Reimagining Loyalty Rewards Programmes via Blockchain: Usage, Loyalty, and Firm Performance

Matthew Kenneth Hendricks
Student Number: HNDMAT008

Submitted in fulfilment of the requirements of the degree PhD in Business Science (BUS6000W) in the School of Management Studies, University of Cape Town

Supervisors: Professor Ines Meyer (administrative) and Dr Benedikt Hirschfelder (primary)
Co-supervisor: Dr Siphiwe Dlamini

September 2024

PLAGIARISM DECLARATION

1. I know that plagiarism is wrong. Plagiarism is using another one’s work and pretending that it is my own.
2. I have used the Harvard referencing guide for citation and referencing. Each contribution and quotation from the work of other people has been cited and referenced.
3. This thesis is my own work.
4. I have not allowed, and will not allow anyone, to copy my work.

Signature:

Date: September 2024

Turnitin Score: 8%

Acknowledgements

I would like to dedicate this thesis to my father, Barry Paul Hendricks. He taught me how to be brave and tackle the challenge of a PhD – one step at a time, just like our hikes up Table Mountain. I would also like to thank my partner Stephanie Wild, and my supervisors: Benedikt Hirschfelder, Siphiwe Dlamini, and Ines Meyer for their support and assistance with this thesis.

III List of acronyms

- **BBLP:** Blockchain-based loyalty programme
- **DOI:** Diffusion of Innovation Theory
- **LP:** Loyalty programme
- **PEOU:** Perceived ease of use
- **PU**: Perceived usefulness
- **SEM:** Structural equation modelling
- **TAM:** Technology acceptance model
- **TCCM:** Theory, Context, Characteristics, Methods
- **TOE:** Technology, Organisation and Environment
- **UTAUT:** Unified Theory of Technology Acceptance
- **WoM:** Word of mouth

Abstract

The emergence of blockchain technology is poised to revolutionise the loyalty programme (LP) landscape. Still, there is a dearth of research exploring the factors that influence the acceptance and resultant loyalty creation of blockchain-based LPs. This study examines the relationship between technological acceptance, loyalty creation, redemption and word-of-mouth yielded by a blockchain-based loyalty programme (BBLP). Employing the Diffusion of Innovation Theory and the Technological Acceptance Model (TAM), the study investigates the intention to use a BBLP as influenced by the perceived ease of use and usefulness of a BBLP. An integrated model combining the theories of Watson et al. (2015), Davis (1985) and Rogers (1995) was analysed in three separate but interrelated, descriptive, cross-sectional survey studies. In Study One (N = 995), the factors which influence the perceived ease of use, perceived usefulness, and ultimate intention to utilise a BBLP were examined. Study Two (N = 756) focused on the factors which contribute to the development of behavioural and attitudinal loyalty towards a BBLP, and the relationship that the intention to use a BBLP has with behavioural and attitudinal loyalty. Lastly, Study Three (N = 1157) focused on the relationship between the intention to use a BBPL and attitudinal and behavioural loyalty, as well as the relationship that behavioural and attitudinal loyalty has with word-of-mouth (WoM) and redemption. Redemption is typically neglected in the literature as a specific outcome, with only a handful of studies examining it as a specific variable. The perceived value of cryptocurrency, trust in blockchain and cryptocurrency, are emerging antecedents that are focused upon. This study is one of few that the perceived value of cryptocurrency is examined as an LP reward, which influences both PEOU and PU. The data was analysed using PLS-SEM and the software SmartPLS 4. The intention to use a BBLP and both behavioural and attitudinal loyalty were found to influence each other and enhance WoM. Attitudinal loyalty influenced redemption, though no significant link was found between behavioural loyalty and redemption. Managers should carefully consider their incentive strategies for a BBLP by incorporating relative advantage, satisfaction, trust, and commitment to drive loyalty.

Table of Contents

Chapter 1:

Introduction and Background of the Study

Introduction

Loyalty programmes (LP) have been referred to as important elements of sales and marketing programmes (American Airlines Group Inc, 2022), as a key driver of revenue generation (American Airlines Group Inc, 2022; Southwest Airlines Co, 2022) and as drivers of repeat business, an area of strong competition, and a differentiator that can distinguish and drive consumer preferences (Marriott International, 2022). Since, according to a KPMG (2019) report, mature brands generate 85% of their growth from their most loyal customers, the popularity of LPs among businesses is understandable. The LP landscape is expected to surpass US$217 billion by 2028 (Research and Markets, 2024) and in Europe, 60% of retailers had adopted LPs by 2020 (Bombaij & Dekimpe, 2020).

LPs can be defined as a marketing initiative that aims to build customer loyalty by providing benefits to participants in the LP (Yi & Jeon, 2003). However, LPs have been more broadly defined as any incentive system that aims to enhance customers' consumption behaviour over time without a change in price or core offering (Henderson et al., 2011). LPs can take many forms. The first LP started as early as 1896 with stamps provided to customers by the Sperry and Hutchinson company (Lacey & Sneath, 2006). In 1981, when stamps had become unpopular, American Airlines launched its frequent flyer programme, which led to a boom in LPs used in the United States and the rest of the world (Lacey & Sneath, 2006). Today, point-based LPs participants are popular across industries. Participants earn points from the issuer which can be redeemed for a variety of benefits including more products and services, as well as fiat money (Chun et al., 2020).

Despite their popularity, there are aspects to LPs subject to criticism. First, loyalty points accrued by customers can represent substantial value. It has been observed that as many as 70% of LP benefits do not get redeemed (Bijmolt et al., 2011). Estimates of unclaimed loyalty points were as high as US$100 billion in 2017 (Bond Brand Loyalty, 2017). As a promise for a future service, accrued points represent a liability for firms. These liabilities, in turn, can have a significant impact on the firm's earnings and profitability (Chun et al., 2020). In 2022, hotel chain Marriott International reported LP liabilities amounting to US$6.6 billion (an increase of US$123 million dollars from 2021) which accounted for 24% of the company's total liabilities (Marriott International, 2022). In the airline industry, American Airlines's LP liabilities were US$9.1 billion or 19% of the company's total liabilities in 2022 (American Airlines Group Inc, 2022). Similarly, Delta Airlines had US$7.9 billion in LP liabilities, comprising 20% of its total liabilities in 2022 (Delta Airlines Inc, 2022). These figures speak to the low redemption rates of loyalty points. It has been suggested that redemption rates are as low as 13.6% globally and 14% in South Africa (Yang et al., 2019). In addition, LPs are costly to operate and overemphasise financial dividends to create customer loyalty (Bond Brand Loyalty, 2023). Only 37% of respondents in a survey by KPMG (2019), involving 18 520 consumers in 20 countries, identified points and rewards as relevant to winning their loyalty. Instead, they favoured transparency and honesty. Lastly, to ensure that LPs do, in fact, maintain customer loyalty, they require continuous development so that they are adapted in line with changing consumer preferences (KPMG, 2019). KPMG (2019) reported that 75% of consumers would switch to a company with a better LP and 96% of customers agreed that LPs could be improved. Consequently, entire business units have been created to focus on the technological advancement of LPs, such as JetBlue ventures, which focuses on innovation in loyalty distribution and revenue of the airline JetBlue (JetBlue Airways Corporation, 2022).

Most importantly, though, the effectiveness of LPs has been questioned by firms, academics and consumers (Kim et al., 2003; Wait, 2022). In the United States, consumers, on average, belonged to 19 LPs but only actively participated in 9.3 of them (Bond Brand Loyalty, 2024). This was similar in Canada, where consumers, on average, belonged to 15 LPs but actively participated in 57% of them (Bond Brand Loyalty, 2023). In the retail sector, 59% of consumers used even their favourite LP less than once a week (KPMG, 2019). Further, those who do not redeem rewards have been found to be less loyal to the brand (Fromhart & Therattil, 2016; Bond Brand Loyalty, 2016). Since they are less loyal, they are also less likely to recommend the brand, and remain loyal after a bad experience (KPMG, 2019).

Often, technology has driven LPs to evolve, and those that embraced it have thrived. From there, technological advances in computation technologies, big data, and personal-information collection drove further changes to LPs. Data has been heralded as the 'new oil', recognising its value in the 21st century (Hirsch, 2013). Big data has enabled companies to make LPs more effective and profitable, aided by the nature of LPs that lend themselves to the collection of data (Stourm et al., 2020). Through a virtuous cycle, big data makes LPs more effective, and big data is easily collected using these very LPs (Stourm et al., 2020). By design, LPs encourage consumers to self-identity to reap rewards tied to their transactional data, providing a 360-degree view of the customer (Stourm et al., 2020). The next technological innovation, blockchain, will drive the next significant change for LPs. Emerging research has shown that BBLPs can transform business-to-consumer (B2C) relations and are perceived more positively by consumers (Treiblmaier & Petrozhitskaya, 2023). Tan and Saraniemi (2023) focused on how blockchain changes buyer-seller relationships in three keyways. First, blockchain technology transforms traditional buyer-seller relationships by making transactions more automated and discrete, reducing the need for control (Tan & Saraniemi, 2023). Second, with blockchain-based exchanges, trust shifts from being between individuals to being centred around the technology itself (Tan & Saraniemi, 2023). Thirdly, in blockchain-enabled exchanges, structural components take precedence over social and relational trust, which becomes less significant or even absent (Tan & Saraniemi, 2023). This is an early indication of this new technology's transformative potential, possibly akin to big data's impact on LPs.

Firms are already noting risks and opportunities created by LPs because of technological advancements (Marriott International, 2022). They are also actively exploring BBLPs. Nuraini (2022) identified seven existing BBLPs, including KrisPay by Singapore Airlines, Chanticleer Holdings, American Express and Boxed collaboration, AirBaltic's integration of non-fungible tokens (NFTs), Venmo, Shake Shack, and Loyal. This is not surprising, given the benefits of BBLPs for firms and end-users, which include cost reductions, channel harmony, improved audibility, security, privacy, better exchangeability and transferability of points, and faster and almost instant accrual and redemption. Marketing scholars have argued that blockchain technology might transform the marketing process and significantly impact marketing outcomes for firms and customers (Treiblmaier & Petrozhitskaya, 2023). LPs are one of the ways that blockchain can impact marketing outcomes (Rejeb et al., 2020). Blockchain technology presents an opportunity to reimagine and revitalise LPs for consumers and businesses. Through the publicity of cryptocurrency, Bitcoin has become synonymous with blockchain technology. However, Bitcoin is only one application of blockchain technology. Blockchain is a digital database of transactions (or a distributed ledger). This database is decentralised, and all transactions are verified and approved by a network of computers before they enter the ledger (Morkunas et al., 2019). Importantly, smart contracts can be implemented on top of blockchains (Zheng et al., 2020). These are contractual clauses that are enforced automatically (and independently) when certain conditions are met (Zheng et al., 2020). For example, Matthew and Stephanie agree on a US$100 penalty for violating a contract and they create a smart contract on the blockchain. If Matthew violates the clauses of the contract, US$100 will automatically be paid from Matthew's deposit (Zheng et al., 2020). These types of contracts create a high level of access control and enforcement, as they are recorded as unalterable transactions on the blockchain (Zheng et al., 2020).

Research gaps

This thesis addresses four contextual and six theoretical gaps in the literature, expanded upon in the preceding paragraphs.

Few articles explore the intersection of blockchain and marketing, as it is a relatively recent field (Antoniadis et al., 2019; Jain et al., 2021; Wasiq et al., 2023). As a result, this emerging area demands focused research (Jain et al., 2021). Initially, academic interest was slow, but numerous articles have since been published on blockchain and marketing (Treiblmaier & Petrozhitskaya, 2023; Tan et al., 2024). However, the specific intersection between blockchain and loyalty programmes remains under-researched, with limited publications on the topic. Researchers like Treiblmaier and Petrozhitskaya (2023) have begun to address these gaps. Yet, more rigorous academic research is required to fully explore the potential of blockchain within loyalty programmes to build on these initial, early findings.

Further, Li et al. (2018) found that few papers address the incentives for adopting blockchain. Antoniadis et al. (2019) also called for more research on the factors influencing blockchain adoption by firms and consumers in a marketing context. The explanatory power of TAM in a blockchain context has also been examined by only a few authors (Hamdan et al., 2022; Kamble et al., 2019). Existing findings suggest that PEOU and PU influence the intention to use cryptocurrency (Sohaib et al., 2019), blockchain-based research-sharing frameworks (Shrestha & Vassileva, 2019), cryptocurrency transactions (Taheri Tolu et al., 2022), cryptocurrency payments (Guych et al., 2018), and blockchain technology (Kamble et al., 2019; Liu et al., 2021). However, it has not yet been examined in a blockchain-loyalty context.

More specifically, limited research exists on the relationship between compatibility, innovativeness, complexity, and relative advantage in a blockchain context (Hamdan et al., 2022; Kamble et al., 2019, 2021; Kumari & Devi, 2023; Ullah et al., 2021), highlighting the need to explore these variables in a blockchain-loyalty context. This is important given the impact blockchain is poised to have on marketing. Brauer and Linnala Eriksson (2020) suggest that blockchain will broadly influence big data and digital marketing, specifically impacting fraud, customer data, and its ownership and control. Morkunas et al. (2019) demonstrate blockchain's impact on business models, affecting customer segments, channels, value propositions, customer relationships, and partnerships from a marketing perspective.

This focus is even more important given that whether LPs generate loyalty is still debated despite decades of academic research on their effectiveness (Belli et al., 2022). BBLPs may significantly contribute to this debate on effectiveness. A recent meta-analysis highlighted that LP-design factors, such as structure, reward content, and reward delivery, affect LP effectiveness (Belli et al., 2022). Furthermore, blockchain has the potential to impact rewards and structure substantially. For instance, tokenisation can transform rewards or loyalty points, enabling faster redemption (Chavez et al., 2022). It also allows consumers to use and exchange points more easily, even rewarding them in cryptocurrency (Treiblmaier & Petrozhitskaya, 2023; Udegbe, 2017). In terms of structure, increased interoperability allows for more cost-effective and scalable multi-vendor LPs, enhancing reward options and enabling faster point accumulation (Rejeb et al., 2020).

Similarly, research on the broader concept of loyalty is also prolific, while still widely debated. Researchers have adopted varied approaches to understanding loyalty (Watson et al., 2015). Bennett and Bove (2001) noted that, even after 70 years, there was no common method for measuring loyalty. Cengiz and Akdemir-Cengiz (2016) reviewed brand loyalty research from 2001 to 2015 and found that most studies did not specify their measurement approach, highlighting the need for a consensus in the field. Watson et al.'s (2015) meta-analysis provided a model to understand common antecedents and outcomes of loyalty as a multi-dimensional construct. To the author's knowledge, this is the first time that any part of the model proposed by Watson et al. (2015) has partially been examined empirically or in a blockchain-marketing context. Examining this model may, therefore, shed light not only on its applicability to blockchain but also on creating a common method for understanding and measuring loyalty.

Previous models have merged technology acceptance and loyalty, particularly in satisfaction-loyalty models (Niu et al., 2021; Agag et al., 2019). However, a comprehensive model that examines the link between technology acceptance, two-dimensional loyalty, and firm outcomes (redemption and word-of-mouth, or WoM) has not yet been attempted. The relationship between perceived value, engagement behaviour (which includes redemption) and loyalty has only been empirically tested by one recent study (Meyer-Waarden et al., 2023). The proposed model examined in this thesis may apply to any new technology where the ultimate goals are loyalty, redemption, and WoM. It proposes a framework that can be built upon to understand the effectiveness and impact of new loyalty technologies.

The antecedents to PEOU and PU are examined to thoroughly explore this unified acceptance-loyalty-outcome model. These antecedents are based on prior literature, with a focus on the perceived value of cryptocurrency and trust in blockchain and cryptocurrency as influencers of PEOU and PU. Trust and perceived value are well-studied antecedents in the technology acceptance literature (Queiroz et al., 2021; Aghdaie et al., 2012; Gefen et al., 2003). To a limited extent, they have also been studied in a blockchain context (Liu et al., 2021; Guych et al., 2018). However, the existing literature typically focuses on trust and value when examining the acceptance of the technology itself (blockchain or cryptocurrency), largely overlooking how trust in blockchain and cryptocurrency may affect the acceptance of the underlying solution powered by blockchain technology. This may be because applications of blockchain are currently limited, leading to gaps in the literature. To the author's knowledge, this is the only study that proposes the perceived value of cryptocurrency as an antecedent to both PEOU and PU.

This thesis, however, focuses on the value of the reward (cryptocurrency) for participating in the LP and the underlying technology (blockchain) rather than the solution itself. This approach is based on the theory that perceptions of the potential reward for participating in an LP and the underlying technology may significantly affect usage. The perceived trust in cryptocurrency is a major driver of purchasing decisions (Steinmetz et al., 2021). Only 23% of respondents trust the price stability of cryptocurrency (Bearingpoint, 2018). This affects the acceptance of LPs that reward participants with cryptocurrency. Even if a BBLP does not use cryptocurrency rewards, consumer confusion between blockchain and cryptocurrency may affect acceptance.

While emerging literature examines the perceived value of cryptocurrency (Gupta et al., 2023; Shuhaiber et al., 2023) and trust (Islam et al., 2023; Mendoza-Tello, 2019), the literature remains extremely limited, and it is not in the blockchain-marketing context. This thesis, therefore, sheds light on how the underlying technology driving an LP may influence usage, which subsequently has implications for any new technology shaping an LP. It also has important implications for how these new technologies are positioned and marketed. For example, if trust and value in the underlying technologies drive acceptance, this will influence how firms position the new technology as a benefit to using their LPs.

There is limited literature which examines loyalty two-dimensionally, and this is another important gap this thesis addresses. Viewing loyalty as a single construct can lead to misleading results; it should be examined as multi-dimensional (Kamran-Disfani et al., 2017; Watson et al., 2015), with researchers beginning to validate this perspective (Cifci & Erdogan, 2016). There is severely limited research, however, examining the relationship satisfaction, incentivisation, commitment, relative advantage and trust have with behavioural and attitudinal loyalty overall, especially in a blockchain or loyalty context (Al-dweeri et al., 2017; Cifci & Erdogan, 2016; Gecti & Zengin, 2013; Haverila et al., 2022; Inoue et al., 2017; Kamran-Disfani et al., 2017). Although these antecedents to loyalty have been examined before, this thesis contributes meaningfully to the field by adding to the more limited literature in the two-dimensional context. More specifically, this thesis contributes significantly to the literature by exploring relative advantage's effect on behavioural and attitudinal loyalty. This contribution is important, as relative advantage has been shown to have varied effects on loyalty one-dimensionally (Rambocas & Arjoon, 2012; Jamshidi & Kuanova, 2020; Dixon et al., 2005; Yun et al., 2012).

The model proposed by Watson et al. (2015) focused on performance as a firm outcome, whereas this thesis examines redemption as a specific outcome of loyalty. Reward redemption effects are largely overlooked in the literature, with most research focusing on the appeal of different reward categories and their relationship with revenue (Dorotic et al., 2014). Smith and Sparks (2009) were among the first to explore the relationship between loyalty and redemption through interviews with 20 women in a UK retailer's point-based LP. They found that the act of redemption itself creates positive feelings, enhancing the LP provider's standing among consumers attracted by point accumulation despite price differentials. Evidence suggests that traditional LPs have complex processes that delay the crediting of points to customers (Treiblmaier & Rozrozhitskaya, 2023). Redemption literature may be limited because it is included more broadly as part of customer engagement, including redemption, reading company emails, and sharing information (Meyer-Waarden et al., 2023). However, as mentioned before, even the link between the broader conception of customer engagement and loyalty is under-researched, with only one pioneering study by Meyer-Waarden et al. (2013) examining the linkage empirically. Therefore, not only is the examination of redemption important, given the lack of literature focusing on it, but also given the impact of firms who face issues with redemption affecting their evaluation of LP effectiveness.

Purpose of this study

The purpose of this thesis is to comprehensively examine the usage and effectiveness of an LP delivered through a new technology (blockchain) that is poised to transform LPs. This is done by focusing on a BBLP and examining the behavioural intention to use a BBLP, loyalty generation and firm outcomes (WoM and redemption), and their interrelationship. Understanding this can help firms design, market, and invest in better LPs that can help them overcome the current redemption and usage problems, making practitioners and academics doubt their effectiveness.

Research objectives, questions and hypotheses

This thesis has two key research objectives (ROs) and two secondary research objectives, which informed four research questions (RQs). These objectives and questions are detailed below. How the research objectives and questions are interconnected with different studies and how the research questions informed the hypotheses are also described.

Primary research objectives:

RO 1: Examine the impact of technological acceptance of BBLPs on the formation of consumer loyalty.

RQ 1.1: What relationship does the intention to use a BBLP have with behavioural and attitudinal loyalty?

RO 2: Investigate how loyalty towards a provider of a BBLP influences key firm outcomes, including redemption behaviour and word-of-mouth promotion.
RQ 2.1: What relationship does attitudinal and behavioural loyalty have with redemption and WoM?

Secondary research objectives:
RO 3: Determine the antecedents of the intention to use a BBLP.
RQ 3.1: What factors influence the PEOU, PU, and ultimate intention to utilise a BBLP?

RO 4: Determine the antecedents of the generation of attitudinal and behavioural loyalty for a BBLP.
RQ 4.1: What factors contribute to the development of behavioural and attitudinal loyalty towards a BBLP?

Table 1. The link between the studies and the research objectives and questions

Study	Research Objective Addressed	Research Questions Addressed
Study One	RO 3: Determine the antecedents of the intention to use a BBLP.	RQ 3.1: What factors influence the PEOU, PU, and ultimate intention to utilise a BBLP?
Study Two	RO 4: Determine the antecedents of the generation of attitudinal and behavioural loyalty for a BBLP. RO 1: Examine the impact of technological acceptance of BBLPs on the formation of consumer loyalty.	RQ 4.1: What factors contribute to the development of behavioural and attitudinal loyalty towards a BBLP? RQ 1.1: What relationship does the intention to use a BBLP have with behavioural and attitudinal loyalty?
Study Three	RO 1: Examine the impact of technological acceptance of BBLPs on the formation of consumer loyalty. RO 2: Investigate how loyalty towards a provider of a BBLP influences key firm outcomes, including redemption behaviour and word-of-mouth promotion.	RQ 1.1: What relationship does the intention to use a BBLP have with behavioural and attitudinal loyalty? RQ 2.1: What relationship does attitudinal and behavioural loyalty have with redemption and WoM?

The hypotheses below operationalise the above research questions.
Hypotheses that explore the relationship between technology acceptance, loyalty, and firm outcomes
H1: PEOU (H1a) and the PU (H1b) of a BBLP predicts the intention to use a BBLP.
H2: The intention to use a BBLP predicts the behavioural (H2a) and attitudinal loyalty (H2b) exhibited towards BBLPs.

H3: Behavioural loyalty (H3a) and attitudinal loyalty (H3b) exhibited towards BBLPs predict the intention to promote these programmes via WoM.
H4: Behavioural loyalty (H4a) and attitudinal loyalty (H4b) exhibited towards BBLPs predicts the intention to redeem benefits accrued for these programmes.
H16: Behavioural loyalty (H16a) and attitudinal loyalty (H16b) predict the intention to use a BBLP.

Hypotheses that explore the antecedents to the PEOU and PU of a BBLP
H5: Personal innovativeness predicts a BBLP's PEOU (H5a) and PU (H5b).
H6: Trust in blockchain and cryptocurrency predicts the PEOU (H6a) and PU (H6b) of a BBLP.
H7: The perceived value of cryptocurrency predicts the PEOU (H7a) and PU (H7b) of a BBLP.
H8: Compatibility predicts the PEOU (H8a) and PU (H8b) of a BBLP.
H9: Relative advantage predicts a BBLP's PEOU (H9a) and PU (H9b).
H10: Complexity predicts the PEOU (H10a) and PU (H10b) of a BBLP.

Hypotheses exploring the antecedents to the generation of behavioural and attitudinal loyalty exhibited towards a BBLP
H11: Commitment predicts the behavioural (H11a) and attitudinal (H11b) loyalty exhibited for a BBLP.
H12: Trust predicts the behavioural (H12a) and attitudinal (H12b) loyalty exhibited for a BBLP.
H13: Satisfaction predicts the behavioural (H13a) and attitudinal (H13b) loyalty exhibited for a BBLP.
H14: Incentivisation predicts the behavioural (H14a) and attitudinal (H14b) loyalty exhibited for a BBLP.
H15: Relative advantage predicts the behavioural (H15a) and attitudinal (H15b) loyalty exhibited for a BBLP.

Contributions of the study

This thesis contributes to a growing but limited literature examining BBLPs. Rejeb et al. (2020) emphasise this importance, highlighting blockchains' impact on LPs as a pending research area that can change how LPs are created and marketed to make them a more maintainable brand attachment.

Individually, each study uniquely contributes to prior literature. Study One contributes to knowledge by incorporating an integrated model using the TAM model and DOI theory has been suggested to a limited extent in a blockchain context (Knauer & Mann, 2019; Lou & Li, 2017; Ullah et al., 2021). There is limited literature on these integrated models that combine various theories and their explanatory power in blockchain. Furthermore, this study makes a methodological contribution as one of few studies that empirically tested a DOI-TAM model in a blockchain context, using an online survey and PLS-SEM. More specifically, this thesis contributes to understanding how integrated models by combining theories such as TAM and DOI can realise BBLP. Study One further contributes by proposing and validating unique constructs based on the TAM model adapted for a blockchain LP context, namely, trust in blockchain technology and cryptocurrency and the perceived value of cryptocurrency.

Study Two contributes to knowledge in the following ways: first, a combined loyalty-acceptancy model is proposed and tested based on the work of Watson et al. (2015). This is important considering Watson et al.'s (2015) structural model has not been empirically tested before, and loyalty research is yet to reach a consensus on a commonly accepted model to measure loyalty (Bennet & Bove, 2001; Cengiz & Akdemir-Cengiz, 2016). The study further contributes to establishing the link between behavioural and attitudinal loyalty and behavioural intentions to use new technology, which is yet to be attempted by scholars. Furthermore, it sheds light on loyalty as having attitudinal and behavioural components, understanding their effect, and how other variables affect them. Seeing loyalty as a single construct can lead to misleading results (Watson et al., 2015). Lastly, this study highlights the antecedents of loyalty creation in a blockchain-loyalty context, focusing on relative advantage and the role comparing alternatives can play in creating loyalty towards types of LPs. As mentioned before, this focus on relative advantage is an extension of the work of Watson et al. (2015).

Study Three contributes to knowledge by proposing a model incorporating technology, acceptance, loyalty, and firm outcomes. The study underscores the technological journey of a new loyalty technology, from acceptancy to intention to use, to loyalty creation, and finally to creating important firm outcomes in a loyalty context: WoM and redemption. The model highlights the applicability to any new technology where the ultimate goals are loyalty, redemption, and WoM. The study examines redemption as a unique construct and one specific to LPs, adapting the model proposed by Watson et al. (2015), which focused on performance.

Composition of the thesis

This thesis consists of seven chapters. Chapter 1 focuses on the contextual setting, the purpose of this study, and the potential contribution of this thesis. Chapter 2 focuses on a literature review and the development of both hypotheses and a theoretical model. Chapter 3 focuses on the research design and methodology used throughout this thesis. Chapters 4 to 6 focus on the three interrelated studies. These studies will be submitted to journals.

Each study examines a different aspect of the theoretical model. Chapter 4 is based on and focuses on usage factors and the factors that influence the intention to use a BBLP. Chapter 5 is based on Study Two and focuses on loyalty and the factors that influence the creation of behavioural and attitudinal loyalty towards a BBLP provider. Chapter 6 is based on study three and combines everything learned in Study One and Study Two, to examine the creation of firm outcomes (redemption and loyalty) through loyalty and usage. Finally, a chapter that concludes the thesis is presented in Chapter 7.

Chapter 2: Literature Review and Hypothesis Development

Blockchain technology and cryptocurrency

Agrawal et al. (2018) describes blockchain as *"…a public, digital, and distributed database solution providing decentralised management of transactional data."* Blockchain is the underlying technology that makes cryptocurrencies possible, as cryptocurrencies can only be sent or received via the blockchain (Farell, 2015). Cryptocurrencies are digital assets that are not issued by a central party or government. Transactions involving these assets are confirmed and recorded through a decentralised system (blockchain) that utilises a type of security called cryptography (Sun Yin et al., 2019). These digital currencies rely on the exchange of encrypted information to ensure secure and authentic transactions (Farell, 2015).

There is a lack of research focusing on the implementation of blockchain technology within business organisations. An exploration of the effect of blockchain applications on firms and industries can be dissected into three distinct categories: design, measurement and value, and management and organisation (Antoniadis et al., 2019). These categories can be further examined across four key groups: stakeholders and users, society, intermediaries, firms, and the industry, as well as the platforms involved (Antoniadis et al., 2019). Within business organisations, research on blockchain is mainly conceptual or exploratory in nature or focused on design (Agrawal et al., 2018; Casino et al., 2019; Wang et al., 2019). Academics have focused on the impact of blockchain on industries such as finance, agriculture, food, supply chain, energy, and education (Casey et al., 2018; Manski, 2017; Mengelkamp et al., 2018; Treiblmaier & Önder, 2019; Treiblmaier & Petrozhitskaya, 2023; Zheng et al., 2018). Overall, most existing research primarily explores the mechanics of the technology itself, as well as its potential applications and uses within the context of business organisations (Li et al., 2018). In a review paper and across five databases, Li et al. (2018) found no discussion of the blockchain applications for marketing. After initially responding slowly, numerous articles have since been published on blockchain and marketing (Treiblmaier & Petrozhitskaya, 2023).

Bitcoin revolutionised the digital currency market by decentralising the currency and liberating it from centralised control (Farell, 2015). This innovation enables individuals and businesses to engage in electronic transactions directly through a peer-to-peer network. Since gaining significant attention in 2011, Bitcoin inspired the creation of other cryptocurrencies, which have been referred to as altcoins (Farell, 2015).

Applications of blockchain technology and cryptocurrency in marketing

Smart contracts, a key part of blockchain technology, impact LPs (Behrouzi et al., 2023). The terms of an LP can be implemented on top of a blockchain, allowing a firm to reward consumers and profits derived from LPs to be shared with customers with high trust and transparency (Behrouzi et al., 2023). Further, LP tokens (a form of incentive for participating in an LP) can be used to distribute these rewards (Behrouzi et al., 2023). The tokenisation of loyalty points improves the usability of the points considerably. Blockchain technology has specifically been identified as transformative for LPs (Kowalewski et al., 2017). Marketers expect blockchain to have a positive impact on LPs (Lemos et al., 2022)

One of the core features of blockchain technology is that it allows authorised participants to share information easily (Treiblmaier & Petrozhitskaya, 2023). A blockchain platform can allow multiple organisations (through agreement via smart contracts) to exchange tokens between themselves in a secure environment (Behrouzi et al., 2023). Blockchain allows participants in an LP to realise the benefits of multiple LPs that offer the same token on the blockchain network, giving consumers more options (Behrouzi et al., 2023). This improves LPs, as it facilitates the transfer of points between otherwise separate programmes (Treiblmaier & Petrozhitskaya, 2023). Theoretically, these tokens could be traded freely within the network, exchanged for fiat currency, and even used as a medium of exchange if the token was accepted in the economy. Blockchain also allows members to track and store points more efficiently, freeing customers from a disjointed loyalty network (Rejeb et al., 2020).

When using a traditional LP, complex processes cause delays in crediting points to an LP participant's balance (Treiblmaier & Petrozhitskaya, 2023). A BBLP has the potential to provide customers with improved and faster (almost instant) redemption (Treiblmaier & Petrozhitskaya, 2023; Udegbe, 2017), and the ability to exchange currencies in one wallet (Udegbe, 2017). This eliminates the need for consumers to search for each programme's options, limitations, and redemption rules (Udegbe, 2017). This is a significant benefit, as the lack of participation (and redemption) can be explained by problems with interoperability among LPs (Behrouzi et al., 2023). Essentially, customers face difficulties with redemption because each firm has a unique LP structure and design (Behrouzi et al., 2023). Increasing interoperability (through establishing partnerships between firms) has been shown to improve customer experience and increase the frequency of purchases (Bond Brand Loyalty, 2023).

Operating a BBLP also has substantial benefits for those who operate these programmes. Using a single platform and automated agreements via smart contracts, the costs of running an LP through the blockchain are reduced and the efficiency of LPs is increased (Behrouzi et al., 2023). This is because blockchain allows the automation of point issuance, redemption, and transfer via smart contracts, improving the efficiency of an LP (Behrouzi et al., 2023). Further, since there is no intermediary between the firms and a single system, operation costs are reduced (Behrouzi et al., 2023). Operators gain improved tools for analyzing customer data through a BBLP, which provides them with more unified and streamlined data (Hoang et al., 2024).

A BBLP can also improve channel harmony and a consistent brand experience for customers through collaborative design and the development of programmes, possible through utilising blockchain technology (Rejeb et al., 2020). Adding to this, the technology enables better security and less fraud, through the verification of transactions on blockchain networks (Behrouzi et al., 2023; Rejeb et al., 2020). The increased audibility can help companies calculate their loyalty obligations more accurately (Treiblmaier & Petrozhitskaya, 2023). Tokens can encompass overall customer interaction and are not limited to purchases, allowing digital marketing to be synergised with purchases and rewards (Behrouzi et al., 2023). This allows marketers access to more specific customer data that enables the creation of more customisable LPs that have a higher utility to consumers and firms (Antoniadis et al., 2019; Rejeb et al., 2020).

Consumers are also dissuaded from participation in LPs due to privacy concerns that relate to sharing information (Gómez et al., 2012; Sönmeztürk et al., 2020). Privacy and data security are a key concern faced by digital LPs (Zhang, 2024). For consumers who do not belong to any LP, one in six are dissuaded from joining because they must share personal information (KPMG, 2019). Participation in an LP has also been shown to heighten privacy concerns (Hinz et al., 2007). Privacy and security over information are highlighted as aspects of an LP that can erode brand reputation and can create negative feelings and distrust towards a brand (Bond Brand Loyalty, 2023; Johansson & Rystadius, 2022). To earn their loyalty, consumers also favour transparency and honesty over points and rewards (KPMG, 2019). Since, by design, a record on a blockchain is immutable, the transparency and security of the LP is increased. This enables end-users to control access to and sharing of their personal data which is collected when they participate in an LP (Travizano et al., 2020; Treiblmaier & Petrozhitskaya, 2023). Overall, the increased data protection provided by a BBLP may improve customers' participation in LPs.

Owing to these benefits, it is no surprise businesses have started to implement and explore the delivery of LPs via the blockchain. In 2022, Dish, a satellite television company, adopted a backend token-based loyalty system on the Cardano blockchain (Treiblmaier & Petrozhitskaya, 2023). Additionally, Nuraini (2022) identified seven existing blockchain LPs, including KrisPay by Singapore Airlines, Chanticleer Holdings, American Express and Boxed collaboration, AirBaltic's integration of non-fungible tokens (NFTs), Venmo, and Shake Shack, as well as Loyyal.

Ultimately, a BBLP can improve redemption rates through better design, channel harmony, accessibility, and exchangeability than an LP that does not utilise this technology. These benefits cannot be ignored, as prior literature indicates that maintaining an LP is a substantial investment that comes with extra expenses, including operational, marketing, and training costs, without much certainty that the LP will be successful (Lee et al., 2014; Stauss et al., 2005). In addition, prior literature has shown that a BBLP can effectively strengthen customer loyalty (Utz et al., 2023).

Agrawal et al. (2018) outline several categories of LPs that exist: 'punch cards', where a consumer fills a physical or digital punch card to obtain a benefit; point-based programmes in which a user is rewarded with points for performing specific actions; fee-based LPs where a fee is paid for 'unlimited' benefits; cash-back programmes where cash is offered back to a user when they buy a good at a business; non-monetary rewards programmes in which a consumer is enticed to buy a product with a promise of a reward; and coalition programmes in which multiple companies collaborate to increase the programme's flexibility and appeal. It is also possible for a single rewards programme to adopt characteristics from several of these categories.

BBLPs are not a different category of rewards programme or a replacement for an existing LP (Agrawal et al., 2018). This means that any one of the categories mentioned above can be delivered as a blockchain-based programme.

Agrawal et al. (2018) point out that current conceptualisations of loyalty rewards programmes delivered via blockchain are split into those which reward a consumer with generic points and those which use company-specific points. Generic issues utilise universal loyalty cryptocurrencies accepted by all firms that use the currency. These universal loyalty cryptocurrencies can be exchanged for fiat or other cryptocurrencies, adding to their potential appeal to consumers. However, with company-specific points, a consumer can only redeem their points at the firm itself or one of its partners. Delivering company-specific points via blockchain infrastructure would be less efficient and more expensive, thereby eroding its benefit to companies (Agrawal et al., 2018).

Moreover, company-specific points limit the ability of consumers to take advantage of the flexibility that a generic points system can offer. For this reason, this research focuses on a points-based system delivered via blockchain that offers generic points to consumers. This leads to the definition of a BBLP based on the work of Agrawal et al. (2018): a points-based incentive programme that operates using blockchain technology and uses tokens to reward customers for enhancing their consumption behaviour over time.

Customers can purchase from a firm within a loyalty network hosted on the blockchain instead of a centralised loyalty database. This purchase can be tracked on the blockchain, and customers would receive tokens instead of loyalty points stored and generated on the blockchain. These tokens could be viewed and accessed similarly via a platform like a rewards application on a smartphone. Tokens, like points, could be exchanged and redeemed for discounts, free meals, and other value-added services within the loyalty network.

There has been a compound annual growth rate of 64.5% between 2017 and 2020 for blockchain applications within marketing. This is indicative of the interest and applications that marketing has within blockchain (Stallone et al., 2021). Antoniadis et al. (2019) highlights applications of blockchain within marketing to include supply-chain management; payments; marketing management; loyalty programmes; digital marketing; and reviews and credential management (Antoniadis et al., 2019). This is depicted in Figure 2. On the other hand, Rejeb et al. (2020) highlight six research areas: disintermediation, trust, click fraud, transparency, privacy, security and loyalty programmes, as areas that will guide future research that intersects with blockchain and marketing. Brauer and Eriksson (2020) propose that blockchain will influence big data and digital marketing broadly and, more specifically, fraud, customer data, ownership, and control of customer data. More practically, Morkunas et al. (2019) shows the impact of blockchain on business models, which, from a marketing perspective, includes customer segments, channels, value propositions, customer relationships and partnerships.

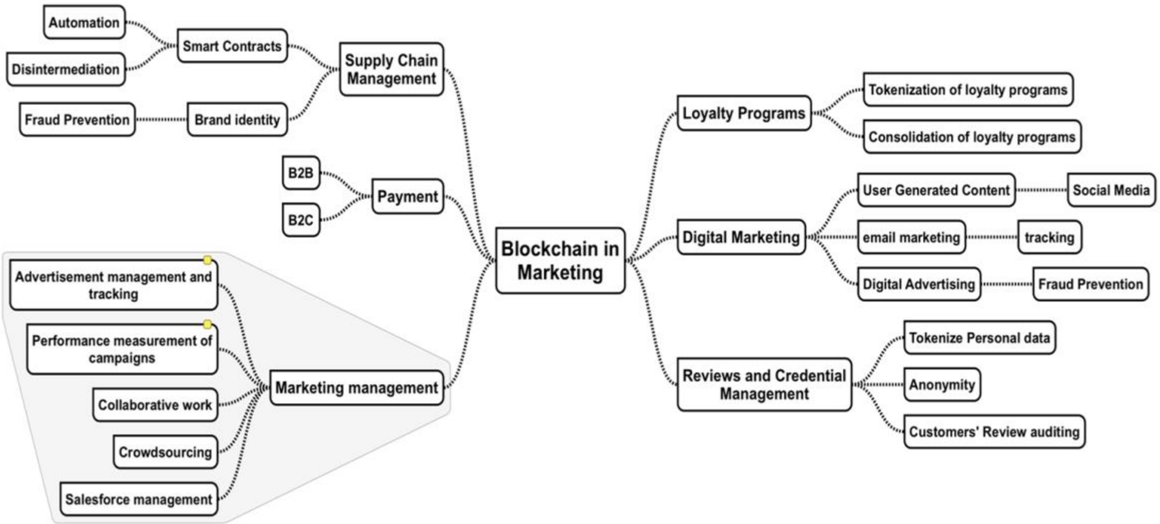

Figure 2. Applications of blockchain to marketing created by Antoniadis et al. (2019)

First, the blockchain, by design, creates trust and transparency (Bezovski et al., 2021). The blockchain is transparent because all transactions on the blockchain are accessible, traceable and auditable (Bezovski et al., 2021). Increased transparency means consumers' actions and behaviours can be analysed and traced (Hakkarainen & Colicev, 2023). This means that the likes and wants of consumers are more easily revealed, which may make consumers more reluctant to perform actions that can harm them in future (Hakkarainen & Colicev, 2023).

Second, transactions are immutable on the blockchain. Immutability means transactions cannot be reversed, which places a higher responsibility on consumers, as they need to avoid mistakes (Hakkarainen & Colicev, 2023). Lastly, the blockchain is decentralised, with no single party in full control (Bezovski et al., 2021). The decentralised nature of the blockchain causes shifts and expands the institutional role of consumers, turning them effectively into prosumers – consumers who consume and produce (Tan et al., 2023). Further, increased trust (partially facilitated by blockchain) alters existing relationships between firms and channels, which can be leveraged (Tan et al., 2023).

The most obvious application of blockchain within marketing is payments. Through cryptocurrency, blockchain facilitates B2C and B2B payments while eliminating intermediaries, reducing transaction costs, and improving profits (Antoniadis et al., 2019). Businesses can innovate by enabling access to these cryptocurrency payments (Hakkarainen & Colicev, 2023). Through the public attention garnered by applications of cryptocurrencies, offering customers cryptocurrency payments can be used as a marketing initiative too (Antoniadis et al., 2019).

Accepting B2C and B2B payments through cryptocurrency also has other implications. Currently marketers rely on data that is obtained from records of payment of the customer for digital-marketing initiatives (Trivedi & Malik, 2021). To further enhance this data, marketers rely on intermediaries for customer data (Pärssinen et al., 2018). The usage of cryptocurrency payments disrupts the collection and usage of customer data by marketers and intermediaries (Trivedi & Malik, 2021). The current data-sharing model allows data to be transferred to the service provider upon agreement of a contract(Hakkarainen & Colicev, 2023). Smart contracts allow users to regain control over their data, allowing them to choose when and with whom to share their data, through automated rules that cannot be altered (Hakkarainen & Colicev, 2023).

This creates problems for marketers for whom it limits knowledge of the customer, of specific targeting initiatives and of product and service personalisation (Bezovski et al., 2021). This will mean, for customer data, companies will have to approach the customer directly (Trivedi & Malik, 2021). The Sovrin Foundation and Datum are examples of institutions focusing on using blockchain to both protect and reward consumers for sharing their data by emphasising the data ownership of the individual (Stallone et al., 2021). Overall, this has obvious implications for a US$200 billion advertising industry, which contains thousands of intermediaries focused on customer data (Pärssinen et al., 2018).

Inherent in the blockchain is the verifiability and immutableness of transactions. This impacts supply-chain management. Smart contracts enable the monitoring of marketing sources, which can be used to verify the authenticity of products and help track suppliers and retailers, shedding light on supply chains while building trust with consumers (Antoniadis et al., 2019; Peres et al., 2023). For supply chains, this means blockchain can help locate inefficiencies and give consumers more visibility of the quality control exercised over a product through its journey from origin to the retailer (Adigüzel, 2021). Blockchain-use cases in the supply chain within marketing focus on replacing supply-chain-management systems (Bezovski et al., 2021). Examples of attempts at using blockchain to impact a supply chain include the IBM food trust and MediLedger (Bezovski et al., 2021).

Blockchain shifts marketing management from a centralised to a decentralised paradigm (Tan et al., 2023). This requires a shift in thinking to a more distributed, ethical philosophy and greater emphasis on engagement with primary and secondary stakeholders (Tan et al., 2023). Blockchain has been heralded as technology that will revolutionise advertising management and markets, by allowing it to be based on trust and transparency (Pärssinen et al., 2018). More specifically, blockchain effects advertising management and connects advertisers more effectively to consumers through the creation of media networks (Peres et al., 2023).

Similarly, sales management is positively impacted by blockchain change monitoring, compensation, and distribution. Blockchain allows more effective and accurate compensation for content creators based on content consumption, tracked and rewarded via tokens (Antoniadis et al., 2019; Peres et al., 2023). Blockchain allows transaction data from multiple sources to be brought together in a distributed database (Peres et al., 2023). This allows more effective usage, management and collection of data (Peres et al., 2023). For example, data on how a customer is exposed to digital marketing across multiple devices can be brought together on a decentralised database that is not owned by a single party, but is governed by smart contracts (Peres et al., 2023). This data can be further enhanced by the elimination of click fraud through blockchain. Computer bots generate false information in the advertising industry, creating mistrust (Gleim & Stevens, 2021). Through authentication and validation of user profiles, the blockchain can help combat click fraud which impacts the credibility and effectiveness of digital marketing (Antoniadis et al., 2019; Gleim & Stevens, 2021; Peres et al., 2023; Rejeb et al., 2020). Authentication and validation on the blockchain also enable the validation of reviews, increasing their credibility, while reviewers can be compensated with tokens for their contribution.

LPs have been highlighted specifically as an area of marketing that will be impacted, leading to the creation of 'creative LPs', revolutionising how LPs are monitored, created and disseminated to consumers (Antoniadis et al., 2019; Gleim & Stevens, 2021; Rejeb et al., 2020). Brands can innovate their LPs using cryptocurrency (Hakkarainen & Colicev, 2023).

Tokenisation allows the integration of all LPs in a single distributed platform to include a more unified view of consumer purchases and interaction with digital marketing (Antoniadis et al., 2019). Real-world applications have already emerged, seeking to capitalise on the changes that loyalty will bring for blockchain, 42.5% of companies focused on loyalty applications in 2021, when 800 blockchain-based companies were analysed (Stallone et al., 2021). Examples of companies exploring this area include Singapore Airlines with its frequent flyer programme and American Express and its rewards programme, as well as Digibits, which is a marketplace for loyalty points (Bezovski et al., 2021).

Furthermore, blockchain also more broadly impacts marketing strategy and more specifically market structures. The peer-to-peer structure of blockchain, with enhanced levels of security and trust, reduces the need for intermediaries, fostering disintermediation (Bezovski et al., 2021; Peres et al., 2023). This results in the co-creation of value (through distributed product design), with lower processing fees for participants (Peres et al., 2023).

Although the internet facilitates direct transactions and payments, blockchain allows market participants to securely connect, communicate, and pay, thereby bringing a true multi-sided market closer to reality (Peres et al., 2023). The distributed nature of blockchain allows for intermediary-free networks without centralised control or influence (Peres et al., 2023). Examples include social networks free from conglomerates; crowdsourcing networks; and media networks where consumers can be paid directly for engaging with digital advertising. For example, the company Brave Browser pays users for watching advertising, while NYIAX (New York Interactive Advertising Exchange) – an exchange – provides advertising inventory as guaranteed contracts (Stallone et al., 2021).

Trends in marketing and blockchain

Wasiq et al. (2023) recently conducted a systematic literature review of research trends in the adoption and applications of blockchain and marketing. The authors present a thematic evolution, which graphically depicts themes in the research area. This is depicted in Figure 3. The size of the bubble corresponds to the number of word occurrences, and the text in the bubbles corresponds to keywords that occurred the most (Khare & Jain, 2022). Basic themes are relevant but less developed than others, indicating opportunities for future research. Motor themes are those that are essential for the study of the topic; emerging or decline themes are, as the term suggests, losing or gaining relevancy in the research area; niche themes are marginally important in the field (Khare & Jain, 2022). As can be seen, research focuses on data privacy, big data, digital storage, blockchain, and sales as motor themes in this subject area.

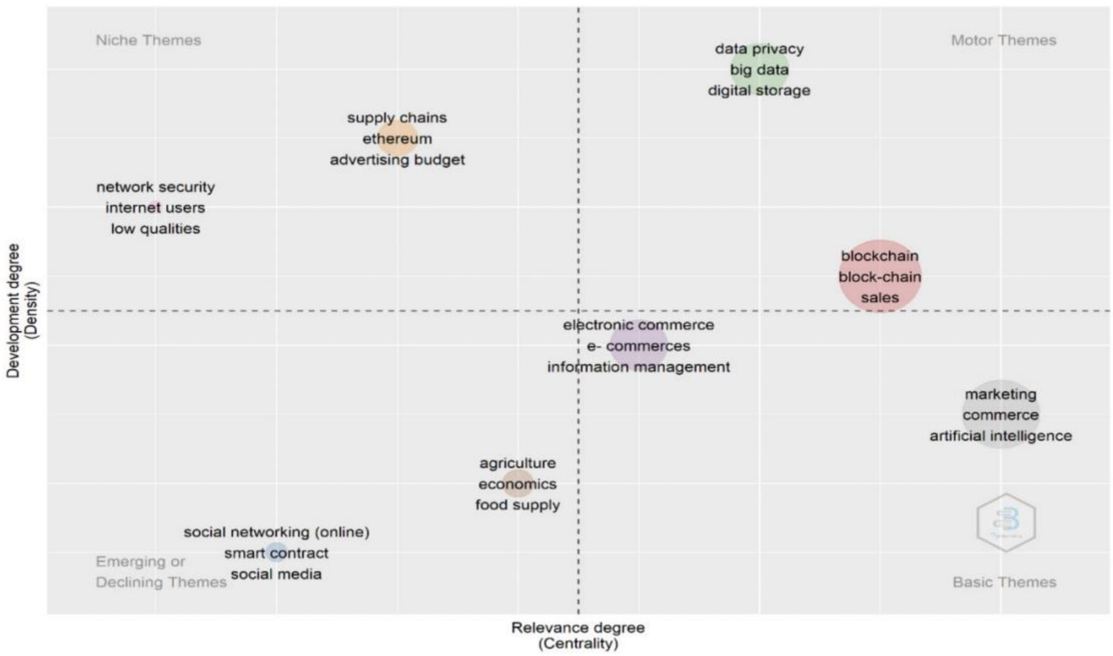

Figure 3. Thematic map by Wasiq et al. (2023) showing research streams and sub-domains in blockchain and marketing

Wasiq et al. (2023) highlight three major streams that require further research to fill gaps in the literature regarding the application of blockchain to marketing: blockchain marketing; blockchain and data; and blockchain data privacy and security. Tan et al. (2024) emphasizes the significance of loyalty as a key driver in adopting blockchain-based marketing within the sharing economy. It also identifies loyalty as a pivotal factor in reshaping the dynamics of customer-brand relationships. Very few articles focus on the intersection of blockchain and marketing, as it is a recent affair (Antoniadis et al., 2019; Jain et al., 2021; Wasiq et al., 2023). This makes it a research stream that requires specific focus (Jain et al., 2021). Overall, this means a key issue in blockchain marketing research is simply the lack of research in this area. The need for research in the area of blockchain and marketing is highlighted by early scoping reviews finding no discussions on blockchain and marketing at all (Li et al., 2018). There is an argument that, even in business organisations more generally, blockchain research is in its infancy with researchers finding most papers are from conference proceedings rather than peer-reviewed journals (Li et al., 2018). However, as noted before, academic interest was initially slow, but numerous articles have since been published on blockchain and marketing (Treiblmaier & Petrozhitskaya, 2023). Given the gap in the research, researchers now need to focus on more specific blockchain-marketing areas, such as LPs. LPs have been cited as one of the important applications of blockchain in the field of marketing (Stallone et al., 2021).

Ultimately, most of the focus of blockchain research is on applications of blockchain and proof-of-concepts. For instance, Li et al. (2018) showed in a scoping review that most academic papers which focus on blockchain in business organisations are focused on the 'how' question, i.e., focusing on a particular business application of blockchain in a specific context. In contrast, very few papers focus on the 'why' question, i.e., emphasising the incentives for adopting blockchain. There is a call for more research that focuses on the adoption of this disruptive technology by firms and consumers and the factors which will influence their adoption in a blockchain-marketing context (Antoniadis et al., 2019; Li et al., 2018). More recent bibliometric and network-based analyses have still found that blockchain marketing has a huge future scope and requires further exploration (Jain et al., 2021). This was still the case in 2023, with a later bibliometric analysis finding that research on blockchain and marketing is fragmented and in its infancy (Wasiq et al., 2023). Few studies have been carried out to understand how blockchain impacts a particular marketing strategy, such as loyalty (Wasiq et al., 2023).

Theories used in LP research.

The literature on LPs focuses on a wide range of areas that affect a consumer's willingness to adopt these programmes, as well as consumers' perceptions and behaviours towards these programmes (Chen et al., 2021). A map of LP research was created by Chen et al. (2021) after conducting a Theory–Context–Characteristics–Methodology (TCCM) review for the last three decades (1989 to 2019). This is shown in Figure 4.

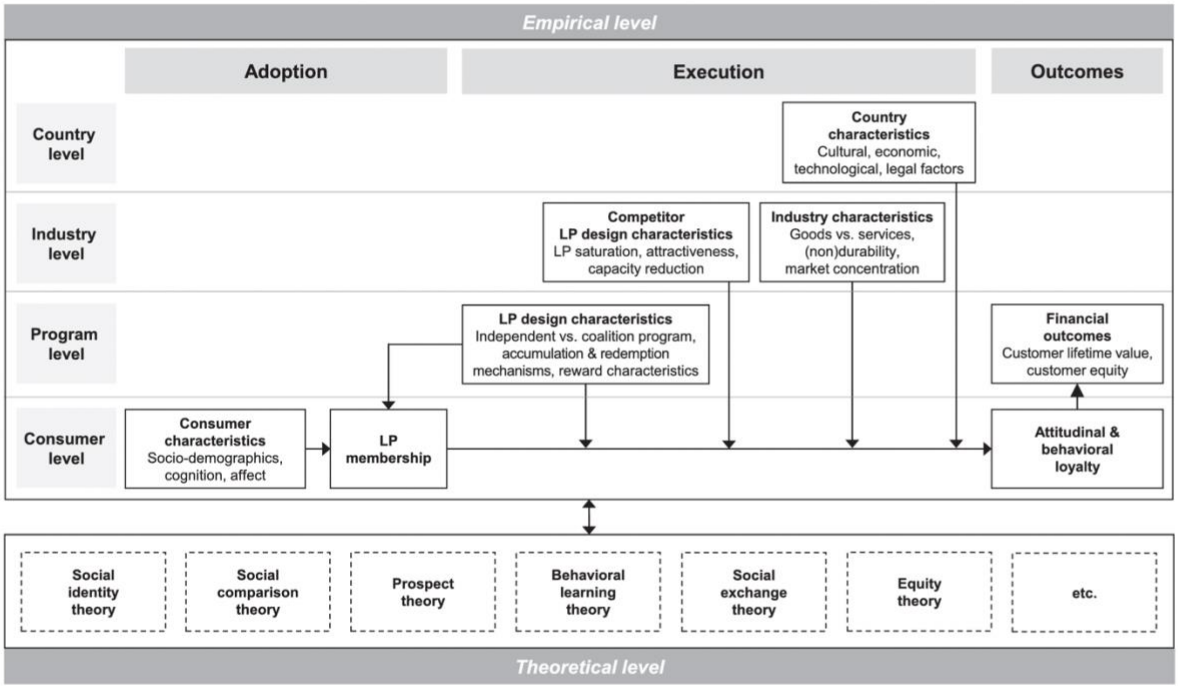

Figure 4. Overview of LP research by Chen et al. (2021)

In Figure 4, the theoretical level comprises theories that are tested in frameworks at the empirical level. Theories focused on LPs can be divided into three groups: (1) status-based mechanisms (status is highly desirable), (2) inertia-based mechanisms (duplications of previous actions), and (3) relationship-based mechanisms (strengthening of relationships between brands and customers) (Chen et al., 2021). First, to explain the status-based mechanism, usually social identity theory or social comparison theory is utilised (Chen et al., 2021). Social identity theory is a way of explaining intergroup behaviour and communication (Harwood, 2020). According to this theory, humans are shaped by the intrinsic value that individuals attribute to their social group memberships, and their inclination to perceive their particular social groups positively (Harwood, 2020). Membership in an LP can provide a sense of community to participants and be a primary motivator for their participation in an LP (Rosenbaum et al., 2005). Social identity is an inherent drive humans have that makes them compare themselves with others to gain a more precise understanding of their own abilities and characteristics (Koivuhovi et al., 2022). LPs offer special and unique benefits which humans can use to compare themselves to others (Chen et al., 2021). This can create comparisons between members of different tiers and between members and non-members (Chen et al., 2021).

Second, inertia-based mechanisms are explained by researchers using prospect and behavioural learning theory. Prospect theory proposes that losses mean more to consumers than gains (Shankar et al., 2003). In a loyalty context, prospect theory means that loyal customers are affected more by the loss in benefits from switching to another provider than by any gains from buying from a new provider (Shankar et al., 2003). Adding to this, loyal customers are not impacted by negative information as much as non-loyal ones (Ahluwalia et al., 1999). Alternatively, behavioural learning theory focuses on the past and present environment, and how it affects an individual's actions (Chen et al., 2021). Behavioural learning theory is often used to explain rewards and a customer's response to them.

Lastly, equity and social exchange theory is used to explain relationship-based mechanisms. Social exchange theory considers interactions between two parties to be like an economic exchange involving costs and benefits (Gefen et al., 2003). According to this theory, participation in the social exchange only occurs if benefits exceed costs. Since a contract does not guarantee benefits in a social exchange, trust helps to create certainty and reduces the fear that benefits will not be realised (Gefen et al., 2003). Additionally, equity theory suggests that individuals involved in exchange relationships evaluate the ratio of what they contribute to what they receive in return (Chen et al., 2021). This is applied to LPs to understand how consumers react differently to an LP, and how rewarding customers too little can lead to dissatisfaction (Chen et al., 2021). It is noteworthy that Chen et al. (2021) found that most studies (51%) between 1989 and 2019 focusing on LPs used specialised or generic theories, and that 39% did not mention any theory at all.

Regarding the interplay between blockchain and loyalty, expectancy theory has been used by Treiblmaier and Petrozhitskaya (2023). More specifically, expectancy theory was used by the authors to examine the variations in consumers' anticipations of future outcomes related to value between a blockchain-based programme and a conventional one. According to Treiblmaier and Petrozhitskaya (2023), expectancy theory suggests that employees' motivation to engage in different activities is determined by their beliefs regarding three key factors: valence (the importance of a specific outcome), expectancy (the belief that increased effort will enhance performance), and instrumentality (the belief that improved performance will result in better outcomes).

Notably, technology acceptance theory was not highlighted by Chen et al. (2021). TAM and

DOI theory focus on the acceptance of new technologies. The reason that TAM and DOI theory have rarely been utilised in the LP literature may be because LPs have not experienced substantial innovation throughout the last three decades or that any innovations have not received sufficient interest by academia. Testing TAM and DOI theory in the context of LPs therefore extends the robustness of alternative theories in the LP literature. Blockchain is poised to transform LPs, and more innovations are likely to affect LPs, creating a need to understand the technology acceptance of these new innovations by firms and customers alike. For example, generative AI is being positioned as transformative for building customer loyalty through improving customer experience quality (Gupta et al., 2024).

Theory, Context, Characteristics, Methods (TCCM) Framework

Knowledge gaps are highlighted using the TCCM framework created by Paul and Rosado-Serrano (2019). The TCCM framework has been used in a marketing as well as loyalty context (Bhaiswar et al., 2022; Chen et al., 2021; Mandler et al., 2021; Roy Bhattacharjee et al., 2022; Singh et al., 2019). In this framework, T stands for theory; C stands for context; C stands for characteristics and M stands for methodology. The methodology followed for the TCCM literature review followed the approach of Singh et al. (2019), who conducted a TCCM literature review in a marketing context. More specifically, Scopus was utilised to conduct a review of all published articles related to blockchain and marketing between 2010 and 2023 or the last ten years. Usage of Scopus is recommended over other databases because it excludes articles from predatory journals and has stringent criteria for submission (Roy Bhattacharjee et al., 2022). Looking at published articles between 2010 and 2023 was adequate considering Bitcoin, which popularised blockchain technology, was only invented in 2008 (Chuen et al., 2017).

