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The Relevance of Cognitive and Affective Factors to Explain the Acceptance of Blockchain Use: The Case of Loyalty Programmes

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Abstract: Blockchain technology has been highlighted as one of the most promising technologies to emerge in the 21st century. However, the expansion of blockchain applications is progressing much more slowly than initially expected, despite its promising properties. These considerations motivate this study, which evaluates the drivers that facilitate the adoption of this technology through blockchain-based loyalty programs (BBLPs). The analytical framework used is the conceptual groundwork known as the cognitive–affective–normative model. Thus, we propose to explain the behavioural intention to use BBLPs (BEHAV) with two cognitive variables, namely perceived usefulness (USEFUL) and perceived ease of use (EASE); two affective variables, namely positive emotions (PEMO) and negative emotions (NEMO); and a normative factor, namely, the subjective norm (SNORM). A partial least squares-structural equation modelling analysis suggests that, to explain the expected response of BEHAV, only the positive relationships of the cognitive constructs with the response variable are significant. The results of the quantile regression suggest that the cognitive constructs, especially USEFUL, have a consistently significant positive influence across the entire response range of the response variable. The affective variables are significant in explaining the lower quantiles of BEHAV but not across the full response range. NEMO consistently has a significant negative influence on BEHAV in the percentiles at or below the median response. PEMO has a significantly positive influence on some of the BEHAV percentiles below the median, although this impact is not consistent across the lower quantiles of the median. The normative variable appears to have a residual influence on BEHAV, which, when significant (at the 90th quantile), is, contrary to expectations, negative. The results highlight that, while cognitive variables are essential in the acceptance of BBLPs, emotions—particularly negative ones—play an especially significant role among potential users whose level of acceptance falls below the central trend.

Keywords: blockchain; blockchain-based loyalty programs; cognitive–affective–normative model of technology acceptance; emotions; PLS-SEM; quantile regression

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1. Introduction

Blockchain, whose origins can be traced back to 2008 [1], has emerged as one of the most disruptive and revolutionary technologies of the 21st century [2]. Its decentralised nature eliminates reliance on a central authority, reducing the risk of single points of failure and enhancing system resilience against cyberattacks [3]. Furthermore, it offers greater security by validating transactions through multiple nodes, making them highly resistant to tampering [4].

Blockchain is also distinguished by its transparency, as all transactions are publicly accessible, fostering trust among users without the need for intermediaries [3]. Another key feature is the immutability of transactions. Once recorded, they cannot be altered or deleted, ensuring a permanent and reliable record [4]. Additionally, its programmability through smart contracts that execute automatically can increase efficiency and reduce process costs [5].

Blockchain has numerous applications in business management, improving data efficiency, security, and integrity across various sectors. Its potential spans areas such as human resources and finance, enabling organisations to optimise operations and enhance decision-making processes [4]. Specific applications include human resource management, where blockchain ensures secure storage and sharing of employee data, preventing unauthorised access [6]; supply chain management, where its transparency, traceability, and immutability enhance record-keeping [7]; and payment automation, which reduces administrative burdens [6]. The use of smart contracts further allows for the automation of business processes, boosting efficiency and effectiveness [8].

One of the areas where blockchain holds significant potential is marketing and commercialisation [9]. By ensuring data integrity, blockchain can enhance consumer trust and brand value in digital marketing [10]. It can be used to verify the legitimacy of ad interactions, ensuring that advertisers pay only for genuine engagements [11]. Blockchain also improves data exchange between consumers and marketers while safeguarding privacy. Marketers can access verified data directly from consumers, enabling more targeted and personalised marketing campaigns [9].

A particularly promising application of blockchain in marketing and commercialisation is the implementation of loyalty programmes through blockchain-based loyalty programmes (BBLPs) [12]. Loyalty programmes (LPs) are strategic tools employed by businesses to manage customer relationships, aiming to enhance loyalty through purchase-based rewards. These programmes play a critical role in marketing management by fostering customer retention, satisfaction, and long-term commitment [13]. The effectiveness of LPs in building personal attachment depends on factors such as the value, variety, and timing of reward redemption, as well as the relational benefits perceived by customers [14].

However, LPs often neglect factors that can generate negative perceptions among target customers or observers, thereby reducing their effectiveness [15]. Psychological aspects, such as feelings of unfairness or a lack of gratitude, can adversely impact a programme's success [16]. Furthermore, many consumers participate in multiple loyalty programmes, diluting their commitment to any single programme [17]. For LPs to succeed, they must foster emotional attachment rather than simply incentivising repeat purchases [18]. Poorly designed LPs that fail to align with customer motivations or market conditions risk implementing ineffective reward structures [19]. Timing is particularly critical; delayed rewards can diminish the perceived value of gratification, reducing the programme's effectiveness [17].

The application of blockchain to loyalty programmes (LPs) can address several challenges, such as the lack of transparency in rewards and the difficulties in their execution [20], as outlined above. The transparency of blockchain-based loyalty programs (BBLPs) allows businesses and customers to verify point transactions in real time, fostering trust by ensuring fair rule application [21,22]. Its robust security minimises the risk of fraud, as cryptographically sealed transactions are nearly tamper-proof [23]. Blockchain also enables interoperability between programmes across multiple brands, allowing customers to exchange points and increasing their perceived value [23,24].

Smart contracts further enhance BBLPs by executing programme rules automatically, simplifying management and reducing administrative costs [25]. Moreover, blockchain supports innovative loyalty models where customers can earn rewards for additional activities, such as community contributions, and facilitates the tokenisation of rewards, enhancing their appeal [20].

