The Consumer Perspective on Blockchain-Enabled Loyalty Programs

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Submitted to Dr. Horst Treiblmaier

Elena Petrozhitskaya

Student number 1802007

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Affidavit

I hereby affirm that this Master's Thesis represents my own written work and that I have used no sources and aids other than those indicated. All passages quoted from publications or paraphrased from these sources are properly cited and attributed.

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ABSTRACT

In a highly competitive market environment, customer loyalty is a crucial asset of every viable brand. For many years, marketers have used customer loyalty programs (LPs) as an effective tool for customer retention and loyalty strengthening across various industries. Despite the popularity of LPs, recent studies illustrated the declining performance of traditional 'points'/ 'miles'-based programs that show low engagement rates. To get a competitive advantage, brands strive to explore and adopt the opportunities offered by the new technologies. Blockchain technology holds the potential to shift the paradigm in many industries and activities, and marketing is no exception. However, blockchain application in loyalty management is currently mainly experimental, and the effects of blockchain on LPs have not been comprehensively investigated by scholars and practitioners yet.

This study makes an early attempt to dig into the impact of a blockchain-powered LP design on customer perceived value and resulting program loyalty. It considers five distinctive features of the LP design: points usage, the timing of points accrual, offering relevance, points expiration and points transferability. It assesses the level of perceived value and loyalty of blockchain-based LP users in comparison with the users of a traditional LP. By employing a quantitative approach, the data for the study was collected through a structured online survey. The study outcomes conclude that most of the considered blockchain-powered features do trigger a higher level of value perception. In turn, the blockchain-based design of an LP results in higher customer loyalty toward a program compared to a traditional LP.

The second part of the study is devoted to exploring how socio-economic factors such as age, gender, employment status, and income level may impact a blockchain-based LP design perception. Findings suggest that individual factors do not affect perceived loyalty; however, interaction effects of gender*age and gender*income on the overall loyalty toward a blockchain-enabled LP are established.

The third part of the study aims to explore how social media users perceive blockchain-based LPs and traditional LPs. In order to determine the connections, two existing real-world LPs are used. The conducted semantic analysis of data collected from Twitter reveals that users are more favorable to a blockchain-backed solution.

Keywords: blockchain, loyalty programs, perceived value, consumer behavior, customer loyalty

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LIST OF ABBREVIATIONS

B2B	Business-to-Business
B2B2C	Business-to-Business-to-Consumer
B2C	Business-to-Consumer
BaaS	Blockchain-as-a-Service
BCT	Blockchain Technology
COVID-19	Coronavirus Disease 2019 (SARS-CoV-2)
CRM	Customer Relationship Management
CTP	Customer Tier Program
FFP	Frequent Flyer Program
FRP	Frequency Reward Program
IoT	Internet of Things
LP	Loyalty Program
P2P	Peer-to-Peer
PoW	Proof-of-work
SIA	Sinapore Airlines
SC	Smart Contract
SKU	Stock Keeping Unit
TPS	Transaction-per-Second

1. INTRODUCTION

1.1. Problem definition

Over the past years, the evidence of declining brand loyalty and customer disenchantment with the rewards received within traditional ‘points’/‘miles'-enabled LPs has been growing (Brashear-Alejandro et al., 2016; KPMG International, 2018). With the COVID-19 outbreak, customer loyalty became even harder to get; the majority of consumers reported trying new shopping behaviors during the lockdowns and intended to continue exploring new brands (McKinsey & Company, 2020). The total number of LPs memberships continues the stable growth while only less than half of all registered customers actively participate in LPs (Bond Brand Loyalty, 2019). From the customer perspective, lack of incentives and personalization, inconvenient redemption rules, and security concerns are identified as the most prominent pain points of the majority of current LP schemes. Blockchain is deemed to become a disruptive technology prophezied to reinvent how businesses operate across many sectors (Zheng et al., 2018). Marketing is no exception: BCT holds the potential to revolutionize design of LPs, their tracking, and interaction with users (Rejeb et al., 2020). There are pioneers in the industry that already switch their LPs to blockchain-enabled designs and companies offering B2B2C out-of-the-box blockchain and smart contracts-powered software solutions. Nonetheless, the area of blockchain application to loyalty management remains new and underexplored, especially from an academic perspective.

1.2. Research aims and objectives

This thesis’ research continues exploring blockchain application to LP schemes and, more specifically, it compares the user perception of blockchain-based LPs compared to traditional LPs. It uncovers the impact of blockchain-powered features of an LP design on customer value perception and loyalty toward an LP. To accomplish the research objective three following research questions are posed:

- *How do blockchain-powered features of LP design influence customer value perception and loyalty towards the program?*
- *Do socioeconomic factors have an impact on customer loyalty towards the LP design with the blockchain-powered features?*
- *How do Twitter users perceive a blockchain-based LP compared to a traditional LP?*

To answer the first two questions, prototypes of a traditional LP and a blockchain-based LP were designed. These designs included five distinctive features: how loyalty points are redeemed, the immediacy of points accrual, the offers relevance, the validity period of loyalty points, and their transferability. The following six directional sub-hypotheses to answer the first research questions were formulated:

$H_{Loyalty}$: Blockchain-enabled LP triggers a higher level of loyalty than a traditional LP.

H_{11}: A higher number of available loyalty points redemption options trigger a higher level of perceived value and loyalty.

H_{12}: Immediate loyalty points accrual triggers a higher level of perceived value and loyalty than a delayed one.

H_{13}: Personalized customer-tailored offers trigger a higher level of perceived value and loyalty than non-personalized generic offers.

H_{14}: Loyalty points with no expiration date trigger a higher level of perceived value and loyalty than loyalty points with an expiration deadline.

H_{15}: Loyalty points transferable to other peers trigger a higher level of perceived value and loyalty than non-transferable ones.

To answer the second research question, the following non-directional hypothesis was posed:

H_2: Socioeconomic factors have an impact on the program loyalty towards the blockchain-based LP.

1.3. Prior research

As already mentioned previously, the topic of blockchain application to LPs has not been widely covered and systematically assessed by scholars, especially the value perception of blockchain-powered LPs and resulting program loyalty. This thesis will build on the following prior research: (1) Yi & Jeon (2003) studied how LPs affect value perception, program, and brand loyalty without focusing on a blockchain that even did not exist by then. They concluded that the involvement rates highly moderate the effects of LPs on customer loyalty. “Under high-involvement conditions, value perception of the loyalty program influences brand loyalty both directly and indirectly through program loyalty. Under low-involvement conditions, there is no direct effect of value perception on brand loyalty” (Yi & Jeon, 2003, p.229). (2) Kreis & Mafael (2014) formulated a theoretical framework that views features of LP design as a moderating tool establishing the relationship between customer motives and perceived value. The part of this framework related to the value perception formed the basis of a conceptual framework implemented in this study. (3) Wang et al. (2018, 2019a, 2019b) explored how blockchain affects value creation in the LP context. They offered a theoretical framework that connected customer needs to partake in an LP (guided by self-determination theory) with the key natures of blockchain-based loyalty platforms. The effects of blockchain application on customer motivations that have an impact on value perception were examined. Their exploratory studies concluded that key natures of a blockchain-enabled design improve customer perceived value by satisfying customer’s intrinsic and extrinsic motivations.

1.4. Structure of the thesis

Chapter 2 presents a broad overview of the extant literature on customer loyalty, LPs, their design and effectiveness, customer perceived value, traditional LPs challenges, blockchain technology, its application to LPs, implications of such implementation, and an overview of already existing pioneer blockchain solutions for loyalty management. Chapter 3 describes the methodology used for this thesis. It depicts the design of used prototype LPs, including five specific features, represents a conceptual research framework, hypotheses, variables, measure development, data collection, and analysis procedures. Chapter 4 outlines the reliability analysis of the sample, results received from the non-parametric Mann-Whitney U test that was performed to answer hypotheses of study 1, and two-way ANOVA test results for study 2. The Twitter data analysis follows it to reveal customer sentiments on both types of examined LPs - blockchain-based and traditional ones. Chapter 5 summarises the findings and marks the thesis' contribution to knowledge, discusses research limitations, and draws paths for future research in the area of blockchain application to LPs.

2. LITERATURE REVIEW

This chapter provides a brief overview of the basic concepts required for further research. In the beginning, the introduction to the terms customer loyalty and loyalty programs (LPs) is given. Further, the author provides an overview of the main components of an LP design, outlines how they may impact a customer perceived value, and gives a summary of existing viewpoints on the effectiveness of modern LPs. Onwards, the status quo of the loyalty industry is discussed, particularly in the light of a COVID-19 pandemic. Current challenges of the traditional LP schemes from the consumer's and LP provider's perspectives are argued further, which brings to an attempt to analyze why the extant loyalty schemes are ripe for some disruptive innovation, which possibly could be a blockchain technology (BCT). The pros and cons of such an application are examined further, followed by several examples of already existing pioneer blockchain-enabled loyalty platforms.

2.1. Customer loyalty

Customer loyalty is a paramount concept in marketing literature as well as in marketing practice. According to Dick and Basu (1994), it indicates the strength of the relationships between a consumer and enterprise, which encompasses two aspects:

- *the behavioral* decision of a consumer to continue buying a product from a specific company or reusing their services over time rather than buying from multiple suppliers;
- *attitudinal* attachment to the brand or company.

The behavioral dimension of loyalty describes the purchase patterns, such as retention, shopping frequency, and volume. Attitudinal loyalty, in turn, implies a psychological attachment to a brand and is expressed in satisfaction, level of commitment, trust, involvement, positive attitude, etc. (Bijmolt et al., 2011; Kumar & Reinartz, 2018). Demonstration of behavioral loyalty does not necessarily entail attitudinal loyalty, as it can be caused by the lack of available alternatives, which does not represent a genuine customer loyalty (Dick & Basu, 1994; Whyte, 2004). Therefore to achieve continuous effects on consumer loyalty, brands should focus not only on increasing behavioral loyalty but also should emphasize fostering attitudinal loyalty. (García Gómez et al., 2006).

Extensive studies done over the past decades support the notion that customer loyalty can be viewed as a precious intangible asset for every successful business strategy. Reichheld and Sasser (1990) suggested that an increase in customer retention rates by 5% will subsequently lead to an increase in profits by 25% to 95%, as well it may cost five times more to acquire a new customer than to retain an already existing one (Reichheld & Sasser, 1990; Altinkemer & Ozcelik, 2009). Brands should praise their loyal customers for several reasons: customers who are loyal to a brand tend to make purchases more often, generating higher sales and profits

(Jacoby & Chestnut, 1978), they encourage word-of-mouth and reinforce cross-selling effects to other products or services of a company (Webster Jr., 1994). Moreover, according to Reichheld and Teal (2011), loyal customers tend to be less price-sensitive.

2.2. Loyalty programs

With an immense variety of extant loyalty creation schemes, it is not easy to establish one universal definition of LP that would fit all of them. Nonetheless, every LP, regardless of the design, is a customer relationship management (CRM) tool for growing and sustaining a market share through generating rewards for customers based on their repeat purchase behavior (Kumar & Reinartz, 2018; Reinartz, 2006; Vinod, 2011) in this way enhancing customer's loyal behavior (Melnyk & Bijmolt, 2015; Sharp & Sharp, 1997; Yi & Jeon, 2003). The definition is fair for both B2B and B2C markets (Bijmolt et al., 2011). LPs are often referred in the literature as reward programs (Blattberg et al., 2008).

According to a traditional points-based LP scheme, with every transaction, customers earn loyalty points (miles/credits/coins/tokens or another variation of internal LP currency). Later, customers can convert accumulated points into discounts, cash rebates, free products, or they could bring a user to the higher tier, which will provide access to additional benefits. Prior studies (Bijmolt et al., 2011; Blattberg et al., 2008; Dorotic et al., 2012) illustrate that there are three mechanisms that might trigger such behavior:

- *points pressure:* when LP participants see that only X points separate them from collecting a reward - they will make additional purchases in order to achieve a goal (Kivetz et al., 2006; Nunes & Drèze, 2006b; Taylor & Neslin, 2005). The more attractive a reward is, the stronger is the pressure.

- *rewarded behavior:* after obtaining a reward, LP participants perceive to be more connected to LP provider; hence their behavioral and attitudinal responses (according to customer loyalty definition in section 2.1) are affected (Palmatier et al., 2009; Taylor & Neslin, 2005).