To find articles on Scopus, you are required to build a search query. The search query used keywords focused on the focus of this thesis: the interplay between blockchain, cryptocurrency, loyalty, and technology acceptance. This results in the query being built as follows:

> ((Abstract-Title-Keyword (‘blockchain’) OR ((Abstract-Title-Keyword (‘cryptocurrency’) AND Abstract-Title-Keyword (‘LPs’) OR Abstract-Title-Keyword (‘Loyalty’) OR Abstract-Title-Keyword (‘technology acceptance’) OR Abstract-Title-Keyword (‘technology adoption’).

Only English journal articles focusing on the subject area *business management and accounting* were included. Thereafter, articles were refined to exclude those with less than five citations, except for those in the current year (2023). Thereafter, articles published in journals that are rated B and above were deemed eligible from the ABDC JQL, 2022 list, which is a global benchmark for business journals (Pawar, 2023; Bhattacharjee et al., 2022). This resulted in 169 journal articles that were considered. Thereafter, the abstracts of the articles were reviewed and studies that did not match the scope of this thesis were removed (Roy Bhattacharjee, Pradhan & Swani, 2022). In total, 68 journal articles were considered; this is a sufficient sample, based on the work of Pawar (2023), who considered 52 articles.

Theory

Table 1 summarises the theories that were found. Forty articles were found that used at least one theory. The most popular theories, DOI theory, TAM, Unified Theory of Technology Acceptance, and the Technology, Organisation and Environment Framework (TOE), are discussed. Notably, eight studies used a combination of these theories together. Self-determination theory is also discussed, as it is the only theory that was applied in a blockchain-loyalty context.

Table 1. Theories applied in a blockchain and loyalty, marketing, or technology acceptance context

Theory	#	% of articles	Examples
Technology Acceptance Model (TAM)	14	35%	Karamchandani et al. (2020); Li, Xue et al. (2021)
Technology, Organisation and Environment Framework (TOE)	9	23%	Caldarelli et al. (2021); Dehghani et al. (2022); Orji et al. (2020); Wamba et al. (2020)
Unified Theory of Technology Acceptance (UTAUT)	8	20%	Queiroz et al. (2021); Tran and Nguyen (2021); Wong et al. (2020)
Diffusion of Innovation Theory (DOI)	6	15%	Erol et al. (2022); Grover et al. (2019); Helliar et al. (2020)
Other theories (may be applied in addition to TAM, TOE, or IDT)	19	48%	Utz et al. (2023); Walsh et al. (2021); Wang et al. (2019)

Technological Acceptance Model

The TAM is the most popular theory that was found. TAM was created by Davis (1985). The TAM is a well-cited popular model because of its simplicity and understandability (King &

He, 2006). TAM has been utilised globally to assess the acceptance of a wide range of information systems (Bryan & Zuva, 2021). This model measures technology adoption by analysing consumer attitudes towards that technology. In addition, the TAM is influenced by the theory of reasoned action and the theory of planned behaviour (Lu et al., 2005). According to Lu et al. (2005), these theories suggest a relationship between actions and intentions. Further, according to this theory, intentions are governed by normative (perception of social pressures to act) and behavioural beliefs (positive or negative evaluation of working in a certain way).

The TAM has been critiqued for assuming that users of a technology are passive absorbers who do not invent new use cases for a technology (Salovaara & Tamminen, 2009). Instead, technology acceptance should be understood more heterogeneously, where usefulness is shaped by the user (Salovaara & Tamminen, 2009). Using a subjective evaluation like interpersonal influence to measure behavioural intention to use a technology in the TAM has also been critiqued (Ajibade, 2018). The use of subjective evaluation breaks down in a work environment when superiors can direct employees to use certain technologies and their choice is limited (Ajibade, 2018; Strudwick, 2015). Adding to this, scholars view the underlying behaviour as unquantifiable due to the influence of subjective factors, such as personal attributes and traits (Ajibade, 2018). Other authors have critiqued the TAM for omitting the impact of social influence and failing to incorporate social change processes (Dash et al., 2011). Social influence pressures users to use a new technology because they perceive it is important for them to do so by peers (Dash et al., 2011). Overall, these critiques suggest that PU and PEOU do not determine a user's willingness to use a new technology and, instead, external factors are more influential on usage intentions (Ajibade, 2018).

The TAM has been extended into TAM2 and TAM3. TAM was extended by Venkatesh and Davis (2000) to TAM2, which proposed antecedents and moderators of PU (Venkatesh & Bala, 2008). These antecedents and moderators can be broadly categorised as system characteristics and social influence (Venkatesh & Bala, 2008). In TAM2, individuals form opinions on the PU of a technology based on an evaluation of whether a system can get a job done for them (Venkatesh & Bala, 2008). TAM has been extended by Venkatesh and Bala (2008) with the determinants of PEOU to form an integrated model called TAM3 (Ferri et al., 2021). TAM3 suggests new antecedents of PEOU and PU and proposes that there are no crossover effects between PEOU and PU (Venkatesh & Bala, 2008). Experience is also suggested as a moderator between PEOU and PU; computer anxiety and PEOU; and PEOU and behavioural intention.

Technology, Organisation and Environment (TOE) Framework

The TOE framework was created by Tornatzky and Fleischer (1990). It is an organisation-level theory based on the contingency theory (Baker, 2012). Contingency theory suggests that an organisation's effectiveness relies on its alignment with external conditions and adaptability to environmental demands (Bryan & Zuva, 2021). Its resilience is influenced by a combination of internal elements, such as organisational size and strategy, and external factors, like the surrounding environment (Bryan & Zuva, 2021).

According to the TOE framework, successful technological adoption is determined by technological (T), organisational (O) and environmental (E) factors. This incorporates endogenous and external factors. Technological and organisational factors are endogenous, whereas the environmental factors account for external influences on technological adoption (Caldarelli et al., 2021). It includes all technologies currently in use and available to the firm in the marketplace (Baker, 2012). Technologies currently in place at a firm, limit the scope of technological innovation, while innovations outside the firm show them what is technologically possible (Baker, 2012). The organisational context focuses on resources and features of the firm, which include communication, firm size, slack and procedures (Baker, 2012). These factors have been found to influence adoption, for example, product champions, and an innovative culture created by top management (Baker, 2012). Lastly, the environmental context consists of industry structures, technological services providers and the legal environment (Baker, 2012). For example, competition and firms in rapidly growing industries stimulate the adoption of innovation, while government regulation can detract or encourage the adoption of innovations (Baker, 2012). It has been argued that TOE has more explanatory power than other adoption theories (TAM and UTAUT) because it brings together human and non-human factors (Awa et al., 2017). TOE has been applied to studies including blockchain (Caldarelli et al., 2021; Orji et al., 2020; Wamba et al., 2020; Yeh & Chen, 2018). There is very little critique on the TOE framework, possibly because it is generic, consistent with theories like DOI (Baker, 2012; Rogers, 1995; Zhu & Kraemer, 2005). Some of the critiques have emphasised the model's inability to account for variations in different contexts and its failure to explain technology adoption variances fully (Bryan & Zuva, 2021). To address these shortcomings, researchers suggest incorporating additional variables, such as sociological factors, cognitive variables, technology readiness, managerial capabilities, security concerns, government policies, and cultural influences to refine the TOE framework (Bryan & Zuva, 2021).

Unified Theory of Technology Acceptance (UTAUT)

UTAUT was developed by Venkatesh et al. (2003) to address shortfalls in earlier theories: DOI theory (Rogers, 1995), theory of reasoned action (Fishbein, 1979) and the theory of planned behaviour (Ajzen, 1991). UTAUT explains technology adoption through a lens of usefulness, and whether a technology can improve the performance of an individual's task (Gao & Bai, 2014). UTAUT suggests that performance expectancy, effort expectancy, social influence and facilitating conditions influence the behavioural intention to use a technology (Jain et al., 2021). The UTAUT model's moderators include age, gender and experience (Jain et al., 2021). The UTAUT2 model is a further development of the UTAUT model by Venkatesh et al. (2012) that includes hedonic motivation, price value and buying habits, which are cost considerations. The link between behavioural intention and behaviour has been critiqued by Bagozzi (2007) as it disregards the wide range of factors that can influence whether an individual acts on their intention. For example, the influence of an instructor's attitude on the behavioural intention of a student to use a technology (Adov et al., 2017). Recently, Blut et al. (2021) has cast doubt on the assumed robustness of UTAUT and proposed four new endogenous mechanisms: costs of technology, personal innovativeness, user education and technological compatibility. Regarding blockchain, some authors have utilised UTAUT to examine the acceptance of a tourism blockchain (Chang et al., 2022), adoption by non-experts (Pieters et al., 2022), blockchain adoption by SMEs (Khazaei, 2020), and adoption in the banking sector (Jena, 2022).

Diffusion of Innovation (DOI) Theory

The DOI theory theoretically explains how likely consumers are to adopt an innovation (Rogers, 1995). Diffusion refers to the process by which individuals convey new or existing innovations through specific channels within a defined timeframe among various social-system members (Bharadwaj & Deka, 2021). The theory explains how the views of people or organisations (who perceive an innovation as novel) determine how an innovation is disseminated throughout a social system (Erol et al., 2022). The speed at which people or organisations adopt an innovation allows people or organisations to be categorised from those that adopt it the most quickly (innovators) to those that adopt it last and resist the innovation – laggards (Erol et al., 2022).

Innovation theory includes five essential characteristics (Agi & Jha, 2022; Lou & Li, 2017).

1. **Compatibility:** Innovations consistency with the end-user's values.
2. **Relative Advantage:** The degree to which an innovation is better than the idea it replaces.
3. **Complexity:** How easy it is for a user to understand and use the innovation.
4. **Trialability:** Degree to which innovation needs to be experienced before its adopted.
5. **Observability:** Degree to which innovations can be visible to other people.

DOI theory has been applied in various contexts, including marketing (Lou & Li, 2017; Su et al., 2022; Sundstrom, 2014). It has also been applied to blockchain (Bharadwaj & Deka, 2021; Drljevic et al., 2022; Erol et al., 2022; Grover et al., 2019; Lou & Li, 2017; Ullah et al., 2021). A key limitation of DOI is its focus on individual decision-making processes (Parker & Castleman, 2009). Further, it does not take into account that knowledge of a new technology does not necessarily result in adoption nor does it consider how knowledge is acquired (Parker & Castleman, 2009). Further, DOI can miss important factors involved in the diffusion of complex technologies (Lyytinen & Damsgaard, 2001). It omits the learning-intensive features of new technology and the critical role of institutional structures, for example (Lyytinen & Damsgaard, 2001).

Self-Determination Theory (SDT)

Self-determination theory (SDT) was created by Deci and Ryan (1985), and posits that humans are organisms actively trying to find ways to satisfy their basic needs (Wang et al., 2019). According to Wang et al. (2019), the basic needs identified by SDT are autonomy (desire to initiate our own action), competence (capability in expressing and exercising capabilities) and relatedness (desire for interaction and connectedness within communities). These needs are satisfied through self-determined extrinsic motivation and intrinsic motivation (Wang et al., 2019). Four dimensions based on SDT theory for LP participation were put forward by Wang et al. (2019). One is based on extrinsic motivation: economy or saving money from LPs. Three are based on intrinsic motivation: autonomy, competence, and relatedness. This theory was tested in an exploratory case study, based on a blockchain-based loyalty platform in China, BubiChain.

Context

The industries and countries that have been studied are summarised in Table 2 and Table 3. This is based on the methodology of Roy Bhattacharjee et al. (2022). Eleven of the studies involved more than one country. Table 2 indicates that most of the journal articles or publications are based in Asia (33%), owing to the contribution of India and Pakistan (17%) of which only one study was based in Pakistan. The dominance of Asia may be explained by increases in technological advancements over the past decade (Bhattacharjee et al., 2022). This may have stimulated interest in blockchain technology.

Table 2 indicates that supply chain broadly dominates blockchain research, focusing on either marketing or technological acceptance. Only 14% of studies that were investigated intersect with marketing or business management, which is the focus of this thesis.

Table 2. Countries investigated in blockchain and loyalty or technology acceptance research

Country	# of studies	%
America		
North America (USA, Canada)	4	6%
South America (Brazil)	2	3%
Asia		
East Asia (China, Taiwan, South Korea, Japan)	4	6%
India and Pakistan	12	17%
Middle East (Saudi Arabia, UAE)	2	3%
Southeast Asia (Malaysia, Vietnam, Philippines, Singapore)	5	7%
Europe		
Southern Europe (Italy, Greece)	6	9%
UK	1	1%
Central Europe (Germany, Netherlands)	4	6%
Western Europe (France)	1	1%
Scandinavia	0	0%
Australia	0	0%
New Zealand	0	0%
Africa (Nigeria, Kenya)	2	3%
No Country Reported	26	38%

Table 3. Topics investigated in blockchain and loyalty or technological acceptance research

Topic	# of studies	%
Supply Chain	20	29%
Finance	6	9%
Tourism	4	6%
Marketing	5	7%
Agriculture and Food	6	9%
Technology and Information Management	7	10%
Business Management	5	7%
Transportation and Logistics	6	9%
Other (Public Policy, Economics, Engineering, Healthcare, Fashion)	10	13%

Characteristics

Twenty-nine studies contained at least one dependent and one independent variable. Two of the 29 studies contained mediating variables. Studies often contain more than one dependent and independent variable. According to the approach followed by prior studies, variables are reported on in Table 4 and segregated into independent, dependent and mediating variables (Pawar, 2023; Roy Bhattacharjee, Pradhan & Swani, 2022). Owing to the frequent usage of TAM, TOE, UTAUT and DOI, it is expected that the most common dependent variable relates to behavioural intention to use a technology, which is common across all three models and theories. Specifically, research focuses on blockchain technological adoption, and only one study focused on cryptocurrency adoption.

As taken from the TOE, most studies focused on readiness, regulation, or competitive pressure. This means most studies focus on both endogenous and exogenous variables of technological acceptance. Readiness is an endogenous variable, whereas regulation and pressure are exogenous in TOE. Only two studies were found that included mediating variables. Table 4 highlights numerous research gaps. First, the table exemplifies a lack of research covering the intersection between blockchain and loyalty. No variables were found that focus on loyalty (attitudinal or behavioural) or are related to LP design, effectiveness, or outcomes (performance or WoM). The same can be said about the antecedents to behavioural and attitudinal loyalty (commitment, satisfaction, and incentives). Second, no studies examined the perceived value of cryptocurrency, or personal innovativeness as independent variables. Prior research supports perceived value and innovativeness as being important variables in the context of technology acceptance (Bigne-Alcaniz et al., 2008; Lee et al., 2007; Obal, 2013; Pagani, 2004).

Table 4. Dependent and independent variables

Variables	# of studies	%	Examples	Contributing Theory
Dependent Variables				
Intention to use or adoption	12	41%	Behavioural intention to use blockchain technology, auditors' intention to use blockchain technology, behavioural intention to adopt blockchain technology, adoption of blockchain, blockchain adoption, intention to adopt blockchain technology, adoption of Bitcoin infrastructure, cryptocurrency adoption	TAM, TOE, UTAUT, DOI
Ease of use or usefulness	4	14%	PEOU, PU	TAM
Independent Variables				
Readiness, regulation or pressure	19	66%	Technology readiness, organisational readiness, legislation and regulation, regulatory and governance standards, trading partner pressure, competitive pressure, external pressure, training & education, presence of training facilities	TOE
Advantage, compatibility, complexity	11	38%	Relative advantage	DOI, TOE
Ease of use, benefits	8	28%	Ease of being tried and observed, perceived benefits, perceived EBC benefits	TAM
Trust	6	21%	Blockchain trust, trust in others	N/A
Know-how and competence	6	21%	Technical know-how, technology competence, knowledge of blockchain technology, computer self-efficacy	Resource-based view (RBV), integrated model of information systems adoption, TAM3
Support	5	17%	Top management support, management support	Resource-based view, TOE
Control	3	10%	Perceived behaviour control, perception of external control	TAM3, TPB
Effort or performance	3	10%	Effort expectancy, performance expectancy	UTAUT
Mediating Variables				
Regulatory support	1	3%	N//A	N/A
Helpfulness	1	3%	N/A	Theory of trust in a specific technology

Methodology

Table 5 shows 68 studies that were divided into one of four categories: qualitative, quantitative, mixed methods and critical examinations or reviews. Critical examinations and reviews were defined as studies that either did systematic literature reviews or were generalised discussions of the implications of blockchain for a specific context, such as information management (Upadhyay, 2020), marketing (Kumar et al., 2021), supply-chain management (Di Vaio & Varriale, 2020), tourism (Rashideh, 2020) and accounting (Kokina et al., 2017). Most quantitative studies relied on surveys as research instruments.

In Table 6, studies were categorised into those that used SEM, systematic literature reviews, case studies, Decision-Making Trial, and Evaluation Laboratory (DEMATEL) and case studies. Fifty-five studies had a methodology and data-analysis technique that could be clearly identified. DEMATEL is a quantitative approach used to measure interactive effects by analysing interdependence and association (Xu et al., 2023). Some studies utilised multiple methodologies and data-analysis techniques. The table shows that SEM is favoured as a data-analysis approach; 12 of 17 studies that used SEM utilised PLS-SEM.

Table 5. Analysis of methodologies

Categorisation	# of studies	%	Examples
Quantitative	31	46%	Kamble et al. (2019); Wamba et al. (2020); Wong et al. (2020)
Qualitative	19	25%	Caldarelli et al. (2021); Sydow et al. (2020); Walsh et al. (2021)
Critical examination or review	17	25%	Kumar et al. (2021); Upadhyay (2020)
Mixed methods	1	1%	Dehghani et al. (2022)

e

Categorisation	# of studies	%	Examples
Structural equation modelling	17	31	Karamchandani et al. (2020); Queiroz et al. (2021); Wamba et al. (2020)
Systematic literature review	11	20	Grover et al. (2019); Vu et al. (2023)
Decision-Making Trial and Evaluation Laboratory (DEMATEL)	4	7	Kumar et al. (2022); Xu et al. (2023)
Case studies	4	7	Balasubramanian et al. (2021); Xu et al. (2022)

Summary of findings of TCCM framework

The TCCM framework created by Paul and Rosado-Serrano (2019) was used to analyse literature which focuses on blockchain and its intersection with loyalty or technological acceptance. It was found that the TAM was the most used theory, followed by TOE and UTAUT. Only four studies were found that focus on the intersection of blockchain and marketing (Gleim & Stevens, 2021; Kumar et al., 2022; Tran & Nguyen, 2021; Utz et al., 2023; Wang et al., 2019). In these studies, theories UTAUT and self-determination theory were used. Further, only two of the studies focused on loyalty (Utz et al., 2023; Wang et al., 2019). The literature typically focuses on the intention to use a technology as a dependent variable and independent variables derived from the TOE framework, specifically readiness, pressure, and regulation.

This underscores the need for further research on the intersection of blockchain and marketing, particularly blockchain loyalty. Of the 68 studies reviewed, only four address blockchain and marketing, with just two focusing on blockchain and loyalty. This aligns with recent bibliometric analyses indicating that blockchain's impact on marketing is a nascent and fragmented field with significant potential (Jain et al., 2021; Wasiq et al., 2023). The existing studies primarily focus on UTAUT and self-determination theory, highlighting the need to explore other theories, such as TAM and DOI, within the blockchain-marketing context. While TAM is prevalent in loyalty-focused acceptance research, it remains underexplored in blockchain marketing. Additionally, there is a need to investigate loyalty-specific theories beyond self-determination theory.

Addressing these gaps, this thesis focuses on blockchain-loyalty, contributing to the limited literature on this intersection. By employing a DOI-TAM model instead of UTAUT and exploring Watson et al.'s (2015) loyalty model, which does not rely on self-determination theory, this study examines theories that have been rarely tested in this context. This approach also introduces new independent variables that diverge from the TOE framework, drawing instead from DOI-TAM and Watson et al.'s (2015) loyalty model.

Literature review and hypothesis development

In this section, the literature that led to the development of the theoretical model is examined. The journey from exposure to intention to use, loyalty creation, and finally to firm outcomes is examined. This section also suggests hypotheses related to the theoretical model. Literature relating the antecedents to acceptance and loyalty is discussed in the further sections.

Rationale for theories used

DOI and TAM are information-system theories that focus on the adoption of technology (Oliveira & Martins, 2011). DOI is an organisational and individual level adoptions model, while TAM is operating at an individual level only. DOI and TAM have common theoretical foundations which complement each other (Roussou & Stiakakis, 2016). Both models focus on usage as an independent variable (Khan & Woosley, 2011). Both TAM and DOI assume that those who adopt a technology make rational decisions which are technologically savvy and independent from each other (Khan & Woosley, 2011). TAM focuses on the behavioural intention to use a technology as a dependent factor, with PU and PEOU as independent factors. With DOI, adoption of a technology is dependent, while compatibility, complexity and relative advantage are independent (Khan & Woosley, 2011). TAM can be described as more fundamental, focusing on perceptions, while DOI adds complexity to a focus on behaviours by including time (Khan & Woosley, 2011). Due to common theoretical foundations and overlap, TAM and DOI can be integrated to obtain better results, which can include a greater perception of how an individual embraces a new technology, and confirm each other's validity and reliability (Nezamdoust et al., 2022; Roussou & Stiakakis, 2016). TAM-DOI models have been applied and statistically validated in a blockchain context, such as in the educational sector, by Ullah et al. (2021). A TAM-DOI model has also been applied to understand digital currencies in the European Union (Roussou & Stiakakis, 2016) and the behavioural intention to invest in cryptocurrency (Bharadwaj & Deka, 2021). Studies combining DOI and TAM in other areas also show good results in internet banking and tourism (Cheng et al., 2006; Sigala et al., 2000).

Due to the scarce research focusing on the technology acceptancy of BBLPs, it was necessary to rely on TAM and DOI as theories that apply to a wide variety of contexts. Although using well-cited theories may lead to only incremental theoretical contributions, the findings using these theories could be built upon and form a foundational understanding of the technology acceptance of BBLPs. This is relevant, considering no study has empirically examined a BBLP using a combined DOI or TAM model. Further, unique variables are proposed to add unique contributions to the existing literature surrounding the TAM-DOI theory, namely, the perceived value of cryptocurrency and trust in blockchain and cryptocurrency. For these reasons, DOI and TAM are utilised in this thesis to fill gaps in the literature which focus on acceptancy theories, as highlighted in the earlier TCCM review.

Researchers have adopted varied conceptual approaches to understanding loyalty (Watson et al., 2015). Writing at the start of the 20th century, Bennett and Bove (2001) noted that, after 70 years of research, there was still no common approach to measuring loyalty. Cengiz and Akdemir-Cengiz (2016) reviewed brand loyalty research between 2001 and 2015, concluding that most authors typically do not state their approach to measuring brand loyalty, effectively ignoring prior literature. Furthermore, approaches to measuring brand loyalty were highly diversified, indicative that there needs to be a consensus on how to measure loyalty (Cengiz & Akdemir-Cengiz, 2016). The meta-analysis of Watson et al. (2015) and the resultant structural model provided a model to understand common antecedents to loyalty as a multi-dimensional construct and its outcomes, seeking to add clarity to the varied approaches adopted by researchers. Researchers agree that loyalty is a multi-dimensional construct, making a multi-dimensional model important (Cengiz & Akdemir-Cengiz, 2016).

Prior studies have shown linkages between constructs from the TAM and loyalty. Factors related to technology acceptance can generate loyalty if the technology is used and is understandable (Setiawati et al., 2021). Alternatively, loyalty can influence technology acceptance through positive benefits derived from using or intending to use the service (Martinez-Caro et al., 2013). Setiawati et al. (2021) found that technology acceptance factors did not significantly affect customer loyalty in the packaging industry. However, the sample size was small, at only 150 respondents. In other studies, PEOU and PU have been found to be influential on e-loyalty (Wong et al., 2014). Technology acceptance models have been more broadly combined into so-called satisfaction-loyalty models, where loyalty, satisfaction, PEOU and PU are independent variables, influencing the dependent variable, i.e., the behavioural intention to use or adopt a technology (Niu et al., 2021). PEOU and PU have also been linked to the behavioural intention to use a technology, indirectly through their influence on customer satisfaction (Mai et al., 2013). The behavioural intention to use a technology has also been shown to directly influence e-loyalty in an online banking environment (Martinez-Caro et al., 2013). Overall, this indicates the overlap between loyalty and acceptance models. This sheds light on why loyalty was combined with technology acceptance to form a more holistic understanding of how accepting a new loyalty technology could lead to loyalty outcomes.

The integration of TAM, DOI, and loyalty models provides a robust theoretical framework for understanding BBLPs in this study. TAM and DOI complement each other by addressing adoption at both individual and organizational levels, with TAM focusing on the perceptions of usability and usefulness, and DOI expanding this perspective by incorporating broader factors like compatibility, complexity, and relative advantage over time. These theories are particularly relevant in the blockchain context, where adoption decisions are influenced by both technical factors (addressed by TAM) and broader innovation characteristics (addressed by DOI). Adding the loyalty model enriches this framework by linking technology acceptance to behavioral outcomes such as loyalty, thereby creating a holistic view of how technology acceptance can drive customer retention and engagement in BBLPs. This multi-theory approach not only fills gaps in the literature but also offers a comprehensive foundation for understanding the unique dynamics of blockchain technology adoption and its potential to foster loyalty outcomes.

Technology acceptance

The TAM has been studied in several diverse contexts, including online shopping, internet banking, e-procurement, and electronic toll collection services (Miltgen et al., 2013). Additionally, it has been applied to e-learning in universities (Masrom, 2007), wireless internet (Lu et al., 2003) and automation (Ghazizadeh et al., 2012), when these technologies were relatively new. The TAM is appropriate for new-technology research, such as blockchain. Recent studies have applied the TAM to blockchain and Bitcoin, highlighting its applicability (Folkinshteyn & Lennon, 2016; Khazaei, 2020; Kumari & Devi, 2023; Liu et al., 2021; Lou & Li, 2017; Saputra & Darma, 2022; Tan et al., 2020).

Utilising an explorative, qualitative enquiry, Folkinshteyn and Lennon (2016) reviewed academic and practitioner literature to understand the technology acceptance process of both Bitcoin and blockchain. Their findings highlight two perspectives: developers and end-users, and uncovered factors which influence the perceived risk, PEOU, and PU of Bitcoin and blockchain technology. They found several positive factors that enhance PU and PEOU for both developers and end-users, stemming from increased user control, open-source nature and greater efficiency of transactions. However, they also found the requirements for competent control and the high risks associated with security breaches and errors present significant risks to developers and end-users. Ultimately, the authors found that "*The TAM is a valuable* *framework for continued analysis of this evolving financial technology [blockchain]."* (Folkinshteyn & Lennon, 2016). A later study by Lou and Li (2017) proposed a unified model of DOI theory and the TAM to investigate blockchain technology, and further research to test this model using a web-based questionnaire. To date this has not been done by scholars.

Liu et al. (2021) created a theoretical model based on the TAM, which incorporated the core features of blockchain technology. A total of 254 online surveys were analysed by the authors using Smart-PLS 3. Derived from the TAM, the authors' conceptual model incorporated trust, PU and PEOU as determinants of usage intentions. Related to blockchain technology, the authors proposed that information quality and output quality would impact PU. However, only the relationship between information quality and PU was supported in their data analysis. Trust was shown to be influential on PEOU and PU in a blockchain context. The authors also showed that PEOU and PU were influential on usage intentions in a blockchain context. The findings were limited by the collected data, which was relatively small and only in China. Further, the authors acknowledged that the model's consideration of only three constructs may also limit its explanatory power in a blockchain context.

In Indonesia, the impact of trust on behavioural intention to use a blockchain-related technology was confirmed (Saputra & Darma, 2022). The influence of PU on the intention to use a blockchain technology was validated by a later study by Kumari and Devi (2023), which focused on investment professionals and derived their results from 200 respondents, which were analysed using version SmartPLS 4. Several other authors have utilised the TAM model to study blockchain technology, highlighting its applicability (Ferri et al., 2021; Kamble et al., 2019; Wamba et al., 2020; Yang, 2019). Adding to this, the earlier review of the literature highlights that the TAM is the most common theoretical model to study the intersection of blockchain and loyalty.

The TAM theorises that technological acceptance is influenced by the behavioural intention to use a technology (Lou & Li, 2017). A user's attitude towards a given technology affects the behavioural intention to use the new technology. Attitudes in the model are determined by two factors: PU and PEOU of that technology (Lou & Li, 2017). The relationship between these two factors and the behavioural intention to use technology has been examined by several studies, including studies focusing on blockchain technology or loyalty (Chiu et al., 2009; Dirsehan, 2020; Folkinshteyn & Lennon, 2016; Kamble et al., 2019; Knauer & Mann, 2019;

Lou & Li, 2017). The relationship between PEOU and PU with the intention to adopt blockchain has been validated in a blockchain context by Kamble et al. (2019). Hamdan et al. (2022) found support for a relationship between PEOU and the intention to adopt blockchain technology and did not evaluate PU. This led to the following hypotheses:

H1: PEOU (H1a) and the PU (H1b) of a BBLP predicts the intention to use a BBLP.

Loyalty and technology acceptance

At first, studies focused on loyalty in a one-dimensional way, focusing only on the behavioural components of loyalty (Bodet, 2008). Behavioural loyalty can be defined as a readiness to act in a way that favours one entity over another (Watson et al., 2015). This one-dimensional view was first critiqued by Day (1976), as being too focused on the behavioural components of loyalty (Bodet, 2008). This led to the inclusion of attitudinal features of loyalty. Attitudinal loyalty relates to the cognition by a consumer that one entity is more favourable than another (Watson et al., 2015). This led to the current stance on loyalty as consistent with two key elements: behavioural and attitudinal.

Satisfaction-loyalty models can enhance the understanding of the behavioural intentions to use a technology (Niu et al., 2021). Agag et al. (2019) utilised the TAM to study the intention to play online games. As part of the study, the relationship between the intention to play online games and the creation of loyalty was analysed. Their study confirmed an association between the intention to play online games and loyalty. A connection between the behavioural intention to use technology and loyalty was also established by Bouagina and Triki (2013) and Martinez-Caro et al. (2013) in a banking context.

Further support in an online shopping environment for the association between the behavioural intention to use technology and loyalty can be found in a study by Tang and Huang (2015). In the same vein, and utilising theory underpinning the TAM, attitude has been found to significantly influence loyalty, in a study by Ruiz-Mafe et al. (2014) in an online social network setting. Notably, in a transportation context, a model that proposed a direct relationship between behavioural intention and loyalty was rejected by Niu et al. (2021).

PU, an antecedent of an intention to use a technology product, directly influences loyalty intention (Chiu et al., 2009; Cyr et al., 2006). The relationship between PU and loyalty was also validated in a study by Wong et al. (2014) who studied loyalty online. Wong et al. (2014) found a relationship between PEOU and loyalty, providing further support for a connection between the antecedents of technology use and loyalty.

Overall, prior literature supports a relationship between the intention to use technology and loyalty. However, this relationship may be explained by a direct effect on attitude and, thus, loyalty and indirectly through the antecedent to an intention to use technology (PEOU and PU). Therefore, it is recommended that loyalty should be reported separately as an attitude and behaviour because the effect of antecedents to attitudinal and behavioural loyalty varies (Watson et al., 2015).

Loyalty programmes encompass the strategies implemented by companies to foster and sustain customer loyalty (Treiblmaier & Petrozhitskaya, 2023). LPs are presented in the literature as a key marketing tool to generate loyalty (Kwiatek et al., 2021). Firms want an LP to generate loyalty. LPs are used to target and retain customers (Chen et al., 2021). BBLPs lead to improvements in transferability, timing of earned points, usage, relevance, and expiration compared to traditional LPs (Treiblmaier & Petrozhitskaya, 2023). This meant it was important to examine the generation of both behavioural and attitudinal loyalty. Therefore, it is expected that:

H2: The intention to use a BBLP predicts the behavioural (H2a) and attitudinal loyalty (H2b) exhibited towards BBLPs.

Word of mouth (WoM)

WoM is often referenced when defining loyalty, highlighting its importance to a study (Choi et al., 2014). However, some scholars argue that WoM should be a separate construct, and its inclusion when conceptualising loyalty should be approached with caution (Söderlund, 2006). The relationship between WoM and loyalty was clarified in a meta-analysis which showed that there is a higher probability that customers who are more loyal will give more favourable recommendations to a firm and vice versa (De Matos & Rossi, 2008). WoM is a consumer's endorsement or promotion of a firm to others (Watson et al., 2015). In this study, WoM is the extent consumers would recommend others to switch to or use a BBLP. This is based on a definition of WoM by Roy et al. (2009). WoM is a critical element that is considered when a consumer makes a buying decision (Wu et al., 2016). WoM has also become more important with the popularity of social media (Donthu et al., 2021). Compared to advertising, WoM is more credible and persuasive (Rahman et al., 2021). WoM has been found to effect purchasing intentions (Lee et al., 2019; Park et al., 2021) and enhance mobile banking adoption (Shankar et al., 2020).

It has been suggested that a customer is loyal because they believe that the value derived from consuming a good or service is greater than the costs associated with this consumption (Casaló et al., 2008). As a result of the perception of receiving more excellent value, a customer is motivated to promote a firm through WoM (Casaló et al., 2008).

Loyalty has also been viewed as an antecedent to WoM because more loyal consumers give more positive recommendations, are more motivated to process new company information and are more resistant to being persuaded against the company they are loyal towards, according to De Matos and Rossi (2008), citing Dick and Basu (1994).

WoM has been shown to have an interrelationship with technology acceptance. WoM has been shown to affect 76% of purchase decisions (Jalilvand et al., 2017). Favourable WoM has also increased adoption rates (Keller, 2007; Reingen, 1987). It is widely accepted that WoM is essential in creating feelings and actions among customers (Roy et al., 2009). This is because WoM is perceived as trustworthy and reliable because of the personal nature of these types of communication (Roy et al., 2009). This has led to WoM being perceived as a competitive advantage for businesses (Mazzarol et al., 2007). WoM has also been shown to lead to higher retention rates, spending, and recommendations from the customers of firms (Zeithaml, 2000).

WoM is a behavioural outcome of e-loyalty (Srinivasan et al., 2002). Behavioural loyalty has also been shown to directly affect WoM (Roy et al., 2009). WoM has also been shown to positively impact behavioural loyalty (Garnefeld et al., 2011). However, other studies have disputed this and shown no effect between WoM and two variables indicative of behavioural loyalty (purchase and continuance intentions) (Kaur et al., 2021). More generally, loyalty and WoM have been positioned as interrelated, in early studies by Hagel (1999) and Dick and Basu (1994). Later studies confirmed this, and. when studying brand loyalty, Liao et al. (2010) discovered evidence that substantiates a relationship between brand loyalty and WoM. Further, prior literature has also shown that online WoM has a relationship with loyalty (Ajina, 2019).

Loyalty has been linked to WoM communication. Akbari et al. (2016) found evidence of a relationship between loyalty and WoM communication in a banking context. The existence of this relationship has also been shown in the context of electronic banking (Casaló et al., 2008). In the context of service failures by firms, customer loyalty and WoM exhibited a relationship (Choi et al., 2014). Tripathi (2017) also established this relationship in a restaurant context. This demonstrates that the relationship between WoM and loyalty has been shown in various contexts.

Loyalty programmes help build brand equity through several mechanisms, including increasing the propensity of a consumer to engage in WoM promotions of the brand (Nastasoiu & Vandenbosch, 2019). Thus, the study hypothesises that:

H3: Behavioural loyalty (H3a) and attitudinal loyalty (H3b) exhibited towards BBLPs predict the intention to promote these programmes via WoM.

Redemption

A lack of redemption limits how effectively an LP can increase spending through breaking down the point-pressure mechanism (Gabel & Guhl, 2022). This is depicted in Figure 5. Through a point-pressure mechanism, when the consumer's point balance is low, consumers are internally motivated to accumulate points for rewards in the future and spend more doing so (Bijmolt et al., 2011). As points earn and the threshold to claim a future reward gets closer, consumers increase their purchases to claim the reward sooner (Kivetz et al., 2006). Prior literature is indicative that LPs enhance sales, but this effect may differ depending on the consumer's initial purchase rate at the stores in question (Bies et al., 2021). It has been shown that awarding points to consumers proportionally to their spending may ultimately lead to more purchases (Bijmolt et al., 2011; Chaudhuri et al., 2019). However, the extent of the actual spending increases is moderate and not exceptional, according to prior literature (Bijmolt et al., 2011; Liu, 2007).

A lack of motivation to redeem rewards creates a vicious cycle in which participants in the LPs never receive the rewards needed to reinvigorate motivation to participate in LPs (Dorotic et al., 2014). Receiving rewards would create positive feelings towards the LP provider, stimulating consumer motivation to spend and participate in the LP through a reward-behaviour mechanism (Blattberg et al., 2008; Kopalle et al., 2012). Thus, a vicious cycle ensues in which consumers lose interest, and the redemption of points becomes paramount to the continued success of an LP but is not happening because customers have lost interest in participating in the LP. A mechanism to increase customer expenditure through leveraging customer data also suffers when interest declines in an LP. This mechanism relies on utilising customer data to deliver targeted marketing, which in turn leads to more expenditure by customers (Gabel & Guhl, 2022). When customers spend less, there is less customer data (such as purchase histories) to aid personalised marketing. This only adds to the problem of worsening expenditures in a less effective LP.

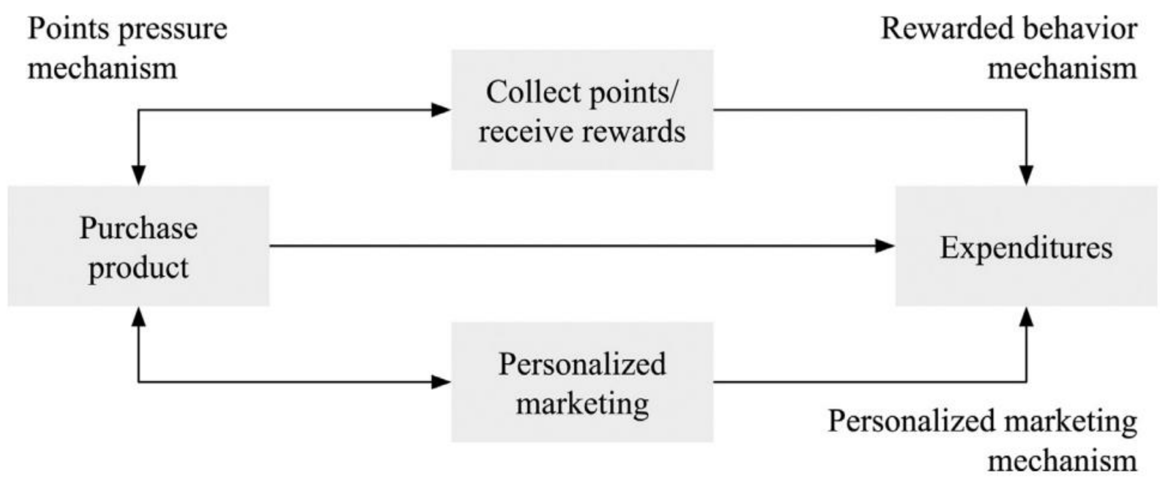

Figure 5. Model provided by Dorotic et al. (2014)

In a loyalty context, performance has been defined broadly as enhancements experienced by a seller (Watson et al., 2015). This can include sales, profit, and other measurable changes to seller performance. In this study, the focus is on redemption rather than performance. Redemption is the intention to redeem loyalty points with a seller, leading to increased customer redemption rates. An increase in redemption can be seen as a performance enhancement, as it has been shown that benefits are created for sellers when point redemption occurs (Li et al., 2021). These benefits include improved customer attitudes relating to the loyalty provider, increased spending after the redemption period, and creating consumer habits that encourage increased spending (Henderson et al., 2011; Smith & Sparks, 2009; Taylor & Neslin, 2005). However, these benefits will only result if actual redemption occurs.

Unfortunately, redemption rates are typically low, and one-third of loyalty points are not redeemed. Making matters worse, unredeemed points become liabilities on the balance sheets of businesses (Li et al., 2021). This is because legally, when a consumer has a possibility of obtaining products at a lower price with loyalty points, they acquire a right which must be accounted for as a liability on a business's balance sheet (Treiblmaier & Petrozhitskaya, 2023). The problems associated with redemption for LPs highlight the importance of their inclusion in this study.

Consumers redeem and collect points to attain a reward (Smith & Sparks, 2009). The design of a loyalty scheme can affect redemption (O'Brien & Jones, 1995). PEOU, comprehension of the LP, speed of point accumulation, and the probability of attaining rewards will probably affect redemption (Smith & Sparks, 2009). A BBLP will probably improve the PEOU, rate of point accumulation, and the likelihood of achieving rewards. This is because the tokenisation of loyalty points allows consumers to redeem points more efficiently, increasing the possibility of attaining rewards. If several firms adopt BBLPs, the PEOU and speed of point accumulation will probably improve. This leads to increasing redemption through a better-designed loyalty scheme.

According Dorotic et al. (2014), citing Taylor and Neslin (2005), through long-term relationship-building reward redemption can increase longer-term loyalty. This may result from respondents feeling that, when they redeem points, they have gained something for nothing, which creates positive feelings towards a firm (Smith & Sparks, 2009). This underscores that redemption and loyalty are interlinked. This increases the firm's standing with a consumer and encourages the consumer to make ongoing purchases (despite price differentials), which generates both attitudinal and behavioural loyalty (Smith & Sparks, 2009).

The greater likelihood of purchasing probability which exists before the reward persists into the post-reward period; however, this is of a relatively short duration, between two and seven weeks (Kopalle et al., 2009; Taylor & Neslin, 2005). However, it is important that the customer redeems points and values the reward for any reward behaviour effects to occur (Dorotic et al., 2014).

Reward redemption effects are largely ignored in the literature, and scholars have principally concentrated on the appeal of dissimilar reward categories and their relationship with revenue

(Dorotic et al., 2014). Smith and Sparks (2009) conducted one of the first studies which explored the relationship between loyalty and redemption through thematic interviews with 20 women who were part of a UK retailers' points-based LP. Smith and Sparks (2009) found that the act of redemption itself creates positive feelings which increase the standing of the LP provider for consumers who are attracted by the point accumulation from ongoing purchases, despite price differentials that may exist. Traditional LPs have complex background processes that cause delays in the crediting of points to a customer (Treiblmaier & Petrozhitskaya, 2023). A BBLP has the potential to provide customers with improved and faster (almost instant) redemption (Treiblmaier & Petrozhitskaya, 2023; Udegbe, 2017) and the ability to exchange currencies in one wallet (Udegbe, 2017). This eliminates the need for consumers to search for each programme's options, limitations, and redemption rules (Udegbe, 2017). Therefore, it is expected that:

H4: Behavioural loyalty (H4a) and attitudinal loyalty (H4b) exhibited towards BBLPs predicts the intention to redeem benefits accrued for these programmes.

Resultant conceptual model

An integrated conceptual model is illustrated below in Figure 6. This model utilises the TAM to understand usage intentions and their antecedents in a blockchain-loyalty context based on the work of Davis (1985). This is combined with the work of Watson et al. (2015), which investigated the relationship between loyalty and firm outcomes. Uniquely the model incorporates redemption as an essential firm outcome in a blockchain-loyalty context instead of performance, enhancing its applicability to LPs. The final combined model illustrates the relationship between acceptance, loyalty, and firm outcomes.

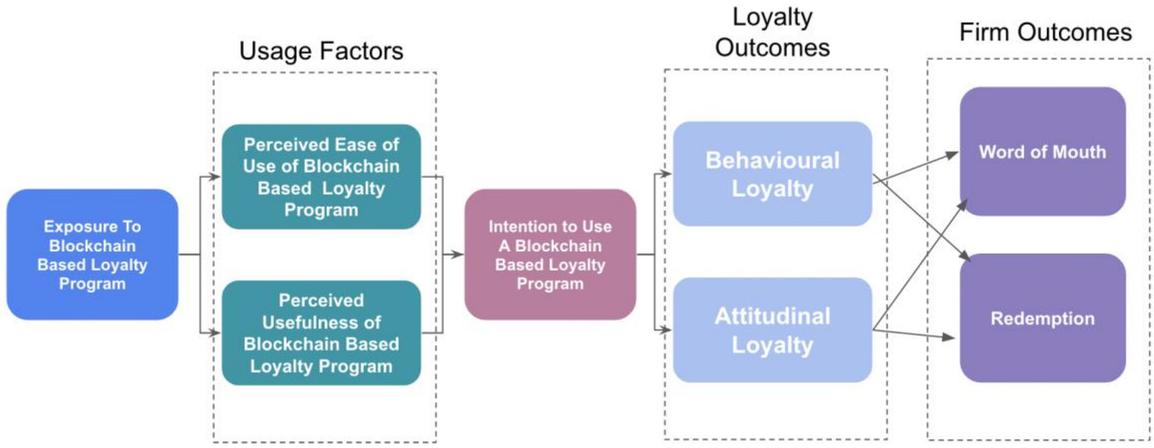

Figure 6. Integrated acceptance-loyalty-outcome model based on the work of Watson et al. (2015) and Davis (1985)

Literature Review – Antecedents of technology acceptancy

In this section, literature is presented that relates to the antecedents of technology acceptance. Hypotheses stemming from this literature are suggested, which culminate in the presentation of a theoretical model to examine the TAM and its antecedents in a blockchain-loyalty context.

Personal innovativeness

Personal innovativeness has been defined as an openness to change or to a new technology (Joo et al., 2014; Van Raaij & Schepers, 2008). It has also been defined as "…*the willingness of an individual to try out a new information technology*." (Agarwal & Prasad, 1998).

Highly innovative people actively look for information about new ideas (Lu et al., 2005). Due to their ability to cope with uncertainty, they create more favourable intentions towards accepting a new technology (Lu et al., 2005). Agarwal and Prasad (1998) applied these ideas to technology acceptance research. The authors proposed that, through synthesising information, users with greater personal innovativeness are likely to have more favourable beliefs about a new technology (Lu et al., 2005). BBLPs only appeared in 2017, with the Green Power and Travala projects, according to a review by Abooleet and Kinnett (2023). This means personal innovativeness is highly relevant to a new application based on a new technology like blockchain. High levels of uncertainty can relate to this new type of LP, which can be overcome more quickly if the user exhibits qualities of innovativeness. It has been shown that managers with higher personal innovativeness are more likely to develop positive attitudes, which in turn increases their chance of trying blockchain technology (Khazaei, 2020).

Miltgen et al. (2013) included innovativeness in their study as a predictor of compatibility, PEOU, and the behavioural intention to use biometric technology (a relatively new technology at the time). Through an online survey and data analysis, the authors confirmed that innovativeness directly affected the behavioural intention to use biometric technology. However, the indirect effect on PEOU and PU was not confirmed.

Contrary to Miltgen et al. (2013), Fagan et al. (2012) explored the technology acceptance of a virtual simulation and found that personal innovativeness was influential on both PEOU and PU. This relationship between personal innovativeness on PEOU and PU was also confirmed by Lu et al. (2005). Bigne-Alcaniz et al. (2008) found that innovativeness influenced PEOU in an online-shopping environment. The effect of personal innovativeness on PEOU was also confirmed in a mobile learning environment by Joo et al. (2014) and Van Raaij and Schepers (2008). Still, no significant effect was confirmed between personal innovativeness and PU by the scholars. Personal innovativeness has also been shown to influence the PEOU of cryptocurrency (Nuryyev et al., 2020). The relationship between PEOU and PU with personal innovativeness can be described as unsettled literature. Some literature finds proof of its existence, and others dispute it. Aiming to shed some light on this variable's relationship with PEOU and PU, innovativeness was included as an influencer of both PEOU and PU. It is therefore expected that:

H5: Personal innovativeness predicts a BBLP's PEOU (H5a) and PU (H5b).

Trust in blockchain technology and cryptocurrency

Trust has been defined in an e-commerce context as a willingness to become vulnerable to a web retailer after considering the web retailer's characteristics (Pavlou, 2003). In this study, trust in blockchain technology is the willingness to become vulnerable to using cryptocurrency and blockchain as part of an LP after considering the characteristics and perceptions that define this relatively new technology. It became important to examine trust in blockchain and cryptocurrency as they are intertwined with the delivery of a BBLP. Further, a BBLP tokenises loyalty points. These tokens can take the form of cryptocurrencies which can only be facilitated through blockchain. Cryptocurrency and, by association, blockchain have been associated with illicit activities. For example, Bitcoin together with the dark web provide opportunities to conduct criminal activity (Dearden & Tucker, 2023). Some cryptocurrencies are also notorious for their volatility (Arli et al., 2021). For example, Bitcoin went from USD 0.07 in 2009 to US$20 089 in 2017 (Kjærland et al., 2018). It is noteworthy that trust in the underlying technology (blockchain) and the potential reward for participation (cryptocurrency) in a BBLP were examined rather than trust in the technology itself (BBLP). In prior studies using the TAM, trust is usually assessed in relation to the technology whose use is being examined. For example, when the intention to use mobile banking is examined, trust in mobile banking and not the underlying technology is examined (Aldammagh et al., 2021; Muflih, 2023). This is understandable, given that the technology driving the solution is usually of little relevance to acceptance. This is different in the case of a BBLP, largely due to its association and connection with cryptocurrency. A major driver of the purchasing decisions of cryptocurrency is perceived trust. (Steinmetz et al., 2021). Further, only 23% of respondents trust cryptocurrencies' price stability (Steinmetz et al., 2021). This has obvious implications for usage acceptance of an LP that rewards participants with cryptocurrency. Arguably, even if the BBLP does not reward the participant with cryptocurrency, whether a consumer can know the difference between blockchain and cryptocurrency is questionable.

Trust lowers apprehension towards using a new technology, which encourages a user to learn about the PU or benefits of a new technology (Miltgen et al., 2013). For example, blockchain technology and cryptocurrency are critical components of a BBLP. The greater the trust in these technologies, the greater the willingness to utilise these programmes through PEOU and PU. Trust is viewed as a fundamental element in the usage of cryptocurrencies (Treiblmaier & Önder, 2019).

Trust helps to create certainty and reduces the fear that benefits will not be realised (Gefen et al., 2003). For example, Gefen et al. (2003) hypothesised that trust would increase the PU of a website by improving the ultimate benefits of using the website (getting the product or service from a provider who is honest, caring, and able to deliver).

The importance of trust is also highlighted in the commitment-trust theory developed by Morgan and Hunt (1994). This theory proposes that trust and relationship commitment are key to attracting and retaining customers (Mukherjee & Nath, 2007). This is because trust and relationship commitment encourage marketing professionals to preserve relationship investments through cooperation, focus on long-term benefits not attractive short-term alternatives, and prudence regarding high-risk options (Mukherjee & Nath, 2007).

Pavlou (2003) and McCloskey (2006) hypothesised that trust would influence PEOU and PU. Trust is uninfluential on PU in other studies. For example, a study by Aghdaie et al. (2012) proved that trust had no relationship with the PU of viral marketing. Trust has been studied and suggested as an independent variable in a blockchain context (Orji et al., 2020; Queiroz et al., 2021; Treiblmaier & Önder, 2019; Wamba et al., 2020). Liu et al. (2021) examined the intention to use a blockchain and found that trust influenced PEOU and PU. On the other hand, focusing on cryptocurrency payments, Guych et al. (2018) found that trust influenced PU but did not affect PEOU. Thus, the study hypothesises that:

H6: Trust in blockchain and cryptocurrency predicts the PEOU (H6a) and PU (H6b) of a BBLP.

Perceived value of cryptocurrency

Perceived value is a *"…consumer's overall assessment of the utility of a product based on perceptions of what is received and what is given*" (Zeithaml, 1988). In a blockchain context, perceived value of blockchain has focused on the perceived benefits and perceived costs of implementing a blockchain system (Walsh et al., 2021). In this thesis, perceived value is defined as a consumer's assessment of the utility of cryptocurrency based on perceptions of what is received and what is given. Therefore, the perceived value of cryptocurrency is likely to directly affect the intention to use a BBLP, as it will determine the value ascribed to rewards for participating in such a programme. Perceived value can explain user acceptance. This is because user acceptance is a cognitive process, much like consumer behaviour that focuses on the decision-making's mental aspects (Turel et al., 2007). Notably, the focus was on the perceived value of cryptocurrency, not the technology the use of which is being examined, which is usually the case.

Perceived value directly influences the behavioural intention to use technology (Kim et al., 2008; Turel et al., 2007). Pakrou and Amir (2016) confirmed this direct effect's presence when analysing cryptocurrency's acceptance. Perceived value has been found to have no impact on behavioural intention and is an influencer of both PEOU and PU (Chen et al., 2016).

Furthermore, prior studies have confirmed the effect of perceived value on PEOU (Lee et al., 2012; Obal, 2013). Adding to this, a relationship between perceived value and PU has been confirmed in prior studies (Lee et al., 2007; Obal, 2013; Pagani, 2004). In a blockchain context, perceived value has been studied and found to reduce an individual's resistance to using blockchain (Walsh et al., 2021). Perceived switching benefits and the simplicity of infrastructure were also found to have a positive effect on the perceived value of blockchain (Walsh et al., 2021). Due to the interconnection that cryptocurrencies have with a BBLP as a reward, the following relationship was examined:

H7: The perceived value of cryptocurrency predicts the PEOU (H7a) and PU (H7b) of a BBLP.

Diffusion of innovation theory

Compatibility, relative advantage, and complexity are reliably related to technical innovations based on a meta-analysis by Tornatzky and Klein (1982). Additionally, this study omitted trialability and observability, due to the newness of BBLPs and the lack of adoption by businesses. It is not feasible to ask a respondent a question on testing and require a respondent to observe a technology currently in its infancy and still being refined.

Several studies have integrated the TAM and DOI theories (Chang et al., 2008; Hardgrave et al., 2003; Wu et al., 2005). It has also been suggested that combining the TAM with other theories, like DOI theory, improves the explanatory power of the TAM and helps the model cope with ever-changing technological innovation (Min et al., 2019). The earlier analysis of the literature (using the TCCM framework) showed that limited literature focuses on a marketing-blockchain context. Furthermore, models which have integrated TAM and diffusion theory focus on a blockchain context and are limited and focus on national development (Bhimani et al., 2022) or supply chain (Agi & Jha, 2022). This study applies DOI theory to blockchain technology and adds to the limited understanding of the applicability of this model to a blockchain context. Only 6% of studies were found to utilise DOI theory to understand blockchain acceptance directly. It is also the first study to examine the relevance of DOI theory to a blockchain-loyalty context.

Compatibility

Compatibility exists when technology is consistent with a user's beliefs, value system, habits, and experiences (Rogers, 1995). For example, suppose a BBLP aligns with an end user's beliefs, principles, and way of doing things. In that case, there is a higher probability that a customer will view the technology as useful and easy to use. Compatibility is vital in examining PU and PEOU (Min et al., 2019). Studies by Zhang et al. (2008) and Agarwal and Prasad (1999) have shown that compatibility influences technological adoption.

Several studies described below have examined a relationship between the TAM constructs, PEOU, and PU. Compatibility was found to affect PU but not PEOU by Chau and Hu (2001) and Lee et al. (2011) in a later study. The effect of compatibility on PU was confirmed in studies by Chang et al. (2008) and Wu et al. (2005). In addition, it directly affects the behavioural intention to use technology. A relationship between compatibility and PEOU as well as PU was found by Al-Rahmi et al. (2019) and Min et al. (2019). Compatibility has been studied in a blockchain context by several authors, adding to its applicability as an independent variable in a blockchain-loyalty context (Agi & Jha, 2022; Hamdan et al., 2022; Kamble et al., 2019; Kamble et al., 2021; Orji et al., 2020). In a blockchain-supply-chain context, Kamble et al. (2019) found evidence in an empirical study that compatibility influenced PU. Still, the relationship between compatibility and PEU was not supported. The lack of a relationship between PEOU and compatibility in a blockchain context is supported by Hamdan et al. (2022). However, these studies focused on a blockchain context, not a blockchain-loyalty context, which meant that the effect of compatibility on PEOU and PU was examined in the following hypothesis:

H8: Compatibility predicts the PEOU (H8a) and PU (H8b) of a BBLP.

Relative advantage

Relative advantage involves assessing whether a new technology provides advantages over its predecessor (Rogers & Shoemaker, 1971). Consumers will probably evaluate the benefits offered by a traditional LP when deciding whether to utilise a BBLP. If they feel a BBLP has more advantages, this may lead to higher PU and PEOU for a BBLP. Relative advantage is one of the best factors which predict whether someone will use a new technology (Lee et al., 2011; Shih & Fang, 2004). Moreover, a relationship between relative advantage and behavioural intention to use technology has been observed in a study by Lee et al. (2011). However, the relationship between relative advantage, PEOU, and PU can be described as under-researched

(Al-Rahmi et al., 2019). A relationship between relative advantage and PEOU and PU was confirmed by Lee et al. (2011). Additionally, recent studies by Al-Rahmi et al. (2019) and Min et al. (2019) confirmed the presence of this relationship. Several authors have examined the relationship between relative advantage in a blockchain context (Agi & Jha, 2022; Hamdan et al., 2022; Kamble et al., 2019; Kamble et al., 2021; Wong, Lai-Wan et al., 2020). Kamble et al. (2021) found that relative advantage influences PU but does not influence PEOU in a blockchain context. Since a different result may exist in a blockchain-loyalty context, the compatibility relationship that PEOU and PU exhibited was examined.

The market for LPs is saturated, and consumers have several options. A BBLP has several advantages over a traditional LP, because of blockchain. As mentioned before, BBLPs offer several advantages over traditional LPs relating to the usage of points or tokens, accrual of points, relevance of offers, expiration of points, and transferability. If these benefits are perceived as significant compared to a traditional LP, it may increase perceptions of ease of use and usefulness. Thus, it is expected that:

H9: Relative advantage predicts a BBLP's PEOU (H9a) and PU (H9b).

Complexity

Complexity describes how challenging technology is to decipher and utilise (Rogers & Shoemaker, 1971). Complexity will lower the intention to use a BBLP by reducing the technology's PEOU and PU. The constructs of PEOU and complexity are similar (Min et al., 2019). However, PEOU focuses on salient beliefs or perceptions, whereas complexity can be used to understand functional aspects of a technology (Min et al., 2019). Studies have also supported the inclusion of these variables as separate constructs, displaying sufficient discriminant validity between them (Min et al., 2019).

A relationship has been observed between complexity and PU (Hardgrave et al., 2003). This relationship was confirmed by Lee et al. (2011) and Min et al. (2019). The authors also established a connection between complexity, behavioural intention to use technology, and PEOU. In a study by Al-Rahmi et al. (2019), the PEOU and complexity were found to exhibit a relationship. Still, the relationship between the complexity exhibited with PU was unsupported. In a blockchain context, complexity has been studied by several authors, which supported the inclusion of complexity as an independent variable (Agi & Jha, 2022; Hamdan et al., 2022; Kamble et al., 2019; Kamble et al., 2021; Orji et al., 2020). In studies in a blockchain context, complexity has been found to influence PEOU (Hamdan et al., 2022; Kamble et al., 2021). Complexity has also been found to be uninfluential on PU in a blockchain context (Kamble et al., 2019; Kamble et al., 2021). Notably none of these studies focused on a blockchain-loyalty context or on a BBLP. This led to the inclusion of hypotheses that examined the effect of compatibility on both PEOU and PU.