Despite blockchain's existence since 2008 and the widespread recognition of its potential, its adoption has been slow among industries and consumers, particularly in non-financial applications [26]. A significant number of consumers lack awareness of how to access and benefit from blockchain-based applications, which poses a barrier to widespread use [27]. Additional commonly cited barriers include technological volatility, regulatory uncertainty, a lack of standardisation, and insufficient technological understanding [20,26]. The decentralised nature of blockchain complicates its monitoring by governments. This lack of supervision by public entities results in regulatory uncertainty [26] and is an additional challenge for its widespread adoption [27].

While extensive literature exists on the determinants of blockchain adoption for cryptocurrencies [28] and its acceptance in supply chain management [29], studies exploring blockchain adoption in other fields remain limited. As Taherhoost [29] highlights, research on blockchain applications in marketing, such as BBLPs, is virtually nonexistent [30].

According to [29], the most widely used theoretical frameworks for analysing the acceptance of blockchain applications are the Technology Acceptance Model (TAM) [31] and the Unified Theory of Acceptance and Use of Technology (UTAUT) [32]. In this study, we propose employing an extension of these models, the cognitive–affective–normative (CAN) model, developed in [33]. The CAN model builds on TAM by incorporating affective variables, which are typically overlooked in the analysis of blockchain application acceptance.

Specifically, this research aims to explain behavioural intention to use BBLPs through two cognitive variables (perceived usefulness and perceived ease of use), two affective variables (positive feelings and negative feelings), and one normative variable (subjective norm). Attitudes towards technology and the variables shaping such judgments vary among participants. These attitudes, in turn, shape the probability weighting biases in behaviour within multiple interdependent subsystems managed by different operators [34]. This is the case of a decentralised system such as blockchain [1]. In this study, however, we retain the term behavioural intention (or intention to use the technology), commonly employed by technology acceptance psychometric models and consumer psychology studies, such as [31–33] or this study, rather than terms like behavioural decision-making or probability weighting bias, which are more typical of behavioural studies adopting a game theory perspective, such as prospect theory [34].

The proposed model is depicted in Figure 1. On the basis of the theoretical foundation of the CAN model, we develop the following research questions (RQs).

RQ1—what is the explanatory and predictive ability of the CAN model for behavioural intention towards the use of BBLPs?

RQ2—what is the influence of explanatory variables across the entire range of potential responses for the behavioural intention variable, including central tendencies and deviations from the central trend?

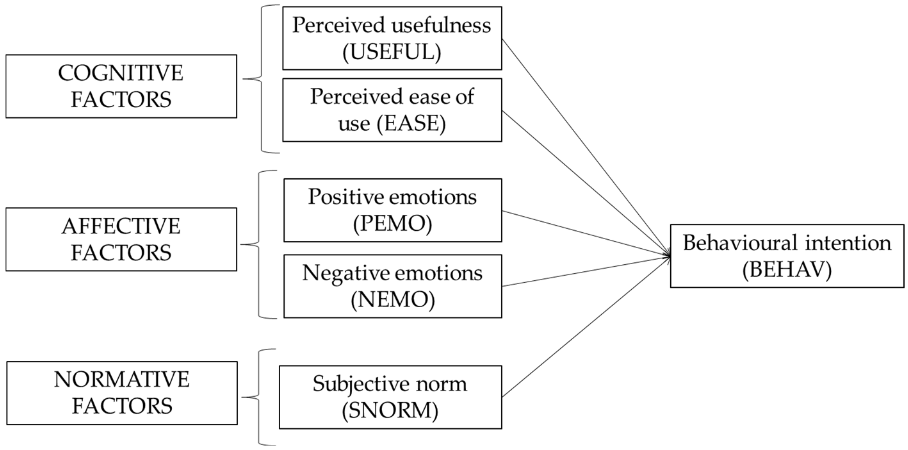

Figure 1. Theoretical groundwork used in this paper.

2. Hypothesis Development

2.1. Cognitive Variables

The factors labelled cognitive in the CAN model [33] are perceived usefulness (USEFUL) and perceived ease of use (EASE). These are the foundational constructs of the TAM [31] and UTAUT [32] acceptance models.

BBLPs offer several advantages in terms of utility compared to traditional programmes. First, they provide innovative services inherent to a shared economy, delivering value in the use of LPs concerning usage, accumulation, relevance, expiration, and transferability [20]. Second, blockchain technology enables the creation of a decentralised point alliance, breaking data interaction barriers between platforms and enhancing the usability of loyalty points through a blockchain-mediated trading mechanism [23].

Perceived usefulness is often the most significant variable in blockchain-based applications. This perspective extends to cryptocurrencies [35–39], supply chain management [7,40,41], finance and banking [42–44], academic applications [45], and internal organisational processes that require a certain level of security and trust [46,47].

Perceived ease of use has also been widely emphasised as a variable warranting special consideration, as the perception that blockchain applications do not provide user-friendly interactions inhibits their adoption by potential users [37]. Overcoming usability challenges in decentralised applications requires a user-centric design [48], ensuring that platforms are intuitive and encouraging sustained use [49]. When users perceive sufficient technological, organisational, network, and human support while using blockchain, they are more likely to engage with this technology [50].

The reviewed literature highlights perceived ease of use as a relevant factor in the acceptance of blockchain technology applications. This includes investments in cryptocurrencies [37], supply chain management [7,50], finance and banking [43], educational applications [51], and internal organisational processes [47,52,53] across industries such as aviation and tourism [54,55].