- *personalized marketing:* LPs gather personal data about their participants, which afterward is used to reinforce their behavioral and attitudinal responses (Bijmolt et al., 2011; Cvitanović, 2018, Dorotic et al., 2012).

The LPs effects on member behavioral and attitudinal responses rely on the design of a specific LP (Dorotic et al., 2012; Keh & Lee, 2006; Wirtz et al., 2007).

The progenitor of all modern LPs was a frequent flyer program (FFP) of Texas International Airlines, launched in 1979, which used mileage tracking schemes to offer rewards to its passengers for distance traveled with their airline. Soon after, AAdvantage by American Airlines in 1980 followed, that provided their frequent flyers with special fares (Kumar & Reinartz, 2018). Thereafter, LPs have been adopted by firms across many industries such as retail, banking, telecom, travel, entertainment, hospitality, dining, and other areas, becoming prevalent (Blattberg et al., 2008; Blattberg & Deighton, 1996; Dekay et al., 2009; Leenheer & Bijmolt, 2008). Furthermore, LPs have spread into the non-profit sector as well (Bijmolt et al., 2011). Nowadays, LPs are on rising: according to the Accenture Strategy report (2017), more than 90% of companies employ some sort of loyalty program. In the United States of America alone, the number of loyalty memberships has grown at almost 200% in 10 years and counted 3.8 billion in 2016, and this count continued growing (Statista, 2017a). The total worth of the incentive management market is estimated at $10.9 billion by 2024 (Ma, 2020). With such numbers at hand, companies cannot afford to overlook the strategic importance of LP for their businesses.

2.3. Loyalty Program Design

According to Kumar & Reinartz (2006), an LP design should answer the subsequent questions: (a) What are the desired benefits of the demands' side? (b) What are the expected benefits and costs of the supply side, and what are the marketplace characteristics? Prior studies depict an LP design as a combination of 5 fundamental components: structure, rewards type, number of partners, timing, and communication (Bijmolt et al., 2011; Blattberg et al., 2008; Breugelmans et al., 2015; Liu and Yang, 2009; McCall & Voorhees, 2010). Table 2.1 outlines an overview of these key components, providing a classification for every design element.

LP Design Element	Typology		
Structure	Short-term LPs	⟺	Continuous LPs
	Frequency reward LPs	⟺	Customer-tier LPs
Number of LP partners	Sole-proprietary LPs	⟺	LP partnerships
Rewards Type	Monetary/Hard rewards	⟺	Non-monetary/Soft rewards
	Firm-related/Direct rewards	⟺	Non-related/Indirect rewards
Timing	Immediate rewards	⟺	Delayed rewards
Participation requirements	Voluntary	⟺	Automatic
	Open LPs	⟺	Closed LPs
	Automatic points accumulation	⟺	Manual points accumulation

TABLE 2.1: OVERVIEW OF LP DESIGN ELEMENTS

Source: Adapted from Bijmolt et al., 2011; Blattberg et al., 2008; Breugelmans et al., 2015; Kumar & Reinartz, 2018; Liu & Yang, 2009; McCall & Voorhees, 2010.

2.3.1. Structure

Blattberg et al. (2008) discern frequency reward and customer tier program types. Frequency reward LPs (FRPs) represent a "promotional-oriented activity" (Blattberg et al., 2008, p.550): they provide a single reward (discount, free product, cash rebate) in exchange for a certain amount of accumulated points, making no discrimination between the program users (Bijmolt et al., 2011; Blattberg et al., 2008). Customer tier programs (CTPs) designate participants to several segments (in literature also referred to as tiers) based on their actual or potential profitability (Zeithaml et al. 2001) and deliver rewards and benefits according to a customer segment (Blattberg et al., 2008; Kumar and Shah, 2004). The rewards are tier-tailored (Drèze and Nunes, 2009; Lacey et al., 2007), and usually, participants from higher tiers get privileged treatment in order to highlight their importance to the firm and strengthen the 'true' loyalty (Bijmolt et al., 2011; Lacey et al., 2007). Frequent flyer programs (FFPs) are typical representatives of CTPs. For example, Delta Airlines (2021a), with its SkyMiles LP, assigns its' frequent fliers to four "Medallion tiers" based on the number of flights taken with their airline within a recent qualification year: silver, gold, platinum, and diamond. Reaching every next status provides access to the own set of the assigned benefits. Among them increased earnings of miles, preferred seats, flight upgrades for travelers and their companions, waived fees, access to business lounges, priority check-in, boarding, and security line access, premium customer service, and other rewards (Delta Airlines, 2021b). The Customer tier scheme is also popular in the hospitality industry and applies across different worldwide hotel chains: e.g. Hilton Honors, Mariott Bonvoy, World of Hyatt, All (of Accor), etc.

The structure of a LP might be dealt with from a different angle: FRPs serve to provide short-term (often, one-time) promotional rewards. CTPs, on the contrary, are designed to "provide customers with a different long-term level of service or a different product, based on their profitability" (Blattberg et al., 2008, p. 579).

2.3.2. Number of partners

Historically, stand-alone single-branded LPs emerged in the first instance. In sole-proprietary LPs, customers can earn and burn accumulated points only at one partner firm. This type of LPs was found prevailing in former times when many shops offered their branded plastic loyalty cards to the consumers. Multi-partner programs are a more recent invention and represent the next evolutionary step of LPs (Hoffman, 2013). Blattberg et al. (2008) mention that partnering in LPs can take two forms depending on where LP participants "earn" and "burn" their points. (1) If users of Firm A's LP can accumulate loyalty points by making purchases at Firm B, Firm B is Firm's A earn partner. (2) If users of Firm A's LP can spend loyalty points at Firm B, Firm B is Firm's A burn partner. Firm A and Firm B can be mutual earn and burn partners. Participating partners in a coalition LP are typically represented by a mix of different frequently purchased sectors such as grocery, hotels, airlines, fuel, utilities, apparel, dining, cosmetics, and many more (Bijmolt et al., 2011; Dorotic et al., 2012). The advantages and disadvantages of both types of partnership, as well as their challenges and the effects on LP performance, represent a huge field for research and discussion which is not directly related to the objective of this thesis, hence will not further be discussed in this paper. However, following authors offer an immense overview of the topic: Bijmolt et al., 2011; Blattberg et al., 2008; Breugelmans et al., 2015; Dorotic et al., 2012; Hoffman, 2013; Lemon & von Wangenheim, 2009.

2.3.3. Rewards type

Prior literature offers various ways to approach classification of LP rewards, offering several attributes for consideration.

Direct vs. Indirect: Blattberg et al. (2008), Dowling & Uncles (1997), McCall & Voorhees (2010), Yi & Jeon (2003) divide LP rewards into *direct* (products from the firm's offering or similar products that support the firm's value proposition) or *indirect* (other types of rewards not associated with the firm's proposition, could also be cash). There are affirmations of direct rewards preferences over indirect as they strengthen the brand affiliation between customer and LP provider, hence reinforce customer attitudinal loyalty (Roehm et al. 2002; Kivetz, 2005; Keh & Lee, 2006).

Monetary vs. Non-monetary: Monetary (or financial/ hard/ tangible) rewards imply direct economic benefits such as discounts, rebates, or cash. Non-monetary or soft rewards, on the contrary, provide emotional or psychological benefits by offering unique experiences, preferential treatment, upgrades, access to special events, etc. (Bijmolt et al., 2011; Blattberg et al., 2008; Dorotic et al., 2012; Kumar & Reinartz, 2018). The majority of extant studies show that monetary incentives appear more attractive to customers than non-monetary (Bojei et al., 2013; Chandon et al., 2000; Furinto et al., 2009; Jang & Mattila, 2005; Keh & Lee, 2006; Leenheer et al., 2007; Ruzeviciute, R. & Kamleitner, B., 2017; Yi & Jeon, 2003). Nevertheless, hard rewards may distract customer attention from the brand and focus it on attaining the reward itself, which causes spurious loyalty and a downturn in intrinsic motivation (Phillips Melancon et al., 2010; Roehm et al., 2002). Whilst soft rewards cause more robust effects on intrinsic customer motivation by reinforcing attitudinal commitment (Drèze & Nunes, 2009; Phillips Melancon et al., 2010). Customer motivation will be examined more closely in the section 2.2.3.1

More possible classification types are proposed by scholars that are not considered in this paper, such as *Luxury vs. Necessity* (Kivetz & Simonson, 2002; McCall & Voorhees, 2010; Roehm et al., 2002), *Price Discount* vs. *Pre-Committed Price* (Blattebrg et al., 2008; Caminal & Matutes, 1990), *Multiple* vs. *Single* rewards (Lucas, 2002), rewards of varying degrees of attractiveness to the client and their aspirational value (Blattberg et al., 2008; Kumar & Reinartz, 2018; Roehm et al., 2002).

2.3.4. Timing

The immediacy of the reward pertains to the time interval between reward earning and its delivery (Blattberg et al., 2008). In other words, with immediate timing, the LP user gets rewarded instantly at the moment of purchase, while a delayed reward is usually conveyed to LP users via points, which they can accumulate and redeem at a later stage.

Keh & Lee (2006) argued that customers who feel attached and pleased with a brand are more willing to wait for delayed rewards of higher value rather than preferring an immediate reward but of lower value. Moreover, customers are more favorable to delayed rewards that have higher coherence with a consumers' values (e.g., bonus stays at the hotel for a frequent traveler).

Yi & Jeon (2003) approached the same question from the other perspective and found out that displeased or low-involved customers tend to opt for immediate and lower-magnitude rewards. Delayed rewards have a stronger impact on the enrolment decision than immediate ones; therefore, decision-makers are advised to give a preference to this type of reward (Leenheer et al., 2007).

2.3.5. Participation requirements

The way a customer enrolls in an LP and how points get accumulated - is another vital characteristic of LPs.

Voluntary vs. Automatic Enrollment. With automatic enrollment, all company's customers get enrolled in the LP without any differentiation. Automatic enrollment is a preferable option if a company wants to keep track of all customers' transactional data, but hardly possible in the EU due to GDPR regulations. Voluntary programs are more prevalent, as they provide customers with an opportunity to select whether or not they want to participate in a certain LP (Kumar & Reinartz, 2018).

Open & Closed LPs. Open LPs are accessible to a wide public, and anyone can become an LP participant; closed LPs are intentionally restricted to a particular group of participants, usually by means of a membership fee (Kumar & Reinartz, 2018).

Automatic vs. Manual point accumulation. The majority of nowadays LPs accrue points for transactions automatically, once the customer loyalty ID (loyalty card or customer ID code in a mobile app) is presented during the checkout process at the cashier or the customer ID is entered during an online purchase. Some LPs in former times required to enter information about transactions manually. Manual points accumulating systems can be more cost-effective, but they are very inconvenient for an end-user (Kumar & Reinartz, 2018).

2.4. Perceived value

Understanding how various LP design elements undermine loyalty represents a critical question for differentiation. Customers, driven by various needs, perceive the value of certain design elements of an LP in various ways, and thus loyalty is affected differently (Meyer-Waarden, 2017). Customer perceived value is a multidimensional phenomenon. Previous studies (Kreis and Mafael, 2014; Wang et al., 2018, 2019a, 2019b) have connected customer motivations with the actual customer value perception that satisfies the underpinning needs. Namely, three categories are proposed: Economic value, psychological value, and interaction value. *Economic value* stems directly from financial advantages that customer gains from participation in an LP, such as discounted products or gifts offerings. That, in turn, connects to extrinsic stimuli. *The psychological value* that “emphasizes a product’s ability to enhance customer’s self-concept” and can be connected to intrinsic motivation (Wang et al., 2019a p. 4566). *Social value* can be derived from humanlike relationships with the brand and/or feeling of belongingness to a community of like-minded users of the same LP; it also refers to intrinsic motivation. While motivations described in the previous section represent customers’ needs, the perceived value “embodies the overall evaluation of the utility of the LP to satisfy those needs” (Wang et al., 2019b p.399). Customer motivations impact the enhancing a perceived value of engaging with a reward program that acts as “a cognitive driver of subsequent participative behaviors.” (Wang et al., 2019b p.399). Further studies 1 and 2 of this thesis will build on these three categories of perceived value.