Consumers perceive blockchain as complex and difficult to understand, which leads them to miss out on opportunities to use the technology (Knauer & Mann, 2019). Blockchain is the underlying technology which makes a BBLP possible. What follows is that, if consumers are aware that the LP uses blockchain, they will also perceive a BBLP as complex, leading to missed opportunities to realise the benefits of a BBLP. Therefore, it is hypothesised that:

H10: Complexity predicts the PEOU (H10a) and PU (H10b) of a BBLP.

Resultant conceptual model

TAM and DOI have been applied in a blockchain-context before and are popular theories to understand technological acceptance. However, no studies have applied a DOI-TAM in a blockchain, marketing or loyalty context. Furthermore, the perceived value of cryptocurrency and personal innovativeness as an independent variable have yet to be studied in a blockchain context (according to the analysis of the literature using the TCCM framework). Figure 7 provides the illustration of the combined theories.

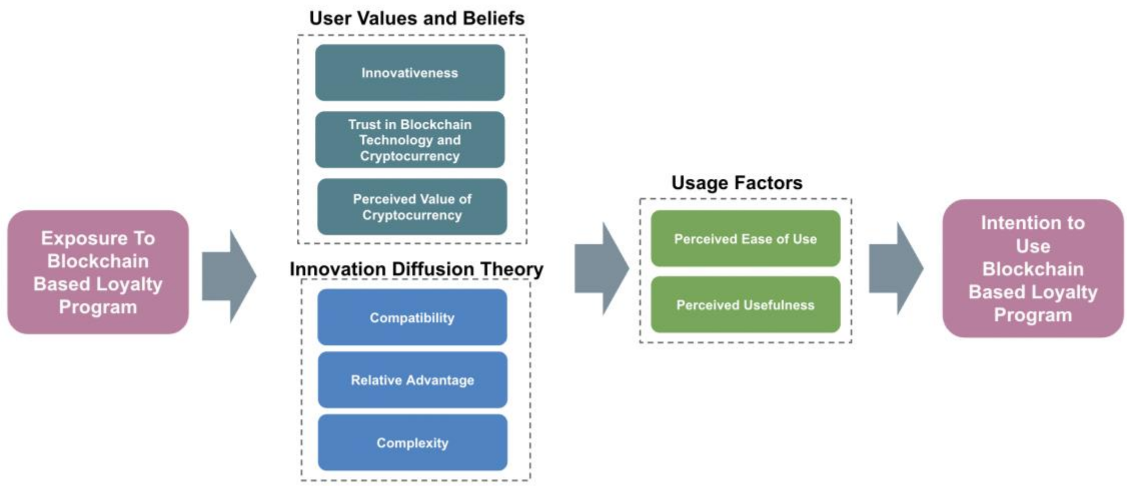

Figure 7. TAM-DOI model

Literature Review – Antecedents to loyalty

Like the previous section, literature related to the antecedents of loyalty is presented. Hypotheses stemming from this literature are suggested, culminating in presenting a theoretical model to examine loyalty and its antecedents.

Loyalty responses

Commitment

Commitment is critical to building a long-term relationship in social exchanges and customer-provider contexts (Dagger et al., 2011). Commitment is a willingness to maintain a trusted relationship (Moorman et al., 1992). In sociology, it has been described as a continuous pursuit of activities regardless of the situation (Becker, 2017). In addition, commitment has been theorised to create loyalty as committed customers view the relationship as essential (Moorman et al., 1992). This creates a desire to continue the relationship (Morgan & Hunt, 1994). This, in turn, helps to create a stable long-term relationship between two parties. Notably, LP participation has been found to have no significant relationship with commitment (Marshall, 2010). However, this programme was not blockchain-based, so that the results may differ.

Loyalty and commitment have been found to exhibit a relationship, according to Dagger et al. (2011). Focusing on the service industry, Dagger et al. (2011) discovered a positive relationship between loyalty and commitment. In the literature, commitment has been separated into affective commitment and calculative or continuance commitment. Affective commitment is an emotional attachment between a customer and a service provider (Cifci & Erdogan, 2016). Calculative commitment involves the measurement of gains and losses from continuing or terminating the relationship with the provider and focuses on switching costs (Cifci & Erdogan, 2016)

When studying affective and calculative commitment in a service context, a relationship between affective commitment and attitudinal loyalty, as well as behavioural loyalty, has been exhibited (Bloemer et al., 2003). Calculative commitment influenced both behavioural and attitudinal loyalty. However, the effect was strong for attitudinal loyalty compared to behavioural loyalty.

Focusing on the Turkey communication sector, Cifci and Erdogan (2016) analysed the effect of affective and calculative commitment on behavioural loyalty. Somewhat supporting the relationships found by Odekerken-Schröder et al. (2003), the authors found a positive relationship between affective commitment and behavioural loyalty. However, a negative relationship between calculative commitment and behavioural loyalty was also found.

Marshall (2010) found evidence of a relationship between affective commitment and calculative commitment and behavioural loyalty. Notably, no relationship was found between calculative commitment and behavioural loyalty or attitudinal loyalty. No support for a relationship between calculative commitment and loyalty could result from a consumer feeling trapped in a relationship (Marshall, 2010). Thus, the behavioural aspects of commitment in this relationship are expected to be more pronounced based on prior literature.

Overall, the relationship between commitment and a unidimensional construct of loyalty is supported by several authors (Bloemer et al., 2003; Dagger et al., 2011; Marshall, 2010). More specifically and two-dimensionally, the relationship between commitment and attitudinal loyalty is supported (Cifci & Erdogan, 2016; Inoue et al., 2017). Viewing loyalty two-dimensionally, commitment has been found to have a direct impact on attitudinal loyalty, but only impact behavioural loyalty indirectly through satisfaction (Dikcius et al., 2019). However, these did not focus on a blockchain-loyalty context. This meant that it was possible commitment could exhibit a relationship with both behavioural and attitudinal loyalty in a new blockchain-loyalty context. Thus, it is expected that:

H11: Commitment predicts the behavioural (H11a) and attitudinal (H11b) loyalty exhibited for a BBLP.

Trust

In a marketing context, trust is a type of confidence in the reliability and integrity of someone else (Watson et al., 2015). In the literature, the effect of trust on the TAM is varied. For instance, trust has a positive relationship with perceived attitudes (Aghdaie et al., 2012; Al-Ajam & Nor, 2013; Chauhan, 2015; Ha & Stoel, 2009). It has also been shown to have a relationship with the PU (Alzubi et al., 2018; Ha & Stoel, 2009; McCloskey, 2006; Pavlou, 2003). Similarly, trust has been shown to affect the PEOU (Alzubi et al., 2018; McCloskey, 2006; Pavlou, 2003). However, some studies have shown that its effect on PU is questionable (Aghdaie et al., 2012). Therefore, trust has been established to have varied effects on all aspects of the TAM.

Trust is an essential variable in relationship building, as a lack of trust in a marketplace that can be described as competitive has a low probability of creating loyalty (Ball et al., 2004). Trust has been shown to have a relationship with behavioural and attitudinal loyalty. Liu et al. (2019) studied and found evidence of a relationship between trust and behavioural loyalty in the hotel industry. Trust affects behavioural and attitudinal loyalty but exhibits a stronger relationship with behavioural loyalty (Sharifi & Esfidani, 2014). In an online environment, website trust influences website loyalty (Horppu et al., 2008). A relationship between trust and loyalty has been confirmed in a wide variety of contexts (Chaudhuri et al., 2001; Moreira & Silva, 2015; Singh et al., 2000; Sirdeshmukh et al., 2002).

Overall, trust has been linked to both behavioural and attitudinal loyalty, with a stronger relationship observed between trust and behavioural loyalty (Sharifi & Esfidani, 2014; Al-dweeri et al., 2017; Gecti & Zengin, 2013). For instance, Liu et al. (2019) reported evidence of a relationship between trust and behavioural loyalty in the hotel industry. Multiple studies in diverse contexts have confirmed the connection between trust and loyalty (Chaudhuri et al., 2001; Moreira & Silva, 2015; Singh & Sirdeshmukh, 2000; Sirdeshmukh et al., 2002). Thus, it is hypothesised that:

H12: Trust predicts the behavioural (H12a) and attitudinal (H12b) loyalty exhibited for a BBLP.

Satisfaction

Satisfaction is the difference between a consumer's expectations and the firm's actual performance (Watson et al., 2015). Prior studies have incorporated satisfaction into the TAM. For example, satisfaction influences PEOU and PU (Wixom & Todd, 2005). In other studies, only PU has been found to affect customer satisfaction, and PEOU was found not to affect (Al-hawari & Mouakket, 2010; Kim et al., 2007). In other studies, PEOU and PU have been found to affect customer satisfaction (George & Kumar, 2013). Notably, in an e-learning environment, attitude towards video-based learning did not determine the level of satisfaction a student experienced with video-based learning (Nagy, 2018). In contrast, satisfaction has been shown to exhibit a relationship and influence continued use in the telecommunication services sector (Lee et al., 2015).

Prospect theory may explain why loyal customers may be more satisfied. Prospect theory proposes that losses mean more to consumers than gains (Shankar et al., 2003). In a loyalty context, prospect theory means that loyal customers are affected more by the loss in benefits from switching to another provider than by any gains from buying from a new provider (Shankar et al., 2003). Furthermore, loyal customers are not impacted by negative information as much as non-loyal ones (Ahluwalia et al., 1999).

Prior literature shows evidence of a relationship between loyalty and satisfaction (Biscaia et al., 2017b; Jahanshahi et al., 2011; Picón et al., 2014; Sugandini & Wendry, 2017). Moreover, satisfaction has been shown to directly affect attitudinal loyalty (Ruefenacht, 2018) and behavioural intentions (Foroughi et al., 2019). Overall, satisfaction has also been shown to have a relationship with loyalty in the tourism context (Prayag, 2008). However, loyalty and satisfaction differ among consumers. For example, novice customers rely more on satisfaction as a loyalty driver than their experienced counterparts (Dagger & O'Brien, 2010). In online environments, loyalty greatly affects satisfaction (Shankar et al., 2003).

Satisfaction and loyalty are intricately connected, and satisfaction is a core determinant of loyalty (Koo et al., 2020). LPs create customer retention by enhancing customer satisfaction and value for LP participants (Koo et al., 2020). BBLPs can potentially enhance customer satisfaction by improving the transferability and usability of an LP. For example, blockchain allows participants in an LP to realise the benefits of multiple LPs that offer the same token on the blockchain network, giving consumers more options (Behrouzi et al., 2023). Further, Blockchain also allows members to track and store points more efficiently, freeing customers from a disjointed loyalty network (Rejeb et al., 2020). Thus, it is hypothesised that:

H13: Satisfaction predicts the behavioural (H13a) and attitudinal (H13b) loyalty exhibited for a BBLP.

Incentivises

Loyalty incentive programmes give users psychological and economic reluctance to switch to another firm. Agency theory and cognitive learning theory support the idea that loyalty incentives are related to technology usage (Naidoo & Leonard, 2007). Agency theory proposes that a loyalty incentive helps align a consumer's behaviour to the firm's goal of continuously using their product or service (Naidoo & Leonard, 2007). Similarly, cognitive learning theory suggests that loyalty benefits are of value to a consumer and encourage loyalty behaviour and beliefs (Naidoo & Leonard, 2007).

Loyalty incentives and technology use have been examined in South Africa. Naidoo and Leonard (2007) focus on the relationship between loyalty incentives and continued use, using a survey of financial healthcare e-service users. Continuance differs from the intention to use a technology because it focuses more on the post-acceptance stage, where usage becomes part of a user's daily routine. Nevertheless, the authors supported a relationship between continuance and loyalty incentives. Supporting this view, Hwang et al. (2014) found support for an association between loyalty incentives and behaviour, in the healthcare context.

In contrast, in the airline industry, loyalty incentives have also been shown not to be influential on the continued intention of consumers to purchase airline tickets (Koppius et al., 2005). However, this finding was questioned in a later study in a retail context, where perceived incentives affect repurchase intentions (Atchariyachanvanich et al., 2007). Loyalty incentives and technology use are, therefore, unsettled when prior literature is examined.

De Wulf et al. (2001) measured the effect of tangible rewards on perceived relationship investment in a transatlantic survey of three countries (the Netherlands, Belgium, and the United States). The authors' results were mixed. Belgium and the Netherlands exhibited a relationship, but the United States sample did not demonstrate this relationship. A possible reason the authors provided was that the greater abundance of tangible rewards that are a part of LPs in the United States means that their absence disappoints customers but fails to entice them. Evanschitzky et al. (2012) showed that perceived value (includes monetary gains and losses), as well as unique treatments (such as gifts and cards), are influential in creating programme loyalty, indicating that the incentives affect the creation of loyalty. In an ecommerce context, tangible and intangible rewards were found to be significantly related to attitudinal loyalty, but to have a small effect (Haverila et al., 2022). A loyalty card has also increased behavioural and attitudinal loyalty (Demoulin & Zidda, 2008).

Compared to a traditional LP, a BBLP fundamentally changes how rewards or incentives are offered as part of an LP. When a BBLP is utilised, points that are normally accumulated as a reward for participating in an LP become tokens (Treiblmaier & Petrozhitskaya, 2023). Using blockchain, these tokens can be more easily exchanged, transferred to peers, accrued almost instantly, and never expire, creating additional value for customers (Treiblmaier & Petrozhitskaya, 2023). Blockchain also allows participants in an LP to realise the benefits of multiple LPs that offer the same token on the blockchain network, giving consumers more options (Behrouzi et al., 2023). This improves LPs, as it facilitates the transfer of points between otherwise separate programmes (Treiblmaier & Petrozhitskaya, 2023). These tokens could be exchanged for fiat currency, and even used as a medium of exchange if the token was accepted in the economy. Shelper et al. (2018) studied the cryptocurrency LP, Unify Rewards. Participants earned a cryptocurrency called Ether when they made purchases at participating retailers. Participants in this programme can be characterised as well-exposed to traditional points-based LPs. However, the study participants felt this programme was more rewarding than conventional LPs. This made it essential to understand incentivisation in the context of BBLPs. Therefore, it is expected that:

H14: Incentivisation predicts the behavioural (H14a) and attitudinal (H14b) loyalty exhibited for a BBLP.

Relative advantage

Relative advantage encompasses a feeling that the technology being considered is better than the one it supersedes (Lin et al., 2015). If a technology is perceived as advantageous compared to the technology that precedes it, the user will probably be more willing to continue to utilise the product or service (Lin et al., 2015). Relative advantage also discourages a consumer from trying alternatives, creating loyalty towards the particular brand or company (Yun et al., 2012). In an online banking context, relative advantage has been found to have a significant relationship with the generation of customer loyalty (Rambocas & Arjoon, 2012). This relationship in a banking context was also confirmed by Jamshidi and Kuanova (2020), when studying Islamic credit cards. Notably, an earlier study by Dixon et al. (2005) in a retail context found that relative advantage does not correlate with functional store loyalty. Functional store loyalty is the most visible and tangible aspects, including product range, friendliness, convenience, and other elements of the consumer's tangible shopping experience (Dixon et al., 2005). A later study by Lin et al. (2015) focused on smartphones and confirmed that relative advantage positively influenced loyalty. Yun et al. (2012) also confirmed this in a retail context. Several authors have examined the relationship between relative advantage in a blockchain context (Agi & Jha, 2022; Hamdan et al., 2022; Kamble et al., 2019; Wong et al., 2020).

Relative advantage and the behavioural intention to use technology has been observed to have a relationship in studies such as ones by Lee et al. (2011). Relative advantage has been examined extensively and is well established; this variable has often been cited as the best predictor of technology adoption (Choudhury et al., 2008). This study proposes that intention can predict the relative advantage experienced by a consumer. A consumer who has already decided to use technology will probably evaluate it as providing more relative advantage than the technology they have chosen not to use. No research was found that examines the relationship between relative advantage and loyalty as a two-dimensional construct, which only added to the necessity to examine its effect two-dimensionally.

The market for LPs is saturated, and consumers have several options. In the United States, consumers, on average, belong to 18 LPs but only actively participate in 50% of them (Bond Brand Loyalty, 2023). This is similar in Canada, where average consumers belong to 15 LPs but only actively participate in 57% of them (Bond Brand Loyalty, 2023). A BBLP has several advantages over a traditional LP, because of blockchain. As mentioned before, BBLPs offer several advantages over conventional LPs relating to the usage of points or tokens, accrual of points, relevance of offers, expiration of points, and transferability. If these benefits are perceived as significant compared to a traditional LP, it may lead to greater loyalty. This led to the examination of the following hypothesis:

H15: Relative advantage predicts the behavioural (H15a) and attitudinal (H15b) loyalty exhibited for a BBLP.

The behavioural intention to use and loyalty

Agag et al. (2019) utilised the TAM to study the intention to play online games. In their study, the authors analysed and confirmed the relationship between the intention to play online games and the creation of loyalty. A relationship has been demonstrated between behavioural intention to use technology and loyalty by other authors, such as Bouagina and Triki (2013) and Martinez-Caro et al. (2013), in a banking context. Further support in an online shopping environment for the relationship between the behavioural intention to use technology and loyalty can be found in a study by Tang and Huang (2015). Utilising theory underpinning the TAM, the attitude has been found to significantly influence loyalty in a study by Ruiz-Mafe et al. (2014) in an online social-network setting. Notably, in a transportation context, a model that proposed a direct relationship between behavioural intention and loyalty was rejected by Niu et al. (2021).

Using blockchain technology may create more positive experiences and greater emotional attachment, for two main reasons. First, blockchain, by design, creates trust and transparency (Bezovski et al., 2021). Second, blockchain allows participants in an LP to realise the benefits of multiple LPs that offer the same token on the blockchain network, giving consumers more options (Behrouzi et al., 2023). Theoretically, these tokens could be traded freely within the network, exchanged for fiat currency, and even used as a medium of exchange if the token was accepted in the economy. These benefits and positive consumer experiences generate higher behavioural and attitudinal loyalty levels and lead to stronger behavioural intentions to use a BBLP. It is hypothesised that:

H16: Behavioural loyalty (H16a) and attitudinal loyalty (H16b) predict the intention to use a BBLP.

Resultant conceptual model

The resultant conceptual model below in Figure 8 is based on the model provided by Watson et al. (2015). Watson et al. (2015) attempted to demystify the wide variety of conceptual approaches researchers have used to examine loyalty. The authors did this using item-level coding of loyalty research, which was tested using a random-effect meta-analysis of reliability, structural path analysis and multivariate moderation analysis. Watson et al. (2015) created a model based on the results of the structural path analysis, which used this meta-analytic data. This model included trust, commitment, satisfaction, and loyalty incentives, which are also included in the conceptual model in Figure 7. The relative advantage was added because of the literature which supports its relationship with loyalty (Lin et al., 2015; Rambocas & Arjoon, 2012; Yun et al., 2012). It is acknowledged by Watson et al. (2015) that a limitation of their study was that they may have missed some loyalty constructs, as their analysis was limited to constructs that had sufficient data, supporting the inclusion of relative advantage in the model in this study.

The work of Watson et al. (2015) did not link loyalty to technological acceptance. The proposed relationship between behavioural and attitudinal loyalty and usage intentions is novel. It is based on prior studies which have shown evidence that acceptance and loyalty have a relationship (Agag et al., 2019; Bouagina & Triki, 2013; Martinez-Caro et al., 2013; Tang & Huang, 2015). Therefore, this study expands on the model of Watson et al. (2015) by exploring relative advantage, proposing a relationship between loyalty and technology acceptance. Additionally, to the author's knowledge, this is the first-time the model has been tested empirically and in a blockchain-loyalty context.

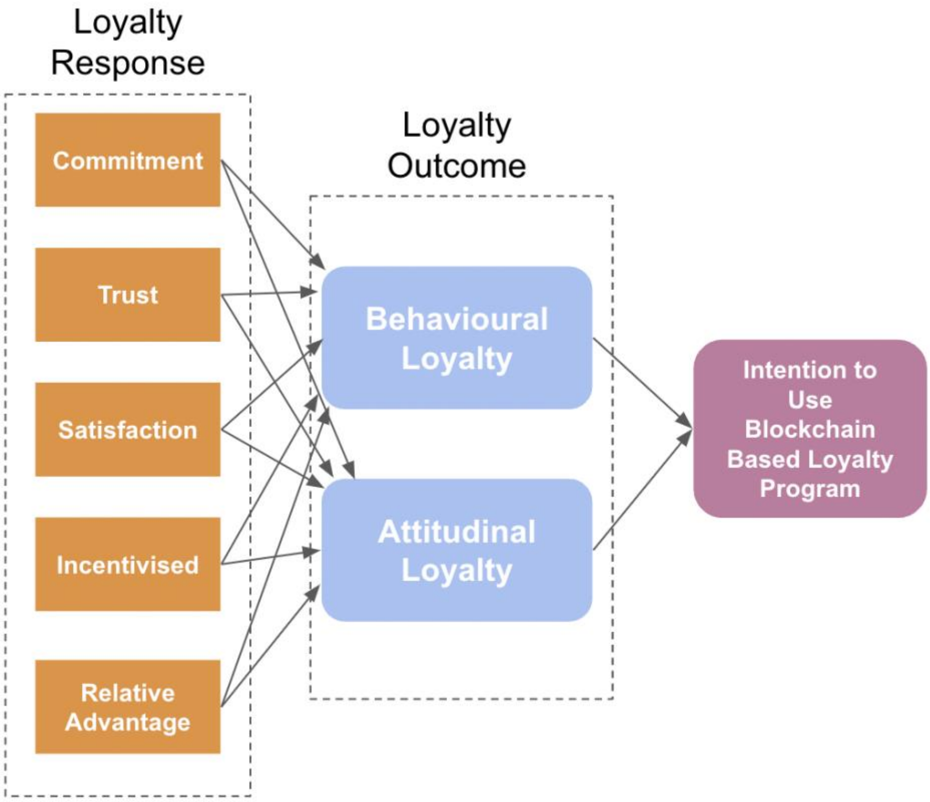

Figure 8. Conceptual model based on the work of Watson et al. (2015) and Davis (1985)

The integrated theoretical model is indicated in Figure 8. This model comprehensively sheds light on how firm outcomes (word of mouth and redemption) are generated through loyalty outcomes and usage. It also comprehensively sheds light on the factors that influence usage (PEOU and PU), as well as loyalty outcomes (behavioural and attitudinal loyalty). The combined model is the first to examine behavioural and attitudinal loyalty (as well as their antecedents) and firm outcomes in a blockchain-context. It sheds light on the relevance and importance of TAM, DOI, and loyalty theories to understanding LPs in a blockchain context, which has not been done before. It also adds to only a few studies that focus on the intersection of blockchain and marketing.

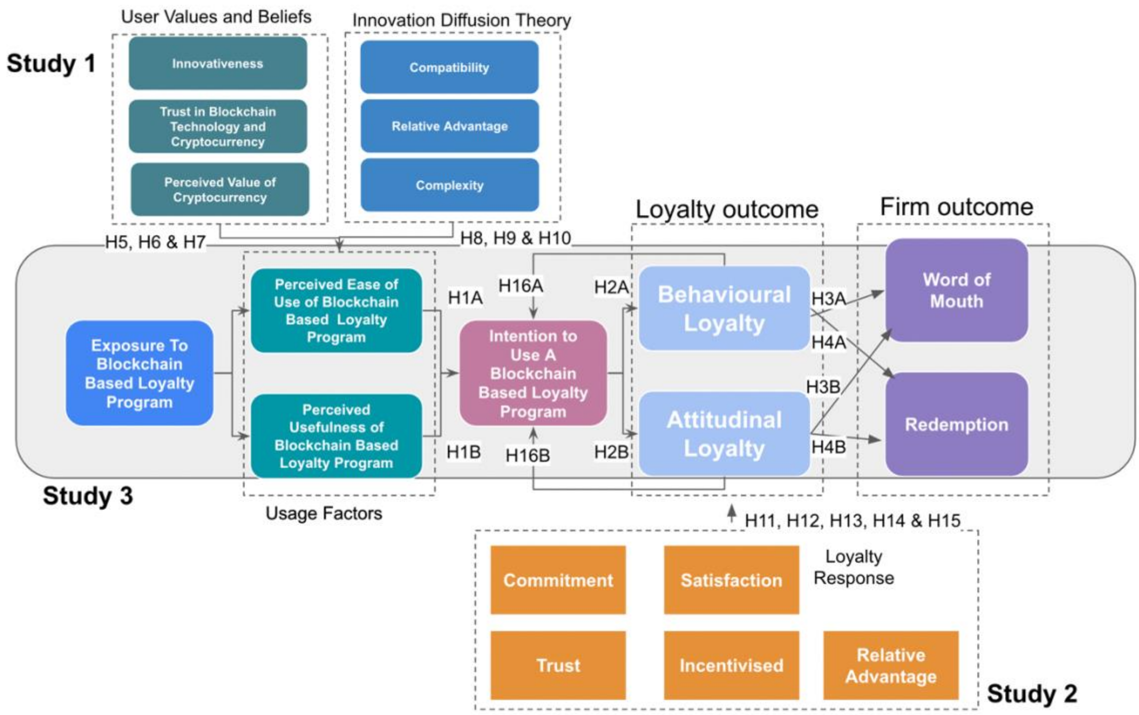

Figure 8. An integrated acceptance-loyalty-outcome model developed by Hendricks et al. (2022)

Summary of key gaps

In summary, the literature reveals several key gaps that this thesis aims to address. First, while blockchain technology has shown potential in marketing and loyalty programmes, its application in BBLPs remains underexplored, particularly regarding the drivers of adoption and the integration of technology acceptance models. Second, limited research exists on how constructs like perceived value and trust influence blockchain adoption in loyalty contexts, particularly when these factors are tied to rewards such as cryptocurrency. Third, existing loyalty research lacks consensus on measurement approaches and often overlooks two-dimensional loyalty (behavioural and attitudinal), which is critical for understanding outcomes like redemption and word-of-mouth. Lastly, gaps exist in the exploration of antecedents to loyalty and their relationship with firm outcomes in blockchain contexts. Addressing these gaps, this thesis develops a unified framework combining technology acceptance and loyalty models to explore the adoption and effectiveness of BBLPs, setting the stage for its research objectives.

Chapter Summary

This chapter was focused on both building and justifying the theoretical model which is examined in this thesis. Blockchain was found to have several applications to marketing, including marketing management; supply-chain management; payments; digital marketing; and most importantly LPs. As mentioned before, despite a wide range of applications, very few articles focus on the intersection of blockchain and marketing, as it is a recent matter (Antoniadis et al., 2019; Jain et al., 2021; Wasiq et al., 2023). There is a call for more research on the adoption of blockchain technology by firms and consumers, particularly in a blockchain-marketing context (Antoniadis et al., 2019; Li et al., 2018). Recent bibliometric and network-based analyses indicate that blockchain marketing has significant potential and requires further exploration (Jain et al., 2021). As of 2023, research on blockchain and marketing remains fragmented and in its infancy (Wasiq et al., 2023). Few studies have examined how blockchain impacts specific marketing strategies, such as loyalty (Wasiq et al., 2023) and this remains the case in 2024.

A pioneering study by Treiblmaier and Petrozhitskaya (2023) investigated blockchain-based loyalty programmes (BBLPs), using a small consumer survey and Twitter analysis. However, their study focused on expectancy theory to understand perceptions of BBLPs, whereas this thesis employs TAM-DOI theory and Watson et al.'s (2015) work to examine technology acceptance, loyalty generation, and firm outcomes. Treiblmaier and Petrozhitskaya (2023) emphasised BBLP properties and the perceived differences between BBLPs and traditional loyalty programmes, which is not the focus of this thesis. Instead, this research concentrates on how BBLPs are accepted and generate both loyalty and firm outcomes.

The TCCM review revealed the need for research that focuses on blockchain and marketing. Only four studies were found in TCCM that focus on the intersection of blockchain and marketing (Gleim & Stevens, 2021; Kumar et al., 2022; Tran & Nguyen, 2021; Utz et al., 2023; Wang et al., 2019). Only two of the studies focused on the more niche area of loyalty and its intersection with blockchain and marketing (Utz et al., 2023; Wang et al., 2019). This substantiated the need for more research into blockchain and its intersection with marketing, due to the numerous applications of blockchain to marketing, and the absence of research in this area, which is even more applicable to loyalty as a more niche marketing field.

This led this thesis to focus on the intersection of marketing and blockchain by examining a blockchain-based LP. A theoretical model that combined technology-acceptance theories, namely, DOI and TAM, was utilised to do this. These theories were combined because they have common theoretical foundations, which, once integrated, lead to better results

(Nezamdoust et al., 2022; Roussou & Stiakakis, 2016), for example, greater perception of how an individual embraces a new technology and confirms each other's validity and reliability (Nezamdoust et al., 2022; Roussou & Stiakakis, 2016). The relevance of using a combined TAM-DOI model to understand technology acceptance was further substantiated by its use by authors in a blockchain context (Roussou & Stiakakis, 2016; Ullah et al., 2021).

The explanatory power of TAM in a blockchain context has been examined by only a handful of authors (Hamdan et al., 2022; Kamble et al., 2019). PEOU and PU have been found to influence the intention to use cryptocurrency (Sohaib et al., 2019), blockchain-based research-sharing frameworks (Shrestha & Vassileva, 2019), cryptocurrency transactions (Taheri Tolu et al., 2022), cryptocurrency payments (Guych et al., 2018), and blockchain technology (Kamble et al., 2019; Liu et al., 2021). However, it has not been examined before in a blockchain-loyalty context. Further, the relationships between compatibility, innovativeness, complexity, and relative advantage have been studied to a limited extent by authors in a blockchain context (Hamdan et al., 2022; Kamble et al., 2019; Kamble et al., 2021; Kumari & Devi, 2023; Ullah et al., 2021). This made it important to add to the limited literature examining these variables in a blockchain-loyalty context.

Unique antecedents to PEOU and PU were proposed, namely, trust in blockchain and cryptocurrency and perceived value of cryptocurrency. It is noteworthy that trust in the underlying technology (blockchain) and the potential reward for participation (cryptocurrency) in a BBLP will be examined rather than trust in the technology itself (BBLP). In prior studies using the TAM, trust is usually assessed in relation to the technology of which the use is being examined. The same can be said about perceived value. Examining these unique antecedents therefore can advance the understanding of the potentially unique impact that the cryptocurrency and blockchain has on the PEOU, PU and ultimately usage intentions of a BBLP.

A loyalty dimension was also added to the model, given the relevance of loyalty in the examination of a blockchain-based LP. The meta-analysis of Watson et al. (2015) and the resultant structural model provided a convenient and simple model to understand common antecedents to loyalty, such as a multi-dimensional construct. Understanding loyalty as a multi-dimensional construct and finding a simple model to include was critical, given that there is no consensus on the conceptual approaches to understanding and measuring loyalty (Bennett &

Bove, 2001; Cengiz & Akdemir-Cengiz, 2016; Watson et al., 2015). However, researchers do tend to agree that loyalty is a multi-dimensional construct, making a multi-dimensional model important (Cengiz & Akdemir-Cengiz, 2016). The use of a model that combines loyalty and technology acceptance was supported by prior research that has done the same (Martinez-Caro et al., 2013; Niu et al., 2021; Setiawati et al., 2021; Wong et al., 2014).

Support for examining loyalty two-dimensionally is further supported by the severely limited research examining the relationship satisfaction, incentivisation, commitment, relative advantage and trust have with behavioural and attitudinal loyalty overall, especially in a blockchain or loyalty context (Al-dweeri et al., 2017; Cifci & Erdogan, 2016; Gecti & Zengin, 2013; Haverila et al., 2022; Inoue et al., 2017; Kamran-Disfani et al., 2017). This made the examination of these factors important to include in the conceptual model. Furthermore, the conceptual model extends the work of Watson et al. (2015) to include relative advantage as an antecedent to the generation of behavioural and attitudinal loyalty. The relationship between relative advantage and a unidimensional conception of loyalty has been examined by several authors (Jamshidi & Kuanova, 2020; Lin et al., 2015; Rambocas & Arjoon, 2012). No research was found which examines the relationship between relative advantage and loyalty as a two-dimensional construct, empirically.

The model of Watson et al. (2015) focused on WoM and firm outcomes. The replacement of performance with redemption is a further theoretical adaption of the model proposed by Watson et al. (2015) and adds to the limited literature examining how the generation of loyalty can lead to an LP-specific outcome, i.e., redemption. As mentioned before, accrued, unredeemed points can represent substantial value. Estimates of unclaimed loyalty points were as high as US$100 billion (Bond Brand Loyalty, 2017). As a promise for a future service, these accrued points represent a liability for a firm (Chun et al., 2020). The lack of redemption limits how effectively an LP can increase spending through breaking down the point-pressure mechanism. This mechanism pushes consumers to spend, because a points balance is low (Bijmolt et al., 2011).

This is the first time an integrated model incorporating technology, acceptance, loyalty, and firm outcomes has been proposed. This model explains the technological journey of a new loyalty technology, from acceptance to intention to use, to loyalty creation, and finally to creating critical firm outcomes in a loyalty context: WoM and redemption. This model may have applicability to any new technology where the ultimate goals are loyalty, redemption, and WoM.

In summary, this thesis adds to literature in several important ways. First, it validates the exploratory power of a DOI-TAM model in a blockchain-loyalty context. Second, it adds to the literature by investigating a new variable, the perceived value of cryptocurrency, and trust in blockchain and cryptocurrency while also unravelling the impact of personal innovativeness on the perceived ease of use (PEOU) and perceived usefulness (PU) of a BBLP for the first time. Thirdly, it also expands on the model of Watson et al. (2015) in a blockchain-loyalty context by examining relationships that behavioural and attitudinal loyalty has with the intention to use a BBLP, redemption and relative advantage. How this thesis will achieve this is explained in the next chapter, focusing on the research design and methodology.

Chapter 3: Research Design and Methodology

Research methodology

This thesis aimed to understand the technological journey of an emerging loyalty technology, from acceptance to intention to use, to loyalty creation, and finally to creating critical firm outcomes in a loyalty context: WoM and redemption. In the sections that follow, attention is directed towards the research design, research strategy, data-collection procedures, sampling techniques, questionnaire development, measurement considerations, scaling methodologies, and data-analysis methodologies employed across all three studies.

Research design and strategy

A research design is a plan of action which shows how the research problem will be answered and often involves a description of how data will be collected (Saunders et al., 2019b). A research design contains three layers: research layers, research strategies and research approaches (Saunders et al., 2019).

The purpose of research can be classified into one of the following types of studies: exploratory, evaluative, descriptive or combined (Saunders et al., 2019). First, exploratory studies focus on understanding a problem when there is a high degree of uncertainty (Saunders et al., 2019). Second, descriptive research seeks to elucidate and characterise various phenomena, such as marketplace attributes (Malhotra et al., 2017). Thirdly, explanatory studies establish cause-and-effect associations or causal relationships between variables (Birks & Malhotra, 2006; Saunders et al., 2019). The fourth type of study, evaluative studies, focus on discovering how something works (Saunders et al., 2019). Lastly, a combined study uses two or more methods in the research design (Saunders et al., 2019). This thesis, comprising three studies, is explanatory as it examines causal relationships between variables derived from TAM, DOI theory, and loyalty theory.

Research strategies can be characterised into seven categories: experiments, surveys, case studies, action research, grounded theory, ethnography, and narrative enquires (Saunders et al., 2019b). These research strategies can be described simply as a plan of action to achieve an objective (Saunders et al., 2019). No research strategy is superior to another, and the choice of research strategy is guided primarily by the research question and objectives (Saunders et al., 2019). Other considerations include current knowledge, time, available resources, and philosophical considerations (Saunders et al., 2019). Due to its popularity in business and management research, this thesis uses a survey for all three studies (Saunders et al., 2019). The use of surveys in prior research to investigate blockchain, loyalty and technology acceptance supported this research strategy as a way to answer the research questions (Alazab et al., 2021; Borhani et al., 2021; Kumari & Devi, 2023; Lou & Li, 2017; Stallone et al., 2021).

The way qualitative and quantitative methods are combined is referred to as the research choice (Saunders et al., 2019). Quantitative research designs can be either mono- or multiple-method studies (Saunders et al., 2019). A mono method involves using a single method of data collection, whereas multiple methods use several data-collection techniques (Saunders et al., 2019). This study uses a mono method with a deductive approach. Primary data is acquired through an online questionnaire specifically designed to address the primary research objectives. All three studies employ a quantitative research strategy.

Time horizons are longitudinal or cross-sectional (Saunders et al., 2019). Cross-sectional studies provide a snapshot to the researcher, whereas cross-sectional studies can be described as a series of snapshots taken over a period (Saunders et al., 2019). Due to time and resource constraints, all three studies use a single cross-sectional design. This involves gathering data at a single point in time from a sample of the population (Malhotra et al., 2017). This differs from multiple cross-sectional designs, by which multiple respondent samples are obtained, and data is gathered only once from each respondent (Malhotra et al., 2017).

Research approaches

Choosing an appropriate research approach is fundamental to the design, methodology, data collection process and analysis techniques. Research approaches can be categorised into three approaches: qualitative, quantitative and mixed methods (Creswell & Creswell, 2017). Qualitative research is a method used to explore the meanings individuals or groups assign to social or human issues (Creswell & Creswell, 2017). It involves flexible questions, data collection in natural settings, and inductive analysis that moves from specifics to broader themes (Creswell & Creswell, 2017). Researchers focus on interpreting meaning and capturing the complexity of the situation in a flexible final report (Creswell & Creswell, 2017).

Quantitative research tests objective theories by analysing relationships among measurable variables (Creswell & Creswell, 2017). Data is typically collected through instruments and analysed using statistical methods (Creswell & Creswell, 2017). The final report follows a structured format: introduction, literature review, methods, results, and discussion (Creswell & Creswell, 2017). Researchers in this approach work deductively, aim to minimize bias, control for alternative explanations, and seek to generalize and replicate findings (Creswell & Creswell, 2017).

Mixed methods research involves collecting both quantitative and qualitative data, integrating them, and applying specific designs that may include philosophical assumptions and theoretical frameworks (Creswell & Creswell, 2017). The key idea is that combining both data types offers deeper insights than either quantitative or qualitative data alone (Creswell & Creswell, 2017).

When choosing a research approach, Creswell and Creswell (2017) recommend considering the research problem and questions, personal experiences, and the intended audience. In terms of the research problem, a quantitative approach is preferred if the study seeks to identify factors influencing an outcome or determine the best predictors of outcomes. This rationale guided the use of a quantitative approach in this thesis. Regarding personal experiences, the researcher had previously employed a quantitative approach in their master's research, leading to a preference for this method. Finally, concerning the audience, the research was aimed at an academic readership and journal editors, where quantitative, qualitative, and mixed methods could all be suitable. However, given the other considerations, a quantitative approach was deemed most appropriate.

Sampling

To obtain information from the population, two methods can be used: census or sample. A census involves a complete account of the entire population related to the market research problem, whereas a sample represents only a portion of this population (Malhotra et al., 2017). Due to a limited budget and time constraints, all the studies used a sample instead of a census. Statistics are utilised to draw conclusions about the entire population when using a sample.

Definition of the target population

The target population consists of respondents 18 years and older who are residents anywhere in the world. Minors were not of specific interest to the study and were excluded. This target population was chosen because minors and those who are not of working age are unlikely to be users of loyalty rewards programmes because they lack the purchasing power to participate in these LPs meaningfully. This is supported by data that indicates that older consumers tend to use LPs more. For example, shoppers who are 65 and older report the most frequent usage of loyalty cards (Tighe, 2022). Subscription to loyalty rewards programmes is also highest among those adults aged 45-64 (Guttmann, 2021). Despite the high participation in LPs among adults aged 45-64, the target population for all the studies includes anyone aged 18-64. Adults aged below 45, can still meaningfully participate and benefit from a BBLP. Their spending power and increasing the participation of these adults in this age group may also be of interest to firms, making their participation in these studies highly relevant.

Sample frame

A sampling frame encompasses a methodology employed to identify and delineate the unique characteristics of a particular target population (Malhotra et al., 2017). In the context of this study, the sampling frame encompasses a random selection of individuals aged 18 years and above. To ensure conformity with the criteria stipulated by the sampling frame, the questionnaire incorporates filter questions.

Selection of sampling technique

One of the pivotal determinations in sample techniques revolves around the choice between probability and non-probability sampling. Malhotra et al. (2017) highlight that non-probability sampling relies on the researcher's intuition or judgement. Conversely, probability sampling integrates chance as a fundamental element in the sample selection process (Malhotra et al., 2017). For practical considerations, this study opted for non-probability sampling, specifically employing convenience sampling. Convenience sampling is a technique that involves acquiring a sample in the most convenient manner at the researcher's discretion (Malhotra et al., 2017).

Convenience sampling presents several advantages compared to other sampling methods, such as being the least expensive and time-consuming approach to sampling a population (Malhotra et al., 2017). Additionally, this technique offers enhanced accessibility to the sample, facilitates simpler measurement, and provides greater ease of assistance (Malhotra et al., 2017). Nevertheless, it is important to acknowledge the limitations associated with this technique, including potential selection bias and the sample's lack of representativeness of any specific population (Malhotra et al., 2017).

Determination of sample size

For sample size, it is crucial to consider the minimum requirements of the statistical software being used (Wong et al., 2013). This study utilised SEM. According to Wong et al. (2013), the Partial Least Square-SEM (PLS-SEM) method allows for analysing complex cause-and-effect relationships between independent and dependent constructs. To ensure an adequate sample size for PLS-SEM marketing research, Wong et al. (2013) recommend a minimum sample size based on the number of arrows pointing at a latent variable in the theoretical framework. Specifically, for 2 arrows, a minimum sample size of 52 is recommended; for 3 arrows, 59; and 10 arrows, 91. Additionally, other sources suggest sample sizes between 100 and 200 as a good starting point for PLS-SEM analysis (Hoyle, 1995). Barclay et al. (1995) provide a rule suggesting that the sample size should be at least ten times the maximum number of structural paths directed at a latent variable anywhere in the path model. Recent published research on blockchain using PLS-SEM has used small sample sizes ranging from 120 to 180 participants (Alharbi & Sohaib, 2021; Sohaib et al., 2019). The final sample sizes for studies One, Two and Three were 705, 480 and 902 respectively.

Table 7. Summary of Sampling

Target Population	Adults who are 18 years and older
Sampling Frame	Non-probability sampling
Sampling Technique	Convenience sampling
Sample Size for Entire Thesis	1200
Final Sample for Each Study	705 (Study One), 480 (Study Two), 902 (Study Three)
Implementation of Sampling Process	Participants were asked to give active consent to participate in the research. They were also notified that they can withdraw from the research at any time. Thereafter, the respondent was shown a video that included a text description describing a BBLP's functionality. After viewing the video, they were asked to complete the rest of the questionnaire.

Table 8 provides a snapshot of the samples for each study. It shows that most respondents were between 18 and 24 years old, and that convenience sampling was used for all three studies.

Study Three required the use of a data-collection company, Yazi, because responses obtained using convenience sampling were insufficient.

Table 8. Snapshot of samples

Study	Number of respondents	Sources	Demographic details of respondents (where available)
Study One	995	**Convenience sampling:** Distribution of an online survey to the researcher's own network as well as the distribution of the survey to students at the University of Cape Town through email.	68% → 18-24 years old, 21% → 25-34 years old, 9% → above the age of 34 years old.
Study Two	756		77% → 18-24 years old, a 13% → 25-34 years old, 3% → above the age of 34 years old.
Study Three	1157	**Convenience sampling and data-collection company:** Distribution of an online survey to the researcher's own network as well as the distribution of the survey to students at the University of Cape Town through email. A market research company called Yazi was used. Yazi is a South African based company whose respondents are located throughout Africa and are reimbursed in return for answering surveys.	48%→ 18-24 years old, 36%→ 25-34 years old, 8%→ 35-44 years old 5%→ 45-54 years old, 3%→ 55-64 years old

Questionnaire design

This section outlines the objectives and creation process of the questionnaire used in the study. As the study involved human subjects, ethical considerations were considered in its design and execution, with relevant clearance documents attached in Appendix A.

To ensure informed consent, an extensive introduction was provided at the commencement of the survey, elucidating the study's purpose, guaranteeing anonymity, and emphasising the protection of personal information. Consent was sought and obtained for the utilisation and dissemination of the data provided for research purposes, in accordance with the guidelines stipulated by the Commerce Faculty Ethics Research Committee. After obtaining consent, respondents were presented with a video accompanied by a textual description outlining the functionality of a BBLP.

The questionnaire was organised into distinct sections, each centred around the constructs and sub-constructs delineated in the integrated model pertinent to each individual study. Lastly, the concluding section comprised questions pertaining to classification and identification information. This sequencing deliberately mitigated any potential barriers that may impede respondents from answering the questions. Birks and Malhotra (2006) recommended incentives to participants in the form of voluntary entry into a prize draw for an online shopping voucher. This value exchange was offered as a token of appreciation for their time and effort invested in completing the survey.

Measurement and scaling

Measurement involves connecting numbers and symbols to represent objects based on predefined rules (Malhotra et al., 2017). Conversely, the technique of scaling entails assigning numerical values to objects according to predetermined rules (Birks & Malhotra, 2006).

Scaling techniques can fall into two categories: comparative and non-comparative scales (Malhotra et al., 2017). Comparative scales involve the direct comparison of objects, while non-comparative scales necessitate the independent scaling of each object within the set (Malhotra et al., 2017). Although both techniques possess their own advantages, non-comparative scales find wider application in market research (Malhotra et al., 2017). Two common types of non-comparative scaling techniques are continuous rating scales and itemised rating scales (Malhotra et al., 2017). Continuous rating scales allow respondents to place a mark anywhere along the scale, but this approach can introduce reliability issues and pose challenges for scoring (Malhotra et al., 2017), thus limiting its utilisation in market research. Conversely, itemised scales, which entail associating a number or descriptor with each category, are more commonly employed in market research (Malhotra et al., 2017). This study utilised an itemised scale known as a Likert scale. The Likert scale measures the degree of agreement or disagreement with specific statements about the objects under examination (Malhotra et al., 2017). A Likert scale is easy to create and participants can easily understand how it works, making it ideal for online surveys (Malhotra et al., 2017). However, it also takes longer to complete than other itemised scales and can be difficult to interpret (Malhotra et al., 2017).

Malhotra et al. (2017) recommend that measurement scales encompass five to nine categories. For this study, a five-category scale was adopted, ranging from ‘strongly agree’ to ‘strongly disagree,’ with one neutral option provided. The ideal number of categories is unsettled and has been debated in the literature for decades (Altuna & Müge Arslan, 2016). Five categories were used because shorter rating scales are easier to use (Taherdoost, 2019). A five-category scale is also preferred, at least when measuring compulsive buying behaviour (Choudhury et al., 2014). Recent literature focusing on blockchain and technology acceptance also supports the use of five categories (Alazab et al., 2021; Kamble et al., 2019; Lou & Li, 2017).

This scale is considered balanced, as it offers two negative and two positive options (Malhotra et al., 2017). A balanced scale is necessary to obtain objective data (Malhotra et al., 2017). All scale categories were labelled to ensure clarity, and robust anchors were employed. The wording of scale items can influence the distribution of responses, with stronger anchors resulting in more pronounced distributions (Malhotra et al., 2017). An odd number of categories was selected to accommodate respondents who may provide neutral responses, as Malhotra et al. (2017) recommended. The survey questionnaire can be found in Appendix B.

Measurement items for Study One

Study One consisted of three to six items per construct. These constructs were operationalised using a five-point Likert scale. The construct focusing on users' beliefs and values was subdivided into innovativeness, trust in blockchain technology and cryptocurrency, and the perceived value of cryptocurrency. Constructs focusing on DOI were subdivided into compatibility, relative advantage, and complexity. Usage factors were subdivided into PEOU and PU. The literature outlined in Table 9 was used to operationalise items. Owing to the lack of research focusing on the user acceptance of BBLPs, questions were adapted from various studies focusing on user acceptance in other areas. This included the user acceptance of mostly new technologies at the time: biometrics, transportation (Uber and eco-friendly), new hotel systems, and smartwatches. Further information on the connection between individual questions and the literature which inspired them is visible in the appendix (8.2.1).

Table 9. Measurement scales – Study One

Items relating to	Literature on which the items were based	Items	# of scales
Innovativeness	Miltgen et al. (2013)	I am among the first to try out new technologies	3
		When I hear about a new technology, I look for ways to adopt it	
		I like to experiment with new technologies	
Trust in blockchain	Miltgen et al. (2013)	I trust Blockchain Technology,	6
		I trust Cryptocurrencies like Bitcoin	

technology and cryptocurrency		I trust the underlying technology which drives Cryptocurrencies like Bitcoin	
		I trust blockchain-based loyalty programs	
		I think Blockchain Technology is reliable.	
		I think Cryptocurrencies are reliable	
Perceived value of cryptocurrency	Kim et al. (2008)	Investment of time and effort in receiving Cryptocurrency would be profitable for me	5
		There is a benefit in using cryptocurrency	
		There is no loss in using Cryptocurrency	
	Chen et al. (2016)	Cryptocurrency has value to me	
	Martignoni et al. (2008)	Cryptocurrency would be useful for me to have	
Compatibility	Miltgen et al. (2013)	I think using a Blockchain-based Loyalty Program would fit well with the way that I like to use loyalty programs	3
		Using a Blockchain-based Loyalty Program would fit into my lifestyle	
		The benefits of using a Blockchain based Loyalty Program are apparent to me	
Relative advantage	Min et al. (2019)	Compared to the existing loyalty program I use, a Blockchain-based Loyalty Program would make it easier to redeem any benefits I earned as part of a loyalty program	3
		Compared to the existing loyalty program I use, a Blockchain-based Loyalty Program would make it easier for me to get rewarded.	
		Compared to the existing loyalty program I use, loyalty programs that do not use a Blockchain, a Blockchain-based Loyalty Program would make it easier to earn benefits from a loyalty program.	
		Compared to the existing loyalty program I use, a Blockchain-based Loyalty Program would make it easier to manage the benefits that I earn as part of a loyalty program	
Complexity	Karahanna et al. (1999)	I believe that using a Blockchain- Based Loyalty Program requires technical skills.	5
		I believe that using a Blockchain-Based Loyalty Program will require a lot of mental effort	
		I believe that using a Blockchain-Based Loyalty Program would be frustrating	
		A Blockchain-Based Loyalty Program would confuse me	
		A Blockchain-Based Loyalty Program would be complex to use	
PEOU	Miltgen et al. (2013)	I don't think it would be hard to use a Blockchain-based Loyalty Program	5
		Using a Blockchain-based Loyalty Program would likely require minimum of effort	
		It would be easy to get a Blockchain-based Loyalty Program to do what you want it to do	
		Learning to use a Blockchain-based	

		Loyalty Program would be easy for me	
		I would find a Blockchain-based Loyalty Program easy to use	
PU	Choe and Noh (2018)	Using a Blockchain-based Loyalty Adapted Program would be useful in my daily life	4
		Using a Blockchain-based Loyalty Program would make my daily life more efficient	
		Using a Blockchain-based Loyalty Program would make my loyalty reward experience more efficient	
		Using a Blockchain-based Loyalty Program would make my loyalty reward experience more useful	
Intention to use a BBLP	Miltgen et al. (2013)	I would sign-up for a Blockchain-based Loyalty Program as soon as possible	5
		I would use a Blockchain-based loyalty Program soon after it is launched	
	Choe and Noh (2018)	I will use a Blockchain-based Loyalty Program in the future.	
		I will try to use a Blockchain-based Loyalty Program.	
		I am willing to use a Blockchain-based Loyalty Program.	

Measurement items for Study Two

As with Study One, the second study consisted of three to five items for eight constructs. Loyalty response was subdivided into commitment, trust, satisfaction, incentivisation, and relative advantage. Loyalty outcomes were subdivided into behavioural and attitudinal loyalty. Due to the limited literature and studies which focus on BBLPs, items were taken from and adapted from the loyalty literature. This included loyalty literature which focuses on the banking, hotel, retail, and online sectors. The literature that was used in the creation of each construct is listed in Table 10 below. Further information on the connection between individual questions and the literature which inspired them is visible in the appendix (8.2.2).

Table 10. Measurement scales – Study Two

Items relating to	Literature on which the items were based	Items	# of scales
Intention to use a BBLP	Miltgen et al. (2013)	I would sign-up for a Blockchain-based Loyalty Program as soon as possible	5
	Choe and Noh (2018)	I would use a Blockchain-based loyalty Program soon after it is launched	
		I will use a Blockchain-based Loyalty Program in the future	
		I will try to use a Blockchain-based Loyalty	

		Program	
		I am willing to use a Blockchain-based Loyalty Program	
Commitment	Dagger et al. (2011)	A Blockchain-based Loyalty Program would be important to me	4
		I would care about a Blockchain-based Loyalty Program	
		I would invest effort in a Blockchain-based Loyalty Program	
	Pritchard et al. (1999)	My preference for a Blockchain-based Loyalty Program would not easily be change.	
Trust	Liu et al. (2019)	Generally, I would trust a Blockchain-based Loyalty Program	4
		Overall, I can imagine myself confidently relying on a Blockchain-based Loyalty Program	
	Horppu et al. (2008)	I do not think a Blockchain-based Loyalty program would prejudice me.	
	Bashir and Madhavaiah (2015)	I believe it would be safe to use a Blockchain-based Loyalty Program	
Satisfaction	Dagger and O'Brien (2010)	It would be a wise choice to use a Blockchain-based Loyalty Program.	4
		It would satisfy me to use a Blockchain-based Loyalty Programme	
		I would feel good about using a Blockchain-Based Loyalty Program.	
	Biscaia et al. (2017a)	My expectations of a loyalty program would be met by a Blockchain-Based Loyalty Program.	
Incentivised	Naidoo and Leonard (2007)	A Blockchain-based Loyalty Program provides me with adequate incentives to use it.	4
		I would get rewarded appropriately by a Blockchain-Based Loyalty Program for my continued patronage	
	Atchariyachanvanich et al. (2007)	I would get incentives for using a Blockchain-Based Loyalty Program.	
		Blockchain-Based Loyalty Programs provide incentives for continued use.	
Relative advantage	Min et al. (2019)	A Blockchain-based Loyalty Program would make it easier to redeem any benefits earned as part of a loyalty program.	4
		A Blockchain-based Loyalty Program would make it easier to generate rewards for shopping at stores	
		A Blockchain-based Loyalty Program would make it easier to earn benefits from a loyalty program.	
		A Blockchain-based Loyalty Program would make it easier to manage my benefits that I earn as part of a loyalty program.	
Behavioural loyalty	Liu et al. (2019)	A Blockchain-Based Loyalty Program would be my first choice compared to other loyalty programs	3
	Sharifi and Esfidani (2014)	As long I was offered a Blockchain-Based Loyalty Program, it is unlikely that I would opt for another loyalty program.	

		I would rarely consider using another type of loyalty program, if I could use a Blockchain-Based Loyalty Program	
Attitudinal loyalty	Sharifi and Esfidani (2014)	I would say positive things about a Blockchain-Based Loyalty Program	3
	Horppu et al. (2008)	I would pay more attention to a Blockchain-Based Loyalty Program than another type of loyalty program.	
		I would recommend a Blockchain-Based Loyalty Program to anyone who seeks advice on loyalty programs.	

Measurement items for Study Three

The antecedents of the usage of a BBLP were examined in Study One, and the antecedents of behavioural and attitudinal loyalty generation were examined in Study Two. What was left was to understand and create a theoretical model that analysed a user's journey from exposure to a BBLP to the ultimate creation of firm outcomes (redemption and WoM). For consistency, Study Three measured usage factors (PEOU and PU), as well as loyalty outcomes (behavioural and attitudinal), using the same items in studies One and Two. This study operationalised new constructs related to firm outcomes that were subdivided into redemption and WoM. These items were based on literature focused on push and digital coupons, which were innovations at the time, making the items especially relevant in the context of new blockchain technology. Each construct in Study Three contained three to five items that were based on the literature outlined in Table 11. Further information on the connection between individual questions and the literature which inspired them is visible in the appendix (8.2.3).

Table 11. Measurement scales – Study Three

Items relating to	Literature on which the items were based	Items	Number of scales
PEOU	Miltgen et al. (2013)	I don't think it would be hard to use a Blockchain-based Loyalty Program	5
		Using a Blockchain-based Loyalty Program would likely require minimum of effort	
		It would be easy to get a Blockchain-based Loyalty Program to do what you want it to do	
		Learning to use a Blockchain-based Loyalty Program would be easy for me	
		I would find a Blockchain-based	

		Loyalty Program easy to use	
PU	Choe and Noh (2018)	Using a Blockchain-based Loyalty Adapted Program would be useful in my daily life	4
		Using a Blockchain-based Loyalty Program would make my daily life more efficient	
		Using a Blockchain-based Loyalty Program would make my loyalty reward experience more efficient	
		Using a Blockchain-based Loyalty Program would make my loyalty reward experience more useful	
Behavioural intention to use a BBLP	Miltgen et al. (2013)	I would sign-up for a Blockchain-based Loyalty Program as soon as possible	5
		I would use a Blockchain-based loyalty Program soon after it is launched	
	Choe and Noh (2018)	I will use a Blockchain-based Loyalty Program in the future.	
		I will try to use a Blockchain-based Loyalty Program.	
		I am willing to use a Blockchain-based Loyalty Program.	
Behavioural loyalty	Liu et al. (2019)	A Blockchain-Based Loyalty Program would be my first choice compared to other loyalty programs	3
	Sharifi and Esfidani (2014)	As long I was offered a Blockchain-Based Loyalty Program, it is unlikely that I would opt for another loyalty program.	
		I would rarely consider using another type of loyalty program, if I could use a Blockchain-Based Loyalty Program	
Attitudinal loyalty	Horppu et al. (2008)	I would pay more attention to a Blockchain-Based Loyalty Program than another type of loyalty program	3
	Ashley et al. (2016)	I am less likely to shop at stores that don't offer a Blockchain-based loyalty program.	
		I would shop at stores that offer a Blockchain based loyalty program more frequently.	
WoM	Casaló et al. (2008)	I am more likely to shop at stores that offer a Blockchain-Based Loyalty program because the benefits I would receive	3
	Choi et al. (2014)	I would say positive things about a Blockchain-based loyalty program.	
		I would try spread the word about Blockchain-based loyalty programs	
Redemption	Nayal and Pandey (2020)	I will probably redeem the points I gain from a Blockchain-based Loyalty program.	5

		I will use the points I gain on a Blockchain-based Loyalty program if I find something I want to use them on.	
		I would redeem my points I gain from a Blockchain-based Loyalty program for discounts.	
	Achadinha et al. (2014)	Redeeming points gain on a Blockchain-based Loyalty program make me feel good.	
		I would redeem points gained on a Blockchain-based Loyalty program.	

Data collection

Marketing research recognises the importance of data collection, given its direct influence on the error rates associated with a questionnaire (Malhotra et al., 2017). By presenting straightforward questions to comprehend and respond to, the potential for errors can be minimised (Malhotra et al., 2017). Additionally, data preparation requires focused attention, as errors in this stage can significantly impact the results. Therefore, the subsequent section discusses the data-collection process in detail.

The data collection was unlimited, so respondents from any country could answer the online survey. This helped ensure that sufficient sample sizes for each research study were collected. Since respondents were shown a video explaining the loyalty technology, a global audience was able to understand the survey questions easily. The three studies built on each other. This meant that the data collection for each study was done sequentially, starting with Study One and ending with Study Three. All the data was collected from January 2022 to December 2022 via an online survey designed using Qualtrics. The respondents were sent an online survey and were sourced from the University of Cape Town. An email was sent inviting students to participate in the research, in accordance with the University of Cape Town’s policies regarding using students as respondents. A market research company called Yazi was also utilised to source respondents, as well as the researcher’s own network. Yazi is a South African based company whose respondents are located throughout Africa and are reimbursed in return for answering surveys. Yazi was only utilised to collect data for Study Three.

The Ethics Committee of the Faculty of Commerce at the University of Cape Town accepted all three studies, and proof of approval can be found in Appendix A of this study. Following the random selection of a target group, potential participants were presented with an online survey that included a video that exposed them to and explained the basics of a BBLP. This video was essential to ensure participants correctly understood the questions that followed relating to the technology and that every participant had the same base level of understanding.