On this basis, we propose the following:

Hypothesis 1 (H1). *The perceived usefulness of BBLPs is positively correlated with the behavioural intention to use them.*

Hypothesis 2 (H2). *Perceived ease of use of BBLPs is positively correlated with the behavioural intention to use them.*

2.2. Affective Variables

The influence of emotions on the adoption of BBLPs is twofold. First, it is linked to the emotional component inherent in decision-making processes related to consumption [56]. Second, BBLPs involve the use of a novel technology [57]. Loyalty programmes (LPs) that lack emotional engagement are less likely to cultivate long-term loyalty, as customers may perceive their participation as transactional rather than relational [18]. Additionally, adopting a technology in its early stages of introduction, as is the case with blockchain in LPs, requires fostering the perception among potential users that its use is enjoyable. This is especially relevant when, as with BBLPs, use is not mandatory [58]. On the other hand, BBLPs may evoke negative feelings in some users because of phenomena such as technophobia [57] or computer anxiety [59].

In a sentiment analysis of two loyalty programmes (one conventional and one blockchain-based), ref. [20] reported that a significant number of tweets expressed both positive emotions, such as trust, anticipation, and joy, and negative emotions, such as sadness, anger, and disgust. Drawing on the CAN model and inspired by ref. [20], we propose two broad categories of emotions as explanatory variables: positive emotions (PEMO) and negative emotions (NEMO).

In sentiment analyses, trust is arguably the most frequently reported positive emotion regarding blockchain technology [60], and this applies to its use in loyalty programmes as well [20]. Blockchain's key features—decentralisation, immutability, and transparency—offer significant potential to enhance the security, reliability, and privacy of transactions, which can be crucial for fostering cognitive trust among users [7,61,62].

Positive emotions, such as pride and happiness, enhance the effectiveness of loyalty programme structures [63]. Positive emotions are essential for stimulating purchase experiences, and firms consistently seek ways to generate happiness among their customers. Loyalty programmes are widely used tools to achieve these positive feelings [64]. Furthermore, the role of enjoyment in the decision to use technological products has been documented [65]. The feelings of enjoyment and pleasure associated with a technology positively influence users' intentions to adopt it [57].

On the other hand, loyalty programmes are not without flaws and can be categorised into three types: rejection, reduction, and deferral of rewards. These issues may trigger negative emotions, such as anger, regret, and resignation [66]. Negative emotions have a significant effect on engagement with loyalty programmes, often resulting in reduced participation and satisfaction. Feelings such as frustration or disappointment can diminish the perceived value of these programmes, leading customers to disengage from loyalty initiatives [67]. Moreover, when customers encounter service failure or unmet expectations, they are less likely to participate in a programme that does not meet their needs [68].

Technology also affects individuals' psychological well-being, and for some, its use can result in difficulties and frustration [69]. Research has long examined concepts such as technostress, computer anxiety, aversion to computers, technophobia, and cyberphobia, sometimes without clearly differentiating between them [70]. Consequently, the association of a product or process with innovative technology can elicit negative emotions among potential users [57]. Thus, we propose the following:

Hypothesis 3 (H3). *Positive emotions are positively correlated with the behavioural intention to use BBLPs.*

Hypothesis 4 (H4). *Negative emotions are negatively correlated with the behavioural intention to use BBLPs.*

2.3. Subjective Norm

The literature underscores the importance of the subjective norm (SNORM) induced by close individuals, such as family and friends, as a pivotal factor in the CAN model [33]. New products and services in the early stages of development, such as those based on blockchain technology, may require a particularly enthusiastic wave of opinion for adoption, especially if their use demands a notable level of technological literacy [39].

The decision to use blockchain-based technology may be motivated by its association with certain moral and personal values that are favourably perceived by many, such as anonymity, decentralisation, low regulation, security, and privacy [71]. On the other hand, blockchain also presents aspects that may be perceived negatively from a moral standpoint. Some applications of blockchain technology, such as cryptocurrencies, may be used in criminal activities such as money laundering [72]. Other negative aspects from a moral perspective include the high energy consumption of this technology [73] or the difficulty in regulating it [2].

The literature outlines that the subjective norm is a significant factor in explaining adherence to blockchain applications. These uses embed investments in cryptocurrencies [37,39]; supply chain management [40,41]; finance, banking, and accounting [42,52]; and educational use [51]. Thus, we propose:

Hypothesis 5 (H5). *A favourable subjective norm toward BBLPs is positively correlated with the behavioural intention to use them.*

3. Materials and Methods

3.1. The Sample

This study analyses a structured, self-administered online survey completed by individuals aged 18 and older in the spring of 2024. It was distributed to anonymous respondents from the Northeastern United States, which includes the states of Connecticut, Maine, Massachusetts, New Hampshire, and New Jersey, as well as Washington D.C. The initial number of responses collected was 559. After applying quality control measures to filter out inattentive and rushed responses, a final sample of 361 observations was used.

Using G*Power 3.1 software [74], we verified that the sample size allows for a test power of 80% for significance levels of 5% and small effect sizes (0.02) when the significance of the regression coefficients derived from Figure 1 is assessed. This sample size provides 80% power to evaluate the overall model significance, assuming a 5% significance level and a coefficient of determination of at least 2.5%.

Table 1 shows the sample profile. With respect to gender, 199 respondents (55.12%) identified as female, and 159 (44.04%) identified as male. In terms of age, 119 respondents (32.96%) were under 35 years old, 132 (36.57%) were between 35 and 54 years old, and 110 (30.47%) were 55 years or older. With respect to educational level, 130 individuals (36.01%) reported having completed no higher than high school, 192 (53.19%) had a graduate degree, and 31 (8.59%) had postgraduate qualifications. In terms of annual income, 158 respondents (43.77%) reported incomes of less than USD 50,000, 132 (36.57%) were in the USD 50,000 to USD 99,999 range, and 67 (18.56%) reported earning USD 100,000 or more.

