains clearly below the cognitive constructs and does not alter the main managerial conclusion that utility-related beliefs are the key lever for increasing adoption intention.

Table 9. Performance feature importance of explanatory variables in the evaluated neural network architectures and SHAP of the better ANN (NN2).

Factor	PFI (NN1)	PFI (NN2)	PFI (NN3)	PFI (NN4)	PFI (NN5)	SHAP (NN2)
PU	69.52	62.39	55.42	78.48	74.81	51.23
PEoU	14.86	9.72	21.17	11.06	7.53	13.43
PEC	8.91	16.92	7.23	4.92	14.06	6.57
PEM	5.38	4.07	1.98	7.91	3.91	7.08
NEM	1.81	1.10	0.59	0.02	0.15	7.10
SN	3.6	2.33	1.16	3.49	2.11	4.27

Table 10. Pearson correlation between the PFI of the neural networks used and between PFI and SHAP of NN2.

	PFI (NN1)	PFI (NN2)	PFI (NN3)	PFI (NN4)	PFI (NN5)	SHAP (NN2)
PFI (NN1)	1					
PFI (NN2)	0.983	1				
PFI (NN3)	0.980	0.951	1			
PFI (NN4)	0.995	0.973	0.960	1		
PFI (NN5)	0.990	0.997	0.949	0.986	1	
SHAP (NN2)	0.995	0.967	0.975	0.993	0.978	1

6. Discussion

6.1. General discussion of the results

This study examined the factors explaining the adoption of LPs BLC-enabled (i.e., BBLPs) using multilayer perceptron (MLP) neural networks. The findings provide robust evidence in support of both research objectives. Regarding the first objective (RO1), the model shows strong fit and predictive capacity when implemented with neural networks (NNs). For the second objective (RO2), a clear hierarchy of the cognitive, affective, and normative factors influencing behavioral intention was established. The results suggest that cognitive variables—especially perceived usefulness—are the most relevant for understanding BBLP acceptance.

With respect to RO1, the results indicate that all NN architectures evaluated—even the simplest—demonstrated high explanatory power (R^2 exceeding 75%) and strong predictive ability (Q^2 close to 75%). This suggests that the theoretical model, which integrates constructs from UTAUT (Venkatesh et al., 2003), TAM3 (Venkatesh & Bala, 2008), and CAN (Pelegrín-Borondo et al., 2017), is well-aligned with the empirical behavior observed in the sample. Deep learning techniques, particularly MLPs, prove to be effective and valid tools for studying technology acceptance in disruptive contexts such as BLC.

Among the architectures, NN2 (6→13→1) stood out for its superior out-of-sample predictive performance across all indicators (Q^2, RMSE, MAE), while NN5 (6→10→5→1), a more parsimonious two-hidden-layer model, achieved the best overall in-sample fit. This pattern suggests a trade-off between model complexity and predictive stability, indicating that predictive gains do not necessarily increase monotonically with larger architectures and reinforcing the need to carefully calibrate network size—and to rely on repeated out-of-sample evaluation to mitigate overfitting—depending on whether explanation or prediction is the primary goal.

Regarding RO2, the PFI analysis clearly revealed that perceived usefulness (PU) is the most influential construct in predicting the intention to use BBLPs—consistent across all network architectures. This finding aligns with prior literature demonstrating PU's importance in BLC adoption across diverse domains such as cryptocurrencies (Jegerson et al., 2023), supply chain (Bandinelli et al., 2023), accounting (Bouebdallah et al., 2025), education (Al-Hattami, 2024), and food traceability (Nudin et al., 2024).

However, the relative importance of intermediate constructs (PEoU, PEC, PEM) shows sensitivity to the architecture used, reinforcing the value of employing multiple configurations to gain a more nuanced understanding. In contrast, negative emotions (NEM) and subjective norm (SN) consistently ranked as the least relevant factors. While it may be surprising that social influence plays a limited role compared to performance and effort expectancy or facilitating conditions, previous research has similarly reported the nonsignificance of SN in BLC adoption across the supply chain (Alazab et al., 2021; Kamble et al., 2019), cryptocurrency (Arias-Oliva et al., 2019), and food traceability (Ornelas Herrera et al., 2025). Likewise, the low importance of NEM is consistent with previous findings indicating its limited explanatory power in BBLP adoption (Souto-Romero et al., 2025).