Data preparation

Malhotra et al. (2017) outline an eight-step data-preparation process, which includes the following stages: preliminary plan of data analysis, questionnaire check, editing, coding, transcription, data cleaning, statistical adjustment, and selection of data-analysis strategy. These steps were meticulously followed in the present thesis.

After formulating a preliminary data-analysis plan, the first step involved a questionnaire check. This involved reviewing the responses to check for completeness; patterns that indicate that respondents did not understand questions and responses with little variance. Several incomplete responses were noted during this stage. These incomplete responses were excluded from further analysis. This resulted in a reduced sample size for each study. This is depicted in Table 12. As the survey did not contain unstructured questions, the editing step was not extensive, and respondents who indicated they did not consent to the research or did not consent to their response being disseminated (anonymously) were removed. All questions were designed as required and limited to a single response, ensuring accuracy and precision. Coding and transcription were automatically executed by the survey software (Qualtrics), obviating the need for manual transcription. Data-cleaning procedures were then undertaken to eliminate any out-of-range, inconsistent, or extreme-value data points. Qualtrics ensures that data cannot be out of range through its design.

Table 12. Number of respondents who completed the entire survey

Study	Sample size considered for data analysis
Study One	705
Study Two	480
Study Three	902

Regarding potential missing responses, Malhotra et al. (2017) mention case-wise deletion as an option to exclude respondents with omitted data (Malhotra et al., 2017). However, it is important to note that case-wise deletion can result in small sample sizes (Malhotra et al., 2017). This study employed case-wise deletion, as the sample size remained adequate even after removing respondents with missing data. While not always mandatory, statistical adjustment can enhance the quality of data analysis. There are three methods for statistical adjustment: weighting, variable re-specification, and scale transformation (Malhotra et al., 2017). Weighting involves assigning weights to respondents based on their relative importance. Variable re-specification entails forming and modifying new variables, while scale transformation involves manipulating scale values to ensure comparability. The subsequent chapter, which focuses on survey results, provides a comprehensive account of how this study addressed missing responses, conducted statistical adjustment, and approached data analysis in detail.

Data analysis

Visualisation

The theoretical framework was broken down into three parts (and three corresponding studies) for the following two reasons: first, the theoretical model is complex, given the sheer number of variables. Second, the number of constructs in the theoretical model made it unviable to survey respondents without a significant drop-off due to a too-high number of questions.

SEM is a statistical technique combining factor and regression path analyses, as elucidated by Hox and Bechger (1998). It focuses on theoretical constructs represented by latent factors. Steenkamp and Baumgartner (2000) outline three fundamental principles that underpin SEM. First, SEM emphasises the operationalisation of constructs, particularly when a single indicator cannot capture an underlying construct comprehensively. Second, the interrelationship between constructs and measurements is important in theory development and model testing. Lastly, SEM adopts a covariance-based approach that substantially emphasises marketing phenomena. These characteristics render SEM an appropriate tool for visualising the proposed model in this study.

The study employs a type of SEM called partial least squares SEM, which concentrates on the variance associated with latent variables. It proves valuable in exploratory-research contexts featuring limited sample sizes and scant existing literature or theory. In this thesis, PLS-SEM was selected for five reasons. First, PLS-SEM is appropriate when sample sizes are small, and there is little literature or theory related to the topic (Wong et al., 2013). Second, PLS-SEM is appropriate when the structural model is complex, and when the researcher aims to understand theoretical extensions of established theories, or when the predictability of a theoretical framework is being tested (Hair et al., 2019). Thirdly, PLS-SEM has also been shown to be more favourable than covariance-based techniques when analysing the variance between dependent and independent variables (Kabir et al., 2021; Li et al., 2022; Sohaib et al., 2019). PLS-SEM has been shown to be valid for conducting a CFA and provides more reliability and validity than CB-SEM (Afthanorhan, 2013). PLS-SEM may provide excellent reliability and validity because it evaluates composite latent variables and total variance instead of common variance, which is utilised in CB-SEM (Manley et al., 2021). It also does not require normal distributions of data and allows the use of a wide variety of sample sizes (Pérez-Sánchez et al., 2021). Fourth, PLS-SEM has been widely and commonly used to study blockchain, loyalty, and technological acceptance (Jamshidi & Hussin, 2018; Pérez-Sánchez et al., 2021; Queiroz et al., 2021; Sciarelli et al., 2021; Sohaib et al., 2019). Fifth, PLS-SEM also provides the researcher with a wide variety of analysis options, requiring a low number of assumptions and has a user-friendly interface (Matthews et al., 2018).

Measurement model

Regarding the formative measurement model assessment, reliability and validity are analysed in all three studies. Indicator reliability in PLS-SEM is measured using the indicator loadings (Hair et al., 2021). Indicator reliability measures how much of an indicator's variance is explained by the construct, and indicator loadings show bivariate correlations between constructs and the indicators (Hair et al., 2021). Indicator loadings should be above 0.40 (Hair et al., 2021).

Cronbach's alpha and composite reliability were used to measure internal consistency reliability. When using PLS-SEM, Cronbach's alpha is the lower bound, whereas composite reliability is the upper bound, meaning that the actual reliability is somewhere between the value for Cronbach's alpha and the composite reliability (Sarstedt et al., 2021). When using composite reliability, the higher the value, the higher the level of reliability (Sarstedt et al., 2021). The value for composite reliability should be between 0.7 and 0.95 to be indicative of good reliability levels. A cut-off of 0.7 for both composite and Cronbach's alpha is acceptable for PLS-SEM research (Hair et al., 2017).

PLS-SEM uses the average variance extracted (AVE) to measure convergent validity. Convergent validity is the *"…extent to which a construct converges in its indicators by explaining the items' variance*" (Hair et al., 2022). The AVE must exceed 0.50 to be sufficient (Bagozzi & Yi, 1988; Hair et al., 2022; Pallant, 2000). This is because a value of 0.50 indicates that the mean values of the factor loadings of the various items are higher than 0.708, which shows that variances of items and their constructs are meaningful (Hair et al., 2022).

Discriminant validity examines whether constructs are sufficiently unrelated to each other. To measure discriminant validity, the square root of the AVE of each construct is compared to the correlation it has with other constructs (Fornell-Larcker criterion). The square root of the AVE for each construct should be higher than its correlation with other constructs to indicate a sufficient discriminant validity (Fornell & Larcker, 1981). The Fornell-Larcker criterion has been criticised, sometimes viewed as performing poorly, especially when indicator loadings only have a slight variation (Henseler et al., 2015). To address this, the heterotrait-monotrait (HTMT) ratio was proposed as an alternative and superior method to the Fornell-Larcker criterion (Henseler et al., 2015). The HTMT is the "*mean value of the item correlations across constructs relative to the (geometric) mean of the average correlations for the items measuring the same construct*." (Hair et al., 2019). The Fornell-Larcker criterion shows the extent that constructs explain the variance of their own indicators compared to the variance of others (Hair et al., 2022). For the HTMT ratio, the values should be below 0.9 to indicate sufficient discriminant validity (Henseler et al., 2015).

Structural model

The structural model is assessed in four steps, as suggested by Hair et al. (2021) through focusing on collinearity, significance, structural model relationships, explanatory power, and predictive power. All three studies followed the same steps.

Collinearity was assessed because path coefficients in PLS-SEM are based on the ordinary least squares regression of endogenous constructs in relation to their predictor constructs (Hair et al., 2021). Path coefficients can be biased if there are high levels of collinearity for the predictor constructs (Hair et al., 2021). Collinearity is measured using the variance inflation factor (VIF). Values for collinearity should be below 5. Common method bias can be assessed through VIF according to the method suggested by Kock (2015). This involves the creation of a new variable with random values, and creating a model where all the latent variables point to this random variable.

After evaluating collinearity, the structural model must be examined, which shows the proposed hypotheses. This was done using PLS-SEM and a procedure called bootstrapping. Bootstrapping involves many random subsamples from the original data, which are used to estimate the PLS path model (Wong et al., 2013). This study used 5000 subsamples, as recommended by Sarstedt et al. (2017). This provides the coefficient of determination, t-test, and p-values. The path coefficient should be between -1 and +1, and path coefficients greater than -1 or +1 are not acceptable (Hair et al., 2021). A path coefficient close to -1 indicates a strong negative relationship, whereas a path coefficient close to 1 is indicative of a strong positive relationship.

After examining the structural model relationships, the next step is to analyse the coefficient of determination (R^2) to determine the model's explanatory power. The coefficient of determination measures the degree of association between two variables and their relative strength. It shows the model's in-sample predictive power, not the model's out-of-sample predictive power (Hair et al., 2021). R^2 ranges from 0 to 1, with a higher value being better. For marketing research, the coefficient of determination should be at least 0.25 (Wong et al., 2013). As a guideline, the values 0.75, 0.50 and 0.25 correspond to strong, moderate, and weak effects (Hair et al., 2021).

$PLS_{predict}$ was used to assess the out-of-sample predictive power of the model. This indicates the model's ability to accurately forecast future observations (Hair et al., 2021). $PLS_{predict}$ uses k-fold cross-validation. A fold represents a subset within the complete sample, where 'k' denotes the quantity of these subsets (Hair et al., 2021). Essentially, the entire dataset undergoes random division into 'k' equally proportioned segments of data (Hair et al., 2021). To understand the predictive power, the focus should be given to metrics that measure the amount of prediction error relating to endogenous constructs (Hair et al., 2021). The root-mean-square error (RSME) and mean-absolute-error (MAE) are useful for understanding predictive error (Hair et al., 2021). The RSME calculates the square root of the mean of the squared variances between the predicted values and the observed data (Hair et al., 2021). MAE evaluates the average size of the errors in a set of predictions, disregarding their directionality (whether they overestimate or underestimate) (Hair et al., 2021). In most cases, researchers should use the RSME, unless the prediction error distribution is non-symmetric (Hair et al., 2021).

The linear regression model (LM) benchmark should be compared to the RSME or MAE metric to determine the model's predictive power (Hair et al., 2021). If all the indicators' LM values are lower than the RMSE or MAE values, the model has high predictive power (Hair et al., 2021). If the majority or same number of indicators have smaller RSME or MAE values, then the corresponding LM values have medium predictive power (Hair et al., 2021). If the minority of indicators have smaller RSME or MAE values compared to the LM values, the model has low predictive power (Hair et al., 2021). If none of the indicators have lower RSME or MAE values than the LM model value, then it lacks predictive power (Hair et al., 2021). Q^2 or the indicator mean of the holdout sample can be used to understand whether the predictions utilising PLS-SEM are better than the most naïve benchmark (Sarstedt et al., 2021). If Q^2 is greater than 0, the path model outperforms the most naïve benchmark (Sarstedt et al., 2021).

Ethical consideration

To comply with the Commerce Faculty Ethics in Research Committee of the University of Cape Town, all questionnaires were developed and tested following their requirements, since this research involved human subjects. Appendix A provides proof of the acceptance of all three research propositions. The ethical considerations involved ensuring that participants were not put in danger or harmed in any way, including their emotional well-being. Additionally, it was important to ensure that there were no ethical consequences for the supporting institution and that participants were informed of their voluntary participation and the option to withdraw at any time.

Scope and limitations of studies

The next section covers the scope and limitations of this thesis. The methodology, newness, and limited literature on the topic of BBLPs impacted the study. This should be kept in mind when interpreting the results.

Scope

The focus of this study is to build on the limited literature surrounding BBLPs and create a basis for further studies on the topic. Currently, there is a limited amount of literature that focuses on these types of LPs. Literature examining a consumer's journey from exposure to the creation of firm outcomes through loyalty and usage is also limited, and this thesis wishes to add significantly to the body of literature that examines the topic. Beyond the academic scope, this thesis has commercial appeal for practitioners interested in reinvigorating and reinventing their current LPs using blockchain. This research could be used to guide thinking around the topic before any investment is made to use blockchain to reinvigorate an LP.

Limitations

Considering the novelty of the research in BBLPs this study has several limitations. First, respondents under 18 years old were excluded, which may have implications for the study's conclusions regarding age. Second, the study used convenience sampling, limiting the study's generalisability, although the relatively large sample size allowed for meaningful conclusions. Convenience sampling and distributing via the researcher's networks including the university network may have biased the responses to South Africa, with limited applicability globally. Data for Study Three was collected with the help of a local market research agency whose respondents mainly consist of low-income respondents residing in South Africa. This further limits the findings. Another limitation was that data was collected via an online survey, which may have resulted in fraudulent respondents and may not be representative of the entire population. Lastly and importantly, the survey focused on a theoretical application of a BBLP described in a video. This limits the applicability of these findings to real BBLPs which currently exist in the commercial market.

Research method limitations

Research design is never prefect, and all that can be done is to reduce the possibility of forming incorrect conclusions (Saunders et al., 2019). This requires the researcher to focus on reliability and validity (Saunders et al., 2019). Reliability focuses on ensuring the research approach will yield consistent results that can be replicated. In contrast, validity shows the extent to which the results genuinely reflect the intended subject matter (Saunders et al., 2019). The reliability and validity were checked using PLS-SEM 4, allowing the researchers to confirm the reliability and validity of the data through variables such as average variance extracted, composite reliability, and Cronbach's alpha.

There are several threats to reliability and validity: participant error, participant bias, observing error, history, testing, instrumentation, mortality, maturation, and ambiguity of causal direction and observing bias (Saunders et al., 2019). These areas were partly addressed by emphasising at the start of the survey that participation is voluntary and will not lead to negative consequences for withdrawing or refusing to participate. The survey was also structured so that each participant was asked the same questions. Participant error may have still affected the survey results, which is a limitation of the study, as participants were free to answer the survey online at any time of day. Allowing participants to answer the survey freely, at their leisure, was deemed necessary to obtain a sufficient sample, given the researcher's time and resource constraints. Not much was known about the participants. Their prior experience with blockchain was not known. Only information on their age, as well as knowledge of BBLPs and experience with traditional LPs, was gathered. This may have led to several problems with validity, which is a limitation of the study. Additionally, convenience sampling was used; this limits the generalisability of the findings to the general population. However, again this was necessary, given the time and resource constraints of the researcher.

The choice of a quantitative method undoubtedly influenced the results that were obtained. On the other hand, it is not possible to determine the effect of this choice (Saunders et al., 2019). However, the research design and strategy utilised in this study are supported by prior studies focusing on blockchain, marketing and technology acceptance, which used a quantitative method and a single cross-sectional design that was analysed using PLS-SEM (Al Karim et al., 2023; Gil-Cordero et al., 2024; Perez et al., 2020). The TCCM review also supported the approach used in this thesis, given that, after a review of literature focusing on technology acceptance, loyalty and blockchain, most studies were quantitative and utilised structural equation modelling as a date-analysis technique. Overall, this provides substantial support for the chosen research design and strategy.

Chapter summary

This chapter covered all aspects of research design and methodology. The chapter discussed how this thesis targeted 2098 participants who are 18 years or older, as these respondents could meaningfully contribute and benefit from participation in an LP and were determined to be a statistically significant sample size. To obtain this sample, non-probability sampling was used, specifically convenience sampling (and a single cross-sectional design). Next, this chapter discussed how three separate questionnaires were created due to the complexity and the sheer number of questions. All questionnaires contained a five-category Likert scale. Finally, data was collected from January 2022 to December 2022 and subsequently analysed using PLS-SEM.

Chapter 4: Study One

Introduction

Study One examines the antecedents of the intention to use a BBLP, addressing the research question: what factors influence the PEOU, PU, and the intention to use a BBLP? This is done through empirically validating an integrated DOI-TAM model, indicated in Figure 10, and the hypotheses indicated in Table 13.

As mentioned in the section on research gaps, this study contributes to the limited literature on blockchain adoption incentives, responding to calls for more research on factors influencing blockchain adoption in a marketing context (Antoniadis et al., 2019). While pioneering studies have explored technology acceptance in blockchain contexts (Hamdan et al., 2022; Kamble et al., 2019), research remains limited, particularly in a blockchain-loyalty context.

Beyond the contextual contribution, the study explores the perceived value of cryptocurrency and trust in blockchain and cryptocurrency as influencers of PEOU and PU. This study uniquely proposes the perceived value of cryptocurrency as an antecedent to PEOU and PU, focusing on the reward (cryptocurrency) and the underlying technology (blockchain) in loyalty programmes, positing that these perceptions significantly impact usage. To the author's knowledge, this is one of the first studies that proposes the perceived value of cryptocurrency as an antecedent to both PEOU and PU.

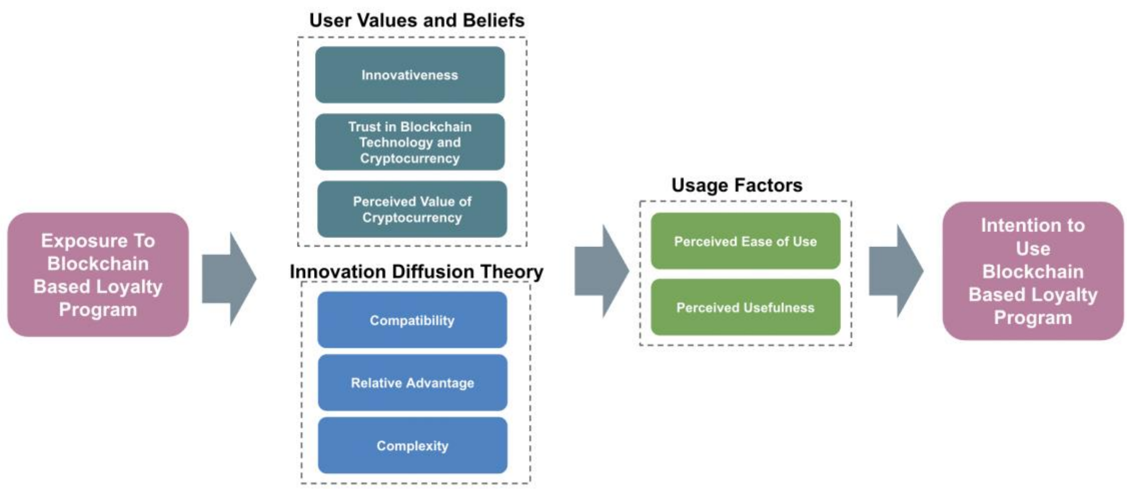

Figure 10. DOI-TAM conceptual model

Table 13. Hypotheses covered in Study One

#	Hypothesis
H1	PEOU (H1a) and the PU (H1b) of a BBLP predicts the intention to use a BBLP.
H2	Personal innovativeness predicts a BBLP's PEOU (H2a) and PU (H2b).
H3	Trust in blockchain and cryptocurrency predicts the PEOU (H3a) and PU (H3b) of a BBLP.
H4	The perceived value of cryptocurrency predicts the PEOU (H4a) and PU (H4b) of a BBLP.
H5	Compatibility predicts the PEOU (H5a) and PU (H5b) of a BBLP.
H6	Relative advantage predicts a BBLP's PEOU (H6a) and PU (H6b).
H7	Complexity predicts the PEOU (H7a) and PU (H7b) of a BBLP.

Results

Results are presented in two parts: a formative measurement model assessment and a structural model assessment. Regarding the formative measurement model assessment, reliability and validity are analysed. Specifically, composite reliability and Cronbach's alpha are used to measure reliability. Next, validity is understood by analysing convergent and discriminate validity using the average variance extracted (AVE), the Fornell-Larcker criterion and heterotrait-monotrait (HTMT) ratios. PLS-SEM uses CFA, shown by using model fit (Dash et al., 2021; Manley et al., 2021).

Next, the structural model is assessed in four steps, as suggested by Hair et al. (2021), by focusing on collinearity, significance, structural model relationships, explanatory power, and predictive power.

Formative Measurement

Reliability

One of the first steps in assessing the reflective measurement model is to examine the indicator loadings (Hair et al., 2019). Indicator reliability measures how much of an indicator's variance is explained by the construct, and indicator loadings show bivariate correlations between constructs and the indicators (Hair et al., 2021). Generally, indicator loadings should be above 0.40 (Hair et al., 2021), but indicator loadings above 0.3 have been deemed acceptable (Hair et al., 2010), especially if the research is exploratory. Furthermore, the AVE for the construct (perceived value) indicated in table 14 is above the recommended threshold of 0.50, meaning the construct still demonstrates adequate convergent validity.

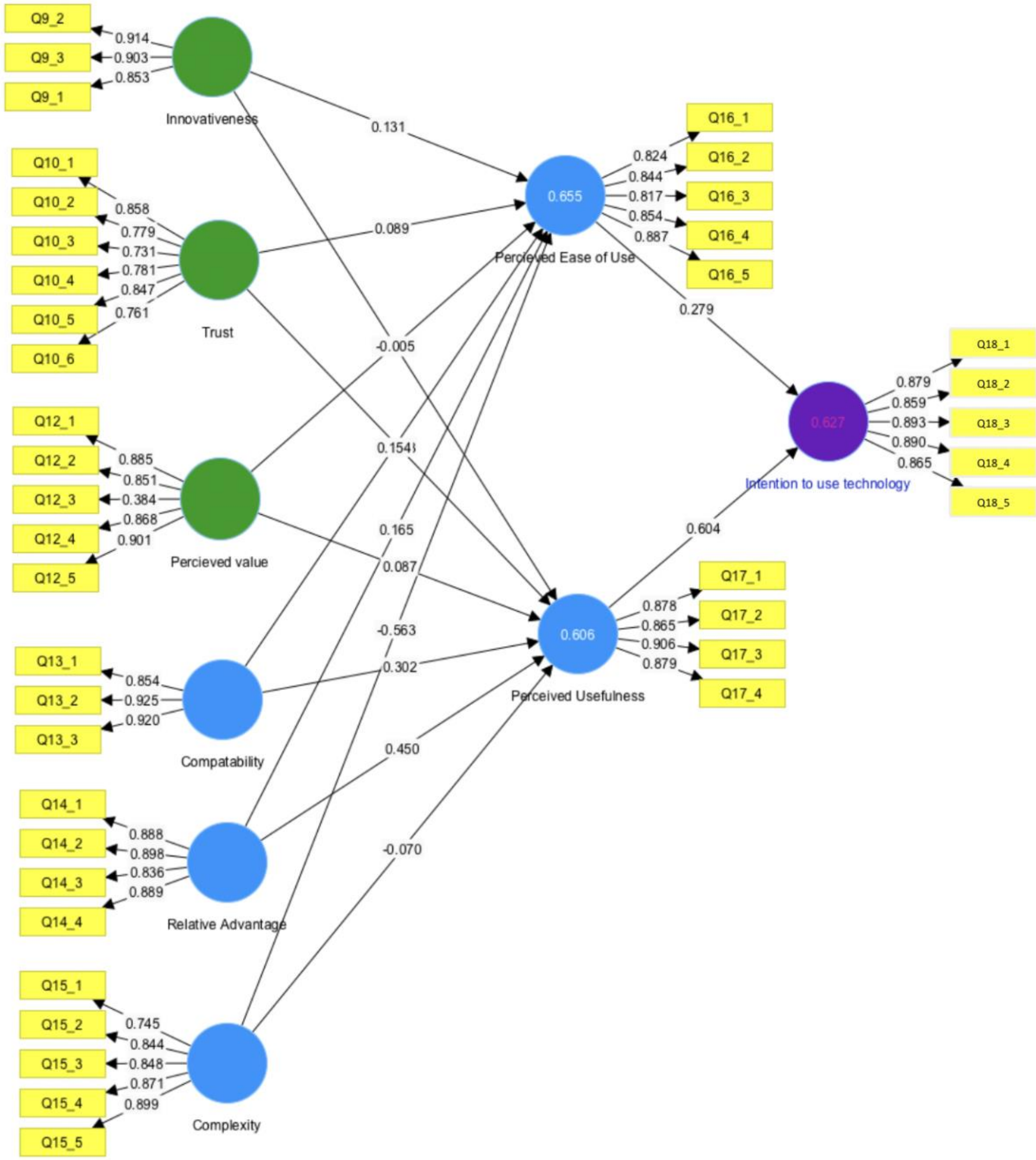

Figure 11. Structural model

Cronbach's alpha and composite reliability were used to measure internal consistency reliability. When using PLS-SEM, Cronbach's alpha is the lower bound. In contrast, composite reliability is the upper bound, meaning that the actual reliability is somewhere between the value for Cronbach's alpha and the composite reliability (Sarstedt et al., 2021). When using composite reliability, the higher the value, the higher the level of reliability (Sarstedt et al., 2021). The value for composite reliability should be between 0.7 and 0.95 to indicate good reliability levels. A cut-off of 0.7 for both composite and Cronbach's alpha is acceptable when conducting PLS-SEM research (Hair et al., 2017). Table 15 indicates that each construct has both a composite reliability and Cronbach's alpha which exceed the cut-off of 0.7, indicating sufficient reliability.

Table 14. Factor loadings

Items relating to	Literature on which the items were based	Items	Notation	Factor Loading
Innovativeness	Miltgen et al. (2013)	I am among the first to try out new technologies	Q9_1	0.853
		When I hear about a new technology, I look for ways to adopt it	Q9_2	0.914
		I like to experiment with new technologies	Q9_3	0.903
Trust in blockchain technology and cryptocurrency	Miltgen et al. (2013)	I trust Blockchain Technology,	Q10_1	0.858
		I trust Cryptocurrencies like Bitcoin	Q10_2	0.779
		I trust the underlying technology which drives Cryptocurrencies like Bitcoin	Q10_3	0.731
		I trust blockchain-based loyalty programs	Q10_4	0.781
		I think Blockchain Technology is reliable.	Q10_5	0.847
		I think Cryptocurrencies are reliable	Q10_6	0.761
Perceived value of cryptocurrency	Kim et al. (2008)	Investment of time and effort in receiving Cryptocurrency would be profitable for me	Q12_1	0.885
		There is a benefit in using cryptocurrency	Q12_2	0.851
		There is no loss in using Cryptocurrency	Q12_3	0.384
	Chen et al. (2016)	Cryptocurrency has value to me	Q12_4	0.868
	Martignoni et al. (2008)	Cryptocurrency would be useful for me to have	Q12_5	0.901
Compatibility	Miltgen et al. (2013)	The benefits of using a Blockchain based Loyalty Program are apparent to me	Q13_1	0.854
		I think using a Blockchain-based Loyalty Program would fit well with the way that I like to use loyalty programs	Q13_2	0.925
		Using a Blockchain-based Loyalty Program would fit into my lifestyle	Q13_3	0.920
Relative advantage	Min et al. (2019)	Compared to the existing loyalty program I use, a Blockchain-based Loyalty Program would make it easier to redeem any benefits I earned as part of a loyalty program	Q14_1	0.888
		Compared to the existing loyalty program I use, a Blockchain-based Loyalty Program would make it easier for me to get rewarded	Q14_2	0.898

		Compared to the existing loyalty program I use, loyalty programs that do not use a Blockchain, a Blockchain-based Loyalty Program would make it easier to earn benefits from a loyalty program.	Q14_3	0.836
		Compared to the existing loyalty program I use, a Blockchain-based Loyalty Program would make it easier to manage the benefits that I earn as part of a loyalty program	Q14_4	0.889
Complexity	Karahanna et al. (1999)	I believe that using a Blockchain- Based Loyalty Program requires technical skills.	Q15_1	0.745
		I believe that using a Blockchain-Based Loyalty Program will require a lot of mental effort	Q15_2	0.844
		I believe that using a Blockchain-Based Loyalty Program would be frustrating	Q15_3	0.848
		A Blockchain-Based Loyalty Program would confuse me	Q15_4	0.871
		A Blockchain-Based Loyalty Program would be complex to use	Q15_5	0.899
PEOU	Miltgen et al. (2013)	I don't think it would be hard to use a Blockchain-based Loyalty Program	Q16_1	0.824
		Using a Blockchain-based Loyalty Program would likely require minimum of effort	Q16_2	0.844
		It would be easy to get a Blockchain-based Loyalty Program to do what you want it to do	Q16_3	0.817
		Learning to use a Blockchain-based Loyalty Program would be easy for me	Q16_4	0.854
		I would find a Blockchain-based Loyalty Program easy to use	Q16_5	0.887
PU	Choe and Noh (2018)	Using a Blockchain-based Loyalty Program would be useful in my daily life	Q17_1	0.878
		Using a Blockchain-based Loyalty Program would make my daily life more efficient	Q17_2	0.865
		Using a Blockchain-based Loyalty Program would make my loyalty reward experience more efficient	Q17_3	0.906
		Using a Blockchain-based Loyalty Program would make my loyalty reward experience more useful	Q17_4	0.879
Intention to use a BBLP	Miltgen et al. (2013)	I would sign-up for a Blockchain-based Loyalty Program as soon as possible	Q18_1	0.879
		I would use a Blockchain-based loyalty Program soon after it is launched	Q18_2	0.859
	Choe and Noh (2018)	I will use a Blockchain-based Loyalty Program in the future.	Q18_3	0.893
		I will try to use a Blockchain-based Loyalty Program.	Q18_4	0.890
		I am willing to use a Blockchain-based Loyalty Program.	Q18_5	0.865

Validity

PLS-SEM uses the average variance extracted (AVE) to measure convergent validity. Convergent validity is the *"extent to which a construct converges in its indicators by explaining the items' variance*" (Hair et al., 2022). The AVE must exceed 0.50 to be sufficient (Bagozzi & Yi, 1988; Hair et al., 2022; Pallant, 2000). This is because a value of 0.50 is indicative that the mean values of the factor loadings of the various items are higher than 0.708, which shows that variances of items and their constructs are meaningful (Hair et al., 2022). Table 14 shows that AVE for each construct exceed 0.5, establishing sufficient convergent validity.

Discriminant validity examines whether constructs are sufficiently unrelated to each other. To measure discriminant validity, the square root of the AVE of each construct is compared to the correlation it has with other constructs (Fornell-Larcker criterion). The square root of the AVE for each construct should be higher than its correlation with other constructs to indicate sufficient discriminant validity (Fornell & Larcker, 1981). The results are shown in Table 15 and suggest that diagonal values (square roots of AVE) are higher than the off-diagonal values, establishing sufficient discriminant validity according to the Fornell-Larcker criterion.

The Fornell-Larcker criterion has been criticised, sometimes viewed as performing poorly, especially when indicator loadings only have a slight variation (Henseler et al., 2015). The heterotrait-monotrait (HTMT) ratio was proposed as an alternative and superior method to the Fornell-Larcker criterion (Henseler et al., 2015). The HTMT is the "*mean value of the item correlations across constructs relative to the (geometric) mean of the average correlations for the items measuring the same construct*." (Hair et al., 2019). The Fornell-Larcker criterion shows the extent to which a construct explains the variance of its own indicators compared to the variance of others (Hair et al., 2022). For the HTMT ratio, the values should be below 0.9 to indicate sufficient discriminant validity (Henseler et al., 2015). The results for the HTMT ratio are shown in Table 16 and are below 0.9, indicative of sufficient discriminant validity.

Table 15. Convergent validity and composite reliability

Constructs	AVE	Composite Reliability	Cronbach's Alpha
Innovativeness	0.793	0.920	0.870
Trust in blockchain technology and cryptocurrency	0.630	0.911	0.886
Perceived value of cryptocurrency	0.664	0.895	0.842
Compatibility	0.811	0.928	0.883
Relative advantage	0.771	0.931	0.901
Complexity	0.711	0.924	0.898
PEOU	0.715	0.926	0.900
PU	0.778	0.933	0.905
Intention to use blockchain technology	0.770	0.943	0.925

Table 16. Discriminate validity values – Fornell-Larcker criterion

	COMP	COMPL	INOV	USE	PU	PEOU	PV	RV	TRUST
COMP	0.900								
COMPL	-0.381	0.843							
INOV	0.273	-0.175	0.890						
USE	0.712	-0.476	0.358	0.877					
PU	0.672	-0.380	0.228	0.757	0.882				
PEOU	0.543	-0.730	0.330	0.609	0.546	0.846			
PV	0.416	-0.151	0.397	0.492	0.402	0.286	0.803		
RV	0.629	-0.373	0.183	0.643	0.712	0.520	0.326	0.878	
TRUST	0.540	-0.323	0.454	0.577	0.465	0.455	0.695	0.384	0.794

Note: INOV: Innovativeness; TRUST: Trust in blockchain technology and cryptocurrency; PERC: Perceived value of cryptocurrency; COMPA: Compatibility; COMPL: Complexity; RV: Relative advantage; PEOU: Perceived ease of use; PU: Perceived usefulness; USE: Intention to use blockchain technology

Table 17. Discriminate validity values - HTMT

	COMP	COMPL	INOV	USE	PU	PEOU	PV	RV	TRUST
COMP									
COMPL	0.409								
INOV	0.302	0.185							
USE	0.784	0.502	0.392						
PU	0.747	0.398	0.253	0.825					
PEOU	0.610	0.800	0.366	0.667	0.604				
PV	0.478	0.161	0.460	0.552	0.460	0.326			
RV	0.700	0.392	0.199	0.699	0.782	0.574	0.376		
TRUST	0.575	0.323	0.535	0.617	0.488	0.483	0.839	0.401	

Note: INOV: Innovativeness; TRUST: Trust in blockchain technology and cryptocurrency; PERC: Perceived value of cryptocurrency; COMPA: Compatibility; COMPL: Complexity; RV: Relative advantage; PEOU: Perceived ease of use; PU: Perceived usefulness; USE: Intention to use blockchain technology

Results of structural model

Collinearity

Collinearity was assessed because path coefficients in PLS-SEM are based on the ordinary least squares regression of endogenous constructs in relation to their predictor constructs (Hair et al., 2021). Path coefficients can be biased if there are high levels of collinearity for the predictor constructs (Hair et al., 2021). Collinearity is measured using the variance inflation factor (VIF). Values for collinearity should be below 5. Table 17 shows that all the VIF values are below the threshold of 5.

Common method bias can be assessed through VIF, according to the method suggested by Kock (2015). This involves the creation of a new variable with random values, and creating a model where all the latent variables point to this random variable. Table 19 shows that all the VIF values are below 3.3 and can thus be considered free of common method bias (Kock, 2015).

Table 18. VIF values

	COMP	COMPL	INOV	USE	PU	PEOU	PV	RV	TRUST
COMP					2.039	2.039			
COMPL					1.265	1.265			
INOV					1.285	1.285			
USE									
PU				1.425					
PEOU				1.425					
PV					2.028	2.028			
RV					1.732	1.732			
TRUST					2.492	2.492			

Note: INOV: Innovativeness; TRUST: Trust in blockchain technology and cryptocurrency; PERC: Perceived value of cryptocurrency; COMPA: Compatibility; COMPL: Complexity; RV: Relative advantage; PEOU: Perceived ease of use; PU: Perceived usefulness; USE: Intention to use blockchain technology

Table 19. VIF values from assessment of common method bias

	VIF
COMP → Random	2.294
COMPL → Random	1.262
INOV → Random	1.320
USE → Random	2.931
PU → Random	1.931
PEOU → Random	1.180
PV → Random	1.938
RV → Random	1.373
TRUST → Random	2.360

Note: INOV: Innovativeness; TRUST: Trust in blockchain technology and cryptocurrency; PERC: Perceived value of cryptocurrency; COMPA: Compatibility; COMPL: Complexity; RV: Relative advantage; PEOU: Perceived ease of use; PU: Perceived usefulness; USE: Intention to use blockchain technology

Significance and relevance of structural model relationships

After evaluating collinearity, the structural model must be examined, which shows the proposed hypotheses. This was done using PLS-SEM and a procedure called bootstrapping.

Bootstrapping involves many random subsamples from the original data, which are used to estimate the PLS path model (Wong et al., 2013). This study used 5000 subsamples, as recommended by Sarstedt et al. (2017). This provides the coefficient of determination, t-test, and p-values. The structural model has eight latent variables and 30 variables. The 30 variables acted as indicators for the eight latent variables. A significance level of 0.05 and using a two-tailed test with a t-value of greater than 1.96 means that the path coefficient is significant (Wong et al., 2013).

The path coefficient should be between -1 and +1, and path coefficients greater than -1 or +1 are not acceptable (Hair et al., 2021). A path coefficient close to -1 indicates a strong negative relationship, whereas a path coefficient close to 1 is indicative of a strong positive relationship. Table 20 shows all the path coefficients to be acceptable and between -1 and +1. Notably all the path coefficients are positive, except for innovativeness and perceived use, as well as perceived value and perceived ease of use. Strong relationships are shown between perceived usefulness and perceived ease of use, as well as relative advantage with perceived usefulness.

Table 20 reveals that the TAM factors innovativeness, trust in blockchain and cryptocurrency, and the perceived value of cryptocurrency exhibit a relationship with the PEOU of a BBLP. However, only the perceived value of cryptocurrency showed a relationship with the PU of a BBLP. This means only H5 was validated in the SEM. H4 and H3 were only partially validated, as no relationship with PU was found when the trust in blockchain and cryptocurrency and a respondent's innovativeness were examined. Prior literature has questioned the relationship between innovativeness and trust with PU, adding validity to the findings in a blockchain context (Aghdaie et al., 2012; Joo et al., 2014; Van Raaij & Schepers, 2008).

The relationship between Relative Advantage and PU is among the strongest, with a path coefficient of 0.450 ($p < 0.001$), indicating that the perceived benefits of blockchain-based loyalty platforms significantly enhance users' perceptions of their usefulness. Similarly, the strong negative relationship between complexity and PEOU ($\beta = -0.563$, $p < 0.001$) highlights that perceptions of technical difficulty can substantially hinder ease of use. These findings align with the foundational principles of DOI and TAM, which emphasize the importance of reducing complexity and enhancing perceived advantages to foster technology adoption

Regarding the factors relating to DOI theory, the proposed relationships between compatibility, complexity, relative advantage, PEOU, and PU were all confirmed. This means H6, H7, and H8 are accepted. In addition, a relationship between PEOU and PU with the intention to use a BBLP was confirmed.

The relationships identified in the analysis are visually represented in Figure 11 which provides a clear summary of the hypothesized pathways and their strengths. The diagram highlights the significant roles of Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) in influencing the use of BBLPs, with path coefficients of 0.604 and 0.279, respectively. Additionally, DOI factors such as Compatibility and Relative Advantage emerge as key predictors of PU, while Complexity has a weaker but negative effect. Notably, Perceived Value demonstrated significant relationships with both PEOU and PU reinforcing its importance.

Table 20. Results of SEM

Hypothesised Relationship		Beta or Path Coefficient	T-Value	P-Value	Hypothesis
PEOU→USE	H1a	0,279	7.567	0	Accepted
PU→USE	H1b	0,604	16.593	0	Accepted
INOV→PEOU	H2a	0.131	4.512	0	Accepted
INOV→PU	H2b	-0,005	0.172	0.863	Rejected
TRUST→PEOU	H3a	0.089	2.249	0.025	Accepted
TRUST→PU	H3b	0,048	0.941	0.347	Rejected
PERC→PEOU	H4a	-0,031	0.905	0.365	Rejected
PERC→PU	H4b	0.087	2.124	0.034	Accepted
COMPA→PEOU	H5a	0.154	4.183	0	Accepted
COMPA→PU	H5b	0.302	7.426	0	Accepted
RV→PEOU	H6a	0.165	4.886	0	Accepted
RV→PU	H6b	0,450	12.311	0	Accepted
COMPL→PEOU	H7a	-0.563	17.716	0	Accepted
COMPL→PU	H7b	-0.070	2.248	0.025	Accepted

Note: INOV: Innovativeness; TRUST: Trust in blockchain technology and cryptocurrency; PERC: Perceived value of cryptocurrency; COMPA: Compatibility; COMPL: Complexity; RV: Relative advantage; PEOU: Perceived ease of use; PU: Perceived usefulness; USE: Intention to use blockchain technology

Explanatory power of the model

Following an examination of the structural model relationships, the next step is to analyse the coefficient of determination (R^2) to determine the model's explanatory power. The coefficient of determination measures the degree of association between two variables and their relative strength. It shows the in-sample explanatory power of the model and not the out-of-sample or predictive power of the model (Hair et al., 2021). R^2 ranges from 0 to 1, with a higher value being better. For marketing research, the coefficient of determination should be at least 0.25 (Wong et al., 2013). As a guideline, the values 0.75, 0.50 and 0.25 correspond to strong, moderate, and weak effects (Hair et al., 2021).

The R^2 value is 0.655 for PEOU. This indicates that the variation in the six latent variables moderately explains 65% of the variation in perceived ease of use of a blockchain-based LP. For PU, 61% of the variation is moderately explained by the six latent variables. Further, 63% of the variation in the behavioural intention to use a blockchain-based LP is moderately explained by PU and PEOU. As all the values for R^2 exceed 0.25, the explanatory power of the model is sufficient and is in the moderate range.

Table 21. Coefficients of determination

	R^2
USE	0.627
PU	0.606
PEOU	0.655

EOU: Perceived ease of use; PU: Perceived usefulness; USE: Intention to use blockchain technology

$PLS_{predict}$ was used to assess the out-of-sample predictive power of the model. This indicates the model's ability to accurately forecast future observations (Hair et al., 2021). $PLS_{predict}$ uses k-fold cross-validation. A fold represents a subset within the complete sample, where 'k' denotes the quantity of these subsets (Hair et al., 2021). Essentially, the entire dataset undergoes random division into 'k' equally proportioned segments of data (Hair et al., 2021). To understand the predictive power, the focus should be given to metrics that measure the amount of prediction error relating to endogenous constructs (Hair et al., 2021). The root-mean-square error (RSME) and mean absolute error (MAE) are useful for understanding predictive error (Hair et al., 2021). The RSME calculates the square root of the mean of the squared variances between the predicted values and the observed data (Hair et al., 2021). MAE evaluates the average size of the errors in a set of predictions, disregarding their directionality (whether they overestimate or underestimate) (Hair et al., 2021). In most cases, researchers should use the RSME, unless the prediction error distribution is non-symmetric (Hair et al., 2021).

The linear regression model (LM) benchmark should be compared to the RSME or MAE metric to determine the model's predictive power (Hair et al., 2021). If all the indicators' LM values are lower than the RMSE or MAE values, the model has high predictive power (Hair et al., 2021). If the majority or the same number of indicators have smaller RSME or MAE values, then the corresponding LM values in the model have medium predictive power (Hair et al., 2021). If a minority of indicators have smaller RSME or MAE values than the LM values, the model has low predictive power (Hair et al., 2021). If none of the indicators has a lower RSME or MAE value than the LM model value, it lacks predictive power (Hair et al., 2021). Q^2 or the indicator mean of the holdout sample can be used to understand whether the predictions utilising PLS-SEM are better than the most naïve benchmark (Sarstedt et al., 2021). If Q^2 is greater than 0, the path model outperforms the most naïve benchmark (Sarstedt et al., 2021).

Table 22. $PLS_{predict}$ results

MV Prediction Summary	Q²predict	PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE
USE_1	0.499	0.737	0.599	0.696	0.561
USE_2	0.451	0.782	0.635	0.747	0.593
USE_3	0.469	0.618	0.461	0.600	0.451
USE_4	0.444	0.628	0.466	0.618	0.460
USE_5	0.461	0.595	0.448	0.591	0.456
PU_1	0.486	0.639	0.490	0.631	0.480
PU_2	0.366	0.699	0.566	0.690	0.560
PU_3	0.493	0.617*	0.461	0.618	0.462
PU_4	0.499	0.594*	0.449	0.596	0.451
PEOU_1	0.444	0.690*	0.492	0.689	0.497
PEOU_2	0.456	0.690*	0.524	0.704	0.534
PEOU_3	0.389	0.706	0.544	0.706	0.544
PEOU_4	0.475	0.636	0.475	0.631	0.470
PEOU_5	0.541	0.584	0.434	0.584	0.441

Note: Perceived ease of use; PU: Perceived usefulness; USE: Intention to use blockchain technology

Table 21 shows that all the indicators have Q^2 values larger than zero, which means the PLS path model outdoes the most naïve benchmark. Comparing the RSME values with the LM values shows that only four indicators (PU_3, PU_4, PEOU_1, PEOU_2) have lower LM values than their corresponding RSME values. The rest of the indicators have higher RSME values than their corresponding LM values. This indicates that the model has low predictive power, according to the interpretation of Hair et al. (2021).

Discussion of results

First, support for the relationship between PEOU and PU with the intention to use blockchain technology sheds light on the explanatory power of the TAM in a blockchain-loyalty context. The in-sample predictive power was in the moderate range, whereas the out-of-sample predictive power was in the low range. This means the model was better at explaining data within the dataset than new unseen data. This indicates that the model does not completely capture the wide range of factors and relationships that affect PEOU, PU, and intention to use a BBLP. This is not unexpected, given the newness of and lack of research on BBLP. These programmes only emerged around 2017 (Abooleet & Kinnett, 2023), and the literature still needs to catch-up to these technological advancements. This model was a first attempt at understanding the factors that influence the uptake and intention to use a BBLP; iteration is required to improve and understand BBLP more deeply. Additionally, the use of convenience sampling may have limited the generalisability of the findings, which may have led to the low out-of-sample predictive power.

Second, PEOU and PU has been found to influence the intention to use cryptocurrency (Sohaib et al., 2019), blockchain-based research sharing frameworks (Shrestha & Vassileva, 2019), cryptocurrency transactions (Taheri Tolu et al., 2022), cryptocurrency payments (Guych et al., 2018), and blockchain technology (Kamble et al., 2019; Liu et al., 2021). The TAM suggests a user's attitude towards a given technology also affects the behavioural intention to use the new technology. Ultimately, the findings of this study show that user attitudes expressed as perceptions of usefulness and ease of use affect the behavioural intention to use blockchain-based LPs.

Thirdly, trust in blockchain and cryptocurrency was found to influence PEOU, but not the PU of a BBLP. This suggests that users who trust the underlying technology (blockchain) and potential reward (cryptocurrency) are more likely to perceive a BBLP as easy to use but will not lead to a perception that the programme contributes to their goals or needs. It is noteworthy that the trust in the underlying technology (blockchain) and the potential reward for participation (cryptocurrency) in a BBLP were examined, rather than trust in the technology itself (BBLP). In prior studies using the TAM, trust is usually assessed in relation to the technology the use of which is being examined. Liu et al. (2021) examined the intention to use a blockchain and found that trust influenced both PEOU and PU. On the other hand, focusing on cryptocurrency payments, Guych et al. (2018) found that trust influenced PU, but did not affect PEOU. Overall, the effect of trust on PEOU and PU in this study contradicts the findings of others, who focus on applications of blockchain technology but not specifically BBLP. On the other hand, the existence of a relationship between trust and PEOU shows that trust does not only influence satisfaction or the intention to use blockchain technology, which prior authors examined and proposed in a blockchain context (Orji et al., 2020; Queiroz et al., 2021; Treiblmaier & Önder, 2019; Wamba et al., 2020).

Another major finding related to personal innovativeness. A relationship was confirmed between innovativeness and PEOU and the lack of relationship exhibited by innovativeness and PU. This suggests that more innovative users will probably perceive a BBLP as easier to use. The lack of a relationship with PU may suggest greater innovativeness will help a user explore a BBLP but will not translate into greater perceptions of utility. This finding is supported by Ullah et al. (2020), who suggested that a lack of awareness of blockchain technology may be driving the relationship between innovativeness and PEOU and PU, which could also be the case here. On the other hand, Sohaib et al. (2019) examined cryptocurrency adoption and found support for the idea that innovativeness influences both PEOU and PU, not only PU. Overall, these findings add to the ongoing debate in the literature on the relationship innovativeness has with PEOU and PU, with scholars finding varied relationships (Bigne-Alcaniz et al., 2008; Fagan et al., 2012; Joo et al., 2014; Miltgen et al., 2013).

Perceived value has shown a relationship with PEOU (Lee et al., 2012; Obal, 2013). Innovativeness has also been shown to have a relationship with PU (Obal, 2013; Pagani, 2004). These are significant findings. In a blockchain context, perceived value has been studied and found to reduce an individual's resistance to using blockchain (Walsh et al., 2021). Perceived value influenced PEOU, but not PU, in this study. Notably, the focus was on the perceived value of cryptocurrency, not the technology of which the use is being examined, which is usually the case. It suggests that users who perceive the potential reward for participating in a BBLP as valuable will be more likely to invest the time and effort in understanding its features and functionalities but will not reduce the perceived complexity of using the programme. However, more research is needed to confirm this and to understand the impact of this new variable on the use of blockchain technology.

Significantly, this study found that the TAM-DOI model is valid in a blockchain-loyalty context. All the factors taken from DOI theory, such as compatibility, complexity, and relative advantage, were shown to have a relationship with PEOU and PU. This provides empirical support for the conceptual model proposed by Lou and Li (2017), which examines these factors' relationship with PEOU and PU in a blockchain context. Several authors have examined the effect of factors derived from DOI on PU and PEOU in a blockchain context (Hamdan et al., 2022; Kamble et al., 2019; Kamble et al., 2021; Kumari & Devi, 2023; Ullah et al., 2021). Notably, all the studies focus on blockchain; however, the studies focus on different contexts, such as supply chain (Hamdan et al., 2022; Kamble et al., 2021), finance (Kumari & Devi, 2023) and education (Ullah et al., 2021).

The findings on compatibility are supported in the context of blockchain-technology acceptance in smart learning environments (Ullah et al., 2021) and partially supported by Kamble et al. (2021) and Kumari and Devi (2023), who found that PU is influenced by compatibility. They are also contradicted by Hamdan et al. (2022), Kumari and Devi (2023) and Kamble et al. (2021), who found that compatibility did not influence PEOU. Overall, the findings suggest that users who perceive a BBLP as being compatible with their current preferences and usage patterns will be more likely to embrace a BBLP as a valuable tool to achieve their loyalty-related goals.

Lastly, for complexity, the findings are supported by prior literature. Complexity has been shown to influence PEOU (Hamdan et al., 2022; Kamble et al., 2021). However, complexity has also been shown to have no relationship with PU (Kamble et al., 2021). The findings show that users who perceive a BBLP as more complex are more likely to find it to be difficult to use and will hinder a user's ability to derive benefits from the programme. Lastly, the findings relating to relative advantage are supported by prior literature focusing on learning environments (Ullah et al., 2021). In supply chains, relative advantage has been shown to influence PU but not PEOU partially supporting the findings (Kamble et al., 2021). The results of this study show that users who perceive a BBLP as having more excellent value compared to alternatives are more likely to find a BBLP to have higher utility and effectiveness, which in turn drives perceived ease of use and usefulness.

Theoretical implications

Significantly, this study contributes to the existing literature by proposing and validating unique constructs based on the TAM but adapted for a blockchain LP context. Trust and perceived value have been shown in a wide variety of prior studies to be an essential antecedent of a new technology's PEOU and PU. This study validated that trust in blockchain technology and cryptocurrency was an antecedent to the PU of a BBLP. Only a handful of studies examine trust in a blockchain context, and none focus on LPs (Orji et al., 2020; Queiroz et al., 2021; Treiblmaier & Önder, 2019; Wamba et al., 2020). This is significant and unique, as to the author's knowledge this is the first-time trust in the underlying technologies of a loyalty solution is examined and positioned as an influencer of acceptance of a new loyalty technology. Similarly, the perceived value of cryptocurrency was validated as an antecedent to PEOU. First, this is significant, as it is the first time the perceived value of cryptocurrency has been proposed and examined as an antecedent to PEOU and PU. Second, this is the first time to the author's knowledge that the perceived value of cryptocurrency as a reward for an LP has been examined.

As noted in the discussion section, authors have examined antecedents to PU and PEOU used in this study in a blockchain context before. However, this literature is scarce, with only a handful of studies examining complexity, relative advantage, compatibility, and innovativeness in a blockchain context (Hamdan et al., 2022; Kamble et al., 2019; Liu et al., 2021; Sohaib et al., 2019; Ullah et al., 2021). Further, results often differ and this study adds literature to the debate on the effect of these factors on PEOU and PU in a blockchain context, and specifically a blockchain-loyalty context.

Contextually, an integrated model combining the TAM and DOI theory has been proposed and studied in prior academic studies (Al-Rahmi et al., 2019; Lee et al., 2011; Min et al., 2019). However, incorporating a model using the TAM model and DOI theory has been applied to a limited extent in a blockchain context (Knauer & Mann, 2019; Lou & Li, 2017; Ullah et al., 2021). This study contributes to the limited literature on these integrated models and their explanatory power in a blockchain context. It is also only one of a few studies empirically tested using an online survey and PLS-SEM. More specifically, this study makes a significant theoretical contribution to understanding how integrated models using the TAM and DOI theory can be used to understand BBLPs. Research focusing on the intersection of loyalty and blockchain is scarce. Few studies have examined how blockchain impacts specific marketing strategies, such as loyalty (Wasiq et al., 2023), and this remains the case in 2024. This extends to research on BBLPs and only a handful of studies exist that cover this specific context (Utz et al., 2023; Wang et al., 2019).

Managerial implications

The findings of this study have significant managerial implications for companies investigating the adoption of BBLP or companies interested in developing blockchain solutions relating to LPs. This study validates that these programmes' PEOU and PU drive the intention to use BBLPs. This implies that consumers who view BBLPs as being easy to use and offering them a high utility will probably use a BBLP. The probability of a high PEOU was found to be dependent on trust, relative advantage, compatibility, complexity, and innovativeness. Complexity was found to be a critical factor in influencing PEOU, and companies designing a BBLP should be mindful of how users perceive how complex using a BBLP would be. For example, a company investing in a BBLP should be mindful of marketing and associating the LP with blockchain, which may create perceptions of complexity, and reduce the willingness to use such a programme. This assertion is likely given the newness of the technology, and how likely it is that users feel familiar or understand how the technology works. It is noteworthy that trust in cryptocurrency and blockchain effects PEOU. This means that companies investing in a BBLP need to help users trust the blockchain technology and the potential reward from using a BBLP-cryptocurrency to encourage use.

To create perceptions that BBLPs have utility and are useful, companies should be mindful of perceptions of the 'reward' of engaging in a BBLP, i.e., cryptocurrency. The perceived value of cryptocurrency was shown to be influential on the PU of programmes. This has implications for decisions on how rewards in a BBLP should be structured. For example, suppose the BBLP chooses to reward a user in cryptocurrency. In that case, it may either discourage or encourage users to view the programme as applicable, depending on their views on cryptocurrency. Users who already are cryptocurrency advocates or investors may view these programmes as having a high utility compared to those who do not. In addition, compatibility, complexity, and relative advantage are also essential, as these constructs were shown to affect perceptions of PU. Relative advantage was found to be the most critical factor in influencing PU. This means that organisations pursuing BBLP should be mindful of how they market and position their BBLP compared to alternatives. If a potential user views a BBLP as superior to a traditional LP, they will probably view it as useful. Practically, this can be done by creating marketing collateral highlighting how a BBLP uses tokenisation to be more useful to customers. The tokenisation of loyalty points allows consumers to track and store points more efficiently, freeing them from a disjointed loyalty network (Rejeb et al., 2020) and eliminates the need for consumers to search for each programme's options, limitations, and redemption rules (Udegbe, 2017).

Overall, the results show that businesses pursuing a BBLP should carefully consider how clearly they associate their BBLP with blockchain through marketing and other information they provide to potential users. Since blockchain is essentially a distributed, decentralised database, customers could be unaware of whether an LP is functioning using blockchain. Associating the BBLP clearly with blockchain can work for or against use of the programme, through complexity, relative advantage and trust in the underlying technology and potential reward for participation (cryptocurrency). For example, Singapore Airlines introduced blockchain technology into its LP (KrisFlyer) through a wallet called KrisPay (Morris, 2018). Viewing the Apple app for KrisPay shows a clear decision to dissociate it from blockchain technology, with no mention of the word *blockchain*.

Limitations and future research

This study is subject to limitations stemming from its utilisation of a non-probability sampling technique, specifically convenience sampling. Consequently, generalisability to the broader population becomes challenging. Additionally, limitations may arise from data collection through an online survey. Potential issues include the presence of fraudulent responses and the fact that online populations may not accurately represent the demographics of the country. These factors necessitate careful consideration when conducting studies using online surveys (Lefever et al., 2007).

The literature debates whether the intention to use a technology is translated into actual use.

This means that a limitation of the study is that actual use was not examined. Prior studies have shown that intended use does not predict actual use (Sarmah et al., 2021; Tao, 2009). However, these inconsistencies may have been caused by inconsistencies in self-reported usage in surveys, which can be biased, relative and unrepresentative of actual usage (Tao, 2009). Other studies have shown that behavioural intention can predict actual usage (Barry & Jan, 2018; Hassler et al., 2022; Kurniasih et al., 2020; Tarhini et al., 2013). After a systematic literature review focused on whether intention translated into actual usage, Turner et al. (2010) found that intention is likely to predict usage.

Respondents answered the survey items based on a knowledge of BBLPs provided in a video and text description. Given its newness, they were unlikely to have prior experience with the technology. A lack of experience with the technology can affect the results of the TAM (Turner et al., 2010). This approach may limit the applicability of the findings to a real-world BBLP which may contain some but not all the features described in the video.

Further studies should examine the appropriateness of blockchain-loyalty solutions by presenting respondents with a real-world application of this technology. Studies focusing on the actual usage of a blockchain-based loyalty programme were not found, although measurement of actual usage has been proposed by Lou and Li (2017). Usage can be measured objectively or subjectively through actual usage logs or self-reported usage (Turner et al., 2010). Investigating usage using either method would add to the limited literature on the topic.

Actual blockchain-loyalty solutions may contain some, but not all, critical features theorised to benefit both companies and businesses. Further, the novel antecedents to the PEOU and PU of blockchain technology, trust in blockchain technology, and the perceived value of cryptocurrency require examination in different contexts and countries.

Conclusion

This study examined BBLPs using an integrated model based on technology acceptance and DOI theory. The model validated the existence of several essential constructs and invalidated others using an online survey and SEM. Compatibility, complexity, and relative advantage were significant influencers of the PEOU and PU of BBLPs.

Personal innovativeness and trust in blockchain technology and cryptocurrency exhibited a relationship with PEOU but not PU. The perceived value of cryptocurrency was found to have a relationship with PU but not PEOU. Lastly, the well-established relationship between PEOU and PU and their impact on intention to use technology was valid when applied to a BBLP context.

Overall, this study added important insight to the under-researched area of BBLPs by examining the use of these programmes using TAM and DOI theory. This revealed unique constructs in a blockchain-based loyalty context, for example, trust in blockchain technology and cryptocurrency and the perceived value of cryptocurrency. This emphasises the importance of cryptocurrency and blockchain as businesses continue to understand BBLPs.

Chapter 5: Study Two

Introduction

Study Two investigates the antecedents of attitudinal and behavioural loyalty in a BBLP and the impact of technological acceptance on consumer loyalty, focusing on the following research questions:

1. What factors contribute to the development of behavioural and attitudinal loyalty towards a BBLP?
2. What is the relationship between the intention to use a BBLP and behavioural and attitudinal loyalty?

This study extends Watson et al.'s (2015) structural model, making significant contextual and theoretical contributions. It addresses the limited literature on blockchain's impact on LP effectiveness, a topic still debated after decades of research. Further, this is the first empirical examination of any part of Watson et al.'s (2015) model in a blockchain-marketing context. Moreover, the study extends the model by examining relative advantage and loyalty to technology acceptance through the intention to use a BBLP. The conceptual model and hypotheses examined in this study are highlighted in Figure 12 and Table 22.

More specifically, the research fills a gap in examining loyalty two-dimensionally, particularly the relationship between satisfaction, incentivisation, commitment, relative advantage, and trust, with behavioural and attitudinal loyalty in a blockchain context. While these antecedents have been studied before (Al-dweeri et al., 2017; Cifci & Erdogan, 2016; Gecti & Zengin, 2013; Haverila et al., 2022; Inoue et al., 2017; Kamran-Disfani et al., 2017), this research explores them in a two-dimensional loyalty context.