Table 1. Sample profile (N = 361).

Variable	Responses	Percentage
Gender		
Female	199	55%
Male	159	44%
Other/nonanswered	2	1%

Table 1. *Cont.*

Variable	Responses	Percentage
Age		
≥18 and ≤34 years	119	33%
≥35 and ≤54 years	132	37%
≥55 years	110	30%
Academic degree		
High school or less	130	36%
Graduate degree	192	53%
Postgraduate degree	31	9%
Other/nonanswered	8	2%
Annual income		
≤USD 49,999	158	44%
≥USD 50,000 to ≤USD 99,999	132	36%
≥USD 100,000	67	19%
Nonanswered	3	1%

3.2. Measurement of Variables

The scales used to measure BEHAV, the cognitive variables (USEFUL and EASE), and the normative variable (SNORM), following the approach [33], are based on those used in [75] in the TAM2. The items on positive and negative emotions were adapted from [76] and took into account the findings [20] in the context of evaluations of LPs. Table 2 presents the items considered. All the questions were answered via an 11-point Likert scale ranging from 0 ('strongly disagree') to 10 ('strongly agree'), with a neutral position corresponding to a score of 5.

Table 2. Items used in the study, descriptive statistics, and VIFs of the outer model.

Item	CA	CR	AVE	Mean	SD	Factor Loading
Behavioural intention (BEHAV)	0.911	0.911	0.918			
BEHAV1: If a brand I use offers a loyalty programme through a BBLP, I will engage with it.				5.014	3.147	0.959
BEHAV2: If a brand I use offers a loyalty programme through a BBLP, I will use it frequently.				4.911	3.141	0.958
Perceived usefulness (USEFUL)	0.933	0.934	0.882			
USEFUL1: The BBLP is useful to me.				5.283	3.053	0.933
USEFUL2: A BBLP allows for more efficient control of transactions within the loyalty programme.				5.357	2.863	0.943
USEFUL3: The BBLP offers more options than traditional programmes for leveraging loyalty programmes.				5.468	2.929	0.943
Perceived ease of use (EASE)	0.900	0.905	0.909			
EASE1: Managing the rewards and tokens associated with BBLPs is clear and understandable.				5.152	2.887	0.957
EASE2: This blockchain-based technology is easy to use.				5.463	2.914	0.949
Positive emotions (PEMO)	0.936	0.939	0.839			
PEMO1: Trust				4.748	2.935	0.900
PEMO2: Anticipation				4.471	2.965	0.932
PEMO3: Surprise				4.490	2.960	0.896
PEMO4: Joy				4.496	3.069	0.935
Negative emotions (NEMO)	0.885	0.952	0.805			
NEMO1: Disgust				2.424	2.801	0.919
NEMO2: Fear				2.950	2.838	0.916
NEMO3: Sadness				2.618	2.965	0.854
Subjetive norms (SNORM)	0.905	0.906	0.913			
SNORM1: The people who are important to me may feel that I should use BBLPs.				4.227	3.042	0.957
SNORM2: The people whose opinions I value believe that I should engage with brands' BBLPs.				4.285	2.954	0.954

3.3. Data Analysis

RQ1, which inquires about the influence of the explanatory variables on the expected response of BEHAV, is addressed via PLS-SEM. PLS-SEM does not impose strict assumptions regarding the normality of the data or require excessively large sample sizes, making it particularly suitable for when there is also an interest in the predictive capability of the model's expected response [77]. It is also the most commonly used methodology in the reviewed studies. The use of PLS-SEM allows for the evaluation of the influence of the CAN variables on the expected response of BEHAV.

RQ2 inquires about the influence of the CAN variables across the entire response range of BEHAV, which is addressed via quantile regression (QR), a method that does not require the assumption of normality in the data [78]. QR allows for the description not only of how the explanatory factors affect the response variable around its central values but also at any quantile of the response variable. In this way, QR provides a more comprehensive view of the relationships between the variables than methods focused on predicting the expected response, such as least squares regression [79].

The PLS–SEM analysis was performed using the SmartPLS version 4.1.0.8 software, following the protocol in [77]. The steps implemented were as follows.

For Step 1, we assessed the reliability of the construct scales by analysing their internal consistency and convergent validity. The former is evaluated using Cronbach's alpha (CA) and composite reliability (CR), both of which should exceed 0.7 and ideally not surpass 0.95. The latter is measured by checking that the average variance extracted (AVE) is at least 0.5 and that the factor loadings for the items exceed 0.702.

For Step 2, the discriminant validity of the scales is verified using the Fornell–Larcker criterion and by assessing the correlations between latent variables [80].

For Step 3, we adjusted the paths from Figure 1 using PLS-SEM with bootstrapping (percentiles) and 10,000 subsamples. The goodness of fit of the model was evaluated via the R^2 coefficient of determination, and its predictive ability was assessed using the Stone–Geisser Q^2.

For Step 4, the collinearity of the adjusted structural model was evaluated by analysing the variance inflation factor (VIF). In this step, we tested the reliability of the hypotheses formulated in Section 2.2 regarding the influence of the evaluated variables on expectations about BEHAV and the effect size of the paths using Cohen's f^2 effect size.