2.5. LP Effectiveness

The assessment of LP effectiveness represents a complex task due to the multidimensional nature of the phenomenon (multiple actors, various LP design elements, different contexts) and numerous methods of approaching the research. Marketing researchers and practitioners have studied LPs extensively and have not come up with a consensus regarding LPs' effectiveness for businesses and aspects that differ a successful LP from an unsuccessful one (Kumar & Reinartz, 2018).

Some of the researchers established positive effects of LPs introduction on customer loyalty, perceived value, engagement, retention, purchase behavior, share-of-wallet, relationships with a firm and revenues (e.g., Bolton et al., 2000; Bombaij & Dekimpe, 2020; Brashear-Alejandro et al., 2016; Bridson et al., 2008; Demoulin & Zidda, 2008; Dorotic et al., 2014; Faramarzi & Bhattacharya, 2021; Gómez et al., 2006; Kivetz et al., 2006; Kopalle et al., 2012; Kreis & Mafael, 2014; Leenheer et al., 2007; Lewis, 2004; Melnyk & Bijmolt, 2015; Meyer-Waarden, 2007; Ruzeviciute & Kamleitner, 2017; Taylor & Neslin, 2005; Verhoef, 2003; Zhang & Breugelmans, 2012). Others have not discovered any significant effects (e.g., Mägi, 2003; Reinartz & Kumar, 2003; Sharp & Sharp, 1997; Steinhoff & Palmatier, 2016; Wang et al., 2016). And some claimed the effectiveness of LPs unconvincing and doubted their worth (e.g., Gustafsson et al., 2004; Henderson et al., 2011; Hennig-Thurau & Paul, 2007; Shugan, 2005).

Table 2.2 summarises the empirical findings from the recent studies that investigated the effectiveness of LPs and the effects of their application in different areas and contexts. The table is sorted by the year of publication descending.

Author (s)	Year	Findings
Positive		
Faramarzi & Bhattacharya	2021	The introduction of LPs on average has a positive impact on a company’s value. The value of LP increases when the perceived risks of purchase decrease.
Bombaij & Dekimpe	2020	Basic LP variant that offers direct and immediate rewards has a positive effect on a retailer's sales productivity (grocery retailers).
Ruzeviciute & Kamleitner	2017	Utilitarian/hard/monetary rewards elicit a very robust attractiveness premium on the level of individual rewards as well as on the level of entire LPs. The effect persisted across various industries and in light of differences in consumption goals (hedonic versus utilitarian).
Brashear-Alejandro et al.	2016	Non-financial benefits from LPs can promote customer-company identification (CCID) by inducing customers' feelings of status and belonging in a company-initiated community.
Melnyk & Bijmolt	2015	Non-monetary discrimination between customers-participants in LP and non-participants is a more influential tool in customer loyalty establishment than monetary incentives.
Dorotic et al.	2014	Redemption of LP reward has a positive impact on LP users’ behavior before and after the redemption.
Kreis & Mafael	2014	Customer LP is an effective tool, it adds to the value of a product or service and creates value by itself.
Kopalle et al.	2012	LP design characteristics (frequency of rewards and customer tier component) generate incremental sales and do not interfere with the other.
Zhang & Breugelmans	2012	LP users are more responsive to reward point promotions than to price discounts of the same monetary value (given the sufficient offering). Furthermore, item-based LPs reduce attrition among existing customers and engage more new customers.
Bridson et al.	2008	LP is a significant predictor of store loyalty, in support of the contention that LPs are capable of engendering loyalty.
Demoulin & Zidda	2008	Compared to unsatisfied customers, customers satisfied with the rewards of LPs are more loyal to the store and allocate a higher proportion of their budget and patronage frequency to the store.
Leenheer et al.	2007	Rather small yet a significant positive effect of LP participants’ on share-of-wallet.
		Each LP generates more additional revenues than additional costs in terms of saving and discount rewards, therefore LPs can be deemed profitable.
Meyer-Waarden	2007	LPs have a positive effect on customer lifetimes and share of customer expenditures at the store level.
Gómez et al.	2006	LP members are more behavioral and affectively loyal than other customers. Few customers change purchase behavior after joining the program.
Kivetz et al.	2006	LP induces purchase acceleration through the progress toward a goal.
Taylor & Neslin	2005	LP increases sales through ‘point pressure’ (short-term) and ‘rewarded behaviors’ (long-term).
Lewis	2004	LP are successful in increasing repeat-purchase rates.
Verhoef	2003	LPs that provide economic benefits have a positive effect on customer retention and customer share development.
Bolton et al.	2000	The members in the LP tend to overlook or discount negative evaluations of the company compared to competitors.
Neutral		
Steinhoff & Palmatier	2016	LP effectiveness is influenced by various aspects of reward delivery, such as rule clarity, reward exclusivity, and visibility.
Wang et al.	2016	The goal achievement within customer loyalty promotion programs increases post-promotion purchasing dramatically while goal failure reduces post-promotion purchasing.
Mägi	2003	Loyalty cards (grocery stores) have mixed effects on consumer behavior (share of purchase and share of visits).
Reinartz & Kumar	2003	Being an LP member does not influence the purchase behavior.
		Events and promotions associated with LP seem to have clear effects on purchase behavior (e.g., purchase acceleration).
		The effects of LP are mostly short rather than the long term. Thus, they seem to work as promotional tools rather than a means to induce loyalty.
Sharp & Sharp	1997	Insignificant loyalty deviation in the purchase behavior of LP members compared to non-members was observed.
Negative		
Gustafsson et al.	2004	The majority of LP members do not perceive their membership as adding value, improving loyalty or contributing to higher commitment (study in Swedish telecom company).
Henderson et al.	2011	LP failure to maintain customers in a longer horizon might be due to a surplus of attention to monetary rewards. Future research should focus on non-monetary benefits.
Hennig-Thurau & Paul	2007	LP can lead to counter-productive results by decreasing customer retention.
Shugan	2005	Many LPs appear unrelated to the cultivation of customer brand loyalty and the creation of customer assets.

TABLE 2.2: KEY STUDIES OF LPS EFFECTIVENESS WITH EMPIRICAL FINDINGS

2.6. Improvement potential for traditional LPs

In a hyper-competitive and turbulent environment, the need for a customer-centric approach has been comprehended by many enterprises, who seek a competitive market advantage and financial performance (Lamberti, 2013). When designing LPs, brands endeavor to assure that customers continue being loyal to their products and services (Rejeb et al., 2020) by building long-lasting customer relationships.

2.6.1. COVID-19 crisis

The importance of establishing trustful relationships with customers became even more evident now in view of the COVID-19 pandemic when millions of people around the globe found themselves locked up at their homes that now became a new hub (KPMG International, 2020b). New reality rewires consumer behavior, needs & expectations sets new norms, and challenges organizations to rethink their businesses and operating models. LPs are no exception (KPMG International, 2020a). Pandemic and the resulting multiple lockdowns around the globe have tremendously facilitated the growth of e-commerce as it ousted offline channels: Adobe (2020) reported an increase in online spending in May 2020 to $82.5 billion both in the U.S. and in major global economies, which is up 77% year-over-year. Nevertheless, this shift made customer loyalty even harder to get: the vast majority of international consumers (>65%) reported trying new shopping behaviors in terms of retailers and brands since the COVID-19 outbreak. The intention to continue such behavior is high and varies between 65% and 92% (McKinsey&Company, 2020).

Although e-commerce is on the rise, total customer spends are going to decrease due to the reduction of disposable income and the psychological impact of the pandemic. Almost half of the consumers (41%) feel financially overwhelmed and vulnerable (KPMG International, 2020b). Value for money will be a key purchase driver for such financially sensitive customers (63%) and will be prevalent for next year or more (KPMG International, 2020a, KPMG International, 2020b). Irrespective of how secure consumers feel financially, all predict a decline in spending in the months to come. Hence, organizations are challenged to adapt to disruption in consumer behavior, they will need to assure first-class customer-relationship management, cultivate trust through communication with existing customers, and provide first-time shoppers with valuable incentives (McKinsey&Company, 2020).

As consumers keep on staying isolated over a longer time, they become more advanced in their use of digital technologies that promote consumption in a more safe, convenient, and efficient manner (Sheth, 2020). Brands will need to invest in new digital communication methods to satisfy newly emerged savvy consumers (KPMG International, 2020a). New habits may stay with customers for a longer time, even post-pandemic, and draw a “new normal” (Sheth, 2020).

2.6.2. Pre-crisis

The call for rethinking and reimagining the traditional points/miles-enabled LPs has been brewing for a long time, even in the pre-COVID-19 world. Over recent years, there is growing evidence of declining brand loyalty identified as a psychological, sociological, and technological issue (KPMG International, 2018). A challenge to define pain points in traditional LPs can be approached from 2 directions: from a provider's and from customer perspectives.

2.6.2.1. LP provider perspective

Businesses make enormous investments into loyalty, and they spend billions of dollars year-to-year for non-cash loyalty incentives (Incentive Federation Inc., 2016), LPs management, and customer acquisition (Deloitte, 2016). Investments in LPs can reach as much as 5% of sales (KMPG LLP, 2016). A massive challenge for LP owners is that LPs "become financial liabilities instead of self-funding business assets" (Banasiewicz, 2005, p.338). Many LPs find their costs buried in each "loyalty" line item which consumes investments at a steady pace over the years (Accenture, 2017) because "revenue attributable to the value of loyalty points must be deferred until the points/miles are redeemed" (Kowalewski et al., 2017, p.4). The reason for that might lie in insufficient customer insights, inadequate LP planning (Banasiewicz, 2005), as well as in the general complexity of LP management (Kumar & Reinartz, 2018). Banasiewicz (2005) brings up a result: customers who are willing to pay a full price are given a discount, no new customers are engaged, no additional sales are gotten off the scheme. Despite the high loyalty investments, according to Accenture (2017), there are several indications that these investments do not deliver all the value they could, and for almost a quarter of consumers, all that spending is even hurting the customer-brand relationship (Accenture, 2017). Without resulting in profitability, customer loyalty holds no significance for a brand (Kumar and Shah, 2004).

Most organizations executives do realize the importance of customer loyalty to their businesses, but very few, in fact, take action: 90% expressed concern about customer loyalty, but only 24% mentioned that they are taking measures to build and sustain customer loyalty as top 10 priority (KMPG LLP, 2016). Another survey of 400 executives in various major industries around the globe revealed that only 42% of respondents deem their firm's customer LP to be effective, and 46% mention that their loyalty strategy lacks innovation (Harward Business Review Analytic Services, 2019). According to this survey, 72% of executives point out that optimizing customer loyalty was a top-five priority for that year. 55% said that they refreshed their LP within the past two years, and 30% of them did this during the past year (Harward Business Review Analytic Services, 2019). These changes in only three years confirms that the shifts in the customer loyalty landscape are ongoing, and businesses try to keep up with them to stay in the game.

2.6.2.2. Consumer perspective

Active participation and satisfaction rates decline. Memberships in LPs continue a stable growth: on average, one consumer has 14.8 registrations in LPs but actively participates only in 6.7 of them (Bond Brand Loyalty, 2019). A survey by Statista (2017b) on consumer attitude towards LPs in Canada elicited that 77% of respondents think that "well functioning LP makes customers more likely to do business with a brand." The same survey indicated that only 36% could say that they are overall satisfied with their LPs. According to a more recent Bond Brand Loyalty report, member satisfaction with reward programs across multiple sectors was down from 47% in 2018 to 44% in 2019 (Bond Brand Loyalty, 2019, pp. 4-5). Furthermore, the study reveals that only 2 in 10 members can say that they are very satisfied with the level of personalization in their LPs. Across the study, there is a shred of evidence that almost one-fifth of LP participants have never redeemed their point. But those who made redemptions with their LPs are 1.6 times more satisfied than non-redeemers. However, the impact of redemption on satisfaction is declining. (Bond Brand Loyalty, 2019, p. 8).

The reasons for growing customer discontent in LPs may lie in the design characteristics of LPs: rewards structure, their timing, and their perceived value for the customer.