Notably, the study examines the effect of relative advantage on both behavioural and attitudinal loyalty, addressing its varied effects in one-dimensional studies (Rambocas & Arjoon, 2012; Jamshidi & Kuanova, 2020; Dixon et al., 2005; Yun et al., 2012). This is the first-time relative advantage has been examined two-dimensionally in the context of blockchain and loyalty programmes, providing a deeper understanding of its influence on consumer loyalty in a BBLP.

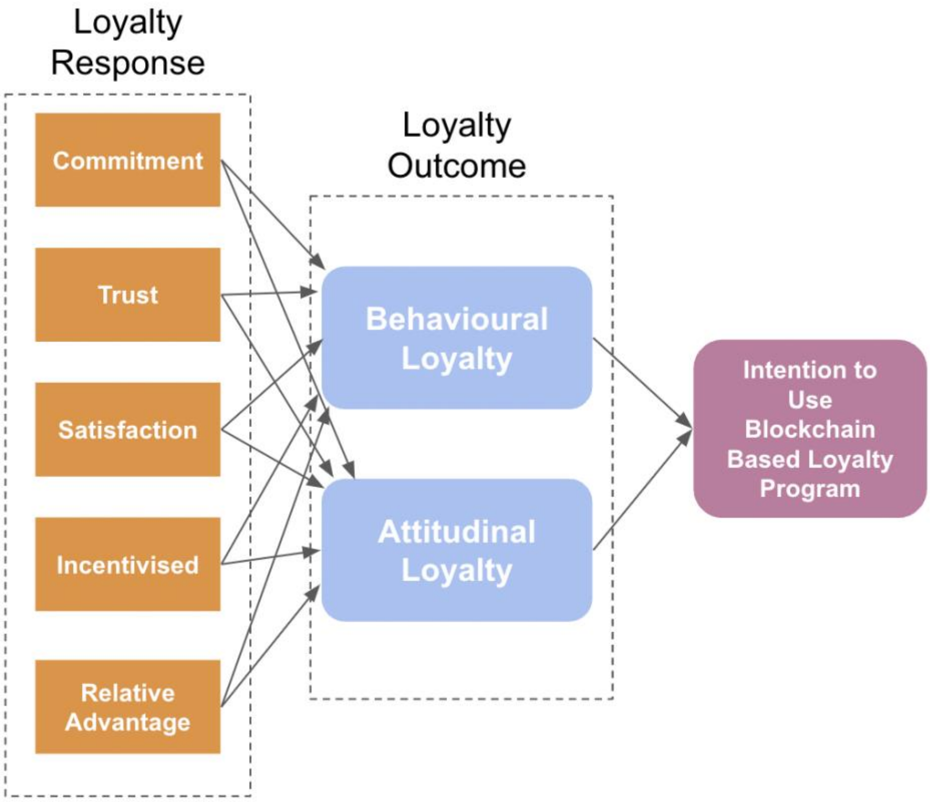

Figure 12. Conceptual model based on the work of Watson et al. (2015) and Davis (1985)

Table 23. Hypotheses covered in Study Two

#	Hypothesis
H11	Commitment predicts the behavioural (H11a) and attitudinal (H11b) loyalty exhibited for a BBLP
H12	Trust predicts the behavioural (H12a) and attitudinal (H12b) loyalty exhibited for a BBLP.
H13	Satisfaction predicts the behavioural (H13a) and attitudinal (H13b) loyalty exhibited for a BBLP.
H14	Incentivisation predicts the behavioural (H14a) and attitudinal (H14b) loyalty exhibited for a BBLP.
H15	Relative advantage predicts the behavioural (H15a) and attitudinal (H15b) loyalty exhibited for a BBLP.
H16	Behavioural loyalty (H16a) and attitudinal loyalty (H16b) predict the intention to use a BBLP.

Results

Results are presented in two parts: a formative measurement model assessment and a structural model assessment. Regarding the formative measurement model assessment, reliability and validity are analysed. Specifically, composite reliability and Cronbach's alpha are used to measure reliability. Next, validity is understood by analysing convergent and discriminate validity using the average variance extracted (AVE), the Fornell-Larcker criterion and heterotrait-monotrait (HTMT) ratios. PLS-SEM uses CFA, which is shown using model fit (Dash et al., 2021; Manley et al., 2021). Next, the structural model is assessed in four steps, as suggested by Hair et al. (2021) by focusing on collinearity, significance, structural model relationships, explanatory power, and predictive power.

Formative measurement model

Reliability

Indicator reliability measures how much of an indicator's variance is explained by the construct, and indicator loadings show bivariate correlations between constructs and the indicators (Hair et al., 2021). Indicator loadings should be above 0.40 (Hair et al., 2021). Figure 13 indicates that all the loadings are above the threshold of 0.4.

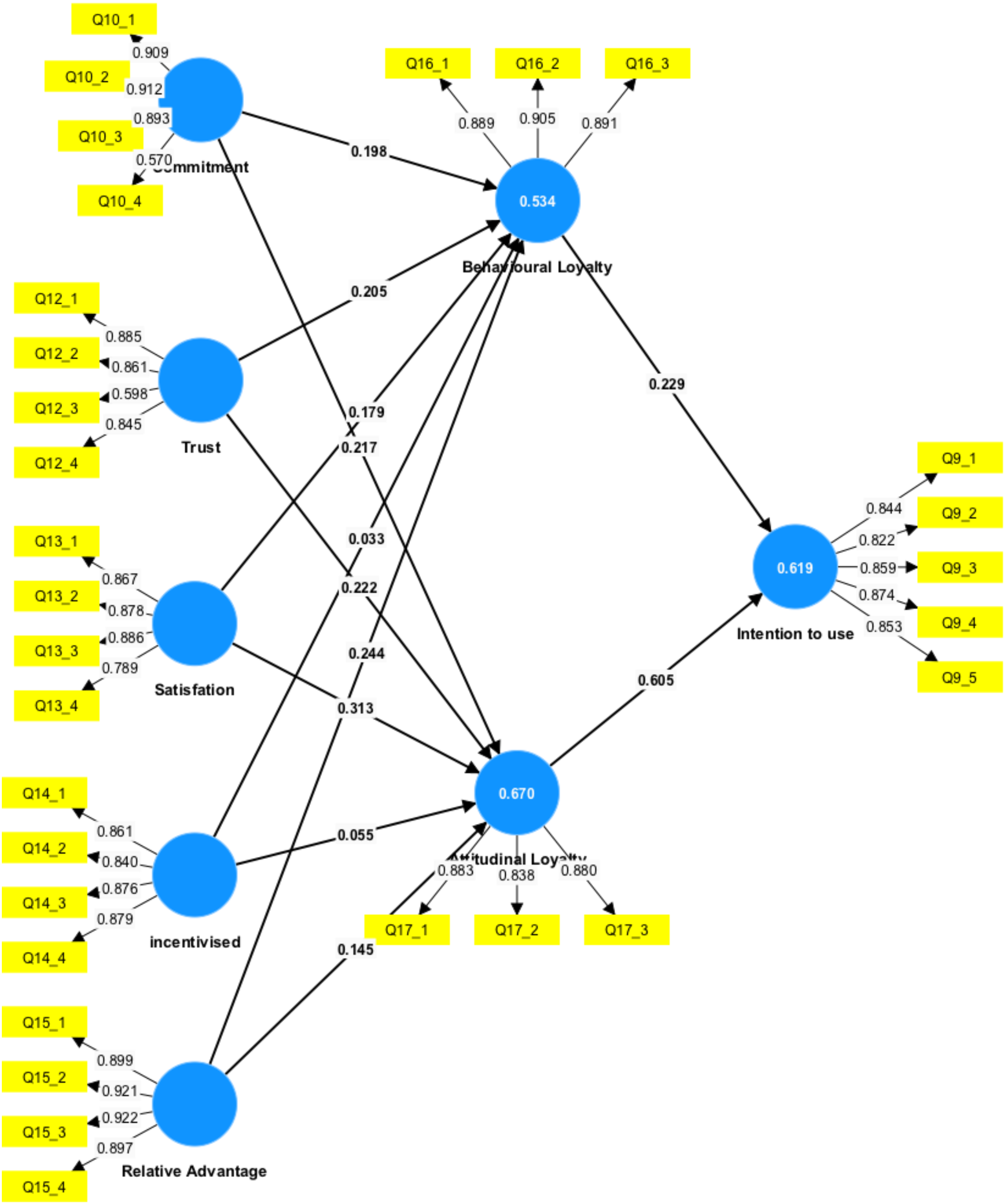

Figure 13. Structural model

Table 24. Factor loadings

Items relating to	Literature on which the items were based	Items	Notation	Factor Loading
Intention to use a BBLP	Miltgen et al. (2013)	I would sign-up for a Blockchain-based Loyalty Program as soon as possible	Q9_1	0.844
	Choe and Noh (2018)	I would use a Blockchain-based loyalty Program soon after it is launched	Q9_2	0.822
		I will use a Blockchain-based Loyalty Program in the future	Q9_3	0.859

		I will try to use a Blockchain-based Loyalty Program	Q9_4	0.874
		I am willing to use a Blockchain-based Loyalty Program	Q9_5	0.853
Commitment	Dagger et al. (2011)	A Blockchain-based Loyalty Program would be important to me	Q10_1	0.909
		I would care about a Blockchain-based Loyalty Program	Q10_2	0.912
		I would invest effort in a Blockchain-based Loyalty Program	Q10_3	0.893
	Pritchard et al. (1999)	My preference for a Blockchain-based Loyalty Program would not easily be change.	Q10_4	0.570
Trust	Liu et al. (2019)	Generally, I would trust a Blockchain-based Loyalty Program	Q12_1	0.885
		Overall, I can imagine myself confidently relying on a Blockchain-based Loyalty Program	Q12_2	0.861
	Horppu et al. (2008)	I do not think a Blockchain-based Loyalty program would prejudice me.	Q12_3	0.598
	Bashir and Madhavaiah (2015)	I believe it would be safe to use a Blockchain-based Loyalty Program	Q12_4	0.845
Satisfaction	Dagger and O'Brien (2010)	It would be a wise choice to use a Blockchain-based Loyalty Program.	Q13_1	0.867
		It would satisfy me to use a Blockchain-based Loyalty Programme	Q13_2	0.878
		I would feel good about using a Blockchain- Based Loyalty Program.	Q13_3	0.886
	Biscaia et al. (2017a)	My expectations of a loyalty program would be met by a Blockchain-Based Loyalty Program.	Q13_4	0.789
Incentivised	Naidoo and Leonard (2007)	A Blockchain-based Loyalty Program provides me with adequate incentives to use it.	Q14_1	0.861
		I would get rewarded appropriately by a Blockchain-Based Loyalty Program for my continued patronage	Q14_2	0.840
	Atchariyachanvanich et al. (2007)	I would get incentives for using a Blockchain-Based Loyalty Program.	Q14_3	0.876
		Blockchain-Based Loyalty Programs provide incentives for continued use.	Q14_4	0.879
Relative advantage	Min et al. (2019)	A Blockchain-based Loyalty Program would make it easier to redeem any benefits earned as	Q15_1	0.899

		part of a loyalty program.		
		A Blockchain-based Loyalty Program would make it easier to generate rewards for shopping at stores	Q15_2	0.921
		A Blockchain-based Loyalty Program would make it easier to earn benefits from a loyalty program.	Q15_3	0.922
		A Blockchain-based Loyalty Program would make it easier to manage my benefits that I earn as part of a loyalty program.	Q15_4	0.897
Behavioural loyalty	Liu et al. (2019)	A Blockchain-Based Loyalty Program would be my first choice compared to other loyalty programs	Q16_1	0.889
	Sharifi and Esfidani (2014)	As long I was offered a Blockchain-Based Loyalty Program, it is unlikely that I would opt for another loyalty program.	Q16_2	0.905
		I would rarely consider using another type of loyalty program, if I could use a Blockchain-Based Loyalty Program	Q16_3	0.891
Attitudinal loyalty	Sharifi and Esfidani (2014)	I would say positive things about a Blockchain-Based Loyalty Program	Q17_1	0.883
	Horppu et al. (2008)	I would pay more attention to a Blockchain-Based Loyalty Program than another type of loyalty program.	Q17_2	0.838
		I would recommend a Blockchain-Based Loyalty Program to anyone who seeks advice on loyalty programs.	Q17_3	0.880

Cronbach's alpha and composite reliability were used to measure internal consistency reliability. When using PLS-SEM, Cronbach's alpha is the lower bound, whereas composite reliability is the upper bound, meaning that the actual reliability is somewhere between the value for Cronbach's alpha and the composite reliability (Sarstedt et al., 2021). When using composite reliability, the higher the value the higher the level of reliability (Sarstedt et al., 2021). The value for composite reliability should be between 0.7 and 0.95 to be indicative of good reliability levels. A cut-off of 0.7 for both composite and Cronbach's alpha is acceptable in PLS-SEM research (Hair et al., 2017). Table 25 indicates that each construct has both a composite reliability and Cronbach's alpha which exceed the cut-off of 0.7, indicating sufficient reliability.

Table 25. Convergent validity and composite reliability

Constructs	AVE	Composite Reliability	Cronbach's Alpha
Commitment	0.695	0.898	0.844
Trust	0.649	0.879	0.819
Satisfaction	0.732	0.916	0.877
Incentivised	0.746	0.922	0.887
Relative Advantage	0.828	0.951	0.931
Behavioural Loyalty	0.801	0.923	0.876
Attitudinal Loyalty	0.752	0.901	0.835
Intention to use blockchain technology	0.724	0.929	0.904

Validity

PLS-SEM uses the average variance extracted (AVE) to measure convergent validity. Convergent validity is the *"extent to which a construct converges in its indicators by explaining the items' variance*" (Hair et al., 2022). The AVE must exceed 0.50 to be sufficient (Bagozzi & Yi, 1988; Hair et al., 2022; Pallant, 2000). This is because a value of 0.50 is indicative that the mean values of the factor loadings of the various items are higher than 0.708, which shows that variances of items and their constructs are meaningful (Hair et al., 2022). Table 25 shows that the AVE for each construct exceeds 0.5, establishing sufficient convergent validity.

Discriminant validity examines whether constructs are sufficiently unrelated to each other. To measure discriminant validity, the square root of the AVE of each construct is compared to the correlation it has with other constructs (Fornell-Larcker criterion). The square root of the AVE for each construct should be higher than its correlation with other constructs, to indicate sufficient discriminant validity (Fornell & Larcker, 1981). The results are shown in Table 26 and indicate that diagonal values (square roots of AVE) are higher than the off-diagonal values, establishing sufficient discriminant validity according to the Fornell-Larcker criterion.

The Fornell-Larcker criterion has been criticised, sometimes viewed as performing poorly, especially when indicator loadings only have a slight variation (Henseler et al., 2015). To address this, the heterotrait-monotrait (HTMT) ratio was proposed as an alternative and superior method to the Fornell-Larcker criterion (Henseler et al., 2015). The HTMT is the "*mean value of the item correlations across constructs relative to the (geometric) mean of the average correlations for the items for item measuring the same construct*." (Hair et al., 2019).

The Fornell-Larcker criterion shows the extent to which a construct explains the variance of its own indicators compared to the variance of others (Hair et al., 2022). For the HTMT ratio, the values should be below 0.9 to indicate sufficient discriminant validity (Henseler et al., 2015). The results for the HTMT ratio are shown in Table 27 and are below 0.9, indicative of sufficient discriminant validity.

Table 26. Discriminate validity values – Fornell-Larcker criterion

	ATTL	BEHL	COMMIT	INCENT	USE	ADV	SATISF	TRUST
ATTL	0.867							
BEHL	0.726	0.895						
COMMIT	0.701	0.629	0.834					
INCENT	0.634	0.560	0.583	0.864				
USE	0.771	0.668	0.704	0.673	0.851			
ADV	0.655	0.625	0.670	0.658	0.647	0.910		
SATISF	0.768	0.663	0.736	0.721	0.777	0.703	0.856	
TRUST	0.664	0.580	0.562	0.592	0.668	0.488	0.695	0.806

Note: ATTL: Attitudinal loyalty; BEHL: Behavioural loyalty; COMMIT: Commitment; INCENT: Incentivised; USE: Behavioural intention to use blockchain technology; ADV: Relative advantage; SATISF: Satisfaction

Table 27. Discriminate validity - HTMT

	ATTL	BEHL	COMMIT	USE	ADV	SATISF	TRUST	INCENT
ATTL								
BEHL	0.847							
COMMIT	0.822	0.721						
USE	0.884	0.743	0.787					
ADV	0.741	0.684	0.745	0.704				
SATISF	0.895	0.747	0.840	0.869	0.775			
TRUST	0.772	0.651	0.652	0.744	0.527	0.788		
INCENT	0.729	0.622	0.662	0.747	0.715	0.812	0.670	

Note: ATTL: Attitudinal loyalty; BEHL: Behavioural loyalty; COMMIT: Commitment; INCENT: Incentivised; USE: Behavioural intention to use blockchain technology; ADV: Relative advantage; SATISF: Satisfaction

Results of structural equation model

Collinearity

Collinearity was assessed because path coefficients in PLS-SEM are based on the ordinary least squares regression of endogenous constructs in relation to their predictor constructs (Hair et al., 2021). Path coefficients can be biased if there are high levels of collinearity for the predictor constructs (Hair et al., 2021). Collinearity is measured using the variance inflation factor (VIF). Values for collinearity should be below 5. Table 28 shows that all the VIF values are below the threshold of 5.

Common method bias can be assessed through VIF, according to the method suggested by Kock (2015). This involves the creation of a new variable with random values, and creating a model where all the latent variables point to this random variable. Table 29 shows that all the VIF values are below 3.3 and can thus be considered free of common method bias (Kock, 2015).

Table 28. VIF values

	ATTL	BEHL	COMMIT	USE	ADV	SATISF	TRUST	INCENT
ATTL				2.115				
BEHL				2.115				
COMMIT	2.456	2.456						
USE								
ADV	2.416	2.416						
SATISF	3.781	3.781						
TRUST	2.031	2.031						
INCENT	2.386							

Note: ATTL: Attitudinal loyalty; BEHL: Behavioural loyalty; COMMIT: Commitment; INCENT: Incentivised; USE: Behavioural intention to use blockchain technology; ADV: Relative advantage; SATISF: Satisfaction; TRUST: Trust

Table 29. VIF values from assessment of common method bias

	VIF
ATTL → Random	2.469
BEHL → Random	2.465
COMMIT → Random	2.347
USE → Random	2.889
ADV → Random	2.249
SATISF → Random	2.664
TRUST → Random	2.024
INCENT → Random	1.332

Note: ATTL: Attitudinal loyalty; BEHL: Behavioural loyalty; COMMIT: Commitment; INCENT: Incentivised; USE: Behavioural intention to use blockchain technology; ADV: Relative advantage; SATISF: Satisfaction; TRUST: Trust

Significance and relevance of structural model relationships

After evaluating collinearity, the structural model must be examined, which shows the proposed hypotheses. This was done using PLS-SEM and a procedure called bootstrapping. Bootstrapping involves many random subsamples from the original data, which are used to estimate the PLS path model (Wong et al., 2013). This study used 5000 subsamples, as recommended by Sarstedt et al. (2017). This provides the coefficient of determination, t-test, and p-values. A significance level of 0.05 and using a two-tailed test with a t-value of greater than 1.96 means that the path coefficient is significant (Wong et al., 2013).

The path coefficient should be between -1 and +1, and path coefficients greater than -1 or +1 are not acceptable (Hair et al., 2021). A path coefficient close to -1 indicates a strong negative relationship, whereas a path coefficient close to 1 is indicative of a strong positive relationship. Table 30 shows all the path coefficients to be acceptable and between -1 and +1. Notably all the path coefficients are positive, except for innovativeness and perceived use, as well as perceived value and perceived ease of use. Strong relationships are exhibited between perceived usefulness and perceived ease of use, as well as relative advantage with perceived usefulness.

Table 30 reveals that all the hypothesised relationships have been accepted except those related to incentives. In addition, relationships between commitment, trust, satisfaction, and relative advantage exhibited by participants were all shown to influence both behavioural and attitudinal loyalty. Notably, a relationship between loyalty (attitudinal and behavioural) with technology use was valid in a blockchain-loyalty context.

Attitudinal Loyalty demonstrates a strong and significant relationship with Use (USE) (β = 0.605, $p < 0.001$), reinforcing its role as a primary driver of behavioural outcomes. Similarly, behavioural loyalty has a smaller but significant effect on Use (β = 0.229, $p < 0.001$), suggesting that both loyalty dimensions play complementary roles in influencing technology adoption. Furthermore, satisfaction exhibits a notable positive effect on both attitudinal Loyalty (β = 0.313, $p < 0.001$) and behavioural loyalty (β = 0.179, $p = 0.006$), underscoring its importance in shaping loyalty outcomes. However, incentives were found to have no significant influence on either dimension of loyalty, indicating that they may not play a major role in this context. These findings provide critical insights into the mechanisms driving loyalty and use in blockchain-based loyalty programs.

Table 30. Results of SEM

H	Hypothesised Relationship	Path Coefficient	T-Value	P-Value	Hypothesis
H1a	BEHL→USE	0.229	4.360	0	Accepted
H1b	ATTL→USE	0.605	11.530	0	Accepted
H2a	COMM→BEHL	0.198	3.927	0	Accepted
H2b	COMM→ATTL	0.217	4.752	0	Accepted
H3a	TRUST→BEHL	0.205	4.496	0	Accepted
H3b	TRUST→ATTL	0.222	5.494	0	Accepted
H4a	SATSIF→BEHL	0.179	2.727	0.006	Accepted
H4b	SATISF→ATTL	0.313	5.221	0	Accepted
H5a	INCENT→BEHL	0.033	0.669	0.503	Rejected
H5b	INCENT→ATTL	0.055	1.111	0.267	Rejected
H6a	ADV→ATTL	0.145	3.068	0.002	Accepted
H6b	ADV→BEHL	0.244	4.331	0	Accepted

Note: ATTL: Attitudinal loyalty; BEHL: Behavioural loyalty; COMMIT: Commitment; INCENT: Incentivised; USE: Behavioural intention to use blockchain technology; ADV: Relative advantage; SATISF: Satisfaction; TRUST: Trust

Explanatory power of the model

Following an examination of the structural model relationships, the next step is to analyse the coefficient of determination (R^2) to determine the model's explanatory power. The coefficient of determination measures the degree of association between two variables and their relative strength. It shows the in-sample predictive power of the model and not the out-of-sample or predictive power of the model (Hair et al., 2021). R^2 ranges from 0 to 1, with a higher value being better. For marketing research, the coefficient of determination should be at least 0.25 (Wong et al., 2013). As a guideline, the values 0.75, 0.50 and 0.25 correspond to strong, moderate, and weak effects (Hair et al., 2021).

The R^2 value is 0.670 for attitudinal loyalty. This indicates that the variation in the five latent variables moderately explains 67% of the variation in attitudinal loyalty. For behavioural loyalty, 53% of the variation is moderately explained by the five latent variables. Further, 62% of the variation in the behavioural intention to use a blockchain-based loyalty programme is moderately explained by attitudinal and behavioural loyalty. As all the values for R^2 exceed 0.25, the explanatory power of the model is sufficient and is in the moderate range.

Table 31. Coefficients of determination

	R^2
ATTL	0.670
BEHL	0.534
USE	0.619

Note: ATTL: Attitudinal loyalty; BEHL: Behavioural loyalty; USE: Behavioural intention to use blockchain technology.

$PLS_{predict}$ was used to assess the out-of-sample predictive power of the model. This indicates the model's ability to accurately forecast future observations (Hair et al., 2021). $PLS_{predict}$ uses k-fold cross-validation. A fold represents a subset within the complete sample, where 'k' denotes the quantity of these subsets (Hair et al., 2021). Essentially, the entire dataset undergoes random division into 'k' equally proportioned segments of data (Hair et al., 2021). To understand the predictive power, the focus should be given to metrics that measure the amount of prediction error relating to endogenous constructs (Hair et al., 2021). The root-mean-square error (RSME) and mean-absolute-error (MAE) are useful for understanding predictive error (Hair et al., 2021). The RSME calculates the square root of the mean of the squared variances between the predicted values and the observed data (Hair et al., 2021). MAE evaluates the average size of the errors in a set of predictions, disregarding their directionality (whether they overestimate or underestimate) (Hair et al., 2021). In most cases, researchers should use RSME, unless the prediction error distribution is non-symmetric (Hair et al., 2021).

The linear regression model (LM) benchmark should be compared to the RSME or MAE metric to determine the model's predictive power (Hair et al., 2021). If all the indicators' LM values are lower than the RMSE or MAE values, the model has high predictive power (Hair et al., 2021). If the majority or same number of indicators have smaller RSME or MAE values than the corresponding LM values, then the model has medium predictive power (Hair et al., 2021). If the minority of indicators have smaller RSME or MAE values compared to the LM values, the model has low predictive power (Hair et al., 2021). If none of the indicators has a lower RSME or MAE value than the LM model value, it lacks predictive power (Hair et al., 2021). Q^2 or the indicator mean of the holdout sample can be used to understand whether the predictions utilising PLS-SEM are better than the most naïve benchmark (Sarstedt et al., 2021). If Q^2 is greater than 0, the path model outperforms the most naïve benchmark (Sarstedt et al., 2021).

Table 32. $PLS_{predict}$ results

MV Prediction Summary	Q²predict	PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE
ATTL_1	0.539	0.570	0.438	0.579	0.434
ATTL_2	0.440	0.762	0.616	0.777	0.620
ATTL_3	0.504	0.656*	0.513	0.652	0.509
BEHL_1	0.531	0.730*	0.596	0.725	0.570
BEHL_2	0.367	0.834	0.673	0.851	0.685
BEHL_3	0.324	0.885	0.714	0.900	0.724
USE_1	0.482	0.719	0.588	0.722	0.570
USE_2	0.402	0.796	0.651	0.802	0.640
USE_3	0.482	0.587	0.434	0.591	0.438
USE_4	0.514	0.582*	0.434	0.573	0.435
USE_5	0.452	0.607	0.443	0.608	0.449

Note: ATTL: Attitudinal loyalty; BEHL: Behavioural loyalty; USE: Behavioural intention to use blockchain technology.

Table 32 shows that all the indicators have Q^2 values larger than zero, which means the PLS path model outdoes the most naïve benchmark. Comparing the RSME values with the LM values shows that all the indicators besides three (ATTL_3, BEHL_1, USE_4) have higher LM values than their corresponding RSME values. This indicates that the model has moderate predictive power, according to the interpretation of Hair et al. (2021).

Discussion of results

These results support the findings of this study by which trust was found to influence behavioural and attitudinal loyalty. However, in contrast to previous studies, trust was found to have a marginally greater influence on attitudinal loyalty. This could be explained by the context (blockchain, BBLPs) which is uncharted territory for this relationship, or because of a novel focus on trust in the technology (blockchain) and the reward (cryptocurrency) instead of trust in the business or brand. Usually, studies focus on trust in the brand, rather than trust in a related technology.

Commitment was found to influence attitudinal and behavioural loyalty. The relationship between commitment and a unidimensional construct of loyalty is supported by several authors (Bloemer et al., 2003; Dagger et al., 2011; Marshall, 2010). More specifically, and two-dimensionally, the relationship between commitment and attitudinal loyalty is supported (Cifci & Erdogan, 2016; Inoue et al., 2017). In one of the few studies focusing on the relationship between commitment and a two-dimensional construct of loyalty, commitment has been found to have a direct impact on attitudinal loyalty, but only impacts behavioural loyalty indirectly through satisfaction (Dikcius et al., 2019). This led the authors to agreeing with the Mpinganjira et al. (2017) findings that commitment is a perception and does not impact actual behaviour directly (Dikcius et al., 2019). The difference in the findings of this study, compared to Dikcius et al. (2019), can be explained by the B2B context their study focused on. Their study was also not focused on LPs or blockchain. Nevertheless, the results show that, at least in the B2C blockchain-loyalty context, commitment is not just a perception but a behaviour as well. More research is required to better understand this.

In offline and online commerce, trust has been shown to have a greater direct effect on behavioural loyalty compared to attitudinal loyalty, and directly influences both attitudinal and behavioural loyalty (Al-dweeri et al., 2017; Gecti & Zengin, 2013). For cell phone users, trust has been shown to have an indirect influence on behavioural and attitudinal loyalty, but to have a slightly larger effect on behavioural loyalty (Sharifi & Esfidani, 2014). In the hotel industry, trust has been shown to influence behavioural loyalty (Liu et al., 2019). Several author studies have shown a relationship between trust and a unidimensional conception of loyalty (Leninkumar, 2017; Marakanon & Panjakajornsak, 2017; Stathopoulou & Balabanis, 2016; Yap et al., 2012).

Viewing loyalty two-dimensionally and in a retail context, satisfaction was found to be influential on attitudinal loyalty, but not behavioural loyalty (Kamran-Disfani et al., 2017). Loyalty, as a unidimensional construct, is influenced by satisfaction, as found by several authors (Biscaia et al., 2017b; Picón et al., 2014; Sugandini & Wendry, 2017). Satisfaction was found to influence behavioural and attitudinal loyalty in this study. This may mean that prospect theory applies to a blockchain-loyalty context and that loyal customers are affected more by the loss in benefits from switching to another provider than by any gains from buying from a new provider. It indicates that trust is a foundational element that influences attitudinal loyalty, by fostering positive consumer perceptions and behavioural loyalty by reducing the perceived risks of participation. The results of this study are consistent with the work of Watson et al. (2015), which demonstrated that satisfaction had a far more significant effect on attitudinal than behavioural loyalty.

Researchers tend to focus on the relationship between incentives and loyalty as a unidimensional construct. Of these studies, several have found a lack of support for a relationship between incentives and loyalty (Adrianto et al., 2023; De Wulf et al., 2001; Koppius et al., 2005). Incentives were found to be uninfluential on continuance intention (Koppius et al., 2005). In a multi-country study on loyalty, some consumers were not enticed by loyalty incentives because of the greater abundance of tangible rewards in some countries leading to more significant disappointment as the incentives fail to attract consumers (De Wulf et al., 2001). Online, incentives have been found to be uninfluential on loyalty as well (Adrianto et al., 2023). Other researchers have found that incentives are influential on loyalty. In an ecommerce context, tangible and intangible rewards were found to be significantly related to attitudinal loyalty, but to have a small effect (Haverila et al., 2022). A loyalty card has also been shown to increase behavioural and attitudinal loyalty (Demoulin & Zidda, 2008).

The lack of a significant relationship between incentives and the creation of both behavioural and attitudinal loyalty in this study may reflect that loyalty cannot be 'bought' and those incentives will not necessarily lead to greater loyalty towards blockchain-based programmes compared to alternatives. It can also be explained by social exchange theory. Social exchange theory considers interactions between two parties to be like an economic exchange involving costs and benefits (Gefen et al., 2003). According to this theory, participation in the social exchange only occurs if benefits exceed costs. Consumers may perceive loyalty as a form of social exchange, where they invest resources in a relationship and expect to receive benefits or incentives in return. Suppose the benefits of using a BBLP are unclear, because there is mistrust in blockchain or cryptocurrency or simply a lack of understanding. In that case, it may break down the cost-benefit analysis.

On the other hand, if the incentives are understood but not considered valuable (and have a low valence), expectancy theory would suggest that their motivation to exhibit loyalty behaviours would break down. According to Treiblmaier and Petrozhitskaya (2023), expectancy theory suggests that employees' motivation to engage in different activities is determined by their beliefs regarding three key factors: valence (the importance of a specific outcome), expectancy (the belief that increased effort will enhance performance), and instrumentality (the belief that improved performance will result in better outcomes). Only 37% of respondents in a global loyalty survey indicated points and rewards were an effective way to secure loyalty (KPMG, 2019). The lack of relationship shows that incentives are even less effective if the technology is new and the method of generating and spending rewards is unclear.

The relationship between relative advantage and a unidimensional conception of loyalty is supported by several authors who have studied this relationship in various contexts (Jamshidi & Kuanova, 2020; Lin et al., 2015; Rambocas & Arjoon, 2012). No research was found that examines the relationship between relative advantage and loyalty as a two-dimensional construct. Relative advantage was examined as an influencer of both behavioural and attitudinal loyalty. This adds a unique focus on an antecedent omitted by Watson et al. (2015), namely, a consumer's willingness to reject a substitute when faced with a choice. It is indicative that relative advantage causes consumers to be more inclined to participate in an LP and influences emotional perceptions, attitudes, and connections to the LP.

Notably, the empirical support of the relationship between relative advantage and loyalty contradicts the recent findings by Suhartanto et al. (2022), who found no support for a relationship between relative advantage and loyalty in the context of artificial-intelligence mobile banking. The differences could be explained by differences in the context and the focus of Suhartanto et al. (2022) on artificial intelligence in the context of banking compared to the focus of this study on blockchain in the context of LPs. More research is needed to clarify whether relative advantage shapes loyalty towards a new technology or whether it only affects use. Several studies have demonstrated the effect of relative advantage on technology use (Al-Rahmi et al., 2019; Lee et al., 2011) but research on its effect on loyalty is lacking.

Overall, the empirical data in this study supports the notion put forward by Watson et al. (2015), that researchers should view loyalty as having a behavioural and attitudinal component. The findings show notable differences in how satisfaction and relative advantage affect loyalty's behavioural and attitudinal parts. Although differences in how trust, commitment, and satisfaction affect behavioural and attitudinal loyalty were also noted, the differences were relatively minor. As mentioned before, seeing loyalty as a single construct can lead to misleading results and it should be separated (Kamran-Disfani et al., 2017; Watson et al., 2015).

Behavioural and attitudinal loyalty was found to influence the intention to use a BBLP. This is indicative that their users who actively engage in a BBLP are more likely to express intentions to use a BBLP. Additionally, users with more positive emotional connections towards a BBLP are more likely to express intentions to use a BBLP. Attitudinal loyalty was found to have a far more significant effect on usage intentions than behavioural loyalty. This indicates the importance of separating loyalty into its behavioural and attitudinal components. One-dimensionally, loyalty has been shown to influence use, by several authors (Agag et al., 2019; Bouagina & Triki, 2013; Martinez-Caro et al., 2013). However, how use affects the attitudinal and behavioural components is unknown. Illuminating the relationship between a two-dimensional conception of loyalty and use is thus a crucial contribution that this study makes to the discourse on loyalty and its link to acceptancy models.

Theoretical implications

Overall, the results validate the model put forward by Watson et al. (2015), which was proposed to bring together the wide variety of conceptual and operational approaches utilised to examine loyalty. An extension of this model to include relative advantage as an antecedent to the generation of behavioural and attitudinal loyalty was supported in the previously mentioned data analysis. Support to extend the model further and view behavioural and attitudinal loyalty as influencers of technology use was also supported, and the model's in-sample and out-of-sample explanatory power was moderate.

For the first time, a combined loyalty-acceptancy theoretical model is proposed and examined empirically, which was built on the work of Watson et al. (2015). To date, satisfaction-loyalty models which incorporate the TAM have been proposed. Still, a comprehensive examination of the link between behavioural and attitudinal loyalty and behavioural intentions to use new technology has not been attempted. The finding that the behavioural intention to use a technology influences both behavioural and attitudinal loyalty is an important theoretical contribution of this study.

It is crucial to view loyalty as having attitudinal and behavioural components and to understand their effect and how other variables affect them. Seeing loyalty as a single construct can lead to misleading results and it should be treated as multi-dimensional (Kamran-Disfani et al., 2017; Watson et al., 2015), and researchers have started to validate that it is multi-dimensional (Cifci & Erdogan, 2016). This study highlights this importance by examining the effect relative advantage, satisfaction, trust, and commitment have with a two-dimensional conception of loyalty that includes the behavioural and attitudinal components. Limited literature examines the relationship these variables have on the attitudinal and behavioural components of loyalty. Ultimately, this study found support and varied relationships that some of these variables had with attitudinal and behavioural loyalty, which adds to the theory surrounding these variables' influence on the attitudinal and behavioural components of loyalty. Lastly, this study comprehensively sheds light on the antecedents of loyalty creation in a blockchain-loyalty context, focusing on relative advantage and the role comparing alternatives can play in creating loyalty towards types of LPs.

Managerial implications

First, the findings of this study have significant managerial implications for companies investigating the adoption of BBLPs. The model validates that behavioural and attitudinal loyalty influences usage intentions. Managers should recognise that behaviours towards and perceptions of BBLPs play a critical role in a potential user's willingness to adopt a BBLP. This means monitoring perceptions and attitude preferences towards a BBLP are important to ensure timely adaptions and adjustments to the LP strategy.

Second, perceptions (or attitudinal loyalty) influence usage intentions much more than behavioural loyalty. Marketers could action this knowledge by ensuring that users' perceptions of BBLPs are positive and remain positive. This could include educational initiatives that help users understand the benefits and features of BBLPs and how BBLPs can increase security, transparency, and usability. Since relative advantage was also found to influence behavioural and attitudinal loyalty, marketing programmes that highlight the benefits for BBLPs compared to traditional LPs may be desirable. Practically, this could be done by highlighting the benefits derived from the tokenisation of loyalty points. This allows consumers to track and store points more efficiently, freeing customers from a disjointed loyalty network (Rejeb et al., 2020). Furthermore, a BBLP has the potential to provide customers with improved and almost instant redemption and exchange for multiple loyalty-point currencies in a single virtual wallet (Udegbe, 2017). This eliminates the need for consumers to search for each programme's options, limitations, and redemption rules (Udegbe, 2017).

Thirdly, the findings of this study also showed that commitment, trust, satisfaction, and relative advantage influence both behavioural and attitudinal loyalty. Satisfaction has the biggest impact on attitudinal loyalty. This suggests that managers should focus on initiatives to improve satisfaction, such as continually improving and enhancing the user experience of a BBLP. Commitment could be enhanced by building a sense of community among users of a BBLP or offering rewards for long-term engagement with the BBLP.

Trust in blockchain and cryptocurrency are influential on the behavioural and attitudinal loyalty exhibited towards a BBLP. This finding is important and shows that marketers will also need to focus on building trust in the underlying technology of BBLPs (blockchain) and the potential reward mechanism (cryptocurrency) to create loyalty and ultimately use. This is an important consideration, depending on how visible it is that the LP is using blockchain. For example, Singapore Airlines introduced blockchain technology into its LP (KrisFlyer) through a wallet called KrisPay (Morris, 2018). Viewing the Apple app for KrisPay shows a clear decision to dissociate it from blockchain technology, with no mention of the word *blockchain*. Some blockchain-based companies, like FlyCoin and Loyyal, are more clearly advertised as blockchain-based LPs, although as B2B companies it is unknown whether the end-user will ever know whether blockchain or crypto is involved. A decision to obscure the association an LP has with blockchain may avoid questions of trust in blockchain and cryptocurrency that will impact a customer's loyalty, but may also minimise the relative advantage, which could enhance the loyalty and ultimately the usage intentions of potential users as well.

Lastly, this study shows that incentivisation does not influence the creation of behavioural and attitudinal loyalty. This means that practitioners should be cognisant that providing more significant incentives for using BBLPs will not lead to greater usage of these programmes, at least not through a loyalty effect. Only 37% of respondents in a global loyalty survey indicated that points and rewards were an effective way to secure loyalty (KPMG, 2019). This may mean that, for BBLPs, rewards are even less effective at generating loyalty compared to traditional LPs. BBLPs may also introduce additional complexity in earning and redeeming rewards, because of cryptocurrency or blockchain technology. This may reduce the impact of incentives on loyalty through a social exchange mechanism, where consumers view the benefit of participating as insufficient to induce loyalty. Overall, this means managers should carefully consider their incentive strategies for a BBLP and focus on other factors, such as relative advantage, satisfaction, trust, and commitment, to drive loyalty instead of incentives.

Limitations

This study is subject to limitations stemming from its utilisation of a non-probability sampling technique, specifically convenience sampling. As mentioned, convenience sampling involves selecting sampling units based on their accessibility or immediate availability to the researcher. Consequently, generalisability to the broader population becomes challenging. Additionally, limitations may arise from data collection through an online survey. Potential issues include the presence of fraudulent responses and the fact that online populations may not accurately represent the demographics of the country. These factors necessitate careful consideration when conducting studies using online surveys (Lefever et al., 2007).

The literature debates whether the intention to use a technology is translated into actual use. This means that a limitation of the study is that actual use was not examined. Prior studies have shown that intended use does not predict actual use (Sarmah et al., 2021; Tao, 2009). However, these inconsistencies may have been caused by inconsistences in self-reported usage in surveys which can be biased, relative and unrepresentative of actual usage (Tao, 2009). Other studies have shown that the behavioural intention can predict actual usage (Barry & Jan, 2018; Hassler et al., 2022; Kurniasih et al., 2020; Tarhini et al., 2013). After a systematic literature review focused around the question of whether intention translated into actual usage, Turner et al. (2010) found that intention is likely to predict usage.

Respondents answered the survey items based on a knowledge of BBLPs provided in a video and text description. It is also unlikely they had prior experience with the technology, given its newness. A lack of actual experience with the technology can affect the results of the TAM (Turner et al., 2010). This approach may limit the applicability of the findings to a real-world BBLP which may contain some but not all the features described in the video. Further studies should examine the appropriateness of blockchain-loyalty solutions by presenting respondents with a real-world application of this technology. Studies focusing on the actual usage of a blockchain-based loyalty programme were not found, although measurement of actual usage has been proposed by Lou and Li (2017). Usage can be measured objectively or subjectively through actual logs of usage or self-reported usage (Turner et al., 2010). Investigating usage using either method would add to the limited literature on the topic.

Further studies should examine the appropriateness of blockchain-loyalty solutions by presenting respondents with a real-world application of this technology. Actual blockchain-loyalty solutions may contain some, but not all, critical features theorised to benefit companies and businesses.

Conclusion

This study examined BBLPs using an integrated model based on technology acceptance and loyalty based on the work of Watson et al. (2015). The model validated the existence of several essential constructs and invalidated others using an online survey and structural equation modelling. Commitment, trust, relative advantage, and satisfaction were significant influencers of behavioural and attitudinal loyalty exhibited towards BBLPs. Furthermore, satisfaction and trust were shown to have significantly different effects on behavioural and attitudinal loyalty, supporting the view that loyalty should be viewed as a two-dimensional construct in a blockchain-loyalty context. Adding to this, behavioural and attitudinal loyalty influenced the usage intentions of BBLPs. However, attitudinal loyalty had a far more significant effect on usage intentions. The proposed relationship between incentivisation and loyalty's behavioural and attitudinal components was not supported. This may reflect that 'loyalty can't be bought' in a blockchain-loyalty context and that companies cannot create greater loyalty towards BBLPs through incentives alone.

Overall, this study added important insight to the under-researched area of BBLPs, by examining the use of these programmes using a model that combines technology acceptance and loyalty. Validation for a two-dimensional loyalty construct was supported. The effect of attitudinal and behavioural loyalty on the TAM added insight into models that seek to understand how loyalty and its antecedents affect the acceptance of new technology.

Chapter 6: Study Three

Introduction

Study Three examines the impact of BBLP technological acceptance on consumer loyalty as well as how loyalty towards a BBLP provider influences key firm outcomes (redemption and WoM), through two key research questions:

1. What relationship does the intention to use a BBLP have with behavioural and attitudinal loyalty?
2. What relationship does attitudinal and behavioural loyalty have with redemption and WoM?

To answer these questions, Watson et al.'s (2015) structural model is combined with the TAM, extending both. Previous models have merged technology acceptance and loyalty, especially in satisfaction-loyalty models (Niu et al., 2021; Agag et al., 2019). However, no comprehensive model has examined the link between technology acceptance, two-dimensional loyalty, and firm outcomes (redemption and WoM). This is a key contribution of this study. Moreover, as mentioned before, loyalty research to date has not focused on the relevance of the TAM. This adds insight into the relevant of new theories within loyalty research. The conceptual model and relevant hypotheses examined in this study are highlighted in Figure 14 and Table 33.

Regarding other contributions, the focus on redemption is significant. The relationship between engagement behaviour (including redemption) and loyalty has only been empirically tested by one recent study (Meyer-Waarden et al., 2023). Through adapting Watson et al.'s (20215) model, this study focuses on redemption instead of performance as a firm outcome. This is significant as reward redemption effects are largely overlooked in the literature, with most research focusing on the appeal of different reward categories and their relationship with revenue (Dorotic et al., 2014) or more generally as part of customer engagement (Meyer-Waarden et al., 2023).

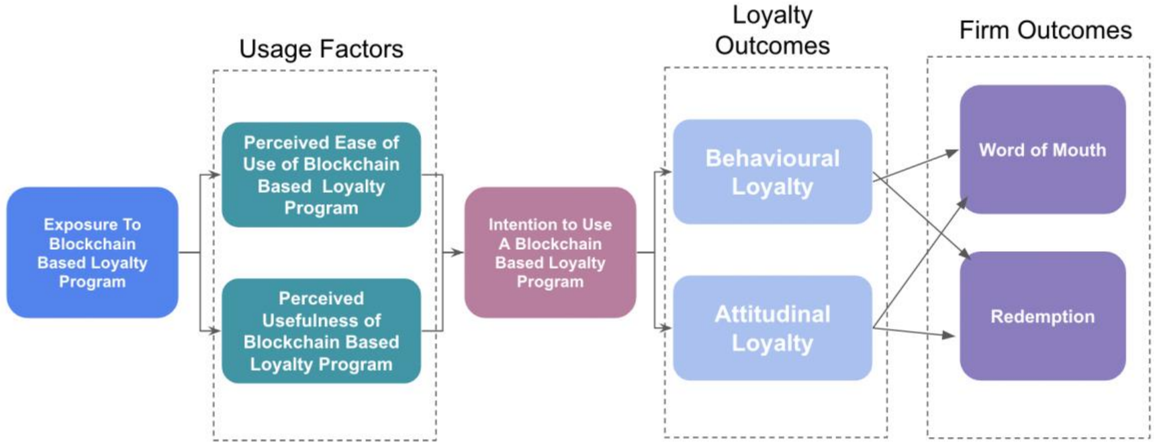

Figure 14. Conceptual model based on the work of Watson et al. (2015) and Davis (1985)

Table 33. Hypotheses covered in Study Three

#	Hypothesis
H1	PEOU (H1a) and the PU (H1b) of a BBLP predicts the intention to use a BBLP.
H2	The intention to use a BBLP predicts the behavioural (H2a) and attitudinal loyalty (H2b) exhibited towards BBLPs
H3	Behavioural loyalty (H3a) and attitudinal loyalty (H3b) exhibited towards BBLPs predict the intention to promote these programmes via WoM.
H4	Behavioural loyalty (H4a) and attitudinal loyalty (H4b) exhibited towards BBLPs predicts the intention to redeem benefits accrued for these programmes.

Results

Results are presented in two parts: a formative measurement model assessment and a structural model assessment. Regarding the formative measurement model assessment, reliability and validity are analysed. Specifically, indicator reliability, composite reliability and Cronbach's alpha are used to measure reliability. Next, validity is understood by analysing convergent and discriminate validity using the average variance extracted (AVE), the Fornell-Larcker criterion and heterotrait-monotrait (HTMT) ratios. PLS-SEM uses CFA, which is shown using model fit (Dash et al., 2021; Manley et al., 2021). Next the structural model is assessed in four steps, as suggested by Hair et al. (2021) by focusing on collinearity, significance, structural model relationships, explanatory power, and predictive power.

Formative measurement model

Reliability

Indicator reliability measures how much of an indicator's variance is explained by the construct, and indicator loadings show bivariate correlations between constructs and the indicators (Hair et al., 2021). Indicator loadings should be above 0.40 (Hair et al., 2021). Figure 15 indicates that all the loadings are above the threshold of 0.4.

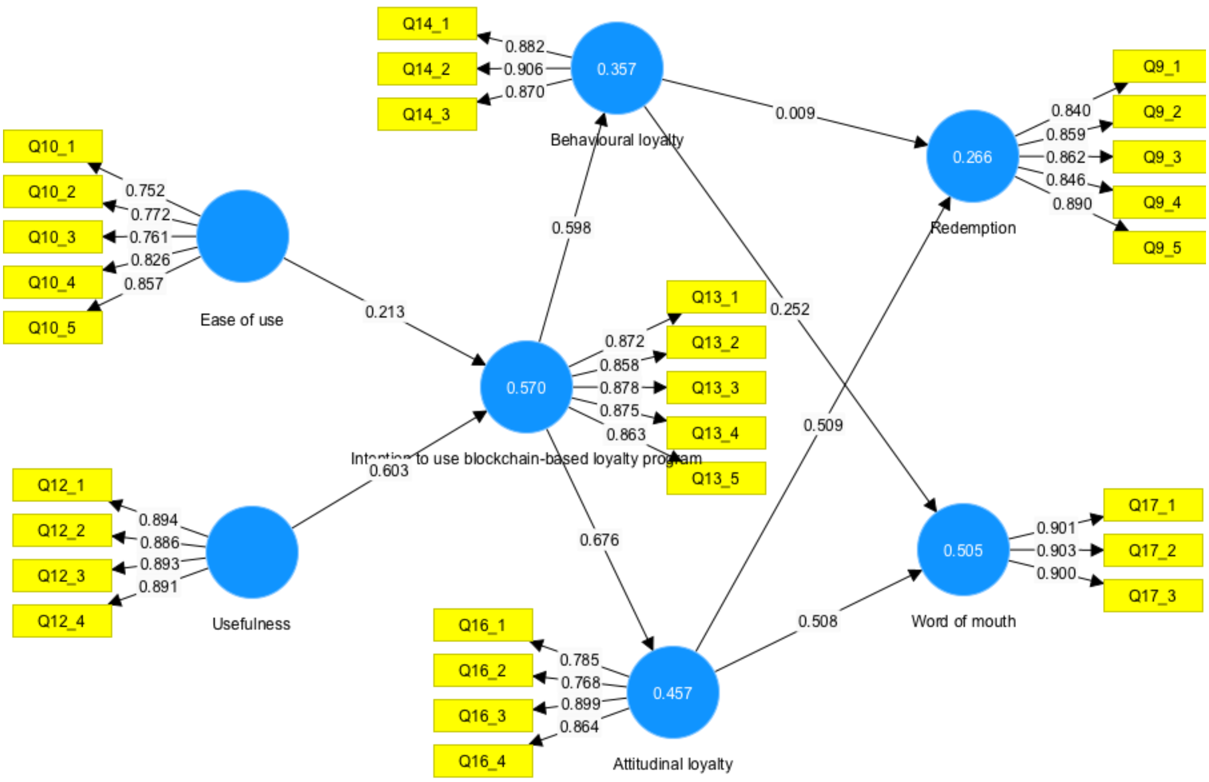

Figure 15. Structural model

Table 34. Factor loadings

Items relating to	Literature on which the items were based	Items	Notation	Factor Loading
PEOU	Miltgen et al. (2013)	I don't think it would be hard to use a Blockchain-based Loyalty Program	Q10_1	0.752
		Using a Blockchain-based Loyalty Program would likely require minimum of effort	Q10_2	0.772
		It would be easy to get a Blockchain-based Loyalty Program to do what you want it to do	Q10_3	0.761
		Learning to use a Blockchain-based Loyalty Program would be easy for me	Q10_4	0.826
		I would find a Blockchain-based Loyalty Program easy to use	Q10_5	0.857

PU	Choe and Noh (2018)	Using a Blockchain-based Loyalty Adapted Program would be useful in my daily life	Q12_1	0.894
		Using a Blockchain-based Loyalty Program would make my daily life more efficient	Q12_2	0.886
		Using a Blockchain-based Loyalty Program would make my loyalty reward experience more efficient	Q12_3	0.893
		Using a Blockchain-based Loyalty Program would make my loyalty reward experience more useful	Q12_4	0.891
Behavioural intention to use a BBLP	Miltgen et al. (2013)	I would sign-up for a Blockchain-based Loyalty Program as soon as possible	Q13_1	0.872
		I would use a Blockchain-based loyalty Program soon after it is launched	Q13_2	0.858
	Choe and Noh (2018)	I will use a Blockchain-based Loyalty Program in the future.	Q13_3	0.878
		I will try to use a Blockchain-based Loyalty Program.	Q13_4	0.875
		I am willing to use a Blockchain-based Loyalty Program.	Q13_5	0.863
Behavioural loyalty	Liu et al. (2019)	A Blockchain-Based Loyalty Program would be my first choice compared to other loyalty programs	Q14_1	0.882
	Sharifi and Esfidani (2014)	As long I was offered a Blockchain-Based Loyalty Program, it is unlikely that I would opt for another loyalty program.	Q14_2	0.906
		I would rarely consider using another type of loyalty program, if I could use a Blockchain-Based Loyalty Program	Q14_3	0.870
Attitudinal loyalty	Horppu et al. (2008)	I would pay more attention to a Blockchain-Based Loyalty Program than another type of loyalty program	Q16_1	0.785
	Ashley et al. (2016)	I am less likely to shop at stores that don't offer a Blockchain-based loyalty program.	Q16_2	0.768
		I would shop at stores that offer a Blockchain based loyalty program more frequently.	Q16_3	0.899
		I am more likely to shop at stores that offer a Blockchain-Based Loyalty program because the benefits I would receive	Q16_4	0.864
WoM	Casaló et al. (2008)	I will point out positive aspects of a Blockchain-based Loyalty Program if anybody criticises it.	Q17_1	0.901
	Choi et al. (2014)	I would say positive things about a Blockchain-based loyalty program.	Q17_2	0.903
		I would try spread the word about Blockchain-based loyalty programs	Q17_3	0.900
Redemption	Nayal and Pandey (2020)	I will probably redeem the points I gain from a Blockchain-based Loyalty program.	Q9_1	0.840
		I will use the points I gain on a Blockchain-based Loyalty program if I find something I want to use them on.	Q9_2	0.859
		I would redeem my points I gain from a Blockchain-based Loyalty program for discounts.	Q9_3	0.862
	Achadinha et al. (2014)	Redeeming points gain on a Blockchain-based Loyalty program make me feel good.	Q9_4	0.846

		I would redeem points gained on a Blockchain-based Loyalty program.	Q9_5	0.890

Convergent validity is when a construct correlates with the items used to measure it (Kamble et al., 2019). For example, it will indicate whether the items used to measure innovativeness are in fact measuring it. This means that a high amount of variance should be present when the indicators of a construct are analysed. Cronbach's alpha and composite reliability were used to measure convergent validity. When using PLS-SEM, Cronbach's alpha is the lower bound, whereas composite reliability is the upper bound, meaning that the actual reliability is somewhere between the value for Cronbach's alpha and the composite reliability (Sarstedt et al., 2021). When using composite reliability, the higher the value the higher the level of reliability (Sarstedt et al., 2021). The value for composite reliability should be between 0.7 and 0.95 to be indicative of good reliability levels. A cut-off of 0.7 for both composite reliability and Cronbach's alpha is acceptable in PLS-SEM research (Hair et al., 2017). Table 35 indicates that each construct has both a composite reliability and Cronbach's alpha, indicating sufficient reliability.

Table 35. Convergent validity and composite reliability

Constructs	AVE	Composite Reliability	Cronbach's Alpha
PEOU	0.631	0.895	0.854
PU	0.794	0.939	0.913
Behavioural intention to use a BBLP	0.755	0.939	0.919
Behavioural loyalty	0.785	0.917	0.865
Attitudinal loyalty	0.690	0.899	0.850
WoM	0.813	0.929	0.885
Redemption	0.739	0.934	0.912

Validity

PLS-SEM uses the average variance extracted (AVE) to measure convergent validity. Convergent validity is the *"extent to which a construct converges in its indicators by explaining the items' variance*" (Hair et al., 2022). The AVE must exceed 0.50 to be sufficient (Bagozzi & Yi, 1988; Hair et al., 2022; Pallant, 2000). This is because a value of 0.50 is indicative that the mean values of the factor loadings of the various items are higher than 0.708, which shows that variances of items and their constructs are meaningful (Hair et al., 2022). Table 35 shows that the AVE for each construct exceeds 0.5, establishing sufficient convergent validity.

Discriminant validity examines whether constructs are sufficiently unrelated to each other. To measure discriminant validity, the square root of the AVE of each construct is compared to the correlation it has with other constructs (Fornell-Larcker criterion). The square root of the AVE for each construct should be higher than its correlation with other constructs to indicate sufficient discriminant validity (Fornell & Larcker, 1981). The results are shown in Table 36 and indicate that diagonal values (square roots of AVE) are higher than the off-diagonal values, establishing sufficient discriminant validity according to the Fornell-Larcker criterion.

The Fornell-Larcker criterion has been criticised, sometimes viewed as performing poorly, especially when indicator loadings only have a slight variation (Henseler et al., 2015). To address this, the heterotrait-monotrait (HTMT) ratio was proposed as an alternative and superior method to the Fornell-Larcker criterion (Henseler et al., 2015). The HTMT is the "*mean value of the item correlations across constructs relative to the (geometric) mean of the average correlations for the items for item measuring the same construct*." (Hair et al., 2019). The Fornell-Larcker criterion shows the extent to which a construct explains the variance of its own indicators compared to the variance of others (Hair et al., 2022). For the HTMT ratio, the values should be below 0.9 to indicate sufficient discriminant validity (Henseler et al., 2015). The results for the HTMT ratio are shown in Table 37 and are below 0.9, indicative of sufficient discriminant validity.

Table 36. Discriminate validity values - Fornell-Larcker criterion

	ATTL	BEHL	EASE	USE	REDEM	USEFUL	WoM
ATTL	0.831						
BEHL	0.719	0.886					
EASE	0.478	0.453	0.794				
USE	0.676	0.598	0.589	0.869			
REDEM	0.516	0.375	0.469	0.630	0.859		
USEFUL	0.662	0.585	0.623	0.736	0.579	0.891	
WoM	0.689	0.617	0.465	0.690	0.555	0.646	0.901

Note: ATTL: Attitudinal loyalty; BEHL: Behavioural loyalty; PEOU: Perceived ease of use; PU: Perceived usefulness; USE: Behavioural intention to use blockchain technology;

REDEM: Redemption; WoM: Word-of-mouth

Table 37. Discriminate validity - HTMT

	ATTL	BEHL	EASE	USE	REDEM	USEFUL	WoM
ATTL							
BEHL	0.843						
EASE	0.550	0.513					
USE	0.753	0.657	0.660				
REDEM	0.566	0.410	0.528	0.688			
USEFUL	0.744	0.651	0.700	0.802	0.631		
WoM	0.789	0.699	0.533	0.764	0.614	0.719	

Note: ATTL: Attitudinal loyalty; BEHL: Behavioural loyalty; PEOU: Perceived ease of use; PU: Perceived usefulness; USE: Behavioural intention to use blockchain technology; REDEM: Redemption; WoM: Word-of-mouth

Results of structural equation model

Collinearity

Collinearity was assessed because path coefficients in PLS-SEM are based on ordinary least squares regression of endogenous constructs in relation to their predictor constructs (Hair et al., 2021). Path coefficients can be biased if there are high levels of collinearity for the predictor constructs (Hair et al., 2021). Collinearity is measured using the variance inflation factor (VIF). Values for collinearity should be below 5. Table 38 shows that all the VIF values are below the threshold of 5.

Common method bias can be assessed through VIF, according to the method suggested by Kock (2015). This involves the creation of a new variable with random values, and creating a model where all the latent variables point to this random variable. Table 39 shows that all the VIF values are below 3.3 and can thus be considered free of common method bias (Kock, 2015).