The implementation of QR was carried out via Gretl version 2003b software [81] in a manner similar to that used by Agarwal et al. [64] and Andrés-Sánchez et al. [82] to handle latent variables measured with psychometric scales. The measurement of reliability, internal consistency, and discriminant validity of the scales was completed in Step 1. Additionally, the quantification of the latent variables was performed via the factor loadings derived from the PLS–SEM regression analysis. We then performed:

Step 5: We estimate the model developed in the theoretical framework via QR at the following quantiles: τ = 0.1, 0.25, 0.4, 0.45, 0.5, 0.55, 0.6, 0.75, and 0.9. We measured the impact of the explanatory variables on the central quantiles of BEHAV (τ = 0.45, 0.5, and 0.55). These results can be used as alternatives to PLS-SEM. While PLS-SEM estimates the expected response values, these quantiles are calculated around the median. Moreover, QR allows us to assess the influence of the CAN variables below the central values (τ = 0.1, 0.25, and 0.4) and above these values (τ = 0.6, 0.75, and 0.9).

4. Results

4.1. Descriptive Statistics and Results of PLS-SEM

Table 2 presents the descriptive statistics of the items. BEHAV is far from the maximum acceptance score (10 points), as the ratings for its two items are close to the neutral value

(5). Similarly, the ratings for the USEFUL and EASE items are slightly above the neutral position but do not exceed six. On the other hand, the scores attained by SNORM and POSEM are slightly below the neutral value (above four but never exceeding five). Finally, negative emotions are rated significantly below the neutral value, as their scores never exceed 3 out of 10. It is also notable that the item ratings exhibit considerable variability, with a standard deviation above three for all items, which should be interpreted in relation to the fact that the scales use eleven points.

Table 2 also demonstrates that the scales used exhibit internal consistency, with both CA and CR exceeding 0.7 but remaining below 0.95, as recommended by [77]. The scales also show convergent validity, as the AVEs exceed 0.5 and the factor loadings are consistently greater than 0.702. In fact, their values indicate the near-complete extraction of all items, as they are 0.9 or higher.

Table 3 shows that the constructs have discriminant validity, as the square roots of the AVEs of all the latent variables are consistently greater than the correlations between the variables. Additionally, the correlations between the variables are almost always less than 0.85.

Table 3. Measures of discriminant validity.

	Discriminant Validity Matrix					
	BEHAV	**USEFUL**	**EASE**	**PEMO**	**NEMO**	**SNORM**
BEHAV	0.958					
USEFUL	0.848	0.939				
EASE	0.779	0.845	0.953			
PEMO	0.608	0.689	0.664	0.916		
NEMO	−0.072	−0.021	−0.067	0.225	0.897	
SNORM	0.515	0.627	0.588	0.765	0.206	0.956

Note: In the discriminant validity matrix, the square root of the AVE is indicated on the main diagonal, and below this, the correlations between the latent variables are displayed.

The results in Table 3 suggest that the sign of the correlations between the explanatory variables and BEHAV is consistent with the hypotheses proposed. It is positive for USEFUL, EASE, PEMO, and SNORM, and negative for NEMO. The positive correlation between PEMO and NEMO is also noteworthy, suggesting that individuals who express more intense feelings of one particular type (positive or negative) towards BBLPs are also likely to exhibit stronger feelings of the opposite type.

Table 4 shows the results of the PLS–SEM fit. The correlation coefficient indicates that the degree of fit of the CAN model to the sample is high (R^2 = 73.3%) and that it has a high predictive capacity (Q^2 = 71.9%). Table 4 also shows that only USEFUL, with a coefficient (β) of β = 0.692 and a *p*-value (*p*) < 0.001, and EASE (β = 0.158, *p* = 0.045) are statistically significant for predicting the expected value of BEHAV. In the first case, the effect size is moderate (f^2 = 0.399), and in the second case, it is small (f^2 = 0.022). Although the direction of the relationship between positive and negative emotions and BEHAV is as expected, this influence is not statistically significant. The relationship of SNORM, which is negative and therefore unexpected, also does not show statistical significance.

Table 4. Results of the estimation of path coefficients and decision-making hypotheses.

Relation	β	VIF	f^2	SD	t-Ratio	*p* Values	Decision
H1: USEFUL -> BEHAV	0.692	4.488	0.399	0.068	10.098	<0.001	Supported
H2: EASE -> BEHAV	0.158	4.25	0.022	0.078	2.001	0.045	Supported
H3: PEMO -> BEHAV	0.088	3.163	0.011	0.087	1.096	0.273	Nonsupported

Table 4. *Cont.*

Relation	β	VIF	f^2	SD	t-Ratio	*p* Values	Decision
H4: NEMO -> BEHAV	−0.052	1.172	0.009	0.031	1.762	0.078	Nonsupported
H5: SNORM -> BEHAV	−0.066	2.565	0.007	0.065	1.098	0.272	Nonsupported

Note: The determination coefficient of the model is R^2 = 73.3%, and Stone and Greisser's Q^2 is 71.3%.

4.2. Results of Quantile Regression Analysis

Table 5 presents the results of the fit of BEHAV around the median (τ = 0.45, 0.5, 0.55). Therefore, regressions, such as PLS-SEM, aim to fit the central values of the response variable. Both USEFUL and EASE are significant, with $p < 0.001$. However, the coefficient (γ) of USEFUL is consistently higher than that of EASE. Additionally, NEMO has a significantly negative impact on the regression performed for τ = 0.45 ($\gamma = -0.064$, $p < 0.001$) and τ = 0.5 ($\gamma = -0.047$, $p = 0.003$), thus confirming the sign predicted in H4.

Table 5. Quantile regression results of BEHAV around its median (τ = 0.45, 0.5, 0.55).