Lack of incentives. According to extant LP schemes, participants can benefit from discounts or monetary rewards through points, miles, gifts, or cashback offered by LP providers, but in any case, customer loyalty has traditionally had a transactional nature. This approach is still valid but only to a limited extent. Just six years ago, conventional monetary rewards were viewed as the single most crucial component of loyalty creation (Harward Business Review Analytic Services, 2019). Since then, the monetary incentives have dropped to fourth place (42% of respondents see it as a key success driver) - displaced by the exceptional customer service (51%), omnichannel access (48%), and ease of use (45%) (Harward Business Review Analytic Services, 2019). Another very fresh survey confirms this: the vast majority of respondents (71%) say that they'd rather prefer LPs that go beyond discounts (Statista, 2020). Kumar and Shah (2004) noticed a growing proclivity among LP providers to offer experiential rewards instead of standard cashback or gift rewards. Such rewards "touch upon the higher level goals and attitudes of the consumers, thereby creating an effect that is enduring and more effective towards engendering steadfast loyalty" (Kumar and Shah, 2004, p. 328).

Personalization is what customers are looking for. By analyzing various customer data collected from different sources and stored in the databases, companies can build up individual customer profiles to design customer-tailored rewards relevant and perceived as high value by the LP users (Kumar and Shah, 2004). Such efforts are highly appreciated by the customers: when personalization is done well, it creates a 6.4x lift in LP participant satisfaction with the LP (Bond Brand Loyalty, 2019). Moreover, 87% of consumers confirm that they are open to brands monitoring details of their online or transaction activity if it results in more personalized and current rewards (Bond Brand Loyalty, 2018). Only 22% of members mentioned that they were satisfied with the level of personalization they received in LPs (Bond Brand Loyalty, 2019), which left a great room for improvement for LP owners. Bond Brand Loyalty Study (2018) indicated that feeling valued, appreciated, and special are important drivers of customer satisfaction, but only 19% of participants say their LP makes them feel special/recognized. Another survey by Statista (2016) revealed that 74% of loyalty card program users in the UK would be more likely to participate in loyalty schemes if rewards were personalized and tailored for them.

Inconvenient redemption rules. The length of time and amount of points required for reward redemption is one of the reasons why customers may abandon an LP they have engaged with earlier (Kumar & Reinartz, 2018; Choi, 2018). Statistics confirm this: more than half of respondents (54%) claimed that the main reason why they dislike LPs is that “it takes too long to earn a reward.” The second reason (39%) in the list: “it is too difficult to earn a reward” (Statista, 2018). Furthermore, narrowly defined programs and cumbersome procedures for points exchange within them, inaccessibility as well as constrained functionality can lead to significant confusion between LP users (Stauss et al., 2005). Another rule that does not add attractiveness to traditional LPs is the points expiration policy. Short expiration periods of loyalty points are one of the leading reasons participants opt out of LPs (Gingiss, 2019; Ma, 2020). Although from an LP owner’s perspective, the expiration of points is justified by writing off some company’s liabilities from the balance sheet (Deloitte, 2016), from the customers perspective, it is a perceived loss that lowers their interest in an LP participation (Shelper et al., 2018).

Security concerns. While subscribing to traditional LPs, customers are asked to fill out a certain form and provide personal information either physically or online/in a mobile app. Further, when a customer makes purchases at a merchant (or a set of merchants in case of coalition LP), transactional information is collected. All the purchase preferences get stored and analyzed to produce an individual user profile that will help a merchant to target a customer more accurately in the future. It is not always comprehensible whether or not the benefits offered LP providers are worth the loss of customer privacy caused by profiling. Due to such privacy issues, LPs get heavily criticized by business experts and consumer associations. (Blanco-Justicia & Domingo-Ferrer, 2016).

2.7. Blockchain technology

Recent technological novelties have discovered new points of advancement for the management of LPs. Digitalization broadens the horizons of interacting with customers, collecting, storing, and using extensive customer data. (Tong et al., 2020). Newly emerging technologies such as mobile capabilities (e.g., digital wallet), APIs, artificial intelligence (AI), machine learning, augmented reality (AR) / virtual reality (VR), customer service chatbots, geospatial services, cloud computing, virtual assistants, natural language processing have the potential to reinvent and already revamping the customer experience and improving customer loyalty strategies (Harward Business Review Analytic Services, 2019). Another groundbreaking technology to add to this list is blockchain (BCT). BCT has been receiving growing attention over the past years as being deemed to become a disruptive technology that will redraw a way of business operation across numerous industries and sectors (Zheng et al., 2018).

2.7.1. The underlying features of BCT

The underlying concept beneath Blockchain is not new. BCT was inspired by the timestamp ordering algorithm that existed in the '90s, which was used to prevent document tampering (Kim & Deka, 2020). An unidentified programmer or a group of people under the name Satoshi Nakamoto continued developing this idea and applied it to create an open-source peer-to-peer (P2P) electronic equivalent of cash. They aimed to facilitate secure online payment mechanisms that would allow sending money directly from one party to another without a need to go through a financial institution. The invention received the name Bitcoin (Nakamoto, 2008). The major goal of Bitcoin's creation was to solve two major problems: the double-spending problem (Chaum, 1992) and the presence of a central trusted third party (Kim & Deka, 2020). Double spending refers to "a potential flaw in a digital transaction in which money can be spent more than once, as the copies sent on the internet are not unique" (Boukis, 2019, p. 308). Since its inception, Bitcoin went through many booms and crashes with the highest peaks in 2017 and 2021 when its price first topped $19,000 in December 2017 and then reached an all-time high of more than $42,000 in early 2021, having surged more than 300% (CNN Business, 2021a). Bitcoin price continued skyrocketing, and already in March 2021, it surpassed $60,000 (CNN Business, 2021b). Bitcoin holds a dominant role in the cryptocurrency market (63.8%), but apart from it, there are more than 9,000 other cryptocurrencies (altcoins) with a global crypto market cap of over $1.92T (CoinMarketCap, 2021), which serves as another illustration of Blockchain's significance.

The main idea behind BCT is a distributed database encompassing timestamped transaction records ("blocks") that are linked together using a cryptographic algorithm, forming a continuously growing chain and shared among participating parties ("nodes") (Iansiti & Lakhani, 2017). Each block contains a hash (unique 30-plus-character alphanumeric address) that is unique and distinguishes it from every other block. A block can be added to the end of a chain only once, and every time a new transaction (e.g., monetary transaction) is checked by the consensus of a majority of the nodes within the P2P network. The check is required to prevent double-spending. A chain represents a public database available for anyone to view. Such transparency makes it impossible for fraudulent transactions to pass the verification. Once a block is created and verified by the network, it can not be altered any longer. (Lim et al., 2019; Zhao et al., 2016). Figure 2.1 visualizes the above-mentioned steps of transaction execution in the blockchain network.

Consensus is reached by the nodes that are not known to each other; hence no prior trust has been established between the peers (Kosba et al., 2016). The consensus protocol eliminates the need for a trusted central party (e.g., a bank, an insurance company, the government, or another intermediary), which would authorize, validate, and, hence, control every transaction processed within the network (Singh & Singh, 2016). The shared responsibility of the nodes within the network reinforces the overall equitability, accountability, and security of the transactions (Filimonau & Naumova, 2020). Given the specific focus of this thesis, no implementation details and technical features of the protocol will be discussed further.

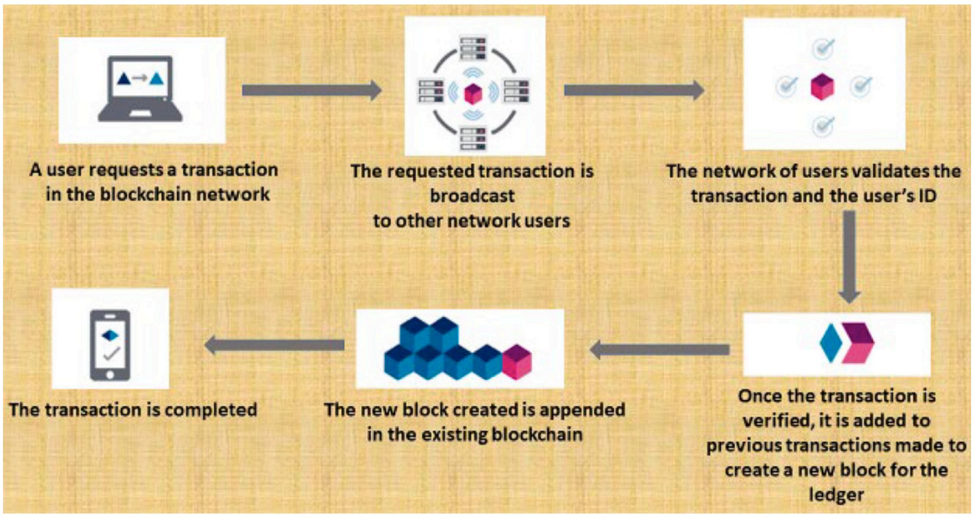

FIGURE 2.1: TRANSACTION STEPS IN THE BLOCKCHAIN NETWORK

Source: Boukis, 2019, p. 309.

2.7.2. BCT applications

BCT has empowered the development of new kinds of platforms, the creation of smart contracts (SC), and the building of whole ecosystems around them (Lauslahti et al., 2017). In its simplest form, a smart contract represents a coded machine-readable program or a transaction protocol that will be executed by a network of mutually distrusting nodes when a set of predetermined terms are met. Execution happens without the interference of an external trusted authority (Lauslahti et al., 2017; Dominguez Perez et al., 2020). SCs mirror real-world contractual agreements with just the only difference - they are completely digital. SCs can be developed on the basis of different blockchain platforms; the most commonly used of them is Ethereum (Alharby & van Moorsel, 2017).

BCT itself is not limited in its applications to the financial sector and cryptocurrencies in particular. It has found an application (mainly via SCs) across multiple domains such as business and industry (energy sector and supply chain), privacy and security (anonymization and secure storage), data management (HR and data distribution), governance (identity management, e-voting, public administration, notary & law, proof of existence), IoT (IoT e-business, distributed device management), integrity verification (insurance, intellectual property, counterfeit), health (electronic health record), education (reputation, certification management), life science and many more. (Casino et al., 2019; Macrinici et al., 2018). Based on intended use purpose, Zhao et al. (2016) determine three generations of BCT: Blockchain 1.0 for digital currency (cryptocurrencies), Blockchain 2.0 for digital finance (encompasses the application of SCs that goes beyond cryptocurrency transactions), and Blockchain 3.0 for digital society (encompasses all other areas of application). Further, in this thesis, the specific application of BCT to customer incentive management and LPs, in particular, will be discussed.

2.7.3. How BCT can disrupt LPs

Applying the principles of a P2P exchange network to LP context, Wang et al. (2018) establish that three parties should run a blockchain-enabled LP: (1) *Issuer*, the entity that defines and generates the points for decentralized exchange; (2) *Company*, the entity that manages an LP and distributes rewards to LP users; and (3) *Customer*, an end-user who collects points for transactions at Company and gets rewards in exchange for them.

Three key elements of such a blockchain-based solution, according to Deloitte (2016), are *a loyalty network platform*, *loyalty tokens*, and *reward applications*. *A loyalty network platform* - a receptacle that accommodates various firms, either big or small ones, and their LPs, facilitating their interaction and interconnection in terms of loyalty points exchange. Within a blockchain-enabled loyalty network platform, LP providers can fully integrate their systems with the promotional activities of other partners from various categories. On the contrary, in traditional LPs, points earned at one merchant could be redeemed only at the same merchant or at the restricted pool of partnering merchants (Wang et al., 2018).

Loyalty token. Once a loyalty transaction is triggered (issuance, exchange, or redemption), a blockchain protocol generates a respective unique encrypted token for it, which serves a basis for all types of rewards, including points. Once a token is created and verified, a ledger is updated accordingly. LP owner governs the rules, how the points behind these tokens are going to be functioning within the loyalty network (Deloitte, 2016). In BC-enabled LPs, points act as an asset, allowing customers to seamlessly earn, burn, merge, transfer their assets as they prefer (Wang et al., 2018, 2019). Within a blockchain-enabled ecosystem, loyalty points can simulate a currency: consumers can effortlessly pay for goods and services with their points obtained from flight mileage, various retailer rewards, hotel stays, gas cards, and other bonuses. Points can also be transferred to other peers at the owner's discretion. For this, customer can use a single digital wallet instead of navigating through multiple accounts and LPs (Wang et al., 2019).