Table 38. VIF values

	ATTL	BEHL	EASE	USE	REDEM	USEFUL	WoM
ATTL					2.067		2.067
BEHL					2.067		2.067
EASE				1.636			
USE	1.000	1.000					
REDEM							
USEFUL				1.636			
WoM							

Note: ATTL: Attitudinal loyalty; BEHL: Behavioural loyalty; PEOU: Perceived ease of use; PU: Perceived usefulness; USE: Behavioural intention to use blockchain technology; REDEM: Redemption; WoM: Word-of-mouth

Table 39. VIF values from assessment of common method bias

	VIF
ATTL → Random	2.925
BEHL → Random	2.409
EASE → Random	1.058
USE → Random	2.818
REDEM → Random	1.700
USEFUL → Random	2.470
WoM → Random	2.332

Note: ATTL: Attitudinal loyalty; BEHL: Behavioural loyalty; PEOU: Perceived ease of use; PU: Perceived usefulness; USE: Behavioural intention to use blockchain technology; REDEM: Redemption; WoM: Word-of-mouth

Significance and relevance of structural model relationships

After evaluating collinearity, the structural model must be examined, which shows the proposed hypotheses. This was done using PLS-SEM and a procedure called bootstrapping. Bootstrapping involves many random subsamples from the original data, which are used to estimate the PLS path model (Wong et al., 2013). This study used 5000 subsamples, as recommended by Sarstedt et al. (2017). The structural model has seven latent variables and 29 variables. The 29 variables acted as indicators for the eight latent variables. At a significance level of 0.05 and using a two-tailed test, a t-value greater than 1.96 means that the path coefficient is significant (Wong et al., 2013). Table 40 indicates which hypotheses were rejected and accepted based on the PLS-SEM analysis.

Path coefficients should be between -1 and +1, and path coefficients greater than -1 or +1 are not acceptable (Hair et al., 2021). A path coefficient close to -1 indicates a strong negative relationship, whereas a path coefficient close to 1 is indicative of a strong positive relationship. Table 40 shows all the path coefficients to be acceptable and between -1 and +1. Notably, all the path coefficients are positive except for innovativeness and perceived use, as well as perceived value and perceived ease of use. Strong relationships are exhibited between perceived usefulness and perceived ease of use, as well as relative advantage with perceived usefulness.

Table 40 reveals that all the hypothesised relationships except those related to behavioural loyalty and redemption have been accepted. Specifically, the well-studied relationship between PEOU and PU and the behavioural intention to use technology was valid in a blockchain-loyalty context. Adding to the scarce literature on loyalty-acceptance relationships, especially those that view loyalty as a two-dimensional construct, a relationship between behavioural and attitudinal loyalty and the behavioural intention to use technology was empirically validated. Lastly, relationships between behavioural and attitudinal loyalty and WoM intentions were validated. Adding a new lens to the scarce literature on redemption-loyalty relationships, this study validated a relationship between attitudinal loyalty and redemption.

The path or beta coefficient can be used to enhance the interpretation of the accepted hypotheses, as it describes the strength of the relationship between the independent or predictor variable and the dependent variables. For example, of all the predictor variables, it is notable that attitudinal loyalty significantly affected WoM more than behavioural loyalty. Similarly, the PU of a BBLP was a far more considerable influencer on behavioural intentions to use technology than PEOU.

PU has a strong and significant effect on the behavioural intention to use a BBLP ($\beta = 0.603$, $p < 0.001$), confirming its central role in driving adoption intentions. Similarly, strongly predicts both behavioural loyalty (($\beta = 0.598$, $p < 0.001$) and attitudinal loyalty ($\beta = 0.676$, $p < 0.001$), demonstrating that actual usage fosters loyalty at both behavioural and attitudinal levels.

In terms of outcomes, attitudinal loyalty shows a strong relationship with WoM (β = 0.508, $p < 0.001$) and redemption (β = 0.509, $p < 0.001$), suggesting that loyalty driven by positive attitudes leads to greater advocacy and engagement in redemption activities. Conversely, behavioural loyalty has a smaller but still significant effect on WoM (β = 0.252, $p < 0.001$) and no significant impact on Redemption (REDEM) (β = 0.009, $p = 0.853$).

Table 40. Results of SEM

H	Hypothesised Relationship	Path Coefficient	T-Value	P-Value	Hypothesis
H1a	PEOU→USE	0.213	5.755	0.000	Accepted
H1b	PU→USE	0.603	16.224	0.000	Accepted
H2a	USE→BEHL	0.598	26.361	0.000	Accepted
H2b	USE→ATTL	0.676	23.164	0.000	Accepted
H3a	BEHL→WoM	0.252	5.878	0.000	Accepted
H3b	ATTL→WoM	0.508	12.176	0.000	Accepted
H4a	BEHL→REDEM	0.009	0.185	0.853	Rejected
H4b	ATTL→REDEM	0.509	10.756	0.000	Accepted

Note: ATTL: Attitudinal loyalty; BEHL: Behavioural loyalty; PEOU: Perceived ease of use; PU: Perceived usefulness; USE: Behavioural intention to use blockchain technology; REDEM: Redemption; WoM: Word-of-mouth

Explanatory power of the model

Following an examination of the structural model relationships, the next step is to analyse the coefficient of determination (R^2) to determine the model's explanatory power. The coefficient of determination measures the degree of association between two variables and their relative strength. It shows the in-sample predictive power of the model and not the out-of-sample or predictive power of the model (Hair et al., 2021).R^2 ranges from 0 to 1, with a higher value being better. For marketing research, the coefficient of determination should be at least 0.25 (Wong et al., 2013). As a guideline, the values 0.75, 0.50 and 0.25 correspond to strong, moderate, and weak effects (Hair et al., 2021).

The R^2 value is 0.457 for attitudinal loyalty. This indicates that the variation in the behavioural intention to use a BBLP weakly explains 46% of the variation in attitudinal loyalty. For behavioural loyalty, 36% of the variation is weakly explained by the variation in the intention to use a BBLP. Further, 57% of the variation in the behavioural intention to use a BBLP is moderately explained by PU and PEOU. Redemption exhibited a weak effect, and 27% of its variance is explained by changes in behavioural and attitudinal loyalty. Lastly, word-of-mouth exhibited a moderate effect, and 51% of its variance is explained by variations in attitudinal and behavioural loyalty. As all the values for R^2 exceed 0.25, the explanatory power of the model is sufficient and is in the moderate range.

Table 41. Coefficients of determination

	R^2
ATTL	0.457
BEHL	0.357
USE	0.570
REDEM	0.266
WoM	0.505

Note: ATTL: Attitudinal loyalty; BEHL: Behavioural loyalty; USE: Behavioural intention to use blockchain technology; REDEM: Redemption; WoM: Word-of-mouth

$PLS_{predict}$ was used to assess the out-of-sample predictive power of the model. This indicates the model's ability to accurately forecast future observations (Hair et al., 2021). $PLS_{predict}$ uses k-fold cross-validation. A fold represents a subset within the complete sample, where 'k' denotes the quantity of these subsets (Hair et al., 2021). Essentially, the entire dataset undergoes random division into 'k' equally proportioned segments of data (Hair et al., 2021). To understand the predictive power, the focus should be given to metrics that measure the amount of prediction error relating to endogenous constructs (Hair et al., 2021). The root-mean-square error (RSME) and mean-absolute-error (MAE) are useful for understanding predictive error (Hair et al., 2021). The RSME calculates the square root of the mean of the squared variances between the predicted values and the observed data (Hair et al., 2021). MAE evaluates the average size of the errors in a set of predictions, disregarding their directionality (whether they overestimate or underestimate) (Hair et al., 2021). In most cases, researchers should use the RSME, unless the prediction error distribution is non-symmetric (Hair et al., 2021).

The linear regression model (LM) benchmark should be compared to the RSME or MAE metric to determine the model's predictive power (Hair et al., 2021). If all the indicators' LM values are lower than the RMSE or MAE values, the model has high predictive power (Hair et al., 2021). If the majority or same number of indicators have smaller RSME or MAE values than the corresponding LM values, then the model has medium predictive power (Hair et al., 2021). If the minority of indicators have smaller RSME or MAE values compared to the LM values, the model has low predictive power (Hair et al., 2021). If none of the indicators has a lower RSME or MAE value than the LM model value, it lacks predictive power (Hair et al., 2021). Q^2 or the indicator mean of the holdout sample can be used to understand whether the predictions utilising PLS-SEM are better than the most naïve benchmark (Sarstedt et al., 2021). If Q^2 is greater than 0, the path model outperforms the most naïve benchmark (Sarstedt et al., 2021).

Table 42: $PLS_{predict}$ results

MV Prediction Summary	Q²predict	PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE
ATTL_1	0.255	0.853	0.692	0.842	0.676
ATTL_2	0.200	0.995*	0.821	0.980	0.801
ATTL_3	0.343	0.756	0.594	0.746	0.576
ATTL_4	0.334	0.746	0.569	0.735	0.550
BEHL_1	0.321	0.792	0.643	0.765	0.616
BEHL_2	0.240	0.891	0.731	0.877	0.711
BEHL_3	0.204	0.952	0.777	0.943	0.763
USE_1	0.439	0.709*	0.548	0.713	0.549
USE_2	0.428	0.733*	0.562	0.738	0.563
USE_3	0.466	0.588*	0.440	0.591	0.438
USE_4	0.400	0.614*	0.453	0.615	0.455
USE_5	0.392	0.607	0.449	0.605	0.444
REDEM_1	0.171	0.649	0.544	0.614	0.483
REDEM_2	0.162	0.670	0.546	0.641	0.490
REDEM_3	0.174	0.659	0.547	0.633	0.507
REDEM_4	0.180	0.723	0.595	0.689	0.550
REDEM_5	0.200	0.660	0.541	0.619	0.474
WoM_1	0.260	0.789	0.608	0.767	0.590
WoM_2	0.278	0.706	0.542	0.678	0.526
WoM_3	0.293	0.798	0.626	0.751	0.577

Note: ATTL: Attitudinal loyalty; BEHL: Behavioural loyalty; USE: Behavioural intention to use blockchain technology; REDEM: Redemption; WoM: Word-of-mouth

Table 42 shows that all the indicators have Q^2 values larger than zero, which means the PLS path model outdoes the most naïve benchmark. Comparing the RSME values with the LM values shows that all the indicators besides five (ATTL_2, USE_1, USE_2, USE_3, USE_4) have lower LM values than their corresponding RSME values. This indicates that the model has low or weak predictive power, according to the interpretation of Hair et al. (2021).

Discussion of results

First, this study significantly contributes to the existing body of literature in several ways. For one, this is the first study that proposes an integrated model incorporating technology, acceptance, loyalty, and firm outcomes. This novel model also explains the technological journey of a new loyalty technology, from acceptancy to intention to use, to loyalty creation, and finally to creating critical firm outcomes in a loyalty context: WoM and redemption. Furthermore, this model may have applicability to any new technology when the ultimate goals are loyalty, redemption, and WoM. Moreover, after analysing this model using structural equation modelling, all the hypothesised connections were empirically validated, except for the relationship between behavioural loyalty and redemption.

The in-sample predictive power was in the weak to moderate range, whereas the out-of-sample predictive power was in the low range. This means the model was slightly better at explaining data within the dataset, than new unseen data (for some constructs). This indicates that the model does not completely capture the wide range of factors and relationships that effect the intention to use a BBLP, behavioural loyalty and attitudinal loyalty. This is not unexpected, given the newness and lack of research focusing on the study: BBLP. These programmes only emerged around 2017 (Abooleet & Kinnett, 2023), and the literature still needs to catch-up.

This model was a first attempt at understanding the factors that influence the uptake and intention to use a BBLP, behavioural loyalty, and attitudinal loyalty in a blockchain context. Iteration is required to improve and understand their relationships more deeply. The model strived for simplicity, and only one to two constructs were used to explain the variance in behavioural loyalty, attitudinal loyalty, WoM and redemption. This impacted the predictive and explanatory power of the model and may have led to the model being oversimplistic.

Additionally, the use of convenience sampling may have limited the generalisability of the findings, which may have led to the low out-of-sample predictive power.

Second, PEOU and PU has been found to influence the intention to use cryptocurrency (Sohaib et al., 2019), blockchain-based research-sharing frameworks (Shrestha & Vassileva, 2019), cryptocurrency transactions (Taheri Tolu et al., 2022), cryptocurrency payments (Guych et al., 2018), and blockchain technology (Kamble et al., 2019; Liu et al., 2021). The TAM suggests a user's attitude towards a given technology affects the behavioural intention to use the new technology. The findings of this study show that user attitudes expressed as perceptions of usefulness and ease of use affect the behavioural intention to use blockchain-based loyalty programmes as well. This adds to the growing body of literature which supports the applicability of the TAM to a blockchain-loyalty context and is one of the very few studies that have empirically examined the direct effect of both PEOU and PU on behavioural intentions in a blockchain context (Dirsehan, 2020; Folkinshteyn & Lennon, 2016; Knauer & Mann, 2019).

Thirdly, the intention to use a BBLP was found to influence behavioural and attitudinal loyalty. One-dimensionally, loyalty has been shown to influence use by several authors (Agag et al., 2019; Bouagina & Triki, 2013; Martinez-Caro et al., 2013). However, how attitudinal and behavioural loyalty affect use can be described as practically non-existent. Illuminating the relationship between use and a two-dimensional conception of loyalty is thus a crucial contribution that this study makes to the discourse on loyalty and its link to acceptancy models. This reflects that, once consumers decide to use technology, they also exhibit loyalty towards this new technology. This finding aligns with TAM, which suggests that behavioural intentions are strong predictors of actual behaviour. These findings show that a user's intention to use a programme is a precursor to behavioural engagement and positive attitudes towards a firm. The finding underscores the importance of user perception and attitude formation in shaping loyalty outcomes. Users' perceptions of the BBLP, including its perceived usefulness, ease of use, and perceived value, play a critical role in shaping their intention to use the programme, which in turn influences their subsequent loyalty behaviours and attitudes.

Fourthly, a relationship between both behavioural and attitudinal loyalty with WoM was confirmed in the data analysis. The link between behavioural loyalty and WoM is supported by self-perception theory, which means that people view themselves as helpful when promoting BBLPs to others (Garnefeld et al., 2011). Overall, the link between loyalty and WoM is supported by authors in other contexts (Akbari et al., 2016; Liao et al., 2010; Roy et al., 2009). However, when viewed as a two-dimensional construct, this study's vital contribution demonstrates the relationship between WoM and both behavioural and attitudinal loyalty. Studies that examine attitudinal and behavioural dimensions of loyalty and WoM can be described as extremely limited. One study focusing on online shoppers supported a relationship between attitudinal loyalty and WoM and did not examine behavioural loyalty (Peña-García et al., 2018). WoM has been investigated one-dimensionally as an outcome of loyalty (De Matos & Rossi, 2008; Wong et al., 2015). Despite few studies examining the relationship between attitudinal loyalty and WoM, this study has shown it to be a far more significant influence of WoM intentions by consumers, indicating the importance of these findings. This reemphasises the importance of measuring loyalty as an attitude and a behaviour. It indicates that users who are both behaviourally and emotionally committed are more likely to advocate BBLP to others.

Lastly, redemption was a unique construct proposed in this study and one specific to LPs, adapting the model proposed by Watson et al. (2015), which focused on performance. As mentioned before, with LPs, redemption is a crucial objective for firms that launch and develop these programmes, as low redemption means low activity and wastage for firms. This highlights the importance of models that examine redemption as a specific firm outcome for loyalty. The proposed relationship between attitudinal loyalty and redemption was confirmed. This suggests that attitudes play a critical role in a user's decision-making process for redeeming rewards. This is an essential contribution to understanding firm outcomes for LPs. It supports the qualitative study of Smith and Sparks (2009), which is the only study focusing on redemption as a firm outcome.

The relationship between redemption and behavioural loyalty was not supported. This appears to be counterintuitive at first. One might expect that customers who act in a way that favours a brand would be more likely to act and redeem accumulated loyalty points to demonstrate their loyalty. However, the lack of relationship between redemption and loyalty may be indicative that customers do not prioritise redeeming the rewards they collect. Customers may not prioritise redemption for several reasons. They may find that rewards offered by a BBLP have a low perceived value, or they may simply perceive redeeming the rewards offered by a BBLP to be confusing or complicated to do. These findings do support statistics showing problems with redemption. For example, redemption rates are as low as 13.6% globally and 14% in South Africa (Yang et al., 2019). The video description of how these rewards could be redeemed in a BBLP may have been too simplistic, complicated or both, adding to a breakdown in the relationship between behavioural loyalty and redemption.

Theoretical implications

This study is the first to examine loyalty creation in a blockchain-loyalty context. For the first time, a combined loyalty-acceptancy theoretical model is proposed and examined empirically. To date, satisfaction-loyalty models which incorporate the TAM have been proposed. Still, a comprehensive examination of the link between behavioural and attitudinal loyalty and behavioural intentions to use new technology has not been attempted. Although the explanatory power of the model can be described as low, this makes an important, early contribution to the literature examining a loyalty-acceptance model in a blockchain-loyalty context, which can be iterated on.

It is crucial to view loyalty as having attitudinal and behavioural components and to understand their effect and how other variables affect them. Seeing loyalty as a single construct can lead to misleading results and it should be separated (Kamran-Disfani et al., 2017; Watson et al., 2015), and researchers have started to validate that it is multi-dimensional (Cifci & Erdogan, 2016). As mentioned before, literature focusing on how use effects attitudinal, and behavioural loyalty can be described as practically non-existent. There is also limited literature examining the effect of behavioural loyalty on WoM and redemption (Perez et al., 2020; Smith & Sparks, 2009). This study thus makes an important theoretical contribution by adding to the limited literature examining these relationships.

As a key contribution, this study proposed redemption as a construct that should be used when examining BBLPs, as it is a problem and key goal for firms who operate LPs. Examining redemption is important, as it has been suggested that redemption rates are as low as 13.6% globally and 14% in South Africa (Yang et al., 2019). These low redemption rates increase the firm’s liabilities, potentially harming the financial health of the company. Further, those who do not redeem rewards have been found to be less loyal to the brand (Fromhart & Therattil, 2016; Bond Brand Loyalty, 2016). Since they are less loyal, the consumer is also less likely to recommend the brand, and remain loyal after a bad experience (KPMG, 2019). It has been observed that as many as 50% and 70% of LP benefits do not get redeemed (Bijmolt et al., 2011).

This is a theoretical extension of the model proposed by Watson et al. (2015), which focused on performance. Illuminating the relationship between use and a two-dimensional conception of loyalty is thus a crucial contribution that this study makes to the discourse on loyalty and its link to acceptancy models. This reflects that, once consumers decide to use technology, they also exhibit loyalty towards this new technology.

Managerial implications

First, the findings of this study have significant managerial implications for companies investigating the adoption of BBLP or companies interested in developing blockchain solutions relating to LPs. This study validates that these programmes' PEOU and PU drive the intention to use BBLPs. This implies that consumers who view BBLPs as being easy to use and offering them a high utility will probably use a BBLP. To action this, managers can focus on designing user interfaces that are easy to understand, and offer features aligned with customers' needs and preferences. This could mean investing in user-experience testing and continually gathering feedback from end-users. Marketing campaigns positioning a BBLP as easy to use and written in simple language could also be used to increase the usage intentions of costumers.

Second, intention to use a BBLP was found to influence behavioural and attitudinal loyalty. Since loyalty is a key goal of LPs, managers should focus on programmes that encourage and promote the adoption of BBLP among customers. This could involve marketing campaigns that highlight the benefits of these programmes, and the offering of incentives to drive an initial engagement in the BBLP. For example, the benefits of tokenisation could be highlighted. The tokenisation of loyalty points allows consumers to track and store points more efficiently, freeing them from a disjointed loyalty network (Rejeb et al., 2020), and eliminates the need for consumers to search for each programme's options, limitations, and redemption rules (Udegbe, 2017). Additionally, marketing initiatives that foster a positive attitude towards a BBLP could be used through transparent communication and the realisation of promised benefits, which can help solidity customer loyalty over time.

Thirdly, behavioural and attitudinal loyalty was found to influence WoM. This suggests that marketing managers should foster strong relationships with their most loyal customers and encourage (and even reward) positive recommendations and referrals. Practically, a firm could implement a loyalty reward scheme for customers who refer others and gather feedback and testimonials to showcase the benefits of participation in a BBLP.

Fourthly, it has been suggested that redemption rates are as low as 13.6% globally and 14% in South Africa (Yang et al., 2019). These low redemption rates increase the firm's liabilities, potentially harming the financial health of the company. Further, those who do not redeem rewards have been found to be less loyal to a company which offers a LP (Fromhart & Therattil, 2016; Bond Brand Loyalty, 2016). Since they are less loyal, the consumer is also less likely to recommend the brand and remain loyal after a bad experience (KPMG, 2019). It has been observed that as many as 50% and 70% of LP benefits do not get redeemed (Bijmolt et al., 2011). The lack of redemption limits how effectively an LP can increase spending through breaking down the point-pressure mechanism. Through a point-pressure mechanism, when the consumer's points balance is low, consumers are internally motivated to accumulate points for rewards in the future and spend more doing so (Bijmolt et al., 2011).

Lastly, since only attitudinal loyalty was found to influence redemption, managers should instead focus on creating positive perceptions towards BBLPs, if redemption is a key goal or problem their BBLP faces. This could be aided by initiatives which enhance perceived rewards, making redemption easier. The customers who advocate and display high levels of attitudinal loyalty should be capitalised on, to encourage redemption behaviour through incentives and promotions. As mentioned before, it is important for managers to keep in-mind that mere participation in a BBLP does not guarantee increased redemption rates, and users who are actively engaged with a BBLP may not make redemptions. Often there is a focus on participation. This means usage and participation rates should be carefully examined to determine if they are leading to actual redemption.

Limitations

This study is subject to limitations stemming from its utilisation of a non-probability sampling technique, specifically convenience sampling. As mentioned, convenience sampling involves selecting sampling units based on their accessibility or immediate availability to the researcher. Consequently, generalisability to the broader population becomes challenging. Additionally, limitations may arise from data collection through an online survey. Potential issues include the presence of fraudulent responses and the fact that online populations may not accurately represent the demographics of the country. These factors necessitate careful consideration when conducting studies using online surveys (Lefever et al., 2007).

The literature debates whether the intention to use a technology is translated into actual use. This means that a limitation of the study is that actual use was not examined. Prior studies have shown that intended use does not predict actual use (Sarmah et al., 2021; Tao, 2009). However, these inconsistencies may have been caused by inconsistences in self-reported usage in surveys which can be biased, relative and unrepresentative of actual usage (Tao, 2009). Other studies have shown that the behavioural intention can predict actual usage (Barry & Jan, 2018; Hassler et al., 2022; Kurniasih et al., 2020; Tarhini et al., 2013). After a systematic literature review focused on the question of whether intention translated into actual usage, Turner et al. (2010) found that intention is likely to predict usage.

Respondents answered the survey items based on a knowledge of BBLPs provided in a video and text description. It is also unlikely they had prior experience with the technology, given its newness. A lack of actual experience with the technology can affect the results of the TAM (Turner et al., 2010). This approach may limit the applicability of the findings to a real-world BBLP which may contain some but not all the features described in the video. Further studies should examine the appropriateness of blockchain-loyalty solutions by presenting respondents with a real-world application of this technology. Studies focusing on the actual usage of a blockchain-based loyalty programme were not found, although measurement of actual usage has been proposed by Lou and Li (2017). Usage can be measured objectively or subjectively through actual logs of usage or self-reported usage (Turner et al., 2010). Investigating usage using either method would add to the limited literature on the topic. Further studies should examine the appropriateness of blockchain-loyalty solutions by presenting respondents with a real-world application of this technology. Actual blockchain-loyalty solutions may contain some but only some of the critical features theorised to benefit both companies and businesses.

Conclusion

This study makes a significant theoretical contribution to understanding acceptance, loyalty, and firm outcomes generated by BBLPs, by creating an integrated model. This is based on the well-researched TAM and a conceptual loyalty-outcome model based on Watson et al. (2015) but adapted to focus on LPs.

This model confirmed the applicability of the technology-acceptance model to a blockchain context, adding to a growing body of literature that is currently under-researched, particularly in an empirical sense. In addition, it provided insight into the relationship between loyalty generation and the behavioural intention to use a BBLP. Attitudinal and behavioural loyalty were related to the intent to use a BBLP. This added to the minimal literature on the relationship between loyalty as a two-dimensional construct, with behavioural intentions exhibited by consumers. Adding further to the minimal literature examining loyalty as a two-dimensional construct, behavioural loyalty influenced consumers' redemption and WoM intentions. Attitudinal loyalty was shown only to influence WoM, but not redemption. Redemption is often included in investigations of firm outcomes derived from loyalty. This is the first study to examine its relationship with behavioural and attitudinal loyalty. This study aims to inspire further research into blockchain LPs, especially from a two-dimensional loyalty perspective, focusing on the essential firm outcome, redemption.

Chapter 7: Conclusions and Recommendations

Introduction

In this final chapter, the findings from all three studies and their interrelationship are presented. First, how the thesis addresses the primary and secondary research objectives is discussed. Thereafter, the chapter will focus on the contributions and implications. Overleaf, Figure 16 depicts the results from studies One to Three. These results are also depicted in Table 43. The numerical values are the t-values at a significance level of 0.05. The red arrows show relationships that were unsupported, whereas the green arrows show relationships that were supported. Notably, the behavioural intention to use a BBLP was examined in both studies One and Three, which is the reason for the two sets of t-values. Similarly, the behavioural intention to use BBLP was examined as an antecedent to the generation of behavioural and attitudinal loyalty. The opposite relationship was also examined (behavioural and attitudinal loyalty as antecedents to the behavioural intention to use a BBLP). As can be seen in Figure 16, the model used to examine loyalty, use and firm outcomes as they relate to a BBLP is complex.

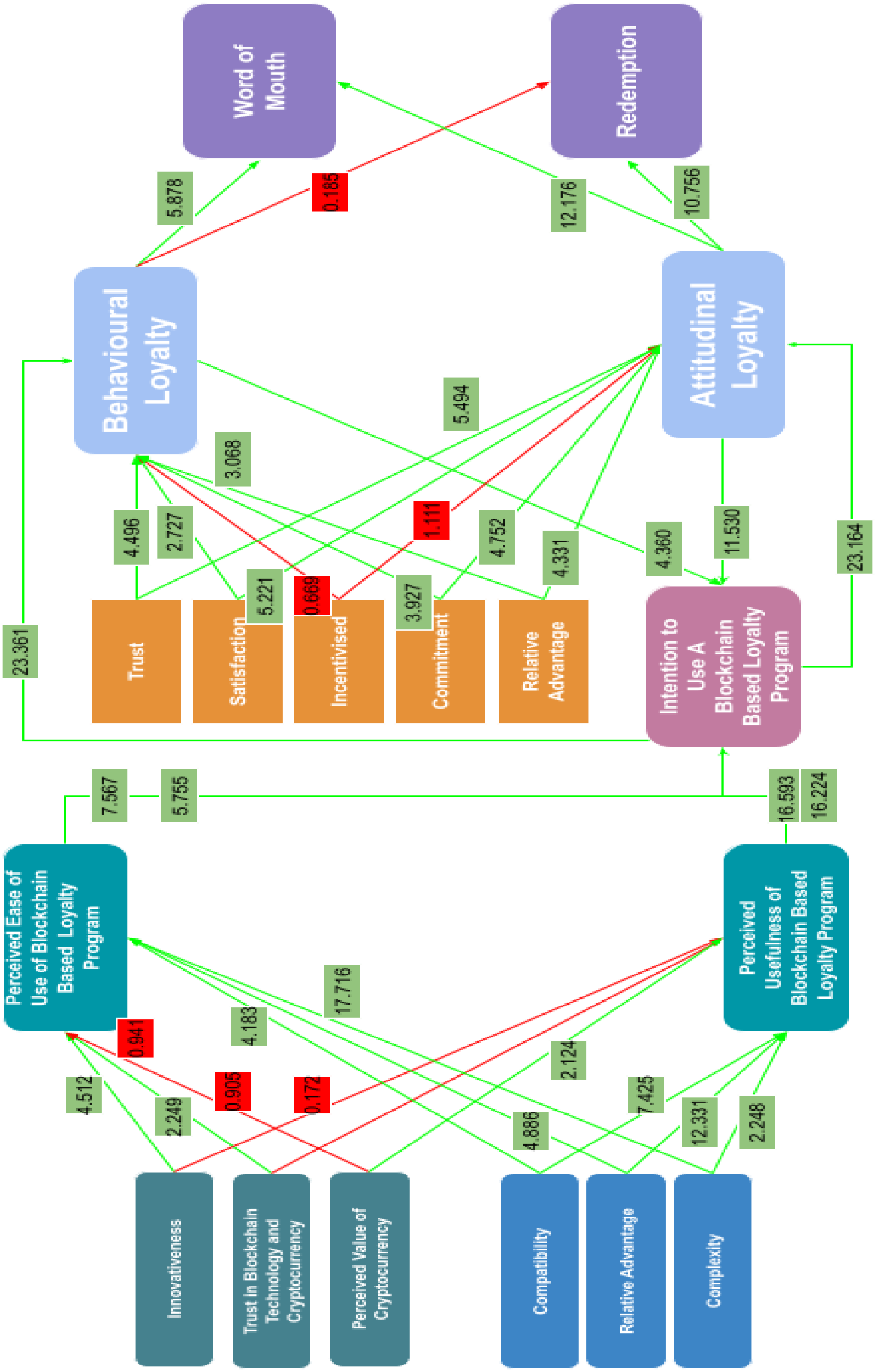

Figure 16. Theoretical model with t-values and supported relationships

Table 43. Results of SEM for all three studies

Hypothesised Relationship	Beta or Path Coefficient	T-Value	P-Value	Hypothesis
Antecedents to PEOU and PU				
INOV→PEOU (H5a)	0.131	4.512	0	Accepted
INOV→PU (H5b)	-0,005	0.172	0.863	Rejected
TRUST→PEOU (H6a)	0.089	2.249	0.025	Accepted
TRUST→PU (H6b)	0,048	0.941	0.347	Rejected
PERC→PEOU (H7a)	-0,031	0.905	0.365	Rejected
PERC→PU (H7b)	0.087	2.124	0.034	Accepted
COMPA→PEOU (H8a)	0.154	4.183	0	Accepted
COMPA→PU (H8b)	0.302	7.426	0	Accepted
RV→PEOU (H9a)	0.165	4.886	0	Accepted
RV→PU (H9b)	0,450	12.311	0	Accepted
COMPL→PEOU (H10a)	-0.563	17.716	0	Accepted
COMPL→PU (H10b)	-0.070	2.248	0.025	Accepted
Antecedents to behavioural and attitudinal loyalty				
COMM→BEHL (H11a)	0.198	3.927	0	Accepted
COMM→ATTL (H11b)	0.217	4.752	0	Accepted
TRUST→BEHL(H12a)	0.205	4.496	0	Accepted
TRUST→ATTL (H12b)	0.222	5.494	0	Accepted
SATSIF→BEHL (H13a)	0.179	2.727	0.006	Accepted
SATISF→ATTL (H13b)	0.313	5.221	0	Accepted
INCENT→BEHL (H14a)	0.033	0.669	0.503	Rejected
INCENT→ATTL (H14b)	0.055	1.111	0.267	Rejected
ADV→BEHL (H15a)	0.244	4.331	0	Accepted
ADV→ATTL (H15b)	0.145	3.068	0.002	Accepted
USE→BEHL (H2a)	0.598	26.361	0.000	Accepted
USE→ATTL (H2b)	0.676	23.164	0.000	Accepted
Firm outcomes (redemption and WoM)				
BEHL→WoM (H3a)	0.252	5.878	0.000	Accepted
ATTL→WoM (H3b)	0.508	12.176	0.000	Accepted
BEHL→REDEM (H4a)	0.009	0.185	0.853	Rejected
ATTL→REDEM (H4b)	0.509	10.756	0.000	Accepted

Antecedents to use (relationship examined twice in Study One and Study Three)				
EASE→USE (H1a)	0,279	7.567	0	Accepted
USEFUL→USE (H1b)	0,604	16.593	0	Accepted
EASE→USE (H1a)	0.213	5.755	0.000	Accepted
USEFUL→USE (H1b)	0.603	16.224	0.000	Accepted
BEHL→USE (H16a)	0.229	4.360	0	Accepted
ATTL→USE (H16b)	0.605	11.530	0	Accepted

Note: INOV: Innovativeness; TRUST: Trust in blockchain technology and cryptocurrency; PERC: Perceived value of cryptocurrency; COMPA: Compatibility; COMPL: Complexity; RV: Relative advantage; PEOU: Perceived ease of use; PU: Perceived usefulness; ATTL: Attitudinal loyalty; BEHL: Behavioural loyalty; COMMIT: Commitment; INCENT: Incentivised; USE: Behavioural intention to use blockchain technology; SATISF: Satisfaction; WoM: Word-of-mouth; REDEM: Redemption

Synopsis of the thesis

This thesis focused on BBLPs and aimed to comprehensively examine what determines their usage, how these programmes may lead to the creation of loyalty, as well as redemption and WoM promotion. Chapter 1 sheds light on current problems relating to LPs by describing the importance of LPs to firms, and how blockchain can transform LPs and add value to both firms and end-users. In this chapter, the purpose and objectives of this thesis were also presented, while Chapter 2 focused on highlighting and examining gaps in the literature relating to the interplay between blockchain, marketing and LPs. To do this, a TCCM review, as well as applications and trends in blockchain-marketing research, were discussed. Ultimately, Chapter 2 culminated in the presentation of hypotheses and a combined acceptance-loyalty-outcome model.

This theoretical model combines several theories. It utilises the TAM and DOI theory to understand the technology acceptance of a BBLP. TAM can be described as more basic, focusing on perceptions, while DOI adds additional complexity to a focus on behaviours by including time as a factor (Khan & Woosley, 2011). Due to the common theoretical foundations and overlap, TAM and DOI can be integrated to obtain better results, which can include a greater perception of how an individual embraces a new technology and confirm each other's validity and reliability (Nezamdoust et al., 2022; Roussou & Stiakakis, 2016). DOI and TAM were combined with a loyalty model proposed by Watson et al. (2015). This provided a convenient and simple model to understand common antecedents to loyalty as a multi-dimensional construct, as well as its outcomes. There is no common approach to understanding and measuring loyalty, with researchers adopting a wide variety of approaches (Bennett & Bove, 2001; Cengiz & Akdemir-Cengiz, 2016; Watson et al., 2015).

Next, Chapter 3 discussed the methodology and research approach used throughout this thesis. More specifically, the chapter focused on the research design, data collection, sampling, questionnaire design, measurement and scaling, and data analysis. The scope and the limitations of the research design were also noted there. Importantly, this thesis utilised convenience sampling and data collected from the researcher's own network, as well as data collected via a market-research agency. PLS-SEM and SmartPLS 4 were used to analyse the data. Chapters 4, 5 and 6 then covered the three studies, which, through empirical examination and online surveys, shed light on the research questions and objectives. Ultimately, this thesis used three different studies because of the complexity of the theoretical model and for practical reasons, as examining the entire theoretical model in one study was deemed impractical because of the sheer number of questions a respondent would need to comprehend and answer.

More specifically, and through Study One, Chapter 4 focused on the technology acceptance of a BBLP and strived to understand the factors which influence the usage of a BBLP. Specifically, Study One focused on understanding the antecedents to the PEOU and PU (two variables instrumental in determining usage intentions). Importantly, through Study One, Chapter 4 proposed two unique constructs: the perceived value of cryptocurrency and trust in blockchain technology and cryptocurrency as antecedents to PEOU and PU. Second, Chapter 5, through Study Two, focused on loyalty and the factors which influence the generation of behavioural and attitudinal loyalty. Through Study Two, Chapter 5 expanded the work of Watson et al. (2015) by suggesting relative advantage as a new antecedent to the generation of behavioural and attitudinal loyalty. A novel relationship was also proposed and examined, namely, the relationships that behavioural and attitudinal loyalty have with the behavioural intention to use a BBLP. Lastly, Chapter 6, through Study Three, examined the link between acceptance, loyalty, and firm outcomes. It examined relationships between loyalty, use and firm outcomes (redemption and WoM).

Ultimately, all together, the studies conducted in chapters 4, 5 and 6 comprehensively examined technology acceptance and loyalty as they relate to a BBLP. Additionally, it examined the link between technology acceptance, loyalty, and firm outcomes. The in-sample explanatory power of all the models was in the moderate range. The out-of-sample explanatory power for all the models was in the weak range, except for the model focusing on loyalty and its antecedents, which was in the moderate range.

Viewed together and not separately, these studies provide additional and important insight into BBLPs. This is possible because some of the relationships and constructs were examined across multiple studies. First, Study One and Study Two show that relative advantage influences the intention to use a BBLP, as well as attitudinal and behavioural loyalty. This underscores the importance of relative advantage when examining a new technology, when alternatives exist and are available to end-users. Second, Study One and Study Two show that trust in blockchain and cryptocurrency were shown to influence the behavioural intention to use a technology, as well as behavioural and attitudinal loyalty. This shows that the underlying technology driving the LP (blockchain), as well as the potential reward (cryptocurrency), influence both loyalty and usage.

Study One and Study Three validated the importance of PEOU and PU and their influence on behavioural intention to use a BBLP. These studies were conducted at different times and using different samples. PEOU and PU are variables derived from the TAM. In the TAM, attitudes are determined by two factors: the PU and PEOU of that technology (Lou & Li, 2017). Together, these results show strong support for TAM and that a user's attitude towards a BBLP affects the behavioural intention to use a BBLP. Lastly, the intention to use a BBLP was examined as an antecedent to loyalty, and loyalty was also examined as an antecedent to the intention to use a BBLP. Both relationships were found to be valid; this shows the multifaceted nature of the relationship between technology acceptance and loyalty. The implications and contributions of the findings of this thesis are discussed in detail later in this chapter.

Addressing the research objectives

Table 44 shows how this thesis addresses the four objectives and four research questions which were the focus of this thesis. As can be seen in the table, this thesis has comprehensively addressed the research questions and confirmed several of the proposed relationships. The contributions and implications of the findings of this thesis are discussed in the next chapter.

Table 44. Addressing the research objectives and research questions

Research Objective Addressed	Research Questions Addressed	Answers to Research Questions
RO1: Examine the impact of technological acceptance of BBLPs on the formation of consumer loyalty.	RQ 1.1: What relationship does the intention to use a BBLP have with behavioural and attitudinal loyalty?	The intention to use a BBLP positively influences and is positively influenced by behavioural and attitudinal loyalty.
RO 2: Investigate how loyalty towards a provider of a BBLP influences key firm outcomes, including redemption behaviour and word-of-mouth promotion.	RQ 2.1: What relationship does attitudinal and behavioural loyalty have with redemption and WoM?	Both behavioural and attitudinal loyalty positively influence WoM. Attitudinal loyalty positively influences redemption. The relationship between behavioural loyalty and redemption is not supported.
RO 3: Determine the antecedents of the intention to use a BBLP.	RQ 3.1: What factors influence the PEOU, PU, and ultimate intention to utilise a BBLP?	The PEOU of a BBLP is influenced by personal innovativeness; trust in blockchain technology and cryptocurrency; compatibility; relative advantage; complexity. The PU of a BBLP is influenced by perceived value of cryptocurrency; compatibility; relative advantage. The behavioural intention to use a BBLP is influenced by PEOU; PU; behavioural loyalty; attitudinal loyalty.
RO 4: Determine the antecedents of the generation of attitudinal and behavioural loyalty for a BBLP.	RQ 4.1: What factors contribute to the development of behavioural and attitudinal loyalty towards a BBLP?	Behavioural loyalty and attitudinal loyalty are influenced by trust in blockchain and cryptocurrency; satisfaction; commitment; relative advantage; the behavioural intention to use a BBLP.

Contributions of the thesis

Overall, the three studies make significant theoretical, empirical, and practical contributions to the existing literature. In the context of blockchain and marketing, these three studies comprehensively examine usage intentions, loyalty generation and firm outcomes and their interrelationship. This adds to the severely limited literature on the intersection of blockchain and LPs. As mentioned before, this is a severely under-researched area. Studies are starting to emerge that cover the intersection of blockchain and marketing. However, this area of research can still be described as limited, especially empirical research as presented in Table 45.

Table 45. Research gaps summarised

Research Gap	Importance
CONTEXTUAL GAPS	
Research focusing on how blockchain technology impacts the effectiveness of LPs	Whether LPs are effective is still debated after 40 years of research, let alone whether blockchain has the potential to enhance LP effectiveness through improved structure and reward mechanisms.
Research focusing on factors influencing blockchain adoption by firms and consumers in a marketing context and incentives for adopting blockchain	There is limited research focusing on this topic, despite its transformative potential for marketing and despite blockchain loyalty practitioners (i.e., companies) already exploring its potential.
The applicability of TAM and DOI to blockchain-loyalty contexts	The applicability of TAM-DOI to blockchain remains unsettled. While there is growing literature on blockchain more broadly, literature focusing on blockchain loyalty is severely limited.
Applicability of the structural model of Watson et al. (2015) to blockchain-loyalty contexts	To date, there is no consensus on how to measure loyalty. Furthermore, the structural model put forward by Watson et al. (2015) has not yet been empirically tested in any context, let alone a blockchain-loyalty one.
THEORETICAL GAPS	
Unified models exploring technology acceptance, loyalty, and firm outcomes	Models typically examine acceptance-loyalty connections without linking them to firm outcomes. Rarely do models explore acceptance-loyalty in two dimensions, and none link acceptance, loyalty, and firm outcomes.
Perceived value of cryptocurrency as an influencer of PEOU and PU	Perceived value is extensively studied, but there is no literature examining the value of a cryptocurrency reward for participation in an LP. There are no studies examining the influence of the perceived value of cryptocurrency on PEOU and PU.
Trust in blockchain and cryptocurrency as an influencer of PEOU and PU	Trust is extensively examined, but there is limited literature on how trust in LP technology and reward mechanisms affects usage.
Examination of antecedents of loyalty two-dimensionally	Literature examining antecedents of loyalty two-dimensionally is still emerging and remains rather limited.
Relative advantage as an influencer of behavioural and attitudinal loyalty	Relative advantage has largely been studied one-dimensionally, with no literature testing its effect on behavioural and attitudinal loyalty.
Redemption as a firm outcome	Literature on redemption as a firm outcome is severely limited, focusing rather on the broader concept of performance or customer engagement.

The earlier TCCM review revealed the extent of this research gap. Only four studies were found that focus on the intersection of blockchain and marketing (Gleim & Stevens, 2021; Kumar et al., 2022; Tran & Nguyen, 2021; Utz et al., 2023; Wang et al., 2019). The lack of research discovered in the TCCM review is mirrored by other authors, who found that there are very few articles focusing on the intersection of blockchain and marketing, as it is a recent occurance (Antoniadis et al., 2019; Jain et al., 2021; Wasiq et al., 2023). Considering BBLPs only emerged around 2017 (Abooleet & Kinnett, 2023) and literature still needs to catch-up, the three studies below were important as an early examination of BBLPs that can be built on by other authors.

This thesis proposed an integrated model incorporating technology, acceptance, loyalty, and firm outcomes. Unlike previous studies, which have primarily focused on individual components in isolation, this model offers a comprehensive framework for understanding the entire technological journey, from initial acceptance to critical firm outcomes such as word-of-mouth (WoM) and redemption. The model's applicability extends beyond BBLPs, potentially serving as a valuable tool for analysing the adoption and utilisation of any new technology aimed at fostering loyalty, redemption, and WoM. By elucidating the intricate relationships between technology acceptance, loyalty creation, and firm outcomes, this study lays the groundwork for future research in diverse technological contexts, where the aim is loyalty, redemption or WoM.

As mentioned previously, one of the key advantages that a BBLP offers is the tokenisation of loyalty points. A cryptocurrency could be offered as a token or reward for participating in a BBLP. Using tokens allows participants to realise the benefits of multiple LPs that offer the same token on the blockchain network, giving consumers more options (Behrouzi et al., 2023). Theoretically, these tokens could be traded freely within the network, exchanged for fiat currency, and even used as a medium of exchange if the token was accepted in the economy. The examination of the impact of potentially being rewarded in cryptocurrency on both loyalty and technology acceptance represents a significant contribution to the understanding of BBLPs. Through the variables of perceived value of cryptocurrency, incentivisation, trust in blockchain, and trust in cryptocurrency, this research delves into the mechanisms through which tokenisation affects consumer perceptions and behaviours within loyalty programmes. By shedding light on these factors, the thesis offers valuable insights into how tokenisation influences usage patterns and the cultivation of loyalty towards firms implementing BBLPs. Overall, this contribution enhances our understanding of the evolving landscape of loyalty programmes and the role of blockchain technology within it. Further, through a thorough analysis of trust in blockchain as a variable influencing POEU, PU and both behavioural and attitudinal loyalty, this study provides valuable insights into the mechanisms through which trust operates within BBLPs.

The contribution of this thesis lies in its recognition of the coexistence of BBLPs alongside LPs, particularly in the short term. By acknowledging that consumers have a choice between loyalty programmes delivered via blockchain and those utilising other forms of technological infrastructure, this research addresses an important aspect of consumer decision-making in the loyalty programme domain. Specifically, the examination of the variable relative advantage provides insights into the factors influencing consumers' perceptions of the benefits associated with BBLPs compared to traditional LPs. The finding that relative advantage influences perceived ease of use (PEOU), perceived usefulness (PU), attitudinal loyalty, and behavioural loyalty highlights the significance of this variable in shaping consumers' attitudes and behaviours towards loyalty programmes. This contributes to a deeper understanding of the dynamics between technological advancements and consumer preferences in the loyalty programme landscape.

Behavioural and attitudinal loyalty was found to influence the behavioural intention to use a BBLP. More specifically, the findings reveal that attitudinal loyalty exerts a far greater influence on technology usage compared to behavioural loyalty. This underscores the importance of considering users' emotional connections and perceptions in predicting their willingness to engage with technology platforms. On the other hand, the behavioural intention to use a BBLP was found to not only influence but be influenced by behavioural and attitudinal loyalty. Interestingly, the behavioural intention to use a BBLP exerted only a marginally greater influence on attitudinal loyalty. This contributes to the multifaceted nature of the relationship between use and loyalty.

The technology acceptance of BBLPs

Study One examined an integrated model combining the TAM and DOI theories. An integrated TAM-DOI model has been proposed and studied in prior academic studies and to a limited extent in a blockchain context (Al-Rahmi et al., 2019; Lee et al., 2011; Min et al., 2019; Knauer & Mann, 2019; Lou & Li, 2017; Ullah et al., 2021). However, this model has not been applied or tested empirically in the context of loyalty, to the author's knowledge. Thus, this study sheds light on the explanatory power of combining TAM and DOI frameworks to understand BBLPs. The models in-sample explanatory power was in the moderate range while the out-of-sample power was weak. Despite this, the model can be built on to further enhance the understanding of BBLPs and what affects their usage.

Both PEOU and PU were found to influence the intention to use a BBLP, but PU was found to be far more influential on use. This was the case in Study One and Study Three, which were conducted at different times using different samples. PEOU and PU has been found to influence the intention to use cryptocurrency (Sohaib et al., 2019), blockchain-based research sharing frameworks (Shrestha & Vassileva, 2019), cryptocurrency transactions (Taheri Tolu et al., 2022), cryptocurrency payments (Guych et al., 2018), and blockchain technology (Kamble et al., 2019; Liu et al., 2021). This study contributes to the existing literature by adding another context to the examination of this relationship, namely, blockchain loyalty programmes.

More importantly, Study One makes two important contributions to the current understanding of the antecedents of PU and PEOU, which are well-studied antecedents to usage intentions in the TAM. The underlying technology – blockchain and a possible reward for participation, cryptocurrency – differentiate a BBLP from a traditional LP. Study One provides early support that these unique components impact the PU and PEOU, and ultimately usage. Specifically, trust in the underlying technology (blockchain) and the reward (cryptocurrency) impacted the PU but not the PEOU of a BBLP. The perceived value of the unique reward, cryptocurrency, impacted PEOU and not PU. Further, the study showed that the well-studied variables innovativeness, compatibility, complexity, and relative advantage are relevant in the context of blockchain, marketing and LPs. Relative advantage was found to be the most influential on PU, where complexity was found to the most influential on PEOU. Further, innovativeness was found to influence PEOU but not PU. The relationship between compatibility, innovativeness, complexity, and relative advantage have been studied to a limited extent by authors in a blockchain context (Hamdan et al., 2022; Kamble et al., 2019; Kamble et al., 2021; Kumari & Devi, 2023; Ullah et al., 2021). Overall, the examination of the antecedents to PEOU and PU (and their varied effects) contributes to the understanding of trust dynamics in the context of BBLPs, and the understanding of factors influencing user perceptions in a blockchain context.

Loyalty and BBLPs

Study Two is the first to examine loyalty creation in a blockchain-loyalty context. For the first time, a combined loyalty-acceptance theoretical model is proposed and examined empirically, which was built on the work of Watson et al. (2015). This study thus contributes to the severely limited research focusing on the explanatory power of a loyalty-acceptance model in a marketing-loyalty-blockchain context.

To date, satisfaction-loyalty models which incorporate the TAM have been proposed. Still, a comprehensive examination of the link between behavioural and attitudinal loyalty and behavioural intentions to use new technology has not been attempted. Use was found to influence both behavioural and attitudinal loyalty, which is an important contribution of the study. Study Two validates the model proposed by Watson et al. (2015), which was proposed to bring together the wide variety of conceptual and operational approaches that have been utilised to examine loyalty.

Furthermore, Study Two extends the model of Watson et al. (2015) to include relative advantage as an antecedent to the generation of behavioural and attitudinal loyalty. The relationship between relative advantage has with a unidimensional conception of loyalty has been examined by several authors (Jamshidi & Kuanova, 2020; Lin et al., 2015; Rambocas & Arjoon, 2012). No research was found which examines the relationship between relative advantage and loyalty as a two-dimensional construct, which makes this an important contribution to the literature.

Moreover, the study enriches existing theoretical frameworks by identifying key factors that influence both behavioural and attitudinal loyalty. By examining the roles of commitment, trust in blockchain and cryptocurrency, satisfaction, and relative advantage, the study provides insights into the multidimensional nature of loyalty formation in the context of technology adoption. There is limited literature which examines these constructs two-dimensionally (Al-dweeri et al., 2017; Cifci & Erdogan, 2016; Gecti & Zengin, 2013; Haverila et al., 2022; Inoue et al., 2017; Kamran-Disfani et al., 2017). Examinations in the context of blockchain are practically non-existent.

Again, it is worth noting that trust in the underlying technology (blockchain) and the potential reward (cryptocurrency) were shown to be influential on behavioural and attitudinal loyalty. These findings contribute to refining theoretical models of technology acceptance by highlighting the interplay between user attitudes, perceptions, and behavioural intentions. The study offers valuable insights into the factors that drive behavioural and attitudinal loyalty in technology adoption contexts. Through data analysis, it was found that commitment, trust in blockchain and cryptocurrency, satisfaction, and relative advantage positively influence both behavioural and attitudinal loyalty among users. Furthermore, the study's findings challenge existing assumptions about the effectiveness of incentives in fostering loyalty. Contrary to expectations, incentives were shown to have no significant influence on either behavioural or attitudinal loyalty. This empirical insight contributes to a more nuanced understanding of the role of incentives in shaping user behaviour and highlights the need for organisations to consider alternative strategies for enhancing user loyalty in technology-driven environments.

The interplay between loyalty and firm outcomes

Uniquely in Study Three, firm outcomes – WoM and redemption – were examined empirically. The model of Watson et al. (2015) focused on WoM and performance as firm outcomes. The replacement of performance with redemption is a theoretical adaption of the model proposed by Watson et al. (2015) and adds to the limited literature examining how the generation of loyalty can lead to an LP-specific outcome, redemption. As mentioned before, accrued unredeemed points can represent substantial value. Estimates of unclaimed loyalty points were as high as $100 billion (Bond Brand Loyalty, 2017). As a promise for a future service, these accrued points represent a liability for a firm (Chun et al., 2020). The lack of redemption limits how effectively an LP can increase spending through breaking down the point-pressure mechanism. This mechanism pushes consumers to spend, because points balances are low (Bijmolt et al., 2011).

The relationship between redemption and attitudinal loyalty was supported in the data analysis, whereas the relationship between redemption and behavioural loyalty was not. On the other hand, both behavioural and attitudinal loyalty were found to influence WoM. However, it is notable that attitudinal loyalty had a far more significant effect on WoM. This shows the complexity of user behaviours in BBLPs and is an important contribution considering only one study (Peña-García et al., 2018) was found which examines WoM and its relationship with loyalty's attitudinal and behavioural components. Overall, the empirical findings provide valuable insights into the factors influencing user intentions, loyalty behaviours, and firm outcomes in the context of blockchain technology.

Implications of the study

The technology acceptance of BBLPs

As mentioned before, Study One examined an integrated model combining the TAM and DOI theories. The model's in-sample explanatory power was in the moderate range while the out-of-sample power was weak. The results suggest that, while the integrated model adequately explains the observed data within the sample used for analysis, its effectiveness diminishes when applied to new, unseen data. This highlights the need for further validation and refinement of the conceptual model in Study One to enhance its predictive accuracy and generalisability. Future research should explore additional factors and interactions that may contribute to a more comprehensive understanding of technology acceptance and diffusion dynamics as they apply to BBLPs.

Trust in blockchain and cryptocurrency was found to influence PEOU but not the PU of a BBLP. This implies that users who trust the underlying technology (blockchain) and potential reward (cryptocurrency) are more likely to perceive a BBLP as easy to use but will not lead to a perception that the programme contributes to their goals or needs. It is noteworthy that trust in the underlying technology (blockchain) and the potential reward for participation (cryptocurrency) in a BBLP were examined rather than trust in the technology itself (BBLP). In prior studies using the TAM, trust is usually assessed in relation to the technology the use of which is being examined. Liu et al. (2021) examined the intention to use a blockchain and found that trust influenced both PEOU and PU. On the other hand, focusing on cryptocurrency payments, Guych et al. (2018) found that trust influenced PU but did not affect PEOU. Overall, the findings may imply that trust influences PEOU and PU differently, depending on the blockchain context.

A relationship was confirmed between innovativeness and PEOU and the lack of relationship exhibited by innovativeness and PU. This suggests that more innovative users are likely to perceive a BBLP as easier to use. The lack of relationship with PU may suggest greater innovativeness will help a user explore a BBLP but will not translate into greater perceptions of utility. This finding is supported by Ullah et al. (2020) in the context of blockchain technology adoption for energy management. Ullah et al. (2020) suggested that a lack of awareness of blockchain technology may be driving such a relationship between innovativeness and PEOU and PU, which could be the case here as well. On the other hand, Sohaib et al. (2019) examined cryptocurrency adoption and found support that innovativeness influences both PEOU and PU and not only PU. Overall, these findings imply that the effect of innovativeness on PEOU and PU in the context of blockchain is unsettled.

Perceived value has shown a relationship with PEOU (Lee et al., 2012; Obal, 2013). It has also been shown to have a relationship with PU (Obal, 2013; Pagani, 2004). In a blockchain context, perceived value has been studied and found to reduce an individual's resistance to using blockchain (Walsh et al., 2021). Perceived value was shown to influence PEOU, but not PU, in this study. It is noteworthy that the focus was on the perceived value of cryptocurrency, not the technology the use of which is being examined, which is usually the case. It suggests that users who perceived the potential reward of participating in a BBLP as valuable will be more likely to invest the time and effort in understanding its features and functionalities but will not reduce the perceived complexity of using the programme.

Regarding compatibility, the findings of this study are supported in the context of blockchain-technology acceptance in smart learning environments (Ullah et al., 2021) and partially supported by Kamble et al. (2021) and Kumari and Devi (2023), who found that PU is influenced by compatibility in a blockchain context. They are also partially contradicted by Hamdan et al. (2022), Kumari and Devi (2023) and Kamble et al. (2021) who found that compatibility did not influence PEOU. This may imply compatibility uniquely influences PEOU in certain blockchain contexts, but not others. Overall, the findings suggest that users who perceive a BBLP as being compatible with their current preferences and usage patterns will be more likely to embrace a BBLP as a valuable tool for achieving their loyalty-related goals.

For complexity, the findings are partially supported by prior literature. Complexity has been shown to influence PEOU (Hamdan et al., 2022; Kamble et al., 2021). However, complexity has also been shown to have no relationship with PU (Kamble et al., 2021). The findings imply that users who perceive a BBLP as more complex are more likely to find it to be difficult to use and this will hinder a user's ability to derive benefits from the programme. Relative advantage was shown to influence both PEOU and PU. This implies that users who perceive a BBLP as having greater value compared to alternatives are more likely to find a BBLP to have higher utility and effectiveness, which in turn drives perceived ease of use and usefulness.

Loyalty and BBLPs

Study Two highlighted the explanatory power of a loyalty-TAM model. By demonstrating explanatory power, the loyalty-TAM model provides valuable insights into why users engage with BBLPs and exhibit loyalty towards them. While moderate explanatory power is a positive finding, there is still room for improvement. Businesses and researchers can further refine the model by incorporating additional variables or refining existing ones to enhance its predictive capabilities. This ongoing refinement process can lead to a deeper understanding of user behaviour and more accurate predictions, ultimately contributing to the development of more effective BBLPs.

Commitment was found to influence attitudinal and behavioural loyalty. The relationship between commitment and a unidimensional construct of loyalty is supported by several authors (Bloemer et al., 2003; Dagger et al., 2011; Marshall, 2010). More specifically, and two-dimensionally, the relationship between commitment and attitudinal loyalty is supported (Cifci & Erdogan, 2016; Inoue et al., 2017). In one of the few studies focusing on the relationship between commitment and a two-dimensional construct of loyalty, commitment has been found to have a direct impact on attitudinal loyalty, but only impacts behavioural loyalty indirectly through satisfaction (Dikcius et al., 2019). This led the authors to agreeing with the Mpinganjira et al. (2017) findings that commitment is a perception and does not impact actual behaviour directly. (Dikcius et al., 2019). The difference in the findings of this study, compared to Dikcius et al. (2019), can be explained by the B2B context their study focused on. Their study was also not focused on LPs or blockchain. Nevertheless, the results imply that at least in a B2C blockchain-loyalty context, commitment is a not just a perception but a behaviour as well. More research is required to illuminate this further.

Trust was found to influence behavioural and attitudinal loyalty. However, in contrast to previous studies, trust was found to have a marginally greater influence on attitudinal loyalty (Al-dweeri et al., 2017; Gecti & Zengin, 2013). This finding suggests that trust plays a crucial role in shaping both behavioural actions and attitudes towards the subject of study. While the finding contrasts with previous studies in terms of the relative influence of trust on attitudinal loyalty, it confirms the overarching importance of trust in loyalty formation.

Satisfaction was found to influence both behavioural and attitudinal loyalty in this study, which may mean that prospect theory applies to a blockchain-loyalty context and that loyal customers are affected more by the loss in benefits from switching to another provider than by any gains from buying from a new provider (Shankar et al., 2003). It indicates that trust is a foundational element that influences attitudinal loyalty, by fostering possible perception, and behavioural loyalty by reducing the perceived risks of participation.

The lack of a significant relationship between incentives and the creation of both behavioural and attitudinal loyalty in this study may reflect that loyalty cannot be ‘bought’ and those incentives will not necessarily lead to greater loyalty towards blockchain-based programmes compared to alternatives. Incentives described as a part of this study included discounts, special offers, and exchanges for fiat currency. The utility of these incentives may not be enough to create a preference for a BBLP, or consumers may be sceptical of LPs that provide incentives. In a multi-country study on loyalty, some consumers were not enticed by loyalty incentives because of the greater abundance of tangible rewards in some countries, leading to more significant disappointment as the incentives fail to attract consumers (De Wulf et al., 2001). It can also be explained by social exchange theory. Social exchange theory considers interactions between two parties to be similar to an economic exchange involving costs and benefits (Gefen et al., 2003). According to this theory, participation in the social exchange only occurs if benefits exceed costs. Consumers may perceive loyalty as a form of social exchange, where they invest resources in a relationship and expect to receive benefits or incentives in return. If the benefits of using a BBLP are not clear, because there is mistrust in blockchain or cryptocurrency or simply a lack of understanding, it may break down the cost-benefit analysis.