Quantile	τ = 0.45		τ = 0.5		τ = 0.55	
Variable	**Coefficient**	***p* Value**	**Coefficient**	***p* Value**	**Coefficient**	***p* Value**
USEFUL	0.748	<0.001	0.774	<0.001	0.781	<0.001
EASE	0.172	<0.001	0.159	<0.001	0.153	<0.001
PEMO	−0.008	0.798	−0.003	0.917	−0.003	0.898
NEMO	−0.064	<0.001	−0.047	0.003	−0.026	0.068
SNORM	−0.005	0.855	−0.015	0.519	−0.014	0.523

Table 6 shows the results of the regressions performed on the lower quantiles of BEHAV (τ = 0.1, 0.25, and 0.4). It can be observed that only USEFUL and NEMO have a significant influence on all three quantiles, with signs as expected. For USEFUL, the coefficients are τ = 0.1 ($\gamma = 0.516$, $p < 0.001$), τ = 0.25 ($\gamma = 0.665$, $p < 0.001$), and τ = 0.4 $\gamma = 0.738$, $p < 0.001$). For NEMO, the coefficients are τ = 0.1 ($\gamma = -0.114$, $p < 0.001$), τ = 0.25 ($\gamma = -0.180$, $p < 0.001$), and τ = 0.4 ($\gamma = -0.081$, $p < 0.001$). While the PEM has a significantly positive impact on the two lower percentiles, with τ = 0.1 ($\gamma = 0.229$, $p = 0.005$) and τ = 0.25 ($\gamma = 0.090$, $p = 0.003$), EASE is significant only at τ = 0.25 ($\gamma = 0.137$, $p < 0.001$) and τ = 0.4 ($\gamma = 0.177$, $p < 0.001$).

Table 6. Quantile regression results of the inferior quantiles of BEHAV (τ = 0.1, 0.25, 0.4).

Quantile	τ = 0.1		τ = 0.25		τ = 0.4	
Variable	**Coefficient**	***p* Value**	**Coefficient**	***p* Value**	**Coefficient**	***p* Value**
USEFUL	0.516	<0.001	0.664	<0.001	0.738	<0.0001
EASE	0.033	0.728	0.137	<0.001	0.177	<0.001
PEMO	0.229	0.005	0.090	0.003	−0.025	0.532
NEMO	−0.114	0.021	−0.180	<0.001	−0.081	<0.001
SNORM	0.045	0.540	−0.029	0.285	−0.001	0.970

Table 7 shows the results obtained from the adjustments associated with the upper quantiles (τ = 0.6, 0.75, 0.9). Both USEFUL and EASE have a significantly positive effect on all quantiles of BEHAV. For USEFUL, the coefficients are τ = 0.6 ($\gamma = 0.780$, $p < 0.001$), τ = 0.75 ($\gamma = 0.743$, $p < 0.001$), and τ = 0.9 ($\gamma = 0.580$, $p < 0.001$). For EASE, the coefficients are τ = 0.6 ($\gamma = 0.155$, $p < 0.001$), τ = 0.75 ($\gamma = 0.242$, $p < 0.001$), and τ = 0.9 ($\gamma = 0.284$, $p < 0.001$). Additionally, it is surprising that, when PEMO and SNORM have a significant influence on BEHAV, this influence is, contrary to expectations, negative. For PEMO, this is observed at τ = 0.75 ($\gamma = -0.039$, $p < 0.001$), and for SNORM, it is observed at τ = 0.9 ($\gamma = -0.130$, $p = 0.040$).

Table 7. Quantile regression results of the upper quantiles of BEHAV (τ = 0.6, 0.75, 0.9).

Quantile	τ = 0.6		τ = 0.75		τ = 0.9	
Variable	**Coefficient**	***p* Value**	**Coefficient**	***p* Value**	**Coefficient**	***p* Value**
USEFUL	0.780	<0.001	0.743	<0.001	0.580	<0.001
EASE	0.155	<0.001	0.242	<0.001	0.284	<0.001
PEMO	0.001	0.968	−0.039	<0.001	0.048	0.489
NEMO	−0.007	0.443	0.012	0.087	−0.039	0.357
SNORM	−0.017	0.188	−0.005	0.637	−0.130	0.040

5. Discussion

5.1. General Considerations

This paper analyses the drivers of acceptance for blockchain-based loyalty programs (BBLPs) using a sample from the northwestern region of the United States on the basis of the cognitive–affective–normative (CAN) technology acceptance model framework [33]. Specifically, it evaluates the impact of cognitive variables, such as perceived usefulness (USEFUL), perceived ease of use (EASE), affective variables, positive emotions (PEMO), and negative emotions (NEMO), and the normative variable, subjective norm (SNORM), on the behavioural intention to use BBLPs. Two research questions (RQs) are proposed. The first (RQ1) examines the explanatory power of the model for predicting expected BEHAV responses. This RQ is answered via PLS-SEM. The second research question analyses how all explanatory factors influence the entire range of BEHAV, including both responses associated with centrality (near the median) and those reflecting overacceptance or underacceptance in relation to the central trend. This second RQ is developed via quantile regression (QR).

The development of RQ1, implemented with PLS-SEM, revealed that the model's fit to the data, according to [77], can be classified as good ($R^2 > 70\%$) and that it has high predictive capacity ($Q^2 > 50\%$). Furthermore, only the positive influence of the two cognitive variables (USEFUL and EASE) on the expectation of BEHAV is statistically significant.