Reward application. Reward application refers to a way how LP participants redeem their rewards within a loyalty network platform. LP providers have the freedom of programming the ways how the reward application connects to the loyalty network and can define the best fitting ways that go inline with their strategic agendas (Deloitte, 2016).

The customer experience can be dramatically upgraded from having plenty of highly fragmented LPs to a single one-stop interlinked loyalty network, like a digital wallet. Rejeb et al. (2020) mention that BCT can facilitate resolving an incompatibility issue within many LP systems, which will result in "increased channel harmony and consistent experience among brands" (Rejeb et al., 2020, p. 7).

Figure 2.2 depicts an insight on one possible scenario of a customer journey in the world of a blockchain-based LPs.

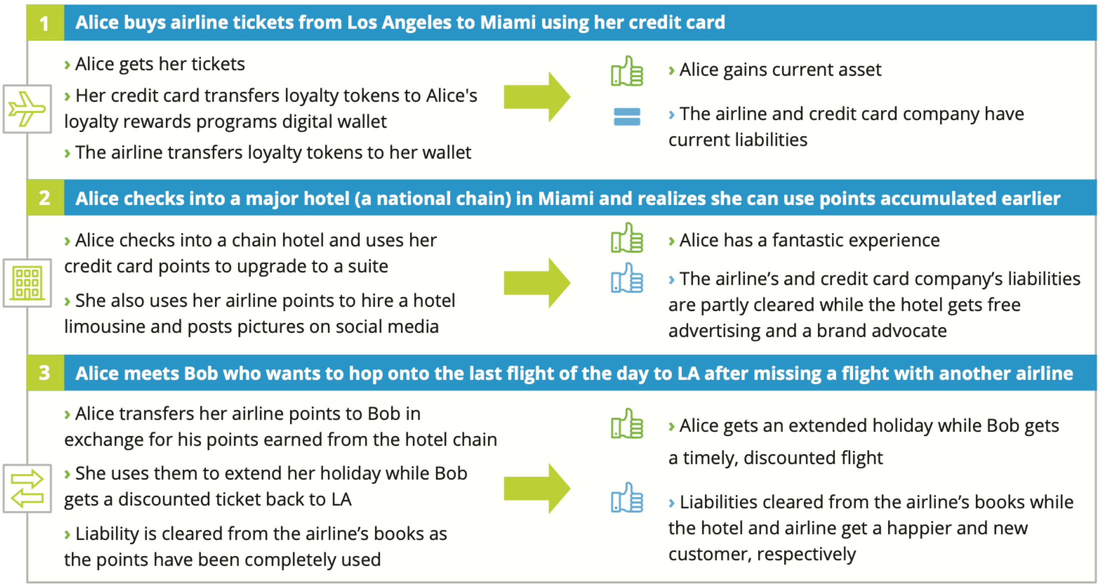

FIGURE 2.2: EXAMPLE OF CUSTOMER JOURNEY WITHIN A BLOCKCHAIN-ENABLED LP

Source: Deloitte, 2016, p.4.

The inherent design of a blockchain-enabled LP can help to "connect the largely disconnected world of loyalty rewards programs, reduce costs, eliminate friction, bring loyalty rewards crediting and redemption into near real time, provide a more secure environment, and facilitate business relationships." (Deloitte, 2016, p.4).

2.7.4. Advantages of adoption

Blockchain-based LPs may be an answer to consumers tired of juggling an array of LPs and eyeing each program's reward options, limitations, and redemption rules. LP providers can also benefit significantly from applying the decentralized nature of BCT to their LPs struggling for success. The advantages of adoption for both parties stem from the following aspects.

Frictionless partner network. BCT is designed to have multiple simultaneous writers within the network (Dominguez Perez et al., 2020). This feature will enable a decentralized blockchain-based LP platform to centralize the fragmented traditional customer LPs. The loyalty tokens seamlessly work across vendors and drastically enhance customer experience by providing frictionless flexibility in loyalty points usage. Although some non-blockchain-based coalition LPs already provide access to the partner network, blockchain can enhance the network effect to make it more pervasive and closer to real-time across more LPs (Deloitte, 2016; Ma, 2020).

From a merchant perspective, being part of such an interlinked platform opens up new business horizons for big and smaller companies. Big established operators can “adopt new service models and offer value-added services to other businesses.” In contrast, smaller ones can “connect with other players in the industry, and scale up their business” (Bhatnagar, 2017, p.4). Figure 2.3 depicts the partner onboarding, usage, management, and evaluating steps of a journey within a BC-enabled loyalty network. A journey that draws avenues across touchpoints with customers and other network participants for customer analytics (including segmentation and personalization), sales forecasts, cross and up-selling, and many other activities.

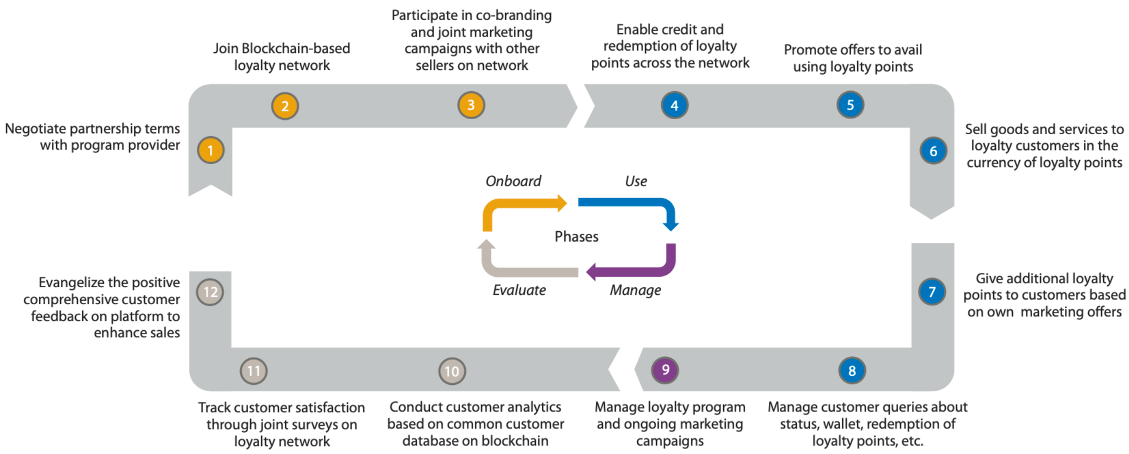

FIGURE 2.3: PARTNER JOURNEY OVERVIEW WITHIN A BLOCKCHAIN-ENABLED LOYALTY NETWORK

Source: Bhatnagar, 2017, p.4.

Lower costs. LP providers and participants can benefit from BCT application to LPs in a cost-cutting context in various ways. (1) Large balance-sheet liabilities of a particular merchant in a traditional LP can be eased by residing the loyalty point liabilities on the vast shared network (Deloitte, 2016; Kowalewski et al., 2017). (2) The use of SCs can reduce a system’s operating costs on the providers' side, eliminating costs stemming from fraud and errors (Bhatnagar, 2017; Deloitte, 2016). (3) In the e-commerce context, the BCT application could help to reduce transaction-associated costs. When LP providers aim for a broader consumer base, not only are they forced to incur costs related to the use of e-commerce platforms but also commissions to payment processors such as credit card or PayPal. In order to stay profitable, merchants are forced to increase the price for end consumers. A BCT application allows direct transactions between merchants and customers, avoiding additional commissions for any intermediaries' services (Lim et al., 2019). (4) Costs associated with customer acquisition (such as direct mail) can also be reduced due to the feasibility of blockchain-enabled LPs operating on social media platforms (Bhatnagar, 2017; Deloitte, 2016).

Security, fraud-proof and traceability. Security is one of the biggest concerns to customers. With a substantial amount of personal and sensitive data involved, brands cannot afford to be dismissive of security (Ma, 2020). As mentioned in section 2.7.1, BCT adopts a ledger of transactions within the network of participants. Applied to LP context, a transaction may represent any manipulation with points - e.g., points are earned, burned, or transferred to another LP participant (Kowalewski et al., 2017). Such tokenization of loyalty points within a blockchain network assures the immutability of transactions. An attempt to alter a block will result in rejection by a majority of the nodes and fraudulent data will not be saved in the ledger. Moreover, the use of SCs eliminates the need of controlling third-party in the process of transaction exchange. SCs are aimed to automate tasks execution based on the predefined set of rules. The implementation of SCs omits any forms of interference by any signatories (Lim et al., 2019).

Near real-time exchange. In traditional LPs, customers do not have sufficient visibility over their loyalty points, which are often credited to them with a significant time delay. The most common reason for that is a lack of coordination between an LP owner and an LP provider (merchant). BCT can enable read and write access to a network for multiple parties in near real-time, so that credited points could be redeemed by a customer straight away, enhancing a customer experience with an LP (Deloitte, 2016).

Loyalty points=digital assets. Within a blockchain-enabled environment, participants can receive complete control over their points and freely dispose of them at their own discretion, making loyalty points to a customer's digital asset (Kowalewski et al., 2017). A customer's digital assets may not have an expiry date (Shelper et al., 2018) and can be freely transferred to any other peer (Wang et al., 2019). This would be seen as a massive advantage from a customer perspective, but not every LP owner may want to achieve a 100% redemption rate. Since that move may not yet be embraced by regulators, "who still will want to see rewards as liabilities on balance sheets of loyalty rewards program providers until they are redeemed, whether this redemption happens quickly or not" (Deloitte, 2016, p. 7).

Visibility over customer profiles generates more value for participants. All transactions within a blockchain network are visible and are accessible in real-time. This enables marketers to grasp a granular overview of customer profiles: customers' prior purchase behavior and redemption preferences (Boukis, 2019). In traditional LPs, the tracking is possible mainly on a purchase level, while in BCT-enabled LP, a breakdown can be done on a product level. Thereby, it will allow marketers to tailor more relevant, personalized, and attractive bundles of rewards for their customers. (Rejeb et al., 2020).

Improvement of corporate brand positioning and brand image. Antoniadis et al. (2019, 2020) mention another indirect benefit stemming from BCT integration in brand LPs: the novelty and hype around BC can be used in marketing to potentially attract new customers and strengthen existing LP's users due to the impact of brand innovativeness on brand loyalty. Pappu and Quester (2016) studied the effects of consumers' perception of brand innovativeness on intangible assets such as brand loyalty. Their study revealed that perceived quality fully transmits the impact of brand innovativeness on brand loyalty. In this vein, Boukis (2019) articulates that the adoption of BCT has the power to enhance a corporate brand's image through the adoption of brand-specific digital currencies and increasing its brand storytelling capabilities.

2.7.5. Caveats for adoption

Just like any other pioneering technology, BCT application for LPs has its' own challenges and obstacles, which scholars and practitioners are arguing. Factors ranging from technical limitations to data privacy matters, acceptance concerns, and other possible challenges may impede the large-scale adoption of blockchain in customer incentive management.

Throughput and scalability. Together with the growing adoption of BCT in various areas, the number of users increases at a steady pace. Over time as bitcoin was gaining more and more popularity, transaction load on the network started to increase drastically, and scalability challenges kicked in (Zhou et al., 2020). Key metrics to measure blockchain scalability include maximum throughput, transaction confirmation latency, bootstrap time, and transaction confirmation costs (Croman et al., 2016). The most significant metric that receives maximum attention and has the strongest impact on the user's quality of experience is throughput (Zhou et al., 2020). Limited block size and block interval of blockchain fail to deliver all transactions submitted by nodes, leading to a serious loss of throughput compared to major payment providers (Dominguez Perez et al., 2020; Lim et al., 2019; Vinod, 2020). For instance, PayPal handles 193 TPSs (transaction-per-second), Visa ~1,700 TPS, while blockchains of the first generation - Bitcoin - only 7 and Etherium only 20 TPS (Mechkaroska et al., 2018). IBM's Hyperledger Fabric deployed in a single cloud data center is claimed to reach over 3,500 TPS (IBM Research Editorial Staff, 2018). Such low throughput could not satisfy the large-scale usage scenarios. Therefore many companies and research groups tried to approach the performance bottleneck and capacity problems of blockchain and suggested many diverse solutions. Proposed solutions, many of which are still under development, include ways of increasing the block size and compressing the blocks, improvements of consensus algorithms, and sharding techniques that allow to increase throughput and decrease transaction latency. All of them strive to achieve decentralization, security, and scalability; however, accomplishing all of them simultaneously appears to be a daunting task (Zhou et al., 2020).