On the other hand, if the incentives are understood but not considered valuable (and have a low valence), expectancy theory would suggest that their motivation to exhibit loyalty behaviours would break down. Only 37% of respondents in a global loyalty survey indicated that points and rewards were an effective way to secure loyalty (KPMG, 2019). The lack of relationship may also show that incentives are even less effective if the technology is new, and the method of generating and spending rewards is not abundantly clear.

Notably, the empirical support for the relationship between relative advantage and loyalty contradicts the recent findings by Suhartanto et al. (2022), who found no support for a relationship between relative advantage and loyalty in the context of artificial-intelligence mobile banking. The differences could be explained by differences in the context and focus of Suhartanto et al. (2022) on artificial intelligence in the context of banking compared to the focus of this study on blockchain in the context of loyalty programmes. However, it may imply that relative advantage is more important in certain blockchain contexts, such as LPs.

Behavioural and attitudinal loyalty was found to influence the intention to use a BBLP. This is indicative that the users who actively engage in a BBLP are more likely to express intentions to use a BBLP. Additionally, users with more positive emotional connections towards a BBLP are more likely to express intentions to use a BBLP. Attitudinal loyalty was found to have a far more significant effect on usage intentions than behavioural loyalty. The findings also show notable differences in how satisfaction and relative advantage affect loyalty's behavioural and attitudinal parts. Although differences in how trust, commitment, and satisfaction affect behavioural and attitudinal loyalty were also noted, the differences were relatively minor. Overall, this implies that it important to measure separately the attitudinal and behavioural components of loyalty. As mentioned before, seeing loyalty as a single construct can lead to misleading results and it should be separated (Kamran-Disfani et al., 2017; Watson et al., 2015).

The interplay between technology acceptance, loyalty, and firm outcomes

A relationship between both behavioural and attitudinal loyalty with WoM was confirmed in the data analysis. The link between behavioural loyalty and WoM may imply that self-perception theory is valid in the context of BBLPs. Self-perception theory suggests that people view themselves as helpful when promoting things to others (Garnefeld et al., 2011).

Studies that examine attitudinal and behavioural dimensions of loyalty and WoM can be described as extremely limited. One study was found focusing on online shoppers and it supported a relationship between attitudinal loyalty and WoM and did not examine behavioural loyalty (Peña-García et al., 2018). Despite few studies examining the relationship between attitudinal loyalty and WoM, this study has shown it to be a far more significant influence of WoM intentions by consumers. This reemphasises the importance of measuring loyalty as an attitude and a behaviour. It implies that users who are both behaviourally and emotionally committed are more likely to advocate BBLP to others.

Redemption was a unique construct proposed in this study and one specific to LPs, adapting the model proposed by Watson et al. (2015), which focused on performance. As mentioned before, with LPs, redemption is a crucial objective for firms that launch and develop these programmes, as low redemption means low activity and wastage for firms. Study Three confirmed a relationship between attitudinal loyalty and redemption, but the relationship between redemption and behavioural loyalty was rejected. This suggests that attitudes play a critical role in a user's decision-making process for redeeming rewards. This may suggest positive perceptions of a BBLP will be more likely to actively engage in redeeming or intending to redeem rewards. Notably, the lack of a relationship between redemption and behavioural loyalty shows that mere participation in a BBLP does not guarantee increased redemption rates, and users who are actively engaged with a BBLP may not make redemptions. This appears to be counterintuitive at first. One might expect that customers who act in a way that favours a brand would be more likely to act and redeem accumulated loyalty points to demonstrate their loyalty. However, the lack of relationship between redemption and loyalty may be indicative that customers do not prioritise redeeming the loyalty points they collect. Customers may not prioritise redemption for several reasons. They may find that rewards offered by a BBLP to have a low perceived value, or they may simply perceive redeeming the rewards offered by a BBLP to be confusing or complicated to do. These findings do support statistics showing problems with redemption. For example, redemption rates are as low as 13.6% globally and 14% in South Africa (Yang et al., 2019). The video description of how these rewards could be redeemed in a BBLP may have been too simplistic, complicated or both, adding to a breakdown in the relationship between behavioural loyalty and redemption.

Managerial implications

The findings of this study have significant managerial implications for companies investigating the adoption of BBLP or companies interested in developing blockchain solutions relating to LPs. This study validates that these programmes' PEOU and PU drive the intention to use BBLPs. This implies that consumers who view BBLPs as being easy to use and offering them a high utility will probably use a BBLP. Managers should also recognise that behaviours towards and perceptions of BBLPs play a critical role in a potential user's willingness to adopt a BBLP. This means monitoring perception and attitude preferences towards a BBLP are important to ensure timely adaptions and adjustments to the LP strategy.

The probability of a high PEOU was found to be dependent on trust, relative advantage, compatibility, complexity, and innovativeness. Complexity was found to be a critical factor in influencing PEOU, and companies designing a BBLP should be mindful of how users perceive how complex using a BBLP would be. For example, a company investing in a BBLP should be mindful of marketing and associating the LP with blockchain, which may create perceptions of complexity and reduce the willingness to use such a programme. This assertion is likely, given the newness of the technology and how likely it is that users feel familiar with or understand how the technology works. It is noteworthy that trust in cryptocurrency and blockchain effects PEOU. This means that companies investing in a BBLP need to help users trust the underlying technology, blockchain, and the potential reward from using a BBLP, cryptocurrency, to encourage use.

Perceptions (or attitudinal loyalty) influences usage intentions much more than behavioural loyalty. Marketers could action this knowledge, by ensuring that users' perceptions of BBLPs are positive and remain positive. To create perceptions that BBLPs have utility and are useful, companies should be mindful of perceptions of the 'reward' of engaging in a BBLP, cryptocurrency. The perceived value of cryptocurrency was shown to be influential on the PU of the programme. This has implications for decisions on how rewards in BBLP should be structured. For example, if the BBLP chooses to reward a user in cryptocurrency, it may either discourage or encourage users to view the programme as useful, depending on their views on cryptocurrency. Users who already are cryptocurrency advocates or investors may view these programmes as having a high utility, compared to those who do not. In addition, compatibility, complexity, and relative advantage are also essential, as these constructs were shown to affect perceptions of PU.

Relative advantage was found to be the most critical factor in influencing PU. Relative advantage was also found to influence behavioural and attitudinal loyalty, underscoring its importance. This means that organisations pursuing a BBLP should be mindful of how they market and position their BBLP compared to alternatives. If a potential user views a BBLP as superior to a traditional LP, it is likely they will also view it as useful and lead to the generation of behavioural and attitudinal loyalty. Practically, this can be done through creating marketing collateral that highlights how a BBLP uses tokenisation to be more useful to customers. The tokenisation of loyalty points allows consumers to track and store points more efficiently, freeing them from a disjointed loyalty network (Rejeb et al., 2020) and eliminates the need for consumers to search for each programme's options, limitations, and redemption rules (Udegbe, 2017).

The results show that businesses pursuing a BBLP should carefully consider how clearly they associate their BBLP with blockchain through marketing and other information they provide to potential users. Since blockchain is essentially a distributed, decentralised database, it is feasible customers could be unaware of whether an LP is functioning using blockchain or not.

Associating the BBLP clearly with blockchain can work for or against the use of the programme, through complexity, relative advantage and trust in the underlying technology and potential reward for participation (cryptocurrency). For example, Singapore Airlines introduced blockchain technology into its LP (KrisFlyer) through a wallet called KrisPay (Morris, 2018). Viewing the Apple app for KrisPay shows a clear decision to dissociate it from blockchain technology, with no mention of the word *blockchain*.

Notably, it was found that trust in blockchain and cryptocurrency are influential on the behavioural and attitudinal loyalty exhibited towards a BBLP. This finding is important and shows that marketers will also need to focus on building trust in the underlying technology of BBLPs (blockchain) and the potential reward mechanism (cryptocurrency) to create loyalty, and ultimately use. This is an important consideration depending on how visible it is that the LP is using blockchain. For example, Singapore Airlines introduced blockchain technology into its LP (KrisFlyer) through a wallet called KrisPay (Morris, 2018). Viewing the Apple app for KrisPay shows a clear decision to dissociate it from blockchain technology, with no mention of the word *blockchain*. Some blockchain-based companies like FlyCoin and Loyyal are more clearly advertised as blockchain-based LPs, although as B2B companies, it is unknown whether the end-user will ever know whether blockchain or crypto is involved. A decision to obscure the association an LP has with blockchain may avoid questions of trust in blockchain and cryptocurrency that will impact a customer's loyalty but may also minimise the relative advantage which could enhance the loyalty and ultimately the usage intentions of potential users as well.

Incentivisation was shown to be uninfluential on the creation of behavioural and attitudinal loyalty. This means that practitioners should be cognisant that providing more significant incentives for using BBLPs will not lead to greater usage of these programmes, at least through a loyalty effect. This means managers should carefully consider their incentive strategies for a BBLP and focus on other factors, such as relative advantage, satisfaction, trust, and commitment, to drive loyalty, instead of incentives.

Behavioural and attitudinal loyalty was found to influence WoM. This suggests that marketing managers should foster strong relationships with their most loyal customers and encourage (and even reward) positive recommendations and referrals. Practically, a firm could implement a loyalty reward scheme for customers who refer others and gather feedback and testimonials to showcase the benefits of participation in a BBLP.

It has been suggested that redemption rates are as low as 13.6% globally and 14% in South Africa (Yang et al., 2019). These low redemption rates increase the firm's liabilities, potentially harming the financial health of the company. Further, those who do not redeem rewards have been found to be less loyal to the brand (Fromhart & Therattil, 2016; Bond Brand Loyalty, 2016). Since they are less loyal, the consumer is also less likely to recommend the brand and to remain loyal after a bad experience (KPMG, 2019). It has been observed that as many as 50% and 70% of LP benefits do not get redeemed (Bijmolt et al., 2011). The lack of redemption limits how effectively an LP can increase spending through breaking down the point-pressure mechanism. Through a point-pressure mechanism, when the consumer's points balance is low, consumers are internally motivated to accumulate points for rewards in the future and spend more doing so (Bijmolt et al., 2011).

Since only attitudinal loyalty was found to influence redemption, managers should instead focus on creating positive perceptions towards the BBLP, if redemption is a key goal or problem their BBLP faces. This would be aided by initiatives which enhance the perceived rewards, making redemption easier, and personalisation recommendations for customers. The customers who advocate and display high levels of attitudinal loyalty should be capitalised on, to encourage redemption behaviour through incentives and promotions. As mentioned before, it is important for managers to keep in mind that mere participation in a BBLP does not guarantee increased redemption rates, and users who are actively engaged with a BBLP may not make redemptions. Often there is a focus on participation. This means usage and participation rates should be carefully examined to determine if they are leading to actual redemption.

BBLPs can help address several key challenges currently facing loyalty programs, including intense competition, low redemption rates, and the increasing demand for personalization (Bond Brand Loyalty, 2024). To combat competition and differentiate their programs, companies should emphasize the unique benefits of blockchain-enabled tokenized rewards, such as enhanced flexibility and transparency. These features allow customers to track, manage, and redeem points seamlessly, offering a significant competitive advantage over traditional loyalty programs. Personalization is another area where BBLPs can excel by leveraging blockchain's secure data-sharing capabilities to provide tailored offers, individualized reward recommendations, and personalized redemption pathways that better align with customer preferences. Additionally, addressing low redemption rates—a major limitation of many loyalty programs—requires simplifying the redemption process. Blockchain's interoperability enables customers to redeem rewards across multiple brands or convert points into cryptocurrency, increasing perceived value and driving attitudinal loyalty, which this study found to be the key driver of redemption. Finally, behavioral and attitudinal loyalty strongly influence WoM referrals, presenting an opportunity for companies to incentivize loyal customers to advocate for the program within their networks. By strategically positioning blockchain as the hidden enabler of these benefits rather than overtly marketing its use, companies can avoid perceptions of complexity while showcasing the practical advantages of BBLPs.

Limitations and future directions

The sampling technique, non-probability sampling, is a limitation. Specifically, the studies used convenience sampling, which means that sampling units were chosen based on accessibility to the researcher. This makes a generalisation about the population challenging. Additionally, collecting data via an online survey may result in limitations, such as the possibility of fraudulent respondents and the fact that internet populations may not be representative of the country's population. These factors need to be considered when conducting studies using online surveys (Lefever et al., 2007). Furthermore, all the studies are limited because respondents answered the survey based on a video and text description of the technology. This may restrict the applicability of the findings to real-world scenarios where BBLPs may have some but not all the described features.

Perceived value of cryptocurrency predicted the PEOU. This is a new variable specific to a blockchain context. Further research should examine and confirm the validity of this variable in other blockchain contexts. The implication that the value of cryptocurrency affects perceptions of the PEOU or PU of a blockchain technology is critical to understand. It may mean that, if the value of a cryptocurrency like Bitcoin falls, usage of blockchain solutions will suffer as well. Despite support in other contexts (Bigne-Alcaniz et al., 2008; Fagan et al., 2012; Miltgen et al., 2013) and in this thesis, authors have not focused on understanding the relevance of personal innovativeness as an antecedent to PEOU and PU in a blockchain context.

A relationship between behavioural and attitudinal loyalty with the behavioural intention to use blockchain technology was supported in this thesis. This is a new relationship, and more research is required to understand and validate the relationship between loyalty and technological acceptance in different contexts. The supported relationship between behavioural and attitudinal loyalty with WoM and redemption requires more specific focus. To date the literature has not examined how a two-dimensional examination of loyalty affects key outcomes: WoM and redemption. The importance of redemption cannot be overrstated as a key outcome of LPs. Despite this, few researchers have focused on redemption, and more research is required to examine redemption as an outcome and key goal, as currently redemption is a key problem faced by LPs (Fromhart & Therattil, 2016).

Conclusion

LPs are important elements of sales and marketing programmes and a key driver of revenue generation (American Airlines Group Inc, 2022; Southwest Airlines Co, 2022). Their importance has made them prolific. For example, in Europe, 60% of retailers have adopted LPs (Bombaij & Dekimpe, 2020). This is unsurprising considering that mature brands generate 85% of their growth from their most loyal customers and 75% of consumers will switch to a company with a better LP (KPMG, 2019). On the other hand, 96% of customers agree that LPs can be improved (KPMG, 2019). To improve LPs, firms are considering the impact of technologies and noting the risks to LPs created by technological advancement (Marriott International, 2022). Owing to these risks, entire business units are created which focus on the technological advancement of LPs, such as JetBlue Ventures (JetBlue Airways Corporation, 2022). A technological advancement that has the potential to transform LPs is blockchain technology, which has specifically been identified as transformative for LPs (Kowalewski et al., 2017). Marketers expect blockchain to have a positive impact on LPs (Lemos et al., 2022). Early adopters have also started to explore the impact of blockchain on LPs. As mentioned in Chapter 1, examples include KrisPay by Singapore Airlines, Chanticleer Holdings, American Express and Boxed collaboration, AirBaltic's integration of non-fungible tokens (NFTs), Venmo, Shake Shack, and Loyyal (Nuraini, 2022).

Despite the transformative impact of blockchain on LPs and their potential impact, there is a dearth of research focusing on the intersection of blockchain and LPs. Research focusing only on the interplay between blockchain and marketing have only started to emerge in some recent studies (Antoniadis et al., 2019; Bezovski et al., 2021; Hakkarainen & Colicev, 2023; Jain et al., 2021; Tan et al., 2020; Wasiq et al., 2023). Naturally, this has led to very few studies focusing on the more specific intersection of blockchain and LPs, which have been explored in even fewer studies (Abooleet & Kinnett, 2023; Behrouzi et al., 2023; Bülbül & İnce, 2018; Lou & Li, 2017; Pramanik et al., 2020; Treiblmaier & Petrozhitskaya, 2023; Udegbe, 2017). This thesis aimed to address the lack of research focusing on the intersection of blockchain and LPs by comprehensively examining the behavioural intention to use a BBLP, loyalty and firm outcomes (redemption and WoM). This was done using a conceptual model that used TAM, DOI theory and a loyalty model created by Watson et al. (2015). Importantly, this model was adapted to be more specific for examining a BBLP and included variables relating to trust in blockchain and cryptocurrency; the perceived value of cryptocurrency; relative advantage; and redemption. Again, due to the complexity and the sheer number of variables, this model was tested using three studies. Each study focused on a different component of the model: Study One focused on understanding the behavioural intention to use a BBLP; Study Two focused on the antecedents of behavioural and attitudinal loyalty and their link to use and Study Three focused on firm outcomes while trying to link use, loyalty, and firm outcomes together in a simple model. All three studies used convenience sampling, PLS-SEM, and the software SmartPLS 3 to analyse the data.

The important contribution of the thesis is that it sheds light on several established relationships that have only been examined to a limited extent or not at all, and in the broader context of blockchain and BBLPs. This includes innovativeness, compatibility, complexity, and relative advantage as influencers of the behavioural intention to use a BBLP. New variables were also introduced and shown to have a varied effect on PEOU and PU, namely, trust in blockchain and cryptocurrency, as well as the perceived value of cryptocurrency.

Viewing and examining loyalty two-dimensionally as a behaviour and attitude is a relatively new concept. A contribution this thesis makes is to examine trust, satisfaction, incentives, commitment, and relative advantage as influencers of both behavioural and attitudinal loyalty. This adds to scarce and limited literature examining these constructs' impact on both behavioural and attitudinal loyalty. A BBLP offers the unique option for a customer to receive cryptocurrency as a reward. This comes with several benefits, including better redemption and exchangeability (Rejeb et al., 2020; Treiblmaier & Petrozhitskaya, 2023; Udegbe, 2017). Incentives were found to be uninfluential on both behavioural and attitudinal loyalty, adding new discourse on the role of incentives in the context of BBLPs.

This thesis also examined redemption owing to its importance in the context of BBLPs and the potential impact BBLPs can have on improving redemption of rewards offered by LPs. As mentioned in Chapter 1, redemption rates are as low as 13.6% globally and 14% in South Africa (Yang et al., 2019) and 50% and 70% of LP benefits do not get redeemed (Bijmolt et al., 2011). Further, those who do not redeem rewards have been found to be less loyal to the brand (Fromhart & Therattil, 2016; Bond Brand Loyalty, 2016). A BBLP can improve redemption through increasing the speed and exchangeability of loyalty points through tokenisation (Rejeb et al., 2020; Treiblmaier & Petrozhitskaya, 2023). This thesis explored redemption through a conceptual model adapted from the work of Watson et al. (2015). Significantly and counterintuitively, behavioural loyalty was found to be uninfluential on redemption. Attitudinal loyalty on the other hand was found to influence redemption. This finding shed light on the potential impact of BBLPs on improving redemption using tokens. Behavioural and attitudinal loyalty were also shown to influence WoM in this thesis.

This thesis aimed to examine the relationship between user acceptance, loyalty, and firm outcomes. Behavioural and attitudinal loyalty were found to influence and be influenced by the behavioural intention to use a BBLP. This established a relationship between acceptance theory through the TAM and DOI, and loyalty theory through the model of Watson et al. (2015). A relationship between loyalty and outcomes was also established. Behavioural loyalty influenced WoM, and attitudinal loyalty influenced both WoM and redemption. Through a comprehensive examination of technology acceptance, loyalty, and firm outcomes (and their linkage), this thesis hopes to inspire further research focusing on the transformative impact of blockchain on LPs, so both firms and consumers can realise the benefits blockchain has to offer.

Reference List

Abooleet, S., & Kinnett, S. (2023). A systematic review of blockchain-based loyalty programs. In *Proceedings of the 56th Hawaii International Conference on System Sciences* (pp. 5323–5332)

Achadinha, N. M.-J., Jama, L., & Nel, P. (2014). The drivers of consumers' intention to redeem a push mobile coupon. *Behaviour & Information Technology, 33*(12), 1306–1316.

Adigüzel, S. 2021. The impact of blockchain in marketing. *Socrates Journal of Interdisciplinary Social Studies*, *10*, 66–97.

Adov, L., Must, O., & Pedaste, M. (2017). Attitudes towards Mobile devices in Estonian basic education: Using the framework of the UTAUT model. In *Learning and Collaboration Technologies. Technology in Education: 4th International Conference, LCT 2017, Held as Part of HCI International 2017, Vancouver, BC, Canada, July 9-14, 2017, Proceedings, Part II 4* (pp. 319-329). Springer International Publishing.

Adrianto, F. A., Yuliana, O. Y., & Jaolis, F. (2023). *Shoppers' loyalty in online marketplace: The impact of interface quality, application incentives, and security/privacy through flow experience*. Petra Christian University.

Afthanorhan, W. (2013). A comparison of partial least square structural equation modeling (PLS-SEM) and covariance based structural equation modeling (CB-SEM) for confirmatory factor analysis. *International Journal of Engineering Science and Innovative Technology*, *2*(5), 198–205.

Agag, G. M., Khashan, M. A., & Elgayaar, M. H. (2019). Understanding online gamers' intentions to play games online and effects on their loyalty: An integration of IDT, TAM and TPB. *Journal of Customer Behaviour*, *18*(2), 101–130.

Agarwal, R., & Prasad, J. (1998). The antecedents and consequents of user perceptions in information technology adoption. *Decision Support Systems*, *22*(1), 15–29.

Agarwal, R., & Prasad, J. (1999). Are individual differences germane to the acceptance of new information technologies? *Decision Sciences*, *30*(2), 361–391.

Aghdaie, S. F. A., Sanayei, A., & Etebari, M. (2012). Evaluation of the consumers' trust effect on viral marketing acceptance based on the technology acceptance model. *International Journal of Marketing Studies*, *4*(6), 79-94.

Agi, M. A., & Jha, A. K. (2022). Blockchain technology in the supply chain: An integrated theoretical perspective of organizational adoption. *International Journal of Production Economics*, *247*, Article 108458.

Agrawal, D., Jureczek, N., Gopalakrishnan, G., Guzman, M. N., McDonald, M., & Kim, H. (2018). Loyalty points on the blockchain. *Business and Management Studies*, *4*(3), 80–92.

Ahluwalia, R., Unnava, H. R., & Burnkrant, R. E. (1999). *Towards understanding the value of a loyal customer: An information-processing perspective* [Report]. Marketing Science Institute.

Ajibade, P. (2018). Technology acceptance model limitations and criticisms: Exploring the practical applications and use in technology-related studies, mixed-method, and qualitative researches. *Library Philosophy and Practice*, 1941.

Ajina, A. S. (2019). The perceived value of social media marketing: An empirical study of online word-of-mouth in the Saudi Arabian context. *Entrepreneurship and Sustainability Issues*, *6*(3), 1512–1527. https://doi.org/10.9770/jssi.2019.6.3(32)

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211.

Akbari, M., Kazemi, R., & Haddadi, M. (2016). Relationship marketing and word-of-mouth communications: Examining the mediating role of customer loyalty. *Marketing and Branding Research, 3*(1), 63–74.

Al Karim, R., Rabiul, M. K., Ishrat, M., Promsivapallop, P., & Kawser, S. (2023). Can blockchain payment services influence customers' loyalty intention in the hospitality industry? A mediation assessment. *Administrative Sciences*, *13*(3), 1–17.

Al-Ajam, A. S., & Nor, K. M. (2013). Internet banking adoption: Integrating technology acceptance model and trust. *European Journal of Business and Management*, *5*(3), 207–215.

Al-dweeri, R. M., Obeidat, Z. M., Al-dwiry, M. A., Alshurideh, M. T., & Alhorani, A. M. (2017). The impact of e-service quality and e-loyalty on online shopping: Moderating effect of e-satisfaction and e-trust. *International Journal of Marketing Studies*, *9*(2), 92–103.

Al-Rahmi, W. M., Yahaya, N., Aldraiweesh, A. A., Alamri, M. M., Aljarboa, N. A., Alturki, U., & Aljeraiwi, A. A. (2019). Integrating technology acceptance model with innovation diffusion theory: An empirical investigation on [sic] students' intention to use e-learning systems. *IEEE Access*, *7*, 26797–26809.

Al-Hawari, M. A., & Mouakket, S. (2010). The influence of technology acceptance model (TAM) factors on students' e-satisfaction and e-retention within the context of UAE e-learning. *Education, Business and Society: Contemporary Middle Eastern Issues, 3*(4), 299–314. https://doi.org/10.1108/17537981011089596

Alazab, M., Alhyari, S., Awajan, A., & Al-Karaghouli, W. (2021). Blockchain technology in supply chain management: An empirical study of the factors affecting user adoption/acceptance. *Cluster Computing, 24*(1), 83–101. https://doi.org/10.1007/s10586-020-03200-4

Aldammagh, Z., Abdeljawad, R., & Obaid, T. (2021). Predicting mobile banking adoption: An integration of TAM and TPB with trust and perceived risk. *Financial Internet Quarterly, 17*(3), 35–46. https://doi.org/10.2478/fiqf-2021-0017

Alharbi, A., & Sohaib, O. (2021). Technology readiness and cryptocurrency adoption: PLS-SEM and deep learning neural network analysis. *IEEE Access*, *9*, 21388–21394.

Altuna, O. K., & Müge Arslan, F. (2016). Impact of the number of scale points on data characteristics and respondents' evaluations: An experimental design approach using 5-point and 7-point Likert-type scales. *Istanbul Üniversitesi Siyasal Bilgiler Fakültesi Dergisi*, (*55*), 1–20.

Alzubi, M. M., Al-Dubai, M. M., & Farea, M. M. (2018). Using the technology acceptance model in understanding citizens' behavioural intention to use m-marketing among Jordanian citizen [sic]. *Journal of Business and Retail Management Research*, *12*(2), 224-231.

American Airlines Group. (2022). *2022 annual report on Form 10-K*. Retrieved January 22, 2024, from https://www.annualreports.com/Click/26617

Antoniadis, I., Kontsas, S., & Spinthiropoulos, K. (2019). Blockchain applications in marketing. In *Proceedings of the 7th International Conference on Computational Methods for Marketing and Innovation* (pp. 124–134).

Arli, D., van Esch, P., Bakpayev, M., & Laurence, A. (2021). Do consumers really trust cryptocurrencies? *Marketing Intelligence & Planning*, *39*(1), 74–90.

Ashley, C., Gillespie, E. A., & Noble, S. M. (2016). The effect of loyalty program fees on program perceptions and engagement. *Journal of Business Research*, *69*(2), 964–973.

Atchariyachanvanich, K., Okada, H., & Sonehara, N. (2007). What keeps online customers repurchasing through the internet? *ACM SIGecom Exchanges*, *6*(2), 47–57.

Awa, H. O., Uko, J. P., & Ukoha, O. (2017). An empirical study of some critical adoption factors of ERP software. *International Journal of Human–Computer Interaction*, *33*(8), 609–622.

Bagozzi, R. P. (2007). The Legacy of the Technology Acceptance Model and a Proposal for a Paradigm Shift. *Journal of the Association for Information Systems*, *8*(4), 244–254.

Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. *Journal of the Academy of Marketing Science, 16*(1), 74–94.

Baker, J. (2011). The technology–organization–environment framework. In Y. K. Dwivedi et al. (Eds.), *Information systems theory: Explaining and predicting our digital society* (Vol. 1,

pp. 231–245). Springer Science and Business Media, LLC.
Balasubramanian, S., Shukla, V., Sethi, J. S., Islam, N., & Saloum, R. (2021). A readiness assessment framework for Blockchain adoption: A healthcare case study. *Technological Forecasting and Social Change*, *165*, Article 120536.
Ball, D., Simões Coelho, P., & Machás, A. (2004). The role of communication and trust in explaining customer loyalty. *European Journal of Marketing, 38*(9/10), 1272–1293. https://doi.org/10.1108/03090560410548979
Barclay, D., Higgins, C., & Thompson, R. (1995). The partial least squares (PLS) approach to causal modeling: Personal computer adoption and use as an illustration. *Technology Studies*, *2*, 285–309.
Barry, M., & Jan, M. T. (2018). Factors influencing the use of m-commerce: An extended technology acceptance model perspective. *International Journal of Economics, Management and Accounting, 26*(1), 157–183.
Bashir, I., & Madhavaiah, C. (2015). Consumer attitude and behavioural intention towards Internet banking adoption in India. *Journal of Indian Business Research, 7*(1), 67–102. https://doi.org/10.1108/JIBR-02-2014-001
Becker, H. S. (2017). Personal change in adult life. In H. S. Becker (Ed.), *Sociological work* (e-book ed.; pp. 275–288). Routledge.
Behrouzi, M., Albadvi, A., & Emaadi Safavi, P. (2023). Designing a blockchain-based customer loyalty programme using design science research method. *The Journal of The Bblutritish Blockchain Association*, *6*(2), 1–8. https://doi.org/10.31585/jbba-6-2-(8)2023
Bennett, R., & Bove, L. (2001). Identifying the key issues measuring loyalty. *Australasian Journal of Market and Social Research*, *9*(2), 27–44.
Beroe Inc. (2019, February 13th). *Loyalty programs market to reach $201 billion by 2022*. PR Newswire. Retrieved August 30, 2022, from https://www.prnewswire.com/news-releases/loyalty-programs-market-to-reach-201-billion-by-2022-according-to-beroe-inc-300794907.html
Bezovski, Z., Jovanov, T., & Temjanovski, R. (2021). The impact and the potential disruption of the blockchain technology on marketing. *Journal of Economics*, *6*(1), 13–23.
Bhaiswar, R., Chawla, D., & Meenakshi, N. (2022). The influence of eWOM communications on intended online purchases: A literature review using TCCM framework and future research agenda. *International Journal of Indian Culture and Business Management, 26*(3), 328–361.
Bharadwaj, S., & Deka, S. (2021). Behavioral intention toward investment in cryptocurrency: An integration of Rogers' diffusion of innovation theory and the technology acceptance model.

Forum Scientiae Oeconomia, *9*, 137–159.

Bhattacharjee, R. D., Pradhan, D., & Swani, K. (2022). Brand communities: A literature review and future research agendas using TCCM approach. *International Journal of Consumer Studies*, *46*(1), 3–28.

Bhimani, A., Hausken, K., & Arif, S. (2022). Do national development factors affect cryptocurrency adoption? *Technological Forecasting and Social Change*, *181*, Article 121739.

Bies, S. M., Bronnenberg, B. J., & Gijsbrechts, E. (2021). How push messaging impacts consumer spending and reward redemption in store-loyalty programs. *International Journal of Research in Marketing*, *38*(4), 877–899.

Bigné-Alcañiz, E., Ruiz-Mafé, C., Aldás-Manzano, J., & Sanz-Blas, S. (2008). Influence of online shopping information dependency and innovativeness on internet shopping adoption. *Online Information Review, 32*(5), 648–667. https://doi.org/10.1108/14684520810914025

Bijmolt, T. H., Dorotic, M., & Verhoef, P. C. (2011). Loyalty programs: Generalizations on their adoption, effectiveness and design. *Foundations and Trends® in Marketing*, *5*(4), 197–258.

Birks, D. F., & Malhotra, N. K. (2006). *Marketing research: An applied approach.* Pearson Education.

Biscaia, A. R., et al. (2017). Assessing customer satisfaction and loyalty in the retail sector. *International Journal of Quality & Reliability Management, 34*(9), 1508–1529. https://doi.org/10.1108/IJQRM-03-2015-0039

Blattberg, R. C., Kim, B. D., & Neslin, S. A. (2008). Frequency reward programs. In *Database marketing* (Vol. 18, pp. 399–416). Springer. https://doi.org/10.1007/978-0-387-72579-6_22

Bloemer, J., & Odekerken-Schröder, G. (2003). Antecedents and consequences of affective commitment. *Australasian Marketing Journal*, *11*(3), 33–43.

Blut, M., Chong, A. Y. L., Tsiga, Z., & Venkatesh, V. (2022). Meta-analysis of the unified theory of acceptance and use of technology (UTAUT): Challenging its validity and charting a research agenda in the red ocean. *Journal of the Association for Information Systems, 23*(1), 13–95. https://doi.org/10.17705/1jais.00719

Bodet, G. (2008). Customer satisfaction and loyalty in service: Two concepts, four constructs, several relationships. *Journal of Retailing and Consumer Services*, *15*(3), 156–162.

Bombaij, N. J., & Dekimpe, M. G. (2020). When do loyalty programs work? The moderating role of design, retailer-strategy, and country characteristics. *International Journal of Research in Marketing*, *37*(1), 175–195.

Bond Brand Loyalty. (2017, May 23). *Customers sitting on $100 billion of unredeemed loyalty* *points*. Prnewswire. Retrieved January 22, 2022, from https://www.prnewswire.com/news-releases/customers-sitting-on-100-billion-of-unredeemed-loyalty-points-623828294.html

Bond Brand Loyalty. (2024). *The Bond Loyalty Report: Public executive summary optimised for impact.* Retrieved December 23, 2024, from https://www.bondbl.com/theloyaltyreport

Bond Brand Loyalty. (2023). *The loyalty report* [Executive Summary]. Retrieved January 23, 2024, from https://info.bondbrandloyalty.com/loyaltyreport-2023-2-0

Bond Brand Loyalty. (2016). *The 2016 Bond Loyalty Report*. Retrieved August 29, 2024, from https://info.bondbrandloyalty.com/hubfs/Resources/2016_Bond_Loyalty_Report_Executive_Summary_US_Launch_Edition.pdf

Borhani, S. A., Babajani, J., Raeesi Vanani, I., Sheri Anaqiz, S., & Jamaliyanpour, M. (2021). Adopting blockchain technology to improve financial reporting by using the technology acceptance model (TAM). *International Journal Of Finance, & Managerial Accounting*, *6*(22), 155–171.

Bouagina, D. J., & Triki, A. (2013). Customer experiential knowledge management (CEKM) – Concept proposition and research framework development. In *European Conference on Knowledge Management* (Vol. 1, pp. 307–314)

Brauer, J., & Eriksson, B. L. (2020). *Blockchain's influence on digital marketing: An exploratory study examining blockchain in relation to big data and digital marketing* (Tech. Rep.). Department of Business Administration, Umeå University.

Bryan, J. D., & Zuva, T. (2021). A review on TAM and TOE framework progression and how these models integrate. *Advances in Science, Technology and Engineering Systems Journal*, *6*(3), 137-145.

Bülbül, Ş., & İnce, G. (2018). Blockchain-based framework for customer loyalty program. In *Proceedings of the 3rd International Conference on Computer Science and Engineering (UBMK)* (pp. 342–346). IEEE. https://doi.org/10.1109/UBMK.2018.8566642

Caldarelli, G., Zardini, A., & Rossignoli, C. (2021). Blockchain adoption in the fashion sustainable supply chain: Pragmatically addressing barriers. *Journal of Organizational Change Management*, *34*(2), 507–524.

Casaló, L. V., Flavián, C., & Guinalíu, M. (2008). The role of satisfaction and website usability in developing customer loyalty and positive word-of-mouth in the e-banking services. *The International Journal of Bank Marketing*, *26*(6), 399–417. https://doi.org/10.1108/02652320810902433

Casey, M., Crane, J., Gensler, G., Johnson, S., & Narula, N. (2018). *The impact of blockchain technology on finance: A catalyst for change* (Tech. Rep.). International Center for Monetary and Banking Studies. Geneva, Switzerland.

Casino, F., Dasaklis, T. K., & Patsakis, C. (2019). A systematic literature review of blockchain-based applications: Current status, classification and open issues. *Telematics and Informatics*, *36*, 55–81.

Cengiz, H., & Akdemir-Cengiz, H. (2016). Review of brand loyalty literature: 2001–2015. *Journal of Research in Marketing*, *6*(1), 407–434.

Chang, M., Walimuni, A. C., Kim, M.-C., & Lim, H.-S. (2022). Acceptance of tourism blockchain based on UTAUT and connectivism theory. *Technology in Society*, *71*, Article 102027.

Chang, S. C., & Tung, F. C. (2008). An empirical investigation of students' behavioural intentions to use the online learning course websites. *British Journal of Educational Technology*, *39*(1), 71–83.

Chau, P. Y., & Hu, P. J. H. (2001). Information technology acceptance by individual professionals: A model comparison approach. *Decision Sciences*, *32*(4), 699–719.

Chaudhuri, A., & Holbrook, M. B. (2001). The chain of effects from brand trust and brand affect to brand performance: The role of brand loyalty. *Journal of Marketing*, *65*(2), 81–93.

Chaudhuri, M., Voorhees, C. M., & Beck, J. M. (2019). The effects of loyalty program introduction and design on short- and long-term sales and gross profits. *Journal of the Academy of Marketing Science*, *47*, 640–658.

Chauhan, S. (2015). Acceptance of mobile money by poor citizens of India: Integrating trust into the technology acceptance model. *Info*, *17*(3), 58–68. https://doi.org/10.1108/info-02-2015-0018

Chen, S.-Y., & Lu, C.-C. (2016). Exploring the relationships of green perceived value, the diffusion of innovations, and the technology acceptance model of green transportation. *Transportation Journal*, *55*(1), 51–77.

Chen, Y., Mandler, T., & Meyer-Waarden, L. (2021). Three decades of research on loyalty programs: A literature review and future research agenda. *Journal of Business Research*, *124*, 179–197.

Cheng, T. E., Lam, D. Y., & Yeung, A. C. (2006). Adoption of internet banking: An empirical study in Hong Kong. *Decision Support Systems*, *42*(3), 1558–1572.

Chiu, C.-M., Lin, H.-Y., Sun, S.-Y., & Hsu, M.-H. (2009). Understanding customers' loyalty intentions towards online shopping: An integration of technology acceptance model and fairness theory. *Behaviour & Information Technology*, *28*(4), 347–360.

Choe, M.-J., & Noh, G.-Y. (2018). Combined model of technology acceptance and innovation diffusion theory for adoption of smartwatch. *International Journal of Contents, 14*(3), 32–38.

Choi, B., & Choi, B.-J. (2014). The effects of perceived service recovery justice on customer affection, loyalty, and word-of-mouth. *European Journal of Marketing, 48*(1/2), 108–131. https://doi.org/10.1108/EJM-06-2011-0299

Choi, J. (2018). Modeling the intergrated customer loyalty program on blockchain technology by using credit card. *International Journal on Future Revolution in Computer Science & Communication Engineering*, *4*(2), 388–391.

Choudhury, S., & Bhattacharjee, D. (2014). Optimal number of scale points in Likert type scales for quantifying compulsive buying behaviour. *Asian Journal of Management Research*, *4*(3), 431–440.

Choudhury, V., & Karahanna, E. (2008). The relative advantage of electronic channels: A multidimensional view. *MIS Quarterly, 32*(1), 179–200.

Chuen, D. L. K., Guo, L., & Wang, Y. (2017). Cryptocurrency: A new investment opportunity? *The Journal of Alternative Investments*, *20*(3), 16–40.

Chun, S. Y., Iancu, D. A., & Trichakis, N. (2020). Loyalty program liabilities and point values. *Manufacturing & Service Operations Management*, *22*(2), 257–272.

Cifci, S. D., & Erdogan, B. Z. (2016). Antecedents and measurement of brand commitment and behavioural loyalty. *Journal of Customer Behaviour*, *15*(4), 321–336.

Creswell, J. W., & Creswell, J. D. (2017). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). Sage Publications.

Cyr, D., Head, M., & Ivanov, A. (2006). Design aesthetics leading to m-loyalty in mobile commerce. *Information & Management*, *43*(8), 950–963.

Dagger, T. S., & O'Brien, T. K. (2010). Does experience matter? *European Journal of Marketing, 44*(9/10), 1528–1552. https://doi.org/10.1108/03090561011062952

Dagger, T. S., David, M. E., & Ng, S. (2011). Do relationship benefits and maintenance drive commitment and loyalty? *Journal of Services Marketing, 25*(4), 273–281.

Dash, G., & Paul, J. (2021). CB-SEM vs PLS-SEM methods for research in social sciences and technology forecasting. *Technological Forecasting and Social Change*, *173,* Article 121092.

Dash, M., Mohanty, A. K., Pattnaik, S., Mohapatra, R. C., & Sahoo, D. S. (2011). Using the TAM model to explain how attitudes determine adoption of internet banking. *European Journal of Economics, Finance and Administrative Sciences, 36*(1), 50–59.

Davis, F. D. (1985). *A technology acceptance model for empirically testing new end-user information systems: Theory and results*. Massachusetts Institute of Technology.

Day, G. S. (1969). A two-dimensional concept of brand loyalty. *Journal of Advertising*

Research, *9*(September), 29–35.

De Matos, C. A., & Rossi, C. A. V. (2008). Word-of-mouth communications in marketing: A meta-analytic review of the antecedents and moderators. *Journal of the Academy of Marketing Science*, *36*(4), 578–596.

De Wulf, K., Odekerken-Schröder, G., & Iacobucci, D. (2001). Investments in consumer relationships: A cross-country and cross-industry exploration. *Journal of Marketing*, *65*(4), 33–50.

Dearden, T. E., & Tucker, S. E. (2023). Follow the money: Analyzing darknet activity using cryptocurrency and the bitcoin blockchain. *Journal of Contemporary Criminal Justice*, *39*(2), 257–275.

Deci, E. L., & Ryan, R. M. (1985). The general causality orientations scale: Self-determination in personality. *Journal of Research in Personality*, *19*(2), 109–134.

Dehghani, M., Kennedy, R. W., Mashatan, A., Rese, A., & Karavidas, D. (2022). High interest, low adoption: A mixed-method investigation into the factors influencing organisational adoption of blockchain technology. *Journal of Business Research*, *149*, 393–411.

Delta Airlines. (2022). *2022 annual report and Form 10K*. Retrieved January 22, 2023, from https://www.annualreports.com/Click/20613

Demoulin, N. T., & Zidda, P. (2008). On the impact of loyalty cards on store loyalty: Does the customers' satisfaction with the reward scheme matter? *Journal of Retailing and Consumer Services*, *15*(5), 386–398.

Di Vaio, A., & Varriale, L. (2020). Blockchain technology in supply chain management for sustainable performance: Evidence from the airport industry. *International Journal of Information Management*, *52*, Article 102014.

Dick, A. S., & Basu, K. (1994). Customer loyalty: Toward an integrated conceptual framework. *Journal of the Academy of Marketing Science*, *22*(2), 99–113.

Dikcius, V., Kirse, S., Casas, R., & Koncanina, A. (2019). Drivers of attitudinal and behavioural loyalty in B-2-B markets. *Engineering Economics*, *30*(1), 94–102.

Dirsehan, T. (2020). Analysis of a blockchain-based website using the technology acceptance model: The case of Save Ideas. *International Journal of Diplomacy and Economy*, *6*(1), 17–25.

Dixon, J., Bridson, K., Evans, J., & Morrison, M. (2005). An alternative perspective on relationships, loyalty and future store choice. *The International Review of Retail, Distribution and Consumer Research*, *15*(4), 351–374.

Donthu, N., Kumar, S., Pandey, N., Pandey, N., & Mishra, A. (2021). Mapping the electronic word-of-mouth (eWOM) research: A systematic review and bibliometric analysis. *Journal of Business Research*, *135*, 758–773.

Dorotic, M., Verhoef, P. C., Fok, D., & Bijmolt, T. H. (2014). Reward redemption effects in a loyalty program when customers choose how much and when to redeem. *International Journal of Research in Marketing*, *31*(4), 339–355.

Drljevic, N., Aranda, D. A., & Stantchev, V. (2022). An integrated adoption model to manage blockchain-driven business innovation in a sustainable way. *Sustainability*, *14*(5), Article 2873.

Erol, I., Neuhofer, I. O., Dogru, T., Oztel, A., Searcy, C., & Yorulmaz, A. C. (2022). Improving sustainability in the tourism industry through blockchain technology: Challenges and opportunities. *Tourism Management*, *93,* Article 104628.

Evanschitzky, H., Ramaseshan, B., Woisetschläger, D. M., Richelsen, V., Blut, M., & Backhaus, C. (2012). Consequences of customer loyalty to the loyalty program and to the company. *Journal of the Academy of Marketing Science, 40*(5), 625–638.

Fagan, M., Kilmon, C., & Pandey, V. (2012). Exploring the adoption of a virtual reality simulation: The role of perceived ease of use, perceived usefulness, and personal innovativeness. *Campus-Wide Information Systems*, *29*(2), 117–127. https://doi.org/10.1108/10650741211212368

Farell, R. (2015). An analysis of the cryptocurrency industry. *Wharton Research Scholars Journal*, *Paper 130*.

Ferri, L., Spanò, R., Ginesti, G., & Theodosopoulos, G. (2021). Ascertaining auditors' intentions to use blockchain technology: Evidence from the Big 4 accountancy firms in Italy. *Meditari Accountancy Research*, *29*(5), 1063–1087.

Fishbein, M. (1979). A theory of reasoned action: Some applications and implications. *Nebraska Symposium on Motivation*, *27*, 65–116.

Folkinshteyn, D., & Lennon, M. (2016). Braving bitcoin: A technology acceptance model (TAM) analysis. *Journal of Information Technology Case and Application Research*, *18*(4), 220–249.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50.

Foroughi, B., Iranmanesh, M., Gholipour, H., & Hyun, S. (2019). Examining relationships among process quality, outcome quality, delight, satisfaction, and behavioral intentions in fitness centres in Malaysia. *International Journal of Sports Marketing and Sponsorship, 20*(3), 374–389.

Fromhart, S., & Therattil, L. (2016, December 10th). *Making blockchain real for customer loyalty rewards programs*. Deloitte Center for Financial Services. Retrieved January 10th, 2021, from https://www2.deloitte.com/content/dam/Deloitte/us/Documents/financial-services/us-fsi-making-blockchain-real-for-loyalty-rewards-programs.pdf

Gabel, S., & Guhl, D. (2022). Comparing the effectiveness of rewards and individually targeted coupons in loyalty programs. *Journal of Retailing*, *98*(3), 395–411.

Gao, L., & Bai, X. (2014). A unified perspective on the factors influencing consumer acceptance of internet of things technology. *Asia Pacific Journal of Marketing and Logistics*, *26*(2), 211–231.

Garnefeld, I., Helm, S., & Eggert, A. (2011). Walk your talk: An experimental investigation of the relationship between word of mouth and communicators' loyalty. *Journal of Service Research*, *14*(1), 93–107.

Gecti, F., & Zengin, H. (2013). The relationship between brand trust, brand affect, attitudinal loyalty, and behavioral loyalty: A field study towards sports shoe consumers in Turkey. *International Journal of Marketing Studies*, *5*(2), 111–119.

Gefen, D., Karahanna, E., & Straub, D. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly, 27*(1), 51–90.

George, A., & Kumar, G. G. (2013). Antecedents of customer satisfaction in internet banking: Technology acceptance model (TAM) redefined. *Global Business Review*, *14*(4), 627–638.

Ghazizadeh, M., Lee, J. D., & Boyle, L. N. (2012). Extending the technology acceptance model to assess automation. *Cognition*, *Technology & Work*, *14*(1), 39–49.

Gil-Cordero, E., Ledesma-Chaves, P., Arteaga Sánchez, R., & Mariano, A. M. (2024). Crypto-wallets revolution! Key factors driving behavioral intention to adopt the Coinbase Wallet using mixed PLS-SEM/fsQCA methodology in the Spanish environment. *International Journal of Bank Marketing, 42*(3), 536–570. https://doi.org/10.1108/IJBM-01-2023-0035

Gleim, M. R., & Stevens, J. L. (2021). Blockchain: A game changer for marketers? *Marketing Letters*, *32*, 123–128.

Gómez, B. G., Arranz, A. M. G., & Cillán, J. G. (2012). Drivers of customer likelihood to join grocery retail loyalty programs: An analysis of reward programs and loyalty cards. *Journal of Retailing and Consumer Services*, *19*(5), 492–500.

Grover, P., Kar, A. K., & Janssen, M. (2019). Diffusion of blockchain technology: Insights from academic literature and social media analytics. *Journal of Enterprise Information Management*, *32*(5), 735–757.

Gupta, R., Nair, K., Mishra, M., Ibrahim, B., & Bhardwaj, S. (2024). Adoption and impacts of generative artificial intelligence: Theoretical underpinnings and research agenda. *International Journal of Information Management Data Insights, 4*(1), 100232. https://doi.org/10.1016/j.jjimei.2024.100232

Guttmann, A. (2021, May 26). Consumers subscribed to a loyalty program in the U.S. by age 2018. *Statista*. Retrieved August 29, 2024, from https://www.statista.com/statistics/1033698/loyalty-program-members-by-age-us/

Guych, N., Anastasia, S., Simon, Y., & Jennet, A. (2018). Factors influencing the intention to use cryptocurrency payments: An examination of blockchain economy. *Munich Personal RePEc Archive*, 1–11.

Ha, S., & Stoel, L. (2009). Consumer e-shopping acceptance: Antecedents in a technology acceptance model. *Journal of Business Research, 62*(5), 565–571.

Hagel, J. (1999). Net gain: Expanding markets through virtual communities. *Journal of Interactive Marketing*, *13*(1), 55–65.

Hair, J., & Alamer, A. (2022). Partial least squares structural equation modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. *Research Methods in Applied Linguistics*, *1*(3), Article 100027.

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2010). *Multivariate data analysis* (6th ed.). Prentice-Hall

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2–24.

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., & Thiele, K. O. (2017). Mirror, mirror on the wall: A comparative evaluation of composite-based structural equation modeling methods. *Journal of the Academy of Marketing Science*, *45*, 616–632.

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). An introduction to structural equation modeling. In *Partial least squares structural equation modeling (PLS-SEM) using R* (pp. 1-29). Springer. https://doi.org/10.1007/978-3-030-80519-7_1

Hair Jr, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial least squares structural equation modeling* (*PLS-SEM) using R: A workbook.* Springer Nature.

Hakkarainen, T., & Colicev, A. (2023). Blockchain-enabled advances (BEAs): Implications for consumers and brands. *Journal of Business Research*, *160*, Article 113763.

Hamdan, I. K., Aziguli, W., Zhang, D., Sumarliah, E., & Usmanova, K. (2022). Forecasting blockchain adoption in supply chains based on machine learning: Evidence from Palestinian food SMEs. *British Food Journal*, *124*(12), 4592–4609.

Hardgrave, B. C., Davis, F. D., & Riemenschneider, C. K. (2003). Investigating determinants of software developers' intentions to follow methodologies. *Journal of Management Information Systems*, *20*(1), 123–151.

Harwood, J. (2020). Social identity theory. In *The International Encyclopedia of Media Psychology*. https://doi.org/10.1002/9781119011071.iemp0153

Hassler, E., MacDonald, P., Cazier, J., & Wilkes, J. (2022). The sting of adoption: The technology acceptance model (TAM) with actual usage in a hazardous environment. *Journal of Information Systems Applied Research, 14*, 12–20.

Haverila, M. J., Haverila, K., McLaughlin, C., & Tran, H. (2022). The impact of tangible and intangible rewards on online loyalty program, brand engagement, and attitudinal loyalty. *Journal of Marketing Analytics*, *10*(1), 64–81.

Helliar, C. V., Crawford, L., Rocca, L., Teodori, C., & Veneziani, M. (2020). Permissionless and permissioned blockchain diffusion. *International Journal of Information Management*, *54*, Article 102136.

Henderson, C. M., Beck, J. T., & Palmatier, R. W. (2011). Review of the theoretical underpinnings of loyalty programs. *Journal of Consumer Psychology*, *21*(3), 256–276.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*, 115–135.

Hinz, O., Gerstmeier, E., Tafreschi, O., Enzmann, M., & Schneider, M. (2007). Customer loyalty programs and privacy concerns. *BLED 2007 Proceedings*, 32. http://aisel.aisnet.org/bled2007/32

Hirsch, D. D. (2014). The glass house effect: Big data, the new oil, and the power of analogy. *Maine Law Review*, *66*(2), 373–395.

Hoang, L. C., Do, M. H. T., Quang, H. T., & Hoang, T. H. (2024). Blockchain technology applications in retail branding: Insights from retailers in the developing world. *Thunderbird International Business Review, 66*(1), 3–18.

Horppu, M., Kuivalainen, O., Tarkiainen, A., & Ellonen, H. (2008). Online satisfaction, trust, and loyalty, and the impact of the offline parent brand. *Journal of Product & Brand Management, 17*(6), 403–413.

Hoyle, R. H. (1995). *Structural equation modeling: Concepts, issues, and applications*. Sage.

Hwang, J. Y., Kim, K. Y., & Lee, K. H. (2014). Factors that influence the acceptance of telemetry by emergency medical technicians in ambulances: An application of the extended

technology acceptance model. *Telemedicine and e-Health, 20*(12), 1127–1134.
Inoue, Y., Funk, D. C., & McDonald, H. (2017). Predicting behavioral loyalty through corporate social responsibility: The mediating role of involvement and commitment. *Journal of Business Research, 75*, 46–56.
Jahanshahi, A. A., Gashti, M. A. H., Mirdamadi, S. A., Nawaser, K., & Khaksar, S. M. S. (2011). Study the effects of customer service and product quality on customer satisfaction and loyalty. *International Journal of Humanities and Social Science, 1*(7), 253–260.
Jain, D., Dash, M. K., Kumar, A., & Luthra, S. (2021). How is blockchain used in marketing: A review and research agenda. *International Journal of Information Management Data Insights, 1*(2), Article 100044.
Jalilvand, M. R., Salimipour, S., Elyasi, M., & Mohammadi, M. (2017). Factors influencing word of mouth behavior in the restaurant industry. *Marketing Intelligence & Planning, 35*(1), 81–110.
Jamshidi, D., & Hussin, N. (2018). An integrated adoption model for Islamic credit card: PLS-SEM based approach. *Journal of Islamic Accounting and Business Research, 9*, 308–335.
Jamshidi, D., & Kuanova, L. (2020). Investigating the customers' drivers of Islamic credit card loyalty and word of mouth. *Journal of Islamic Marketing, 13*(4), 868–886.
Jena, R. K. (2022). Examining the factors affecting the adoption of blockchain technology in the banking sector: An extended UTAUT model. *International Journal of Financial Studies, 10*, 90. https://doi.org/10.3390/ijfs10040090
JetBlue Airways Corporation. (2022). *2022 annual report and Form 10K*. Retrieved January 24, 2024, from https://www.annualreports.com/Click/19750
Johansson, L., & Rystadius, G. (2022). *The privacy club: An exploratory study of the privacy paradox in digital loyalty programs* [Master's thesis, Jönköping International Business School]. Jönköping University.
Joo, Y. J., Lee, H. W., & Ham, Y. (2014). Integrating user interface and personal innovativeness into the TAM for mobile learning in Cyber University. *Journal of Computing in Higher Education, 26*(2), 143–158.
Kabir, M. R., Islam, M. A., Marniati, & Herawati. (2021). Application of blockchain for supply chain financing: Explaining the drivers using SEM. *Journal of Open Innovation: Technology, Market, and Complexity, 7*, 167. https://doi.org/10.3390/joitmc7030167
Kamble, S., Gunasekaran, A., & Arha, H. (2019). Understanding the blockchain technology adoption in supply chains: Indian context. *International Journal of Production Research, 57*(7), 2009–2033.

Kamble, S. S., Gunasekaran, A., Kumar, V., Belhadi, A., & Foropon, C. (2021). A machine learning based approach for predicting blockchain adoption in supply chain. *Technological Forecasting and Social Change*, *163*, Article 120465.

Kamran-Disfani, O., Mantrala, M. K., Izquierdo-Yusta, A., & Martínez-Ruiz, M. P. (2017). The impact of retail store format on the satisfaction-loyalty link: An empirical investigation. *Journal of Business Research*, *77*, 14–22.

Karahanna, E., Straub, D. W., & Chervany, N. L. (1999). Information technology adoption across time: A cross-sectional comparison of pre-adoption and post-adoption beliefs. *MIS Quarterly*, *23*(2), 183–213.

Karamchandani, A., Srivastava, S. K., & Srivastava, R. K. (2020). Perception-based model for analyzing the impact of enterprise blockchain adoption on SCM in the Indian service industry. *International Journal of Information Management*, *52*, Article 102019.

Kaur, P., Dhir, A., Chen, S., & Rajala, R. (2021). Attitudinal and behavioral loyalty toward virtual goods. *Journal of Computer Information Systems*, *61*(2), 118–129.

Keller, E. (2007). Unleashing the power of word of mouth: Creating brand advocacy to drive growth. *Journal of Advertising Research*, *47*(4), 448–452.

Khan, A., & Woosley, J. M. (2011). Comparison of contemporary technology acceptance models and evaluation of the best fit for health industry organizations. *International Journal of Computer Science and Engineering Technology (IJCSET)*, *1*(11), 709–717.

Khare, A., & Jain, R. (2022). Mapping the conceptual and intellectual structure of the consumer vulnerability field: A bibliometric analysis. *Journal of Business Research*, *150*, 567–584.

Khazaei, H. (2020). Integrating cognitive antecedents to UTAUT model to explain adoption of blockchain technology among Malaysian SMEs. *International Journal on Informatics Visualization*, *4*(2), 85–90.

Kim, D., & Chang, H. (2007). Key functional characteristics in designing and operating health information websites for user satisfaction: An application of the extended technology acceptance model. *International Journal of Medical Informatics*, *76*(11–12), 790–800.

Kim, T. G., Lee, J. H., & Law, R. (2008). An empirical examination of the acceptance behaviour of hotel front office systems: An extended technology acceptance model. *Tourism Management*, *29*(3), 500–513.

Kim, W. G., Kim, S. Y., & Leong, J. K. (2003). Impact of guest reward programs on the firms' performance. *Journal of Quality Assurance in Hospitality & Tourism*, *4*(1–2), 87–109.

King, W. R., & He, J. (2006). A meta-analysis of the technology acceptance model. *Information & Management*, *43*(6), 740–755.

Kivetz, R., Urminsky, O., & Zheng, Y. (2006). The goal-gradient hypothesis resurrected: Purchase acceleration, illusionary goal progress, and customer retention. *Journal of Marketing Research*, *43*(1), 39–58.

Kjærland, F., Khazal, A., Krogstad, E., Nordstrøm, F., & Oust, A. (2018). An analysis of bitcoin's price dynamics. *Journal of Risk and Financial Management, 11*(4), 63.

Knauer, F., & Mann, A. (2019). What is in it for me? Identifying drivers of blockchain acceptance among German consumers. *Journal of the British Blockchain Association, 3*(1), 1–16.

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration*, *11*(4), 1–10.

Koivuhovi, S., Marsh, H. W., Dicke, T., Sahdra, B., Guo, J., Parker, P. D., & Vainikainen, M.-P. (2022). Academic self-concept formation and peer-group contagion: Development of the big-fish-little-pond effect in primary-school classrooms and peer groups. *Journal of Educational Psychology, 114*(1), 198–213. https://doi.org/10.1037/edu0000554

Kokina, J., Mancha, R., & Pachamanova, D. (2017). Blockchain: Emergent industry adoption and implications for accounting. *Journal of Emerging Technologies in Accounting*, *14*(2), 91–100.

Koo, B., Yu, J., & Han, H. (2020). The role of loyalty programs in boosting hotel guest loyalty: Impact of switching barriers. *International Journal of Hospitality Management*, *84*, Article 102328.

Kopalle, P. K., Neslin, S. A., Sun, B., Sun, Y., & Swaminathan, V. (2009). *A dynamic structural model of the impact of loyalty programs on customer behavior*. Working paper, Tuck School of Business at Dartmouth.

Kopalle, P., Sun, Y., Neslin, S. A., Sun, B., & Swaminathan, V. (2012). The joint sales impact of frequency reward and customer tier components of loyalty programs. *Marketing Science*, *31*(2), 216–235.

Koppius, O., Speelman, W., Stulp, O., Verhoef, B., & van Heck, E. (2005). Why are customers coming back to buy their airline tickets online? Theoretical explanations and empirical evidence. In *Proceedings of the 7th International Conference on Electronic Commerce (ICEC '05)* (pp. 319–326). Association for Computing Machinery. https://doi.org/10.1145/1089551.1089611

Kowalewski, D., McLaughlin, J., & Hill, A. J. (2017, March 14th). Blockchain will transform customer loyalty programs. *Harvard Business Review*, *14*. https://hbr.org/2017/03/blockchain-will-transform-customer-loyalty-programs

KPMG. (2019). *The truth about customer loyalty*. KPMG. Retrieved January 24, 2024, from https://assets.kpmg.com/content/dam/kpmg/ar/pdf/the-truth-about-customer-loyalty.pdf

Kumar, S., Raut, R. D., Agrawal, N., Cheikhrouhou, N., Sharma, M., & Daim, T. (2022). Integrated blockchain and internet of things in the food supply chain: Adoption barriers. *Technovation*, *118*, Article 102589.