The development of RQ2 with QR allows for a broader and more nuanced perspective on how the CAN variables affect BEHAV. The cognitive variables consistently influence all ranges of BEHAV responses. The exception to this observation is perceived ease of use at the 10th percentile of BEHAV. Using QR, we observe that the positive impact of PEMO and the negative impact of NEMO are significant in the lower quantiles of BEHAV. This is especially true for NEMO, which is consistently significant not only in all the lower quantiles evaluated (10th, 25th, and 40th) but also at the 45th percentile and the median. In contrast, the consistency of the positive influence of PEMO manifests only at the 10th and 25th quantiles of BEHAV. The subjective norm generally has no significant effect on BEHAV. In the only quantile where it does (the 90th quantile), the sign of the relationship is negative, contradicting the hypothesis.

The variables with the greatest impact on explaining the acceptance of BBLPs are the cognitive variables, with perceived usefulness having the most significant influence. This is an expected result, as this variable typically exerts the greatest influence on the acceptance of instrumental technologies [32]. This relevance is evident for both the effect size and path value in the PLS-SEM analysis, as well as in its persistence in significance across all quantiles of BEHAV. This finding is also consistent with the state of the art regarding the acceptance of blockchain applications, such as cryptocurrencies [35,37,39], supply-chain management [40,41], finance and banking [42,44], and academic applications [45].

Perceived ease of use also has a significantly positive influence on the expectation of behavioural intention, although with a smaller effect size than perceived usefulness and with slightly lower consistency across the entire range of BEHAV responses. As discussed in the literature review, the significance of EASE is widely reported in studies of the adoption and use of blockchain applications [7,37,41,43,52,54,55].

Although the two affective variables (PEMO and NEMO) did not show significance in the PLS–SEM fit, they did show significance in certain segments of the BEHAV response ranges. While PEMO only has a positive and significant influence on the two lowest quantiles, the negative influence of NEMO is consistently significant across all lower percentiles and the median. This finding must be understood both in light of the fact that consumer decisions are largely influenced by emotions [56] and that the intention to use new technologies can be driven by emotions such as pleasure and enjoyment derived from their use [58,83] while being hindered in individuals who have an emotional aversion to information technologies and computer use [57,59]. The influence of negative emotions on the acceptance of BBLPs is more consistent than that of positive emotions. This result suggests that in the acceptance of BBLPs, it is more important that there are no issues that generate feelings such as disappointment or anger due to failure or unmet expectations than that induce feelings such as trust or joy.

The results of RQ1 show that SNORM does not have a significant influence on BEHAV. RQ2 also suggests that the influence of SNORM is practically nonexistent across the entire range of BEHAV responses. Notably, there are precedents in the literature where SNORM has been reported as an irrelevant variable in explaining blockchain application acceptance. Such reports have been found in fields such as cryptocurrency investments [35], supply chain settings [40], and finance and banking applications [43].

5.2. Theoretical and Practical Implications

This paper develops an explanatory model of the acceptance of blockchain-based loyalty programs (BBLPs) on the basis of a cognitive–affective–normative (CAN) framework [33], which has proven to be effective in explaining the behavioural intention toward BBLPs. The model fits with PLS-SEM, explaining more than 70% of the variability in the behavioural intention of the sample and showing good predictive capacity, as the Q^2 indicator is >50%. Introducing affective variables into the analysis and complementing the SEM analysis with QR allows for obtaining certain insights that have not been observed in the literature on blockchain acceptance reviewed in Section 2. They are summarised in Table 8.

Table 8. Principal differences between this paper and the mainstream literature on blockchain application acceptance.

Mainstream Literature	Our Focus
Only one regression method is used (usually PLS-SEM or CB-SEM)	PLS-SEM is complemented with QR
The influence of the input variables is measured at the average response of the output variable	The influence of the input variable is measured across the entire response range of the output variable
The hypotheses proposed in the development of the model are accepted or rejected in a binary way	The proposed hypotheses allow not only complete acceptance or rejection but also nuanced acceptance
Most models take into account latent variables of a utilitarian or social norm nature. The only emotion considered is usually trust	The model considers a wide range of emotions, both positive and negative, resulting from the use of new technology, and this is applied to LPs
The subjective norm is often a significant variable in explaining behavioural intention	The social norm is not significant in explaining behavioural intention

We have found that the application of a mix of analytical tools, such as PLS-SEM and QR, provides a deeper understanding of how the potential drivers of BBLP acceptance influence behaviour. In this regard, it is important to highlight that the utility of this mixture of analytical tools, complementing PLS-SEM with other quantitative methods, has been suggested to be highly appropriate for understanding technology acceptance phenomena in numerous studies [44,84]. Moreover, the utility of quantile regression in consumer behaviour studies has been demonstrated by several authors [64,82]. While the exclusive use of PLS-SEM would have led us to conclude that only cognitive variables are relevant for explaining the acceptance of BBLPs, QR has shown that emotional variables, especially negative emotions, must also be considered. QR has also allowed us to observe that, while cognitive variables, particularly perceived usefulness, are consistently significant for explaining behavioural intention across all response ranges. Negative emotions are significant in the quantiles ranging from the median to the 10th percentile, whereas positive emotions are significant only in the lower quantiles.

The results are of interest to companies looking to implement blockchain technology in loyalty program management. The combined use of PLS-SEM and QR enables the establishment of a hierarchy of factors that can influence the successful implementation of blockchain in loyalty programs. The keystone factor is perceived usefulness, as it is the variable with the highest path coefficient and influences the entire range of behavioural intention responses. The promised advantages of blockchain technology for loyalty programs, such as automation in reward acquisition and the possibility of exchanging rewards with other programs or for cryptocurrencies, will become more apparent as its use becomes widespread. As more loyalty programs are powered by blockchain, consumers will be able to experience these benefits firsthand, managing multiple programs through a centralised platform. This helps users maximise their rewards and manage them more efficiently. Additionally, an expansion of BBLPs could foster the creation of more liquid reward markets, where cryptocurrency rewards or tokens can be more easily traded. This liquidity would add value to loyalty program rewards, turning them into more versatile and attractive assets for consumers looking to maximise the benefits offered by loyalty programs.