Customer data privacy. Nowadays, customer data is rapidly gaining crucial importance, becoming "the dominant currency of modern marketplaces" (Boukis, 2019, p. 311). The wide adoption of BCT in general and for LPs, in particular, would result in customer data no longer belonging either to enterprises (LP providers) or anyone else; it resides in the entire nod network. Due to the transparency essence of the blockchain, all other network participants, including end-users and even competitors, might also have access to the data (Iansiti & Lakhani, 2017). For LP owners, this might be very sensitive and(/or) confidential information that they most probably will be reluctant to share (Ma, 2020). Therefore, LP providers should keep a balance between transparency and confidentiality, seeking "to maintain exclusive control over their data, ensuring that no customer personal information enter the transaction stream" (Kowalewski et al., 2017, p.5).

Acceptance. What form an adoption of BCT in loyalty management is likely to take? Speaking about the travel industry, Kowalewski et al. (2017) see a future of blockchain-based loyalty networks as small LPs banding together, eventually developing from four to six major blockchain-enabled LPs, each formed around a major airline, hotel chain, or a group of smaller travel firms. For this to happen, not only huge investments will be required, but also the whole shift of paradigm may be necessary. The way data is stored, accessed, and used within a distributed ledger is different from what LP providers are using now. Adopting blockchain may require re-engineering all business processes (Lim et al., 2019). Therefore, a big part of extant LP operators with already developed and scaled management systems would "understandably be the most hesitant to join an interlinked network that could intersect with their own successful interlinking efforts and reduce their competitive advantage" (Deloitte, 2016).

Among other possible risks of blockchain application for LPs, scholars mention currency devaluation, transaction costs (Kowalewski et al., 2017), and energy consumption, challenges stemming from the Proof-of-work (PoW) mechanism behind blockchain. Miners in a PoW-enabled blockchain constantly rival one other through calculating, which results in a considerable electricity scattering (Zhou et al., 2020).

2.8. Existing blockchain-enabled loyalty solutions

Blockchain adaptation for incentive management is still in its infancy; however, over the past few years, more and more early adopters continued emerging in the market. The author's observations of the existing blockchain-enabled platforms for loyalty management revealed that they can be categorized into two major groups: B2B2C and B2C solutions. B2B2C solutions act as facilitators providing blockchain-enabled eco-systems that can be leveraged by other businesses to launch or transform their existing LPs. B2C platforms deliver blockchain-based LPs to their end consumers. Typically private tokens are used in the background, which allows users to earn, burn and exchange tokens within an eco-system of an LP owner.

2.8.1. B2B2C: BaaS Vendors overview

Some startups currently offer Blockchain-as-a-Service (BaaS) solutions across the globe. They provide out-of-the-box blockchain and SCs-powered software that enables businesses to launch their loyalty platforms or enhance existing ones. Such solutions promise to extend partner network, expand marketing capabilities, bring transparency together with efficiency to the process, and establish a solid connection to the customers, which will add value to a firm and eventually enhance program profitability.

Among already operating market players: Loyyal, Qiibe, Digitalbits, Aetsoft, Incent, Appsolutely, Momentum Protocol, Dragonchain, and others. The offerings and basic information about vendors are summarized in Table 2.3.

2.8.2. B2C solutions overview

For end-users, loyalty points (tokens/internal currency) within a blockchain ecosystem are acquired and saved in one all-purpose digital wallet (Kowalewski et al., 2017). Users get rewarded with blockchain-backed loyalty points for shopping at partner merchants. Alternatively, users can convert tokens from other partnering systems if the LP owner allows. Spending rules are defined by the platform owner and remain at its discretion depending on the type of tokens: company-specific or generic ones. Figure 2.4 represents B2C blockchain-enabled loyalty solutions subcategorization based on the type of tokens used as internal program currency.

Singapore Airlines pioneered in 2018 with their first blockchain-empowered LP KrisPay, which will be in detail described in the next section 2.8.3. Since 2018 some other brands also opted to switch their loyalty management efforts to a BC-enabled platform. Among them Chanticleer Holdings, American Express, and Boxed, Rakuten with their Rakuten Point Mall LP, Amex, Cathay Pacific with Asia Miles LP, AirAsia, and others.

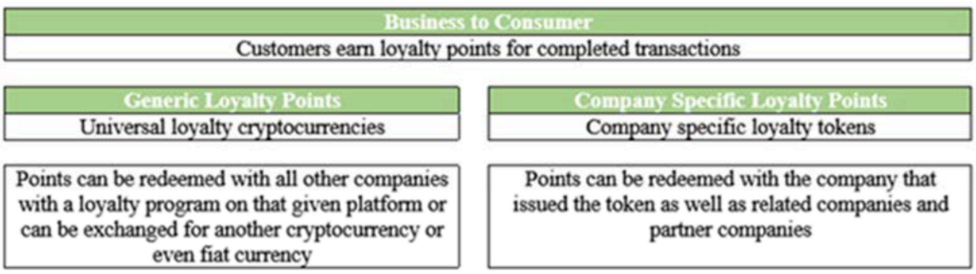

FIGURE 2.4: LOYALTY POINTS WITHIN A BLOCKCHAIN ECOSYSTEM IN B2C SOLUTIONS

Source: Agrawal et al., 2018, p.5.

Vendor Name	Headquarter	Underlying blockchain/ Token	Value Proposition	Products	Major LPs in ecosystem	Homepage
Loyyal	USA	Hyperledger Fabric, not disclosed	"With Loyyal's Blockchain-as-a-Service (BaaS), client's have all-inclusive access to our Platform, enterprise-grade hosting services, development tools, support services, and our ever-growing network of partners." (Loyyal, 2021)	**Loyyal Product Suite** that includes: - "Unlimited API access to the Loyyal Platform; - Entry to Loyyal's network of earning and redemption partners; - Personalized Node Dashboard; - Monthly Support services; - Unlimited support for Severity Level 1-2 issues." (Loyyal, 2021)	Emirates Skywards; Dubai Points;	www.loyyal.com
Qiibee	Switzerland	Qiibee (QBX)	Plug-and-play LP platform that allows firms to run their own branded BCT-based LP. It has easy integration, fast go to the market, and safe infrastructure—a proper fit for stand-alone programs, multi-partner programs, and service providers.	***Loyalty White Label App***-for merchants who would like to launch a LP; ***Loyalty Toolbox***- for merchants who would like to upgrade an existing LP; ***Partner Aggregator*** - for multi-partner program owners who strive to grow a partner network	Sausalitos; Etihad Guest; Louis Erard; Lattesso	https://www.qiibee.com/
DigitalBits	Not specified	DigitalBits (XDB)	DigitalBits represents a blockchain-powered protocol layer created to support consumer digital assets (such as branded stablecoins). Digitalbits supports "the creation and launch of branded cryptocurrencies for specific companies through ecosystem partners." (DigitalBits, 2021, p.3)	DigitalBits blockchain as a transacting and trading layer for diverse digital assets impeded within the existing LPs.	iCash Rewards; Alpha Sigma Capital; Fireblocks	https://digitalbits.io
Aetsoft	Belarus	Tron (TRX)	A self-maintainable blockchain-enabled platform from Aetsoft offers customers highly targeted loyalty programs with flexible, irrevocable, and exchangeable assets (reward points) and a secure system hacker attacks-proof.	Many custom blockchain and automation solutions for enterprises. LPs as a part of them	No information on the homepage	https://aetsoft.net/solutions/blockchain-loyalty/
Incent	Australia	Incent (INCNT)	Incent is an engagement platform that employs its own cryptocurrency token, to reward any digitally-trackable action. Incent allows content creators to grow their fanbase, reward their viewers and monetize their content.	- Ingage: product that targets Millenials and Gen Z. "Ingage uses 'drop codes' – short strings of characters – displayed at intervals within the video stream. Audiences redeem these for INCNT, which is instantly credited to their account on the Incent platform." (Incent, 2020, p.2)	Incent codes are platform agnostic & can be deployed across any live streaming platform	https://incent.com/
Appsolutely	Philippines	LoyalCoin (LYL)	Appsolutely facilitates the improvement of brands ties with their customers by creating digital strategies and launching LPs and mobile apps that enable customer loyalty, engagement and increases brands' value for customers (localized mainly for Filipino businesses)	- LoyalWallet mobile app with LCredits as internal currency; - LoyalClub's Pensionado Card	Gong Cha; Havaianas; Coffee chain Bo's coffee;	https://appsolutely.ph/index.html
Momentum Protocol	Switzerland	The Momentum Token (MMTM)	Blockchain-centric loyalty reward points infrastructure sets up a one-stop-shop for all LPs (online, omnichannel, physical). "Momentum Protocol is a state-of-the-art solution employing AI and blockchain that helps businesses to get insights into customer behavior, in turn driving revenue. This technology also provides individualized incentives to customers, rewarding them for being part of the LP.	- Momentum Protocol Solution Provider Program - MobileBridge software- end-to.end solution on top of the protocol	Burger King; Dansk Supermarked Group; Volkswagen; Galbani; Firelli	https://www.momentumprotocol.com
Dragonchain	USA	Dragonchain (DRGN)	A patented Baas public-private hybrid blockchain platform that allows fast speed to market without the typical barriers found in other blockchains. Key features: Customer Engagement; tokenization of points; Unique, flexible, customizable incentives; interoperability.	Solutions to build a blockchain-based LP from scratch or integrate into existing ones.	No information on the homepage	https://dragonchain.com/

TABLE 2.3: OVERVIEW OF BAAS VENDORS

Source: own research

2.8.3. Kris+ digital wallet

Kris+ before 2020, known as KrisPay, is the world's first blockchain-enabled loyalty digital wallet for Singapore Airlines (SIA)'s FFP KrisFlyer that has been launched in July 2018 (Singapore Airlines, 2018). Kris+ lifestyle app enables users to transfer their KrisFlyer miles (miles they receive for flying with SIA) to units of payment called KrisPay miles, the app's 'background' currency (1 KrisPay mile = 1 KrisFlyer mile). Further, customers can use miles to pay for everyday purchases at partner merchants, either in full if they have enough KrisPay miles or partially offset the redemption. To earn KrisPay miles, customers do not always have to fly; they can pay by cash or card for everyday spends at the partnering merchants and get rewarded for it with KrisPay miles: from hotels, eateries, beauty parlors, and cards to retail, telco and gas stations. KrisPay miles can also be converted from bank partners such as DBS and UOB. Since LP's inception, the merchant network has grown drastically, and now in 2021 counts more than 750 partnering companies island-wide compared to only 18 in 2018 (Singapore Airlines, 2018; Kris+ by Singapore Airlines Mobile App, 2021).

The main idea of the Kris+ app is to become a central customer's touchpoint for all everyday spends, in perspective making usage of all other LPs obsolete. This is being achieved by a rapidly expanding partner network covering a wide range of categories (refer to section 2.7.3). Not to mention frictionless overall customer experience, when KrisPay miles can be earned at one merchant and immediately burned at another one without any waiting times. This would not be possible in a traditional LP due to the latency of data exchange between partners and LP owners. Not only the program value is enhanced for customers by the flexibility in redemption options and frictionless redemption process, but also the airline's liabilities are relieved faster and more efficiently (Vinod, 2020).

Appendix 1 depicts the main stops of the user journey with the Kris+ app.

2.9. Summary

This chapter has provided a theoretical background of brand loyalty, customer motivations, LPs and their designs, customer value perception of an LP, BCT, and a practical overview of existing blockchain applications in the context of LPs. However, due to the relative novelty of the phenomenon, scholars have not yet comprehensively studied and accessed it. A specific focus of this thesis concerns the effects of blockchain-enabled LPs on customer perceived value and attitudes, an area that modern researchers have hardly explored. An early attempt to approach the research questions is presented in the following chapter.

3. METHODOLOGY

3.1. Introduction

This chapter describes the selected method to answer the study research questions. Figure 3.1 depicts the stages of the thesis creation. At first, a pre-study of the topic was performed to define the direction of the study. After gaining an insight into the subject and study purpose definition, an in-depth literature review of extant researches on loyalty, LPs, value perception, BCT, and existing blockchain applications was conducted. Further, a theoretical framework of the research was formulated, followed by the online survey creation. Quantitative data was collected and analyzed employing statistical methods. In parallel, an analysis of Twitter data was conducted in order to find out the customer sentiments on currently existing LPs, both traditional and blockchain-enabled. Further, obtained results were discussed, and conclusions were drawn.