Kumar, V., Ramachandran, D., & Kumar, B. (2021). Influence of new-age technologies on marketing: A research agenda. *Journal of Business Research*, *125*, 864–877.

Kumari, A., & Devi, N. C. (2023). Blockchain technology acceptance by investment professionals: A decomposed TPB model. *Journal of Financial Reporting and Accounting*, *21*(1), 45–59.

Kurniasih, A., Santoso, A., Riana, D., Kadafi, A., Dari, W., & Husin, A. (Eds.). (2020). TAM method and acceptance of COVID-19 website users in Indonesia. IOP Publishing. 012020.

Kwiatek, P., Dženopoljac, V., & Rauf, A. (2021). Loyalty program value: Give me more or treat me better? *Menadžment u hotelijerstvu i turizmu [Management in the hotel industry and tourism]*, 9(2), 11-23. https://doi.org/10.5937/menhottur2102011K

Lacey, R., & Sneath, J. Z. (2006). Customer loyalty programs: Are they fair to consumers? *Journal of Consumer Marketing*, *23*(7), 458–464.

Lee, C. C., Kriscenski, J. C., & Lim, H. S. (2019). An empirical study of behavioral intention to use blockchain technology. *Journal of International Business Disciplines*, *14*(1), 1-21.

Lee, J. J., Capella, M. L., Taylor, C. R., & Gabler, C. B. (2014). The financial impact of loyalty programs in the hotel industry: A social exchange theory perspective. *Journal of Business Research*, *67*(10), 2139–2146.

Lee, S., Park, E., Kwon, S. J., & Del Pobil, A. P. (2015). Antecedents of behavioral intention to use mobile telecommunication services: Effects of corporate social responsibility and technology acceptance. *Sustainability*, *7*(8), 11345–11359.

Lee, T. M., & Jun, J. K. (2007). Contextual perceived value?: Investigating the role of contextual marketing for customer relationship management in a mobile commerce context. *Business Process Management Journal*, *13*(6), 798–814.

Lee, Y.-H., Hsieh, Y.-C., & Hsu, C.-N. (2011). Adding innovation diffusion theory to the technology acceptance model: Supporting employees' intentions to use e-learning systems. *Journal of Educational Technology & Society*, *14*(4), 124–137.

Lee, Y.-K., Park, J.-H., Chung, N., & Blakeney, A. (2012). A unified perspective on the factors influencing usage intention toward mobile financial services. *Journal of Business Research*, *65*(11), 1590–1599.

Lefever, S., Dal, M., & Matthíasdóttir, Á. (2007). Online data collection in academic research: Advantages and limitations. *British Journal of Educational Technology*. 38(4), 574–582.
Lemos, C., Ramos, R. F., Moro, S., & Oliveira, P. M. (2022). Stick or twist: The rise of blockchain applications in marketing management. *Sustainability*, *14*(7), Article 4172.
Leninkumar, V. (2017). The relationship between customer satisfaction and customer trust on customer loyalty. *International Journal of Academic Research in Business and Social Sciences*, *7*(4), 450–465.
Li, C., Swaminathan, S., & Kim, J. (2021). The role of marketing channels in consumers' promotional point redemption decisions. *Journal of Business Research*, *125*, 314–323.
Li, C., Zhang, Y., & Xu, Y. (2022). Factors influencing the adoption of blockchain in the construction industry: A hybrid approach using PLS-SEM and fsQCA. *Buildings*, *12*(9), 1349. https://doi.org/10.3390/buildings12091349
Li, X., Lai, P.-L., Yang, C.-C., & Yuen, K. F. (2021). Determinants of blockchain adoption in the aviation industry: Empirical evidence from Korea. *Journal of Air Transport Management*, *97*, Article 102139.
Li, Y., Marier-Bienvenue, T., Perron-Brault, A., Wang, X., & Paré, G. (2018). Blockchain technology in business organizations: A scoping review. In *Proceedings of the 51st Hawaii International Conference on System Sciences* (pp. 4474–4483). Scholarspace.
Liao, S. H., Chung, Y. C., Hung, Y. R., & Widowati, R. (2010). The impacts of brand trust, customer satisfaction, and brand loyalty on word-of-mouth. In *Proceedings of the 2010 IEEE International Conference on Industrial Engineering and Engineering Management* (pp. 1319–1323). IEEE. https://doi.org/10.1109/IEEM.2010.5674402
Lim, Y. H., Hashim, H., Poo, N., Poo, D. C. C., & Nguyen, H. D. (2019). Blockchain technologies in e-commerce: Social shopping and loyalty program applications. In *Social Computing and Social Media: Communication and Social Communities: 11th International Conference, SCSM 2019, Held as Part of the 21st HCI International Conference, HCII 2019, Orlando, FL, USA, 26–31 July 2019* (pp. 1–10). Springer International Publishing.
Lin, H.-F. (2014). Understanding the determinants of electronic supply chain management system adoption: Using the technology–organization–environment framework. *Technological Forecasting and Social Change, 86*, 80–92.
Lin, T.-C., Huang, S.-L., & Hsu, C.-J. (2015). A dual-factor model of loyalty to IT product: The case of smartphones. *International Journal of Information Management, 35*(2), 215–228.
Liu, M. T., Liu, Y., Mo, Z., Zhao, Z., & Zhu, Z. (2020). How CSR influences customer behavioural loyalty in the Chinese hotel industry. *Asia Pacific Journal of Marketing and*

Logistics, 32(1), 1–22. https://doi.org/10.1108/APJML-04-2018-0160
Liu, N., & Ye, Z. (2021). Empirical research on the blockchain adoption–based on TAM. *Applied Economics*, *53*(37), 4263–4275.
Liu, Y. (2007). The long-term impact of loyalty programs on consumer purchase behavior and loyalty. *Journal of Marketing*, *71*(4), 19–35.
Lou, A. T. F., & Li, E. Y. (2017). Integrating innovation diffusion theory and the technology acceptance model: The adoption of blockchain technology from business managers' perspective. In *Proceedings of the International Conference on Electronic Business* (pp. 299–310). Dubai, United Arab Emirates.
Lu, J., Yao, J. E., & Yu, C.-S. (2005). Personal innovativeness, social influences and adoption of wireless internet services via mobile technology. *The Journal of Strategic Information Systems*, *14*(3), 245–268.
Lu, J., Yu, C., Liu, C., & Yao, J. E. (2003). Technology acceptance model for wireless Internet. *Internet Research, 13*(3), 206–222. https://doi.org/10.1108/10662240310478222
Lyytinen, K., & Damsgaard, J. (2001). What's wrong with the diffusion of innovation theory? The case of a complex and networked technology. In M. A. Ardis & B. L. Marcolin (Eds.), *Diffusing software product and process innovations: IFIP TC8 WG8.6 Fourth Working Conference on Diffusing Software Product and Process Innovations* (pp. 173–190). Springer. https://doi.org/10.1007/978-0-387-35404-0_11
Mai, N. T. T., Yoshi, T., & Tuan, N. P. (2013). Technology acceptance model and the paths to online customer loyalty in an emerging market [Model prihvacanja tehnologije i putevi do online lojalnosti potrosaca na trzistima u razvoju]. *Trziste [Market]*, *25*(2), 231-248.
Malhotra, N. K., Nunan, D., & Birks, D. F. (2017). *Marketing research: An applied approach.* Pearson.
Mandler, T., Sezen, B., Chen, J., & Özsomer, A. (2021). Performance consequences of marketing standardization/adaptation: A systematic literature review and future research agenda. *Journal of Business Research*, *125*, 416–435.
Manley, S. C., Hair, J. F., Williams, R. I., & McDowell, W. C. (2021). Essential new PLS-SEM analysis methods for your entrepreneurship analytical toolbox. *International Entrepreneurship and Management Journal*, *17*, 1805–1825.
Manski, S. (2017). Building the blockchain world: Technological commonwealth or just more of the same? *Strategic Change*, *26*(5), 511–522.
Marakanon, L., & Panjakajornsak, V. (2017). Perceived quality, perceived risk and customer trust affecting customer loyalty of environmentally friendly electronics products. *Kasetsart*

Journal of Social Sciences, *38*(1), 24–30.

Marriott International. (2022). *2022 annual report*. Retrieved January 22, 2022, from https://www.annualreports.com/Click/24645

Marshall, N., & Southeastern, N. (2010). Commitment, loyalty and customer lifetime value: Investigating the relationships among key determinants. *Journal of Business & Economics Research (JBER), 8*(8), 1–10. https://doi.org/10.19030/jber.v8i8.753

Martignoni, R., Stanoevska-Slabeva, K., Mueller, D., & Hoegg, R. (2008). Evaluation of future mobile services based on the technology acceptance model. In *European Conference on Information Systems* (pp. 1190–1203).

Martinez-Caro, E., Cepeda-Carrión, G., & Cegarra-Navarro, J. G. (2013). Applying a technology acceptance model to test business e-loyalty towards online banking transactions. In *Proceedings of the European Conference on Knowledge Management*, *ECKM* (pp. 1190–1203).

Masrom, M. (2007). Technology acceptance model and e-learning. *Technology*, *21*(24), 81.

Matthews, L., Hair, J. F., & Matthews, R. (2018). PLS-SEM: The holy grail for advanced analysis. *Marketing Management Journal, 28*(1), 1-13. https://doi.org/10.1108/IMR-09-2014-0304

Mazzarol, T., Sweeney, J. C., & Soutar, G. N. (2007). Conceptualizing word-of-mouth activity, triggers, and conditions: An exploratory study. *European Journal of Marketing, 41*(11/12), 1475–1494. https://doi.org/10.1108/03090560710821260

McCloskey, D. W. (2006). The importance of ease of use, usefulness, and trust to online consumers: An examination of the technology acceptance model with older customers. *Journal of Organizational and End User Computing*, *18*(3), 47–65.

Mengelkamp, E., Notheisen, B., Beer, C., Dauer, D., & Weinhardt, C. (2018). A blockchain-based smart grid: Towards sustainable local energy markets. *Computer Science-Research and Development*, *33*, 207–214.

Miltgen, C. L., Popovič, A., & Oliveira, T. (2013). Determinants of end-user acceptance of biometrics: Integrating the “Big 3” of technology acceptance with privacy context. *Decision Support Systems*, *56*, 103–114.

Min, H. (2019). Blockchain technology for enhancing supply chain resilience. *Business Horizons*, *62*(1), 35–45.

Min, S., So, K. K. F., & Jeong, M. (2019). Consumer adoption of the Uber mobile application: Insights from diffusion of innovation theory and technology acceptance model. *Journal of Travel & Tourism Marketing*, *36*(7), 770–783.

Moorman, C., Zaltman, G., & Deshpande, R. (1992). Relationships between providers and users of market research: The dynamics of trust within and between organizations. *Journal of Marketing Research*, *29*(3), 314–328.

Moreira, A. C., & Silva, P. M. (2015). The trust-commitment challenge in service quality-loyalty relationships. *International Journal of Health Care Quality Assurance, 28*(3), 253-266. https://doi.org/10.1108/IJHCQA-02-2014-0017

Morgan, R. M., & Hunt, S. D. (1994). The commitment-trust theory of relationship marketing. *Journal of Marketing*, *58*(3), 20–38.

Morkunas, V. J., Paschen, J., & Boon, E. (2019). How blockchain technologies impact your business model. *Business Horizons*, *62*(3), 295–306.

Morris, N. (2018, July 25th). *Singapore Airlines blockchain rewards takes off*. Ledger Insights. Retrieved July 25th, 2023, from https://www.ledgerinsights.com/singapore-airlines-blockchain-rewards/

Mpinganjira, M., Roberts-Lombard, M., & Svensson, G. (2017). Validating the relationship between trust, commitment, economic and non-economic satisfaction in South African buyer-supplier relationships. *Journal of Business & Industrial Marketing*, *32*(3), 421–431.

Muflih, M. (2023), "Muzakki’s adoption of mobile service: integrating the roles of technology acceptance model (TAM), perceived trust and religiosity", *Journal of Islamic Accounting and Business Research*, Vol. 14 No. 1, pp. 21-33. https://doi-org.ezproxy.uct.ac.za/10.1108/JIABR-09-2021-0273

Mukherjee, A., & Nath, P. (2007). Role of electronic trust in online retailing. *European Journal of Marketing, 41*(9/10), 1173–1202. https://doi.org/10.1108/03090560710773390

Nagy, J. T. (2018). Evaluation of online video usage and learning satisfaction: An extension of the technology acceptance model. *International Review of Research in Open and Distance Learning, 19*(1). https://doi.org/10.19173/irrodl.v19i1.2886

Naidoo, R., & Leonard, A. (2007). Perceived usefulness, service quality and loyalty incentives: Effects on electronic service continuance. *South African Journal of Business Management*, *38*(3), 39–48.

Naidoo, V. (2007). Perceived usefulness, service quality, and loyalty incentives: Effects on electronic service continuance. *South African Journal of Business Management, 38*(3). https://doi.org/10.10520/EJC22335

Nastasoiu, A., & Vandenbosch, M. (2019). Competing with loyalty: How to design successful customer loyalty reward programs. *Business Horizons*, *62*(2), 207–214.

Nayal, P., & Pandey, N. (2020). Digital coupon redemption: Conceptualization, scale development, and validation. *Australasian Journal of Information Systems*, *24*, 1–23. https://doi.org/10.3127/ajis.v24i0.2469

Nezamdoust, S., Abdekhoda, M., & Rahmani, A. (2022). Determinant factors in adopting mobile health application in healthcare by nurses. *BMC Medical Informatics and Decision Making*, *22*(1), 1–10.

Niu, Z., Hu, X., Qi, S., Yang, H., Wang, S., & An, S. (2021). Determinants to parking mode alternatives: A model integrating technology acceptance model and satisfaction–loyalty model. *Transportation Research, Part A: Policy and Practice*, *152*, 216–234.

Nuraini. (2022, May 12th). *7 companies adopting blockchain loyalty programs*. Tada. Retrieved May 12th, 2024, from https://blog.usetada.com/en/companies-adopting-blockchain-loyalty-programs

Nuryyev, G., Wang, Y.-P., Achyldurdyyeva, J., Jaw, B.-S., Yeh, Y.-S., Lin, H.-T., & Wu, L.-F. (2020). Blockchain technology adoption behavior and sustainability of the business in tourism and hospitality SMEs: An empirical study. *Sustainability*, *12*(3), Article 1256.

O'Brien, L., & Jones, C. (1995). Do rewards really create loyalty? *Harvard Business Review, 73*(5), 75–82.

Obal, M. (2013). Why do incumbents sometimes succeed? Investigating the role of interorganizational trust on the adoption of disruptive technology. *Industrial Marketing Management*, *42*(6), 900–908.

Odekerken-Schröder, G., De Wulf, K., & Schumacher, P. (2003). Strengthening outcomes of retailer–consumer relationships: The dual impact of relationship marketing tactics and consumer personality. *Journal of Business Research*, *56*(3), 177–190.

Oliveira, T., & Martins, M. F. (2011). Literature review of information technology adoption models at firm level. *Electronic Journal of Information Systems Evaluation*, *14*(1), 110–121.

Orji, I. J., Kusi-Sarpong, S., Huang, S., & Vazquez-Brust, D. (2020). Evaluating the factors that influence blockchain adoption in the freight logistics industry. *Transportation Research, Part E: Logistics and Transportation Review*, *141*, Article 102025.

Pagani, M. (2004). Determinants of adoption of third generation mobile multimedia services. *Journal of Interactive Marketing*, *18*(3), 46–59.

Pakrou, M., & Amir, K. (2016). The relationship between perceived value and the intention of using Bitcoin. *Journal of Internet Banking and Commerce, 21*(2), 1–18.

Pallant, J. F. (2000). Development and validation of a scale to measure perceived control of internal states. *Journal of Personality Assessment*, *75*(2), 308–337.

Park, J., Hyun, H., & Thavisay, T. (2021). A study of antecedents and outcomes of social media

WOM towards luxury brand purchase intention. *Journal of Retailing and Consumer Services*, *58*, Article 102272.

Parker, C. M., & Castleman, T. (2009). Small firm e-business adoption: A critical analysis of theory. *Journal of Enterprise Information Management, 22*(1/2), 167-182. https://doi.org/10.1108/17410390910932812

Pärssinen, M., Kotila, M., Rumin, R. C., Phansalkar, A., & Manner, J. (2018). Is blockchain ready to revolutionize online advertising? *IEEE Access*, *6*, 54884–54899.

Paul, J., & Rosado-Serrano, A. (2019). Gradual internationalization vs born-global/international new venture models: A review and research agenda. *International Marketing Review*, *36*(6), 830–858.

Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. *International Journal of Electronic Commerce*, *7*(3), 101–134.

Pawar, S. K. (2023). Marketing education to international students: A systematic literature review and future research agenda. *International Journal of Consumer Studies*, *47*(1), 42–58.

Peña-García, N., Gil-Saura, I., & Rodríguez-Orejuela, A. (2018). E-loyalty formation: A cross-cultural comparison of Spain and Colombia. *Journal of Electronic Commerce Research*, *19*(4), 336–356.

Peres, R., Schreier, M., Schweidel, D. A., & Sorescu, A. (2023). Blockchain meets marketing: Opportunities, threats, and avenues for future research. *International Journal of Research in Marketing*, *40*(1), 1–11. https://doi.org/10.1016/j.ijresmar.2022.08.001

Dominguez Perez, L. J., Ibarra, L., Alejandro, G.-F., Rumayor, A., & Lara-Alvarez, C. (2020). A loyalty program based on Waves blockchain and mobile phone interactions. *The Knowledge Engineering Review, 35*, e12. https://doi.org/10.1017/S0269888920000181

érez-Sánchez, M. d. Á., Tian, Z., Barrientos-Báez, A., Gómez-Galán, J., & Li, H. (2021). Blockchain technology for winning consumer loyalty: Social norm analysis using structural equation modeling. *Mathematics, 9*(5), 532. https://doi.org/10.3390/math9050532

Picón, A., Castro, I., & Roldán, J. L. (2014). The relationship between satisfaction and loyalty: A mediator analysis. *Journal of Business Research*, *67*(5), 746–751.

Pieters, J. J., Kokkinou, A., & Van Kollenburg, T. (2022). Understanding blockchain technology adoption by non-experts: An application of the unified theory of acceptance and use of technology (UTAUT). *Operations Research Forum, 3*, 1.

Pramanik, B. K., Rahman, A. Z. M. S., & Li, M. (2020). Blockchain-based reward point exchange systems. *Multimedia Tools and Applications, 79*(14), 9785–9798.

https://doi.org/10.1007/s11042-019-08341-2

Prayag, G. (2008). Image, satisfaction and loyalty: The case of Cape Town. *Anatolia*, *19*(2), 205–224.

Pritchard, M. P., Havitz, M. E., & Howard, D. R. (1999). Analyzing the commitment-loyalty link in service contexts. *Journal of the Academy of Marketing Science*, *27*(3), 333–348.

Queiroz, M. M., Fosso Wamba, S., De Bourmont, M., & Telles, R. (2021). Blockchain adoption in operations and supply chain management: Empirical evidence from an emerging economy. *International Journal of Production Research*, *59*(20), 6087–6103.

Rahman, R., Langner, T., & Temme, D. (2021). Brand love: Conceptual and empirical investigation of a holistic causal model. *Journal of Brand Management*, *28*(6), 609–642.

Rambocas, M., & Arjoon, S. (2012). Using diffusion of innovation theory to model customer loyalty for Internet banking: A TT millennial perspective. *International Journal of Business and Commerce*, *1*(8), 1–14.

Rashideh, W. (2020). Blockchain technology framework: Current and future perspectives for the tourism industry. *Tourism Management*, *80*, Article 104125.

Reingen, P. H. (1987). A word-of-mouth network. *Advances in Consumer Research*, *14*(1), 213-217.

Rejeb, A., Keogh, J. G., & Treiblmaier, H. (2020). How blockchain technology can benefit marketing: Six pending research areas. *Frontiers in Blockchain*, *3*, Article 3.

Research and Markets. (2024, April 4). *Global loyalty programs intelligence report 2024: Market to grow by 11.1% to surpass $150 billion this year - Forecasts to 2028*. GlobalNewsWire.https://www.globenewswire.com/en/news-release/2024/04/04/2857513/28124/en/Global-Loyalty-Programs-Intelligence-Report-2024-Market-to-Grow-by-11-1-to-Surpass-150-Billion-this-Year-Forecasts-to-2028.html

Rogers, E. M. (1995). Diffusion of innovations: Modifications of a model for telecommunications. In B. J. Cooper & C. L. Davidson (Eds.), *Die Diffusion von Innovationen in der Telekommunikation* (Vol. 1, pp. 25–38). Springer.

Rogers, E. M., & Shoemaker, F. F. (1971). *Communication of innovations* (2nd ed.). New York: Free Press.

Rosenbaum, M. S., Ostrom, A. L., & Kuntze, R. (2005). Loyalty programs and a sense of community. *Journal of Services Marketing*, *19*(4), 222–233.

Roussou, I., & Stiakakis, E. (2016). Adoption of digital currencies by companies in the European Union: A research model combining DOI and TAM. In *Proceedings of the 4th International Conference on Contemporary Marketing Issues (ICCMI)* (pp. 163). Heraklion,

Greece.
Roy, S. K., Butaney, G., & Bhutaney, B. (2009). Examining the effects of the customer loyalty states on the word of mouth. *Associations for Information Systems*, 1-14.
Ruefenacht, M. (2018). The role of satisfaction and loyalty for insurers. *International Journal of Bank Marketing, 36*(6), 1034-1054. https://doi.org/10.1108/IJBM-10-2016-0152
Ruiz-Mafé, C., Martí-Parreño, J., & Sanz-Blas, S. (2014). Key drivers of consumer loyalty to Facebook fan pages. *Online Information Review, 38*(3), 362-380. https://doi.org/10.1108/OIR-05-2013-0101
Salovaara, A., & Tamminen, S. (2009). Acceptance or appropriation? A design-oriented critique on technology acceptance models. In P. Saariluoma & H. Isomäki (Eds.), *Future interaction design* (Vol. 2, pp. 157-173). Springer.
Saputra, U. W. E., & Darma, G. S. (2022). The intention to use blockchain in Indonesia using extended approach technology acceptance model (TAM). *CommIT* (*Communication and Information Technology) Journal*, *16*(1), 27–35.
Sarmah, R., Dhiman, N., & Kanojia, H. (2021). Understanding intentions and actual use of mobile wallets by millennial [sic]: An extended TAM model perspective. *Journal of Indian Business Research*, *13*(3), 361–381.
Sarstedt, M., Ringle, C. M., & Hair, J. F. (2017). Partial least squares structural equation modeling. *Handbook of market research*, *26*(1), 1–40.
Sarstedt, M., Ringle, C. M., & Hair, J. F. (2021). Partial least squares structural equation modeling. In C. Homburg, M. Klarmann, & A. E. Vomberg (Eds.), *Handbook of market research* (pp. 1–47). Springer International Publishing.
Saunders, M., Lewis, P., & Thornhill, A. (2019). *Research methods for business students* (8th ed.). Pearson Education.
Sciarelli, M., Prisco, A., Gheith, M. H., & Muto, V. (2022). Factors affecting the adoption of blockchain technology in innovative Italian companies: An extended TAM approach. *Journal of Strategy and Management, 15*(3), 495–507. https://doi.org/10.1108/JSMA-02-2021-0054
Setiawati, N. P. A., Sunarsi, D., Nurjaya, S., Manan, A., Nurhadi, A., Erlangga, H., ... & Purwanto, A. (2021). Effect of technology acceptance factors, website service quality, and specific holdup cost on customer loyalty: A study in the marketing department of the packaging industry. *Annals of the Romanian Society for Cell Biology, 25*(3), 12685–12697.
Shankar, A., Jebarajakirthy, C., & Ashaduzzaman, M. (2020). How do electronic word of mouth practices contribute to mobile banking adoption? *Journal of Retailing and Consumer Services*, *52*, Article 101920.

Shankar, V., Smith, A. K., & Rangaswamy, A. (2003). Customer satisfaction and loyalty in online and offline environments. *International Journal of Research in Marketing*, *20*(2), 153–175.

Sharifi, S., & Esfidani, M. R. (2014). The impacts of relationship marketing on cognitive dissonance, satisfaction, and loyalty. *International Journal of Retail & Distribution Management*, *42*(6), 553–575. https://doi.org/10.1108/IJRDM-05-2013-0109

Shelper, P., Lowe, A., & Kanhere, S. S. (2018). Experiences from the field: Unify Rewards—A cryptocurrency loyalty program. In *Proceedings of the Symposium on Foundations and Applications of Blockchain 2018* (pp. 1–9). Los Angeles, CA, USA.

Shih, Y., & Fang, K. (2004). The use of a decomposed theory of planned behavior to study Internet banking in Taiwan. *Internet Research, 14*(3), 213–223. https://doi.org/10.1108/10662240410542643

Shrestha, A. K., & Vassileva, J. (2019). User acceptance of usable blockchain-based research data sharing system: An extended TAM-based study. In *Proceedings of the 2019 First IEEE International Conference on Trust, Privacy and Security in Intelligent Systems and Applications (TPS-ISA)* (pp. 203–208). IEEE. https://doi.org/10.1109/TPS-ISA48467.2019.00033

Sigala, M., Airey, D., Jones, P., & Lockwood, A. (2000). The diffusion and application of multimedia technologies in the tourism and hospitality industries. In *Information and communication technologies in tourism 2000* (pp. 396–407). Springer.

Singh, J., & Sirdeshmukh, D. (2000). Agency and trust mechanisms in consumer satisfaction and loyalty judgments. *Journal of the Academy of Marketing Science*, *28*(1), 150–167.

Singh, S., & Dhir, S. (2019). Structured review using TCCM and bibliometric analysis of international cause-related marketing, social marketing, and innovation of the firm. *International Review on Public and Nonprofit Marketing*, *16*, 335–347.

Sirdeshmukh, D., Singh, J., & Sabol, B. (2002). Consumer trust, value, and loyalty in relational exchanges. *Journal of Marketing, 66*(1), 15–37.

Smith, A., & Sparks, L. (2009). “It’s nice to get a wee treat if you’ve had a bad week”: Consumer motivations in retail loyalty scheme points redemption. *Journal of Business Research*, *62*(5), 542–547.

Söderlund, M. (2006). Measuring customer loyalty with multi-item scales. *International Journal of Service Industry Management*, *17*(1), 76–98. https://doi.org/10.1108/09564230610651598

Sohaib, O., Hussain, W., Asif, M., Ahmad, M., & Mazzara, M. (2019). A PLS-SEM neural network approach for understanding cryptocurrency adoption. *IEEE Access*, *8*, 13138–13150.

Sönmeztürk, O., Ayav, T., & Erten, Y. M. (2020). Loyalty program using blockchain. In *Proceedings of the 2020 IEEE International Conference on Blockchain (Blockchain)* (pp. 509–516). IEEE. https://doi.org/10.1109/Blockchain50366.2020.00074

Southwest Airlines Co. (2022). *2022 annual report and Form 10K*. Retrieved January 24, 2024, from https://www.annualreports.com/Click/22333

Srinivasan, S. S., Anderson, R., & Ponnavolu, K. (2002). Customer loyalty in e-commerce: An exploration of its antecedents and consequences. *Journal of Retailing*, *78*(1), 41–50.

Srivastava, J. D., Kumar, N., & Bisht, H. (2019). Blockchain for loyalty rewards program management. *Journal of Gujarat Research Society, 21*(7), 92–100.

Stallone, V., Wetzels, M., & Klaas, M. (2021). Applications of blockchain technology in marketing: A systematic review of marketing technology companies. *Blockchain: Research and Applications*, *2*(3), Article 100023.

Stathopoulou, A., & Balabanis, G. (2016). The effects of loyalty programs on customer satisfaction, trust, and loyalty toward high- and low-end fashion retailers. *Journal of Business Research*, *69*(12), 5801–5808.

Stauss, B., Schmidt, M., & Schoeler, A. (2005). Customer frustration in loyalty programs. *International Journal of Service Industry Management*, *16*(3), 229–252.

Steinmetz, F., von Meduna, M., Ante, L., & Fiedler, I. (2021). Ownership, uses and perceptions of cryptocurrency: Results from a population survey. *Technological Forecasting and Social Change, 173*, 121073. https://doi.org/10.1016/j.techfore.2021.121073

Stourm, V., Neslin, S. A., Bradlow, E. T., & et al. (2020). Refocusing loyalty programs in the era of big data: A societal lens paradigm. *Marketing Letters, 31*(3), 405–418. https://doi.org/10.1007/s11002-020-09523-x

Strudwick, G. (2015). Predicting nurses' use of healthcare technology using the technology acceptance model: An integrative review. *Computers, Informatics, Nursing, 33*(5), 189–198.

Su, M., Fang, M., Kim, J., & Park, K.-S. (2022). Sustainable marketing innovation and consumption: Evidence from cold chain food online retail. *Journal of Cleaner Production, 340,* Article 130806.

Sugandini, D., & Wendry, B. (2017). Influence of quality relationship and satisfaction on loyalty: Study on supplier in Indonesia. *Journal of Business and Retail Management Research, 11*(4), 46–51.

Suhartanto, D., Syarief, M. E., Chandra Nugraha, A., Suhaeni, T., Masthura, A., & Amin, H. (2022). Millennial loyalty towards artificial intelligence-enabled mobile banking: Evidence from Indonesian Islamic banks. *Journal of Islamic Marketing*, *13*(9), 1958–1972.

Sun Yin, H. H., Langenheldt, K., Harlev, M., Mukkamala, R. R., & Vatrapu, R. (2019). Regulating cryptocurrencies: A supervised machine learning approach to de-anonymizing the bitcoin blockchain. *Journal of Management Information Systems*, *36*(1), 37–73.

Sundstrom, B. (2014). Breaking women's health taboos: Integrating diffusion of innovations theory with social marketing. *Social Marketing Quarterly*, *20*(2), 87–102.

Sydow, A., Sunny, S. A., & Coffman, C. D. (2020). Leveraging blockchain's potential: The paradox of centrally legitimate, decentralized solutions to institutional challenges in Kenya. *Journal of Business Venturing Insights*, *14*, Article e00170.

Taherdoost, H. (2019). What is the best response scale for survey and questionnaire design: Review of different lengths of rating scale/attitude scale/Likert scale. *International Journal of Academic Research in Management, 8*(1), 1–10.

Taheri Tolu, M., Yazdanian, N., Hemmati, H., & Kordlouoie, H. (2022). Accepting financial transactions using blockchain technology and cryptocurrency based on the TAM model: A case study of Iranian users. *Iranian Journal of Accounting, Auditing and Finance, 6*(2), 97–109.

Tan, T. M., Salo, J., Brashear Alejandro, T. G., Tan, G. W.-H., Ooi, K.-B., & Dwivedi, Y. K. (2024). Guest editorial: A blockchain-based approach to marketing in the sharing economy. Journal of Business Research, 177, 114639. https://doi.org/10.1016/j.jbusres.2024.114639.

Tan, T. M., Salo, J., Alejandro, T. G. B., Tan, G. W. H., Ooi, K. B., & Dwivedi, Y. K. (2024). Guest editorial: A blockchain-based approach to marketing in the sharing economy. *Journal of Business Research, 177,* 114639

Tan, T. M., & Saraniemi, S. (2023). Trust in blockchain-enabled exchanges: Future directions in blockchain marketing. *Journal of the Academy of Marketing Science*, *51*(4), 914–939. https://doi.org/10.1007/s11747-022-00889-0

Tan, W. K. A., & Sundarakani, B. (2021). Assessing Blockchain Technology application for freight booking business: A case study from Technology Acceptance Model perspective. *Journal of Global Operations and Strategic Sourcing, 14*(1), 202–223. https://doi.org/10.1108/JGOSS-04-2020-0018

Tang, T.-W., & Huang, R.-T. (2015). The relationships among trust, e-satisfaction, e-loyalty, and customer online behaviors. *International Journal of Business and Industrial Marketing*, *1*(2), 16–25.

Tao, D. (2009). Intention to use and actual use of electronic information resources: Further exploring Technology Acceptance Model (TAM). *AMIA Annual Symposium Proceedings*, 2009, 629–633.

Tarhini, A., Hone, K., & Liu, X. (2013). Extending the TAM model to empirically investigate the students' behavioural intention to use e-learning in developing countries. In *Science and Information Conference (SAI)* (pp. 732–737).
Taylor, G. A., & Neslin, S. A. (2005). The current and future sales impact of a retail frequency reward program. *Journal of Retailing*, *81*(4), 293–305.
Tighe, D. (2022, August 30). Frequency of loyalty card usage for main shopping in the UK 2020, by age. *Statista*. Retrieved August 29, 2024, from https://www.statista.com/statistics/1125630/loyalty-card-usage-rate-for-main-shopping-in-the-uk-by-age/
Tornatzky, L. G., & Klein, K. J. (1982). Innovation characteristics and innovation adoption-implementation: A meta-analysis of findings. *IEEE Transactions on Engineering Management*, *EM-29*(1), 28–45.
Tornatzky, L. G., & Fleischer, M. (1990). *The processes of technological innovation*. Lexington Books.
Tran, L. T. T., & Nguyen, P. T. (2021). Co-creating blockchain adoption: Theory, practice and impact on usage behavior. *Asia Pacific Journal of Marketing and Logistics*, *33*(7), 1667–1684.
Travizano, M., Sarraute, C., Dolata, M., French, A. M., & Treiblmaier, H. (2020). Wibson: A case study of a decentralized, privacy-preserving data marketplace. In H. Treiblmaier & T. Clohessy (Eds.), *Blockchain and distributed ledger technology use cases* (pp. 149–170). Progress in IS. Springer, Cham. https://doi.org/10.1007/978-3-030-44337-5_8
Treiblmaier, H., & Onder, İ. (2019). The impact of blockchain on the tourism industry: A theory-based research framework. In H. Treiblmaier & R. Beck (Eds.), *Business transformation through blockchain: Volume II* (pp. 3–21). Springer International Publishing. https://doi.org/10.1007/978-3-319-99058-3_1
Treiblmaier, H., & Petrozhitskaya, E. (2023). Is it time for marketing to reappraise B2C relationship management? The emergence of a new loyalty paradigm through blockchain technology. *Journal of Business Research*, *159*, Article 113725.
Tripathi, G. (2017). Customer satisfaction and word-of-mouth intentions: Testing the mediating effect of customer loyalty. *Journal of Services Research*, *17*(2), 1–16.
Trivedi, S., & Malik, R. (2021). Role of cryptocurrency in digital marketing. In N. Bahri, N. Boehmer, P. Dhumal, A. Garg, N. Kalyani, A. Kuruvill, R. Nandgoal, T. Raman, H. Schinnenburg, S. Sharma, P. Singh, & Pawan Taneja (Eds.), *Blockchain technology and applications for digital marketing* (pp. 175–185). IGI Global.
Turel, O., Serenko, A., & Bontis, N. (2007). User acceptance of wireless short messaging

services: Deconstructing perceived value. *Information & Management*, *44*(1), 63–73.

Turner, M., Kitchenham, B., Brereton, P., Charters, S., & Budgen, D. (2010). Does the technology acceptance model predict actual use? A systematic literature review. *Information and Software Technology*, *52*(5), 463–479.

Udegbe, S. E. (2017). Impact of blockchain technology in enhancing customer loyalty programs in airline business. *International Journal of Innovative Research and Advanced Studies*, *4*(6), 257–263.

Ullah, N., Alnumay, W. S., Al-Rahmi, W. M., Alzahrani, A. I., & Al-Samarraie, H. (2020). Modeling cost saving and innovativeness for blockchain technology adoption by energy management. *Energies*, *13*(18), Article 4783.

Ullah, N., Mugahed Al-Rahmi, W., Alzahrani, A. I., Alfarraj, O., & Alblehai, F. M. (2021). Blockchain technology adoption in smart learning environments. *Sustainability*, *13*(4), Article 1801.

Upadhyay, N. (2020). Demystifying blockchain: A critical analysis of challenges, applications and opportunities. *International Journal of Information Management*, *54*, Article 102120.

Utz, M., Johanning, S., Roth, T., Bruckner, T., & Strüker, J. (2023). From ambivalence to trust: Using blockchain in customer loyalty programs. *International Journal of Information Management*, *68*, Article 102496.

Van Raaij, E. M., & Schepers, J. J. (2008). The acceptance and use of a virtual learning environment in China. *Computers & Education*, *50*(3), 838–852.

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, *46*(2), 186–204.

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences*, *39*(2), 273–315.

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, *36*(1), 157–178

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425–478.

Vu, N., Ghadge, A., & Bourlakis, M. (2023). Blockchain adoption in food supply chains: A review and implementation framework. *Production Planning & Control*, *34*(6), 506–523.

Wait, M. (2022). Grocery loyalty cards: Do they work? A customer-centred investigation. *Acta Commercii*, *22*(1), 1-9.

Walsh, C., O'Reilly, P., Gleasure, R., McAvoy, J., & O'Leary, K. (2021). Understanding manager resistance to blockchain systems. *European Management Journal*, *39*(3), 353–365.

Wamba, S. F., Queiroz, M. M., & Trinchera, L. (2020). Dynamics between blockchain adoption determinants and supply chain performance: An empirical investigation. *International Journal of Production Economics*, *229*, Article 107791.

Wang, L., Luo, X. R., & Xue, B. (2018). Too good to be true? Understanding how blockchain revolutionizes loyalty programs. In *Proceedings of the 24th Americas Conference on Information Systems* (pp. 1–10). Association for Information Systems. New Orleans, LA, USA.

Wang, L., Luo, X. R., & Lee, F. (2019). Unveiling the interplay between blockchain and loyalty program participation: A qualitative approach based on Bubichain. *International Journal of Information Management*, *49*, 397–410.

Wang, L., Luo, X., Hua, Y., & Wang, J. (2019). Exploring how blockchain impacts loyalty program participation behaviors: An exploratory case study. In *Proceedings of the 52nd Hawaii International Conference on System Sciences* (pp. 1–10). Maui, HI, USA.

Wasiq, M., Bashar, A., Akmal, S., Rabbani, M. R., Saifi, M. A., Nawaz, N., & Nasef, Y. T. (2023). Adoption and applications of blockchain technology in marketing: A retrospective overview and bibliometric analysis. *Sustainability*, *15*(4), Article 3279.

Watson, G. F., Beck, J. T., Henderson, C. M., & Palmatier, R. W. (2015). Building, measuring, and profiting from customer loyalty. *Journal of the Academy of Marketing Science*, *43*(6), 790–825.

Willms, J. (2017, April 17th). *This startup beat out IBM to put RBC's rewards program on the blockchain*. Bitcoin Magazine. Retrieved July 7, 2017, from https://www.nasdaq.com/articles/this-startup-beat-out-ibm-to-put-rbcs-rewards-program-on-the-blockchain-2017-04-18.

Wixom, B. H., & Todd, P. A. (2005). A theoretical integration of user satisfaction and technology acceptance. *Information Systems Research*, *16*(1), 85–102.

Wong, K. K.-K. (2013). Partial least squares structural equation modeling (PLS-SEM) techniques using SmartPLS. *Marketing Bulletin*, *24*(1), 1–32.

Wong, L.-W., Tan, G. W.-H., Lee, V.-H., Ooi, K.-B., & Sohal, A. (2020). Unearthing the determinants of blockchain adoption in supply chain management. *International Journal of Production Research*, *58*(7), 2100–2123.

Wong, M. M., Kwok, M. J., & Lau, M. M. (2015). Spreading good words: The mediating effect of brand loyalty between role model influence and word of mouth. *Contemporary Management Research*, *11*(4), 313–326. https://doi.org/10.7903/cmr.13838

Wong, W. P. M., Lo, M. C., & Ramayah, T. (2014). The effects of technology acceptance factors on customer e-loyalty and e-satisfaction in Malaysia. *International Journal of Business and Society, 15*(3), 477.

Wu, J.-H., & Wang, S.-C. (2005). What drives mobile commerce? An empirical evaluation of the revised technology acceptance model. *Information & Management*, *42*(5), 719–729.

Wu, L., Mattila, A. S., Wang, C.-Y., & Hanks, L. (2016). The impact of power on service customers' willingness to post online reviews. *Journal of Service Research*, *19*(2), 224–238.

Xu, X., Tatge, L., Xu, X., & Liu, Y. (2022). Blockchain applications in the supply chain management in the German automotive industry. *Production Planning & Control*. https://doi.org/10.1080/09537287.2022.2044073

Xu, Y., Chong, H.-Y., & Chi, M. (2023). Modelling the blockchain adoption barriers in the AEC industry. *Engineering, Construction and Architectural Management*, *30*(1), 125–153.

Yang, C.-S. (2019). Maritime shipping digitalization: Blockchain-based technology applications, future improvements, and intention to use. *Transportation Research, Part E: Logistics and Transportation Review*, *131*, 108–117.

Yang, M., Chan, H., Yu, I. Y., & Fock, H. (2019). Consumer motivation for reward pursuit: A culture-based and progress-based model of loyalty program effectiveness. *Journal of Global Marketing*, *32*(4), 255–268.

Yeh, C.-C., & Chen, Y.-F. (2018). Critical success factors for adoption of 3D printing. *Technological Forecasting and Social Change*, *132*, 209–216.

Yi, Y., & Jeon, H. (2003). Effects of loyalty programs on value perception, program loyalty, and brand loyalty. *Journal of the Academy of Marketing Science*, *31*(3), 229–240.

Yap, B. W., Ramayah, T., & Wan Shahidan, N. (2012). Satisfaction and trust on customer loyalty: A PLS approach. *Business Strategy Series*, *13*(4), 154-167. https://doi.org/10.1108/17515631211246221

Yun, Z.-S., Pysarchik, D. T., & Dabas, C. (2012). The determinants of retail loyalty of Indian consumers. *Journal of Food Products Marketing*, *18*(4), 268–286.

Zeithaml, V. A. (1988). Consumer perceptions of price, quality, and value: A means-end model and synthesis of evidence. *Journal of Marketing*, *52*(3), 2–22.

Zeithaml, V. A. (2000). Service quality, profitability, and the economic worth of customers: What we know and what we need to learn. *Journal of the Academy of Marketing Science*, *28*(1), 67–85.

Zhang, Y. (2024). The evolution of loyalty programs in the digital age: A review of consumer engagement and retention strategies. *Business, Marketing, and Finance Open, 1*(2), 1–12

Zhang, N., Guo, X., & Chen, G. (2008). IDT-TAM integrated model for IT adoption. *Tsinghua*

Science and Technology, *13*(3), 306–311.

Zheng, Z., Xie, S., Dai, H.-N., Chen, X., & Wang, H. (2018). Blockchain challenges and opportunities: A survey. *International Journal of Web and Grid Services*, *14*(4), 352–375.

Zheng, Z., Xie, S., Dai, H.-N., Chen, W., Chen, X., Weng, J., & Imran, M. (2020). An overview on smart contracts: Challenges, advances and platforms. *Future Generation Computer Systems*, *105*, 475–491.

Zhu, K., & Kraemer, K. L. (2005). Post-adoption variations in usage and value of e-business by organizations: Cross-country evidence from the retail industry. *Information Systems Research*, *16*(1), 61–84.

Appendix

Ethical clearance (Appendix A)

Faculty of Commerce

Private Bag X3, Rondebosch, 7701
2.26 Leslie Commerce Building, Upper Campus
Tel: +27 (0) 21 650 4375/ 5748 Fax: +27 (0) 21 650 4369
E-mail: jacques.rousseau@uct.ac.za
Internet: www.uct.ac.za
@Commerce UCT **UCT Commerce Faculty Office**

24 02 2022

Matthew Hendricks

School of Management Studies

University of Cape Town

REF: REC 2022/02/022

Reimagining Loyalty Rewards Programs via Blockchain: Usage, Loyalty and Firm Performance

We are pleased to inform you that your ethics application has been approved. Unless otherwise specified this ethical clearance is valid until 31-Dec-2023.

Your clearance may be renewed upon application.

Please be aware that you need to notify the Ethics Committee immediately should any aspect of your study regarding the engagement with participants as approved in this application, change. This may include aspects such as changes to the research design, questionnaires, or choice of participants.

The ongoing ethical conduct throughout the duration of the study remains the responsibility of the principal investigator.

We wish you well for your research.

2022.02.24
20:08:38 +02'00'

Jacques Rousseau
Commerce Research Ethics Chair
University of Cape Town
Commerce Faculty Office
Room 2.26 | Leslie Commerce Building

Office Telephone: +27 (0)21 650 2695 / 4375
Office Fax: +27 (0)21 650 4369
E-mail: jacques.rousseau@uct.ac.za
Website: http://www.commerce.uct.ac.za/com/Ethics-in-Research

Questions (Appendix B)

Paper 1

#	Questions	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree	Source
Innovativeness							
1	I am among the first to try out new technologies						Mitgen, Popovic and Oliveira (2013)
2	When I hear about a new technology, I look for ways to adopt it						
3	I like to experiment with new technologies						
Trust in Blockchain Technology and Cryptocurrency							
4	I trust Blockchain Technology,						Adapted from Mitgen, Popovic and Oliveira (2013)
5	I trust Cryptocurrencies like Bitcoin						
6	I trust the underlying technology which drives Cryptocurrencies like Bitcoin						
7	I trust blockchain-based loyalty programs						
9	I think Blockchain Technology is reliable.						
10	I think Cryptocurrencies are reliable						
Perceived Value of Cryptocurrency							
11	Investment of time and effort in receiving Cryptocurrency would be profitable for me						Adapted from Kim, Lee & Law (2008)
12	There is a benefit in using Cryptocurrency						
13	There is no loss in using Cryptocurrency						
14	Cryptocurrency has value to me						Adapted from Chen & Lu (2016)
15	Cryptocurrency would be useful for me to have.						Adapted from Martignoni, Stanoevska-Slabeva, and Mueller (2008)

Compatibility							
16	I think using a Blockchain-based Loyalty Program would fit well with the way that I like to use loyalty programs						Adapted from Mitgen, Popovic and Oliveira (2013)
17	Using a Blockchain-based Loyalty Program would fit into my lifestyle						
18	The benefits of using a Blockchain-based Loyalty Program are apparent to me						
Relative Advantage							
19	Compared to normal loyalty programs that do not use Blockchain, a Blockchain-based Loyalty Program would make it easier to redeem any benefits I earned as part of a loyalty program.						Min, So and Jeong (2019)
20	Compared to normal loyalty programs that do not use a Blockchain, a Blockchain-based Loyalty Program would make it easier to earn benefits from a loyalty program.						
21	Compared to normal loyalty programs that do not use a Blockchain, a Blockchain-based Loyalty Program would make it easier to manage my benefits that I earn as part of a loyalty program.						
Complexity							
22	I believe that using a Blockchain-Based Loyalty Program requires technical skills.						Karahanna, Straub and Chervany (1999)
23	I believe that using a Blockchain-Based Loyalty Program will require a lot of mental effort.						
24	I believe that using a Blockchain-Based Loyalty Program would be frustrating						
25	A Blockchain-Based Loyalty						

	Program would confuse me						
26	a Blockchain-Based Loyalty Program would be complex to use						
Perceived Ease of Use							
27	I don't think it would be hard to use a Blockchain-based Loyalty Program						Adapted from Mitgen, Popovic and Oliveira (2013)
28	Using a Blockchain-based Loyalty Program would likely require minimum of effort						
29	It would be easy to get a Blockchain-based Loyalty Program to do what you want it to do						
30	Learning to use a Blockchain-based Loyalty Program would be easy for me						
31	I would find a Blockchain-based Loyalty Program easy to use						
Perceived Usefulness							
32	Using a Blockchain-based Loyalty Program would be useful in my daily life.						Adapted from Choh & Noh (2008)
33	Using a Blockchain-based Loyalty Program would make my daily life more efficient						
34	Using a Blockchain-based Loyalty Program would make my loyalty reward experience more efficient						
35	Using a Blockchain-based Loyalty Program would make my loyalty reward experience more useful						
Intention to Use Blockchain Based Loyalty Program							
36	I would sign-up for a Blockchain-based Loyalty Program as soon as possible						Adapted from Mitgen, Popovic and Oliveira (2013)
37	I would use a Blockchain-based loyalty Program soon after it is launched						
38	I will use a Blockchain-based Loyalty Program in the future.						Adapted from Choh & Noh

39	I will try to use a Blockchain-based Loyalty Program.						(2008)
40	I am willing to use a Blockchain-based Loyalty Program.						

Paper 2

#	Questions	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree	Source
Intention to use Blockchain-based loyalty programs							
1	I would sign-up for a Blockchain-based Loyalty Program as soon as possible						Adapted from Mitgen, Popovic and Oliveira (2013)
2	I would use a Blockchain-based loyalty Program soon after it is launched						Adapted from Choh & Noh (2008)
3	I will use a Blockchain-based Loyalty Program in the future.						
4	I will try to use a Blockchain-based Loyalty Program.						
5	I am willing to use a Blockchain-based Loyalty Program.						
Commitment							
6	A Blockchain-based Loyalty Program would be important to me.						Dagger, T.S., David, M.E. and Ng, S., 2011. Do relationship benefits and maintenance drive commitment and loyalty?. Journal of services marketing.
7	I would care about a Blockchain-based Loyalty Program.						
8	I would invest effort in a Blockchain-based						

	Loyalty Program						
9	My preference for a Blockchain-based Loyalty Program would not easily be change.						Pritchard, M.P., Havitz, M.E. and Howard, D.R., 1999. Analysing the commitment-loyalty link in service contexts. *Journal of the academy of marketing science*, *27*(3), pp.333-348.
Trust							
10	Generally, I would trust a Blockchain-based Loyalty Program						Liu, M.T., Liu, Y., Mo, Z., Zhao, Z. and Zhu, Z., 2019. How CSR influences customer behavioural loyalty in the Chinese hotel industry. *Asia Pacific Journal of Marketing and Logistics*.
11	Overall, I can imagine myself confidently relying on a Blockchain-based Loyalty Program						
12	I do not think a Blockchain-based Loyalty program would prejudice me.						Horppu, M., Kuivalainen, O., Tarkiainen, A. and Ellonen, H.K., 2008. Online satisfaction, trust and loyalty, and the impact of the offline parent brand. *Journal of Product & Brand*

							Management.
13	I believe it would be safe to use a Blockchain-based Loyalty Program						Bashir, I. and Madhavaiah, C., 2015. Consumer attitude and behavioural intention towards Internet banking adoption in India. *Journal of Indian Business Research*.
Satisfaction							
14	It would be a wise choice to use a Blockchain-based Loyalty Program.						Dagger, T.S. and O'Brien, T.K., 2010. Does experience matter? Differences in relationship benefits, satisfaction, trust, commitment and loyalty for novice and experienced service users. *European Journal of Marketing*.
15	It would satisfy me to use a Blockchain-based Loyalty Programme						
16	I would feel good about using a Blockchain-Based Loyalty Program.						
17	My expectations of a loyalty program would be met by a Blockchain-Based Loyalty Program.						Biscaia, A.R., Rosa, M.J., e Sa, P.M. and Sarrico, C.S., 2017. Assessing customer satisfaction and loyalty in the retail sector. *International Journal of Quality*

							& Reliability Management.
Incentivised							
18	A Blockchain-based Loyalty Program provides me with adequate incentives to use it.						Naidoo, R. and Leonard, A., 2007. Perceived usefulness, service quality and loyalty incentives: Effects on electronic service continuance. *South African Journal of Business Management*, *38*(3), pp.39-48.
19	I would get rewarded appropriately by a Blockchain-Based Loyalty Program for my continued patronage.						
20	I would get incentives for using a Blockchain-Based Loyalty Program.						Atchariyachanvanich, K., Okada, H. and Sonehara, N., 2007. What keeps online customers repurchasing through the internet?. *ACM SIGecom Exchanges*, *6*(2), pp.47-57.
21	Blockchain-Based Loyalty Programs provide incentives for continued use.						
Relative Advantage							
22	Compared to my current loyalty program….						
23	A Blockchain-based Loyalty Program would make it easier to redeem any benefits earned as part of a loyalty program.						Min, So and Jeong (2019)
24	A Blockchain-based						

	Loyalty Program would make it easier to generate rewards for shopping at stores.						
25	A Blockchain-based Loyalty Program would make it easier to earn benefits from a loyalty program.						
26	A Blockchain-based Loyalty Program would make it easier to manage my benefits that I earn as part of a loyalty program.						
Behavioural Loyalty							
27	A Blockchain-Based Loyalty Program would be my first choice compared to other loyalty programs.						Liu, M.T., Liu, Y., Mo, Z., Zhao, Z. and Zhu, Z., 2019. How CSR influences customer behavioural loyalty in the Chinese hotel industry. *Asia Pacific Journal of Marketing and Logistics*.
28	As long I was offered a Blockchain-Based Loyalty Program, it is unlikely that I would opt for another loyalty program.						Sharifi, S.S. and Esfidani, M.R., 2014. The impacts of relationship marketing on cognitive dissonance, satisfaction, and loyalty: The
29	I would rarely consider using another type of loyalty program, if I						

	could use a Blockchain-Based Loyalty Program.						mediating role of trust and cognitive dissonance. *International Journal of Retail & Distribution Management*.
Attitudinal Loyalty							
30	I would say positive things about a Blockchain-Based Loyalty Program.						Sharifi, S.S. and Esfidani, M.R., 2014. The impacts of relationship marketing on cognitive dissonance, 31satisfaction, and loyalty: The mediating role of trust and cognitive dissonance. *International Journal of Retail & Distribution Management*.
31	I would pay more attention to a Blockchain-Based Loyalty Program than another type of loyalty program.						Horppu, M., Kuivalainen, O., Tarkiainen, A. and Ellonen, H.K., 2008. Online satisfaction, trust and loyalty, and the impact of the offline parent brand. *Journal of Product & Brand*
32	I would recommend a Blockchain-Based Loyalty Program to anyone who seeks advice on loyalty						

	programs.						*Management.*

Paper 3

#		Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree	Source
Perceived ease of use of a Blockchain-based Loyalty Program.							
1	I don't think it would be hard to use a Blockchain-based Loyalty Program						Adapted from Mitgen, Popovic and Oliveira (2013)
2	Using a Blockchain-based Loyalty Program would likely require minimum of effort						
3	It would be easy to get a Blockchain-based Loyalty Program to do what you want it to do						
4	Learning to use a Blockchain-based Loyalty Program would be easy for me						
5	I would find a Blockchain-based Loyalty Program easy to use						
Perceived usefulness of a Blockchain-based Loyalty Program.							
6	Using a Blockchain-based Loyalty Program would be useful in my daily life.						Adapted froom Choh & Noh (2008)
7	Using a Blockchain-based Loyalty Program would make my daily life more efficient						

8	Using a Blockchain-based Loyalty Program would make my loyalty reward experience more efficient						
9	Using a Blockchain-based Loyalty Program would make my loyalty reward experience more useful						
Intention to use a Blockchain based loyalty program							
10	I would sign-up for a Blockchain-based Loyalty Program as soon as possible						Adapted from Mitgen, Popovic and Oliveira (2013)
11	I would use a Blockchain-based loyalty Program soon after it is launched						
12	I will use a Blockchain-based Loyalty Program in the future.						Adapted from Choh & Noh (2008)
13	I will try to use a Blockchain-based Loyalty Program.						
14	I am willing to use a Blockchain-based Loyalty Program.						
Behavioural Loyalty							
15	A Blockchain-Based Loyalty Program would be my first choice compared to other loyalty programs.						Liu, M.T., Liu, Y., Mo, Z., Zhao, Z. and Zhu, Z., 2019. How CSR influences customer behavioural

							loyalty in the Chinese hotel industry. *Asia Pacific Journal of Marketing and Logistics*.
16	As long I was offered a Blockchain-Based Loyalty Program, it is unlikely that I would opt for another loyalty program.						Sharifi, S.S. and Esfidani, M.R., 2014. The impacts of relationship marketing on cognitive dissonance, satisfaction, and loyalty: The mediating role of trust and cognitive dissonance. *Inter national Journal of Retail & Distribution Management*.
17	I would rarely consider using another type of loyalty program, if I could use a Blockchain-Based Loyalty Program.						
Attitudinal Loyalty							
19	I would pay more attention to a Blockchain-Based Loyalty Program than another type of loyalty program.						Horppu, M., Kuivalainen, O., Tarkiainen, A. and Ellonen, H.K., 2008. Online satisfaction, trust and loyalty, and the impact of the offline parent brand. *Journal of*

							Product & Brand Management.
20	I am less likely to shop at stores that don’t offer a Blockchain-based loyalty program.						Ashley, C., Gillespie, E. A., & Noble, S. M. (2016). The effect of loyalty program fees on program perceptions and engagement. Journal of Business Research, 69(2), 964–973. https://doi.org/10.1016/j.jbusres.2015.09.001.
21	I would shop at stores that offer a Blockchain based loyalty program more frequently.						
22	I am more likely to shop at stores that offer a Blockchain-Based Loyalty program because the benefits I would receive.						
Word of Mouth							
23	I will point out positive aspects of a Blockchain based Loyalty Program if anybody criticises it.						Casaló, L.V., Flavián, C. and Guinalíu, M., 2008. The role of satisfaction and website usability in developing customer loyalty and positive word-of-mouth in the e-banking services. *International journal of bank marketing*.
24	I would say positive						Choi, B. and

	things about a Blockchain-based loyalty program.						Choi, B.J., 2014. The effects of perceived service recovery justice on customer affection, loyalty, and word-of-mouth. *European Journal of Marketing.*
25	I would try spread the word about Blockchain-based loyalty programs						
Redemption							
26	I will probably redeem the points I gain from a Blockchain-based Loyalty program.						Nayal, P. and Pandey, N., 2020. Digital coupon redemption: Conceptualization, scale development and validation. *Australasian Journal of Information Systems*, *24*.
27	I will use the points I gain on a Blockchain-based Loyalty program if I find something I want to use them on.						
28	I would redeem my points I gain from a Blockchain-based Loyalty program for discounts.						
29	Redeeming points gain on a Blockchain-based Loyalty program make me feel good.						Achadinha, N.M.J., Jama, L. and Nel, P., 2014. The drivers of consumers' intention to redeem a push mobile coupon. *Behaviour & Information Technology*, *33*(1
30	I would redeem points gained on a Blockchain-based Loyalty program.						

							2), pp.1306-1316.

Certificate of editing (Appendix C)

The Research Faculty

66 Greenfield Rd
Greenside, Johannesburg
2193 South Africa
Tel: +27 (0) 782-1401
www.theresearchfaculty.com

Attention: Matthew Hendricks
University of Cape Town

6 Sep 2024

To whom it may concern

Confirmation of document editing

This letter is to confirm that we have edited the document titled:

> Reimagining Loyalty Rewards Programmes via Blockchain: Usage, Loyalty, and Firm Performance

The document was the work of Matthew Hendricks.

We involved the contributions of one or more subcontractor.

We have edited the document for errors of grammar, punctuation, and style. We also provided the author with a list of aspects needing further correction or attention.

Excluded from the editing work were, if applicable, the annexures, mathematical or statistical formulae, the spelling of authors' names and other proper nouns, fact-checking, foreign-language text, the content of Microsoft Word field codes, the accuracy of cross references or hyperlinks, the order of works within citations, acronym use, the joining or splitting of paragraphs, citation verbs' tense and number, and the use of first-person pronouns.

Yours faithfully

Signed by candidate

Bruce Conradie
Research Support Specialist
The Research Faculty

The Research Faculty (Pty) Ltd is a private company. Registration number 2022/773876/07.
Postal and street address: 66 Greenfield Rd, Greenside, Johannesburg, South Africa, 2193.