6.2. Theoretical and analytical implications

From a theoretical standpoint, this study contributes to the technology adoption literature by validating a model that draws on established frameworks (UTAUT, TAM3, and CAN) in the relatively unexplored context of BBLPs. Unlike traditional models like TAM and UTAUT, the CAN model incorporates affective and normative constructs, offering a more holistic view of consumer behavior. This study confirms that such integration is appropriate and useful when capturing the complexity of emerging technologies such as BBLPs—especially given the relevance of positive emotions in loyalty program adherence.

The consistent dominance of PU as the most influential variable underscores the centrality of cognitive components in shaping behavioral intention—even in contexts where emotions or social norms might be expected to play stronger roles. This highlights that instrumental perceptions—i.e., beliefs about the tangible functional value of the technology—remain the primary driver of acceptance, even among older consumer cohorts.

Moreover, the minimal role of SN invites reconsideration of the weight attributed to social influence in the adoption of highly technical and disruptive innovations. Given that BLC remains perceived as a complex and poorly understood technology among the general public, it is plausible that social pressure does not significantly shape acceptance. This finding is consistent with earlier research noting the limited influence of SN in voluntary contexts such as this (Venkatesh et al., 2003).

Methodologically, the incorporation of NNs represents a significant innovation in technology marketing research. Compared to linear, compensatory models (e.g., SEM, multiple regression), NNs capture nonlinear relationships and threshold effects that more accurately reflect consumer decision processes—especially when mixing cognitive, affective, and normative constructs. The use of interpretability techniques such as PFI enhances transparency and usability, overcoming common criticisms of NN opacity.

Overall, this study not only empirically validates the CAN model applied to BBLPs but also introduces a powerful and replicable deep learning methodology that expands the analytical frontier of technology acceptance research.

6.3. Implications in practice

This study offers several practical insights for loyalty program designers, digital strategists, and marketing professionals considering the adoption of BLC.

First, the dominant role of PU suggests that BBLP initiatives should clearly communicate tangible, functional benefits to users. Marketing efforts should go beyond emphasizing technological novelty and translate advantages into user-relevant terms: greater control, transparency, interoperability, point accumulation and redemption ease, etc.

Second, since PEoU and PEC rank as second-tier factors, user-centered design, intuitive interfaces, and accessible onboarding processes are critical, particularly for demographic groups more resistant to technological change.

Third, although positive emotions are less influential than cognitive factors, their impact is still notable. Companies should consider crafting emotionally engaging user experiences through surprising rewards, gamification, or confidence-building communications to boost technology engagement once functional value has been established.

Lastly, the variability in factor importance across NN architectures suggests that practitioners leveraging predictive models for personalization or segmentation should carefully assess which model best balances fit, interpretability, and stability based on strategic needs.

6.4. Limitations and future research directions

While this study provides significant findings, it also presents limitations that open avenues for future research.

First, the sample is restricted to US-based users aged 45 and older, limiting generalizability to younger cohorts or different cultural contexts. Future studies should compare generational segments (e.g., Millennials, Gen Z) or conduct cross-cultural analyses considering institutional and cultural moderators of BBLP acceptance. In addition, future work could explicitly test moderating effects (e.g., age, gender, digital literacy, and prior BLC experience) to identify boundary conditions of the model across cohorts and markets.

This study relies on self-reported behavioral intentions as proxies for actual adoption, which may overestimate real technology use (Berkowsky et al., 2017). Future research could improve methodological rigor by employing experimental or longitudinal designs that track actual usage over time (Venkatesh et al., 2016). A promising step would be to combine self-reported constructs with behavioral traces (e.g., redemption frequency, wallet activity, program churn) and to evaluate whether the same drivers explain both intention and sustained use.

Third, while PFI proved effective in interpreting model relevance, complementary techniques such as SHAP or LIME are recommended, as they allow both global and individual-level interpretability. Future research could also compare the stability of importance rankings across explainability methods (PFI vs SHAP vs LIME) and across resampling schemes, providing more robust managerial prioritization.

Fourth, although MLPs were used, other deep learning architectures (e.g., recurrent networks, convolutional networks, transformers) could provide additional insights into the dynamics of technology adoption and should be explored in future work. For instance, sequence-based models could be leveraged when longitudinal or interaction data are available, while transformer-based approaches may be useful for integrating text-based inputs.