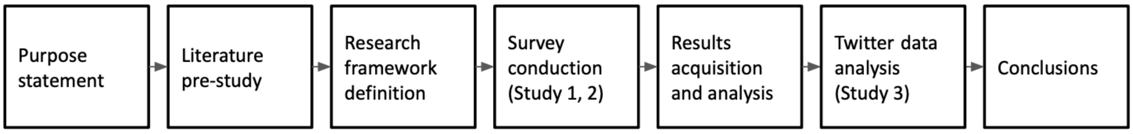

FIGURE 3.1: RESEARCH STAGES

Twitter data analysis for Study 3, in turn, was broken down into the following sub-steps depicted in Figure 3.2:

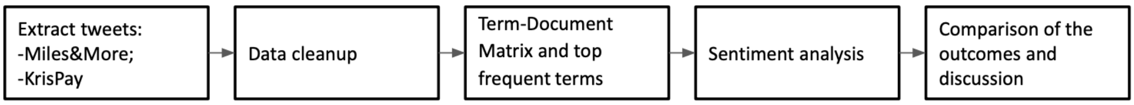

FIGURE 3.2: TWITTER DATA ANALYSIS STAGES

3.2. Selection of methodology

Previous research (Wang et al., 2018, 2019a, 2019b) pioneered in exploring the impact of key techniques of the blockchain-based LPs design on ex(intrinsic) motivations of individuals and their perceived values. The exploratory qualitative research was conducted due to a lack of evidence in the field of knowledge. Current research intends to dig deeper and consider how specific features of blockchain-based LP design can affect customer perceived value and hence the program loyalty. A quantitive research framework was adopted to establish empiric interconnections between examined phenomena.

3.3. Designs of prototype LPs

LPs may vary drastically in their designs. Scholars have established that the selection of design elements (reward options, requirements, choices, deadlines), the way they are employed within an LP, and the way they fit customer motives to partake in an LP directly impact customer loyalty; hence, the effectiveness of an LP (Kopalle et al., 2012, Kreis& Mafael, 2014; Kumar & Shah, 2004; Liu & Yang, 2009; Nunes & Drèze, 2006; Zhang & Breugelmans, 2012).

For the purposes of this thesis's further analysis, comparable LP designs of a traditional points-based LP and a blockchain-enabled LP were examined. Prototypes of the sample LPs considered within this study are real currently existing FFPs: one is blockchain-enabled (Kris +), while second is a traditional miles-based FFP with no BC application (Miles&More). Table 3.1 summarises the key elements of the compared prototype LP designs and how they differ from one another depending on the LP type.

Design element	Blockchain-based LP	Traditional LP
Structure	Frequency reward	
Number of earn partners	Multiple (200+)	
Number of burn partners	Multiple (200+)	Only LP owner
Reward type	Monetary and non-monetary	Non-monetary
	Direct and indirect	
Timing	Delayed and Immediate	Delayed
Participation requirement	Open LP, automatic points accumulation	

TABLE 3.1: DESIGN ELEMENTS OF A PROTOTYPE TRADITIONAL AND A BLOCKCHAIN-ENABLED LPS

Both considered LP prototypes are FRPs, meaning that they provide a one-time reward in exchange for a certain amount of accumulated miles (Blattberg et al., 2008). Both programs have multiple partners in diverse categories where customers can earn loyalty miles. However the way customers can burn their miles varies: traditional LP prototype offers its' customers to exchange loyalty miles for flights/flights upgrades at the airline- LP owner or merchandise in the online shop (household appliances, electronics, clothing, cosmetics, goods for children and more) or exchange loyalty points on discounts on selected services in limited categories. In contrast, the blockchain-enabled LP prototype offers direct reductions for day-to-day purchases at multiple partners together with flight/flight upgrades and merchandise. The timing of an LP prototype also differs: users of a classic LP can only use their miles with a significant delay. Moreover, they need to accumulate a significant amount of loyalty miles in order to be able to redeem them. While blockchain nature allows loyalty miles to be credited to the customer's account immediately and the customer does not have a minimum necessary amount to accumulate, loyalty miles can be burned instantly after accrual.Both LPs are open for everyone to participate and are free of charge; loyalty points are credited automatically to customer accounts.

3.4. Features of a blockchain-based LP in comparison to a traditional LP

As discussed in the previous chapter, the fundamental natures of blockchain enable LPs to have some distinctive features that might be seen as advantages by potential users compared to traditional LPs. This study aims to investigate if the employment of a blockchain-based design to an LP may result in enhanced customer value perception of an LP. Taking into account the the designs of prototype LPs from the previous section 3.3 and prior studies on blockchain essence in application to LPs (refer to in section 2.6.3) it was established that major divergence with traditional points/miles-based LPs lay in loyalty points manipulation and offers relevance. For the purposes of this study, five peculiar features of blockchain-based LPs were selected for further analysis: (1) points usage; (2) timing of points accrual; (3) points expiration; (4) points transferability; (5) offering relevance.

Table 3.2 depicts the detailed clarification of every feature in the context of LP type (traditional LP or blockchain-based LP).

Design feature	Blockchain-based LP	Traditional LP
Points usage	Loyalty points can be used to • make day-to-day purchases at any of the partnering merchants to pay the purchase price in full or partially • buy merchandise at the Airline's online shop (various categories of goods) • buy flights/upgrades at Airline	Loyalty points can be used to • Get discounts for selected services (from travel category: hotels, car rentals) • Buy merchandise at the Airline's online shop (various categories of goods) • Buy flights/upgrades at Airline
Timing of point accrual	Earned points are credited to user account immediately in real-time	Earned points are credited to user account with a delay of several weeks*
Offer relevance	Users can browse all offers as well as receive personalized ones, based on their previous shopping preferences	Users can browse generic offers available for all users
Points validity	Loyalty points have no expiration date	Loyalty points expire after 3 years*
Points transfer-ability	Loyalty points can be transferred to another user	Loyalty points cannot be transferred to an-other user*

*Reverse coded

TABLE 3.2: COMPARED FEATURES OF A PROTOTYPE TRADITIONAL AND A BLOCKCHAIN-ENABLED LPS

3.5. Conceptual Framework

Study 1 aims to examine how LPs' considered features (Table 3.2) impact the customer perceived value of participative behavior across two types of LPs: blockchain-based and traditional points/miles-based. Perceived value was classified according to 3 dimensions: economic value, psychological value, and interaction value (Kreis & Mafael, 2014; Wang et al., 2018, 2019a, 2019b).

Following Yi & Jeon (2003), program loyalty within this study is conceptualized as a consequence of the value perception of the loyalty program. The behavioral component of loyalty could not be controlled as it would require participants to have a real experience with LPs from the research design, which was not feasible to achieve within this study setup. Therefore, the attitudinal aspect of loyalty was considered (Dick and Basu, 1994). Hence program loyalty was defined as a high relative attitude toward the LP (Yi & Jeon, 2003). Figure 3.3 depicts the conceptual framework of this thesis research, showing how LP features are perceived in certain ways by customers and eventually lead to program loyalty.

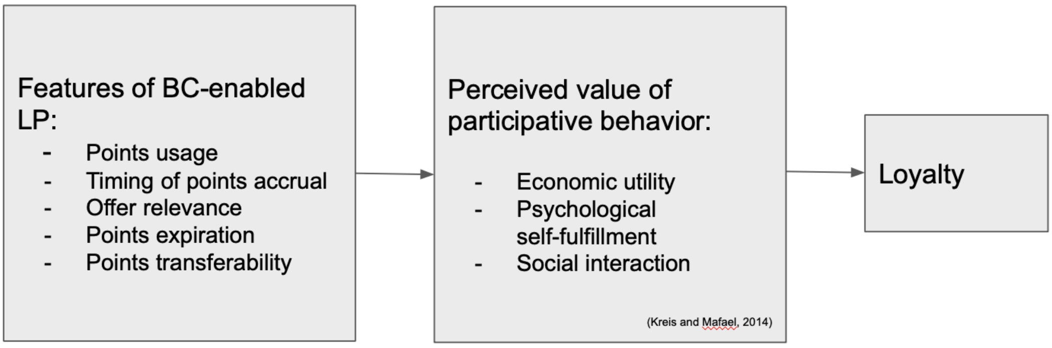

FIGURE 3.3: CONCEPTUAL FRAMEWORK OF LP PARTICIPATIVE BEHAVIOR

Figure 3.4 draws the logical connections between considered features of LPs and perceived value. Only meaningful connections have been considered. The exact set of the measurement items used for each of perceived value entities (economic utiliy, psychological self-fulfilment, social interaction) can be found further in Table 3.3.

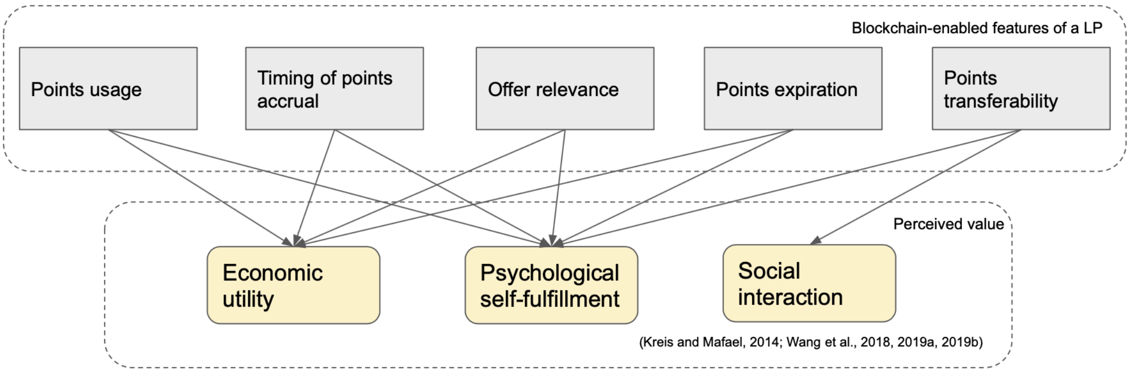

FIGURE 3.4: RELEVANCE OF INTERCONNECTIONS BETWEEN LP FEATURE AND ITS' PERCEIVED VALUE

3.6. Hypotheses

3.6.1. Study 1: Blockchain-enabled features, Perceived Value and Loyalty

The first study examines the impact of blockchain-enabled LP design elements on customer value perception and program loyalty. To answer the research question "How do blockchain-powered features of LP design influence customer value perception and loyalty towards an LP?" the following five directional hypotheses are posed:

H_{11}: Higher number of available loyalty points redemption options triggers a higher level of perceived value and loyalty.

H_{12}: Immediate loyalty points accrual triggers a higher level of perceived value and loyalty than a delayed one.

H_{13}: Personalized customer-tailored offers trigger a higher level of perceived value and loyalty than non-personalized generic offers.

H_{14}: Loyalty points with no expiration date trigger a higher level of perceived value and loyalty than loyalty points with an expiration deadline.

H_{15}: Loyalty points transferable to other peers trigger a higher level of perceived value and loyalty than non-transferable ones.

The final hypotheses to reveal if the Blockchain-enabled LP triggers higher level of loyalty compared to a traditional LP is posed:

$H_{Loyalty}$: Blockchain-enabled LP triggers a higher level of loyalty than a Traditional LP.

3.6.2. Study 2: Socio-Economic Factors and Program loyalty

The second part of the research investigates the impact of socioeconomic factors on the customer attitudes towards the LP design with the blockchain-based features, hence program loyalty. A non-directional, two-tailed hypothesis is posed:

H_2: Socioeconomic factors have an impact on the program loyalty towards the blockchain-based LP.

3.7. Measure development

Due to the absence of existing directly applicable scale for each research element, a multi-item Likert scales were adopted from multiple sources. For perceived value of LP design elements, the seven items selectively picked from Meyer-Waarden (2013) and Kreis & Mafael (2014) were employed based on the relevance of each item to the study purpose. To measure the attitudinal loyalty towards the program three items were adopted from Yi & Jeon (2003). Table 3.3 summaries all the used items presented in order of appearance.

For scale development, 5-point scale was used for both studies 1 and 2 (1 = strongly disagree; 5 = strongly agree).