We have observed that the other cognitive variable explaining the acceptance of BBLPs, perceived ease of use, is also significant in explaining the expected behavioural intention, and this significance is very consistent across the entire response range. This suggests that the usability of the system supporting the loyalty program is a variable that, although not as influential as perceived usefulness, is still highly relevant. This underscores the importance of aspects that enhance the perception of the ease of use of BBLPs, such as providing quality web support [44]. For example, the existence of middleware that helps avoid the difficulties inherent in technology-mediated interactions could be crucial, allowing potential users to engage with BBLPs through user-friendly design and lowering entry barriers [85].

Although emotional variables do not have a significant influence on the expected behavioural intention response, they do have an effect on responses that deviate below the average. Therefore, they are still variables of interest, as these responses may be associated with users who tend to reject BBLPs, even when their perception of the cognitive variables is not unfavourable. The success of BBLP implementation, as with conventional loyalty programs, requires emotional attachment from consumers. In this context, it is important to emphasise that, beyond the need for loyalty programs to meet user needs, ensuring that users perceive them as fair, transparent, and trustworthy, it is also essential that their technological support be perceived in the same way.

5.3. Limitations of the Study and Further Research

The research acknowledges its limitations. The analysis has been conducted exclusively with individuals from the Northeastern United States. Therefore, the conclusions drawn in this paper should be applied with caution outside of this geographical context. Importantly, cultural factors are relevant for understanding behavioural intention towards the use of information technologies [86]. Thus, extending the findings to cultural environments not analysed is a natural line of investigation in the study of information system acceptance [87]. In the case of blockchain technology applications, cultural values, such as individualism versus collectivism [88] and national characteristics [89], are factors that should be considered if the results from this study are to be generalised. The good fit obtained with the proposed technological acceptance model allows us to assume that its application in other cultural contexts should also provide a good fit and, at the same time, allow for capturing the differential aspects of how the explanatory variables influence the perception of BBLPs.

The systematic review [29] shows that TAM-based and UTAUT-based models provide useful explanations for blockchain adoption in various contexts, such as cryptocurrencies, supply chain management, or educational activities. Since CAN is a model derived from these, it is expected to also demonstrate its explanatory capacity for acceptance in these areas. Moreover, it has been shown in different contexts that the emotions elicited by the use of new technologies, whether positive or negative, are relevant for explaining the activities mediated by them. This assertion includes the consumption of cyborg technology [33,90], the use of social robots for showrooming [57], or the use of mobile augmented reality in retail commerce [83]. This reinforces our belief that the application of the proposed CAN model will be suitable for analysing blockchain applications in fields such as marketing (e.g., advertising), as well as in other aspects of business administration (e.g., supply chain management) or social domains (e.g., electronic voting or education).

The implications of this research, which is cross-sectional, may have limited applicability in the medium and long term because of the considerable challenges posed by blockchain technology, such as high energy consumption, integration with legal systems, and governance and regulatory aspects [91]. A more comprehensive understanding of the drivers of BBLP acceptance requires longitudinal studies over time during other stages of blockchain technology implementation, in which its use becomes more widespread, and the current limitations are gradually overcome.

Furthermore, the study of BBLP adoption has been conducted using a technology acceptance model rooted in consumer psychology approaches. Analyses employing alternative approaches, such as behavioural models derived from game theory—like prospect theory, a well-known focus used in assessments of security and privacy [34]—would provide a more comprehensive and in-depth understanding of consumer attitudes towards blockchain-powered LPs.

6. Conclusions

This paper introduces a CAN model to explain the acceptance of BBLPs. The model's fit, evaluated using PLS-SEM, demonstrated strong explanatory and predictive power for the expected behavioural intentions. The study identifies perceived usefulness and perceived ease of use as significant factors in explaining the average behavioural intention, as well as the entire range of responses. Furthermore, emotional factors (positive and negative emotions) were found to be significant in quantiles below the median.

This study uses PLS-SEM and complements its results with quantile regressions. This methodology allows for a more nuanced interpretation of whether the five hypotheses outlined in Section 2 are supported by the statistical evidence. As it is pointed out in Table 8, these hypotheses may be fully supported, unsupported, or partially accepted (or rejected). Hypotheses 1 and 2, concerning the positive impact of cognitive variables on BEHAV, are consistently supported by the results. In the case of USEFUL, this consistency is complete. For EASE, it is nearly complete, as this variable only loses significance in one of the nine adjusted quantile regressions.

With regard to the hypotheses relating to the relationship between PEMO (Hypothesis 3) and NEMO (Hypothesis 4) with BEHAV, we can state that they are partially supported. The positive relationship between PEMO and BEHAV is supported in regressions associated with the lower quantiles, but not in those closer to the median or higher, nor in the PLS-SEM adjustment. The hypothesis of the negative relationship between NEMO and BEHAV is more robust, as it holds across all quantiles at or below the median. However, in quantiles above the median and in the PLS-SEM adjustment, this hypothesis is not supported.

Finally, Hypothesis 5, which posits a positive relationship between SNORM and BEHAV, is not supported by either the PLS-SEM adjustment results or those from the quantile regressions.

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