Finally, while the theoretical model included established constructs, it excluded contextual variables such as digital literacy, prior BLC experience, or risk perception, which could enhance explanatory power—especially in low-familiarity populations. Future studies could extend the framework by incorporating trust, privacy concerns, perceived risk, regulatory perceptions, and reward design characteristics (e.g., tokenization, interoperability, and perceived fairness of rules), which are particularly salient in BBLPs.

Moreover, aligned with recent methodological discussions, an especially promising future direction is to integrate the proposed ANN-based framework with large language models (LLMs) to (i) extract features from unstructured sources (open-ended survey responses, customer feedback, online reviews), (ii) scale data processing, and (iii) potentially enhance predictive accuracy through hybrid pipelines, while preserving transparency through explainable AI techniques (e.g., PFI/SHAP).

Finally, future research could move beyond observational designs by implementing experiments or field studies (e.g., A/B tests of benefit framing, transparency cues, or onboarding support) to assess causal mechanisms and to validate which managerial interventions effectively increase BBLP adoption and continued usage.

7. Conclusions

This study aimed to analyze the factors influencing the acceptance of BBLPs by combining the CAN model with NNs. Based on a representative sample of US consumers aged 45 and older, six explanatory variables grouped into cognitive, affective, and normative dimensions were evaluated, with two main goals: (1) to validate the explanatory and predictive capacity of the model (RO1), and (2) to establish the importance hierarchy of the factors in predicting usage intention (RO2).

The findings yield significant theoretical and practical conclusions. First, all NN models, regardless of complexity, showed excellent fit and predictive performance in Monte Carlo cross-validation. This validates the CAN model as a suitable framework for explaining consumer behavior in the context of emerging technologies like BBLPs, and highlights the power of NNs as tools for modeling complex adoption processes. Importantly, this study shows that ANN-based models can go beyond prediction by delivering interpretable, ranked evidence on the relative contribution of adoption drivers, thereby strengthening the managerial usefulness of deep learning in technology-acceptance research.

Among the architectures, the single-hidden-layer model with 13 neurons (NN2), based on Kolmogorov's theorem, exhibited the best out-of-sample predictive performance. Meanwhile, the more parsimonious hidden two-layer model (NN5) showed the best global in-sample fit. This emphasizes the need to align model architecture with the analytical goal—explanation or prediction—and suggests that predictive gains do not necessarily increase monotonically with architectural complexity, reinforcing the importance of careful calibration to mitigate overfitting and improve generalization.

Second, the hierarchy of factor importance provides actionable insights. PU was confirmed as the most influential determinant, echoing prior findings in technology adoption literature. This highlights that the success of BLC in loyalty settings depends less on its novelty and more on the perceived functional benefits to users. Accordingly, managers should prioritize communicating concrete consumer value (e.g., clearer rewards, flexibility, and transparency) and ensuring that the program delivers visible utility in everyday use.

In contrast, NEM and SN consistently appeared as the least relevant predictors. This suggests that emotional barriers and social pressure do not play a decisive role in adoption decisions for this demographic, partially contradicting models like UTAUT2 where social influence is more prominent. In disruptive and poorly understood technologies such as BLC, consumers seem to rely more on functional criteria than on social cues. This finding is particularly relevant for BBLPs targeting older consumers, as adoption strategies may be more effective when focused on usability and tangible benefits rather than social-proof campaigns.

Lastly, the sensitivity of intermediate factor rankings (PEoU, PEC, PEM) to architecture suggests caution in generalizing results from a single model. Still, the stability of the extremes (PU and NEM) provides confidence in the core findings. Future research may build on this evidence by validating the model with actual usage data as BBLPs mature, extending it to other populations and countries, and testing additional BLC-specific factors (e.g., trust, privacy, and regulatory perceptions).

By combining robust theoretical models with deep learning techniques, this study offers a comprehensive and nuanced understanding of BBLP adoption. It contributes novel empirical evidence on the drivers and barriers of the acceptance of BBLPs and demonstrates the value of NNs as a complementary tool in marketing and consumer behavior research. Overall, the study underscores that explainable deep learning can support both stronger prediction and clearer prioritization of managerial levers for accelerating BBLP adoption among older consumers.

Author contributions

The authors declare to have contributed equally to the manuscript. All authors have read and approved the final manuscript.

Use of AI tools declaration

The authors declare they have used ChatGPT (OpenAI) to improve the readability of this article.

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Conflict of interest

All authors declare no conflicts of interest in this paper

Data Access Statement

Research data supporting this publication are available upon request to any author.

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