Measurement	Source
Perceived value	Kreis & Mafael, 2014; Meyer-Waarden, 2013
Economic value	
It would be economically reasonable for me to become a member of the LP	
LP would give me monetary advantages	
The LP would offer me additional value for my money	
Psychological value	
I would enjoy being a member of a LP	
LP would give me pleasure when I exchange miles	
I feel like the LP makes me special compared to other customers	
Interactional value	
The LP would have social benefits for me	
Program loyalty	Yi & Jeon, 2003
I like the proposed LP more so than other program	
I have a strong preference for the pro- posed LP	
I would recommend the proposed LP to others	

TABLE 3.3: MEASUREMENT ITEMS (STUDY 1 AND 2)

3.8. Data collection

The data for the two studies (1 and 2) was collected via a survey placed on the online platform SoGoSurvey (https://www.sogosurvey.com). The convenience sampling technique was applied for data collection. Link to a survey was distributed via social media among various Facebook communities, mostly local (Austria-based) as well as WhatsApp and Telegram messengers. Besides, author's private and professional networks were involved. Respondents (N=206) were assigned to one of two groups to answer the questions related either to features of a blockchain-powered LP (N=110) or a traditional LP (N=96). Survey participants were prompted to randomly select either 1 or 2 radio buttons in one of the questions to assign them to one of the groups (see Q3 in Appendix 2) Two scenarios were used to manipulate the five features of every type of LP. Participant groups did not have intersections, meaning that one participant answered questions about only one type of LP, either traditional or Blockchain-enabled. Both surveys shared a handful of generic questions about prior experience with LPs, socio-economic factors, and general impressions of the presented LP scenario. A full list of questions can be found in Appendix 2.

The data for Study 3 on the tweets analysis was collected using Twitter Developer API (Twitter Developer Solutions, 2021). Twitter Academic Research Product Track V2 API that offers access to a complete pool of historical data for academic purposes was utilized. The programming language R, software RStudio, package “academictwitteR” and library “academictwitteR" (Barrie & Chun-ting Ho, 2021) were used to extract the tweets. User authentification was performed via OAuth 2.0 Bearer token.

Study 3 analyzed available tweets for two actual existing LPs that served prototypes for Studies 1 and 2: Miles&More (traditional, not blockchain-based) and Kris+ (former KrisPay, blockchain-enabled). To retrieve tweets related to Miles&More the function *get_mentions_tweets* was utilized. All mentions of the Lufthansa Miles&More program's official account (@Miles_and_-More) were considered for the timeframe from 2009-02-01 (date of account creation on Twitter) to 2021-05-21. 4120 tweets retrieved.

Because there is no official account of Kris+ on Twitter, the same function could not be used to collect the tweets related to KrisPay/Kris+. Instead, function *get_all_tweets* retrieved tweets with hashtags #KrisFlyer OR #KrisPay for the timeframe from 2018-07-24 (official release date of KrisFlyer's blockchain-based component) to 2021-05-21. 939 tweets retrieved.

Full R code of data extraction with the respective comments can be found in Appendix 3.

3.9. Variables

For the first study, continuous dependent variables were represented by perceived value of 5 blockchain-enabled LP features, mentioned in Table 3.2 (‘Points usage’, ‘Timing of points accrual’, ‘Offering relevance’, ‘Points expiration’, ‘Points transferability’) and resulting loyalty toward a LP (‘Program loyalty’). Cronbach's α coefficient was established as shown in Table 3.4 to determine inter-item consistency reliability of the various facets of the perceived value of LP design elements and Program loyalty.

All the measurements have appropriate levels of reliability within the factor: Cronbach's α values for calculated scales ≥0.800, which requires more than 0.700 to be considered as reliable. The means and standard deviation of the various attributes of Perceived value, Program loyalty and demographic variables were also computed.

For the second study, a variety of socio-economic factors represented the independent variables. Considered dimensions include gender, age, education level, employment status, income level and region of residence. A complete list of variable values can be found in Appendix 2. (Q15-Q20). Dependent variable was represented by loyalty toward an LP (‘Program loyalty’).

Variables/Items*	Cronbach's α		Number of Elements
	Blockchain LP	Traditional LP	
Economic Utility			
(1) Points usage	0.849	0.833	6
(2) Timing of points accrual	0.927	0.887	6
(3) Offering relevance	0.952	0.906	6
(4) Points expiration	0.956	0.955	6
Psychological self-fulfilment			
(1) Points usage	0.767	0.768	6
(2) Timing of points accrual	0.796	0.845	6
(3) Offering relevance	0.862	0.771	6
(4) Points expiration	0.820	0.878	6
(5) Points transferability	0.869	0.849	4
Social interaction value			
(5) Points transferability	0.869	0.849	4
Program loyalty	0.922	0.926	3

TABLE 3.4: CRONBACH'S ALPHA COEFFICIENTS FOR STUDY VARIABLES

3.10. Data analysis

All subsequent data analysis for studies 1 and 2 was conducted with IBM SPSS Statistics software. Frequency distribution was used to describe the sample. Correlations between the 5 Loyalty Program design attributes and the Program Loyalty were calculated using the Spearman correlation coefficient with the purpose of exploring the non-parametric relationship between the continuous variables. Spearman´s rho (ρ) was used along with demographics factors for in-depth analysis.

To define an appropriate analysis method for studies 1 and 2, the distribution of the sample was checked with he help of Kolmogorov-Smirniov test. As a result, non-parametric analysis method for Study 1 and parametric analysis method for Study 2 were chosen.

Given the nature of the research question in study 1, a non-parametric Mann-Whitney U test was selected to explore whether there is a statistically significant difference in the mean scores for the selected two groups, which in turn requires testing hypotheses H_{11}, H_{12}, H_{13}, H_{14}, H_{15}.

A two-way ANOVA test was used to test the hypothesis of study 2. Two-way ANOVA test allows simultaneous testing for the effects of individual independent variables on the dependent variable and identifies any interaction effect thereafter, which requires testing hypothesis H_2.

The prerequisites to conduct Mann-Whitney U test and two-way ANOVA Test were checked and presented along with the results: (1) Level of measurement for dependent variables are at intervals, (2) Sample was randomly collected, (3) Independence of observations was secured – exclusive groups of respondents, (4) Sample does not have to be normally distributed, (5) Homogeneity of variance (Levene's test for equality of variance) checked.

Study 3 data analysis consisted of the following components: corpus creation and cleanup, term-document matrix creation, and eventually sentiment analysis for both types of the LP. Corpus cleanup removed all the undesirable symbols from the corpus, such as whitespaces, punctuation, stop words in English and German languages, numbers, URLs, retweets, odd symbols…etc. to keep only the semantic part of the tweets. To build a term matrix from the cleaned corpus, the text mining package "tm" was employed (Feinerer et al, 2020). Further sentiment analysis was conducted based on the package "syuzhet" (Jockers, 2020) and plotted using package "ggplot2" (Wickham et al., 2020).

4. RESULTS AND DISCUSSION

4.1. Introduction

This chapter includes all the findings of the research analysis along with statistically proven evidence. A general overview of the data set is presented at the beginning of the chapter, followed by a detailed analysis of features of LPs and perceived value. In this subsection, the chosen attributes of LP design were examined against overall program loyalty to test the aforementioned hypotheses. Study 1 investigates blockchain-enabled features, perceived value and resulting program loyalty; study 2 — socio-economic factors and customer loyalty towards a Blockchain-enabled LP and study 3 provides the outcomes of sentiment analysis conducted for data gathered from Twitter related to blockchain-enabled LP and a traditional one.

4.2. Data Set

4.2.1. Description of the Study 1 and 2 sample

In the study sample, male respondents represented 30.1% (62) of the total, while female respondents represented 69.9% (144). The explanation for the sample skewness lies in the survey distribution method: a link to the survey was posted in (but not limited to) three big Austria-based female Facebook groups (30,000+ members in total). Males to females ratios for a blockchain-based LP and a traditional LP within the sample were 1:3 and 3:5, respectively. In the overall selection, 82.5% (170) were in the 25 – 44 years age group. The ratios between 'Below 34 years' and 'Above 34 years' for a blockchain-based LP and a traditional LP were 2:3 and 1:1, respectively. The Level of Education of the overall sample was distinctively separable to two groups: 'Secondary/ Graduate' and 'Postgraduate' with a 27.6% and 72.4% of share, respectively. Employment of respondents falls into three groups according to the share in the sample; 'Employed for wages' (67.0%),' Self Employed' (18.4%), 'Unemployed' (14.6%). Apparently, the level of income of the respondents varied among three groups: 'Below € 31,000', '€31,000' - €60,000', 'Above €60,000' with a share of 28.2%, 38.6%, and 33.2%, respectively. Regional dispersion of the respondents according to Region of Residence is limited to three regions: 'Western Europe' (47.5%), 'Central and Eastern Europe' (48.5%), 'Americas and Asia' (4.0%). These saturations of data in the categories mentioned above were identified with the purpose of manipulation for further analysis. A complete breakdown of a study sample description can be found in Appendix 4.

4.2.2. Distribution check

A normality assessment of the study sample was conducted. In this assessment, dependent variables were considered in two separate groups; Blockchain-enabled LPs (BCLP), Traditional LPs (Trad. LP). Kolmogorov-Smirnov statistic along with sig<0.05 was used to assess the normality of the distribution of scores. Skewness value and Kurtosis value were used to evaluate the shape of the distribution. Mean and 5% Trimmed Mean values were compared to check the impact of outliers.

Dependent Variable / LP type		Kolmogorov-Smirnov			Descriptive Statistics						
		Statistic	df	Sig.	Mean	5% Trimmed Mean	Median	Variance	Std. Deviation	Skewness	Kurtosis
(1) Points usage	BCLP	0.073	110	0.199	3.433	3.462	3.500	0.771	0.878	-0.417	-0.120
	Trad. LP	0.107	96	0.009	3.457	3.480	3.500	0.666	0.816	-0.464	0.409
(2) Timing of points accrual	BCLP	0.087	110	0.040	3.483	3.516	3.667	0.872	0.934	-0.516	-0.270
	Trad. LP	0.087	96	0.067	3.033	3.040	3.000	0.819	0.905	-0.025	-0.002
(3) Offering relevance	BCLP	0.141	110	0.000	3.271	3.296	3.500	1.209	1.099	-0.268	-0.941
	Trad. LP	0.073	96	0.200	3.002	3.010	3.000	0.933	0.966	-0.244	-0.361
(4) Points expiration	BCLP	0.167	110	0.000	3.776	3.848	4.000	1.098	1.048	-0.937	0.175
	Trad. LP	0.125	96	0.001	3.233	3.248	3.000	1.211	1.100	0.030	-0.783
(5) Points transferability	BCLP	0.122	110	0.000	3.641	3.710	3.750	1.150	1.072	-0.709	-0.064
	Trad. LP	0.073	96	0.200	3.245	3.267	3.250	1.137	1.066	-0.143	-0.594
Overall Loyalty	BCLP	0.137	110	0.000	3.573	3.611	3.667	0.910	0.954	-0.369	-0.168
	Trad. LP	0.159	96	0.000	2.705	2.678	3.000	0.970	0.985	0.176	-0.265

TABLE 4.1: NORMALITY ASSESSMENT FOR TYPES OF LP

Results from the Table 4.1 suggest that 4 sample items deviate from the normal distribution, one for a Blockchain-based LP (BCLP) and three for a Traditional LP (Trad. LP). However, Skewness and Kurtosis values for all instances indicated a level of deviation from the ideal normal distribution shape. Comparison of Mean and 5% Trimmed Mean values indicate that there are no extreme outliers with a strong influence on the mean. In conclusion, it is evident that assuming a normal distribution for all dependent variables is unrealistic. Therefore, Non-Parametric analysis method for Study 1 and Parametric analysis method for Study 2 were preferred.

4.3. Study 1 findings: Blockchain-enabled features, Perceived Value and Loyalty

4.3.1. Mann-Whitney U test

In order to test the hypotheses, Mann-Whitney U test - Independent Samples was performed to compare the mean scores of two different groups of respondents (Group 1: Blockchain-enabled LP; Group 2: traditional LP). 95% of the confidence interval was assumed. Levene's test for equality of variance was performed to check whether two groups have equal variances (Table 4.3). All the p-values > 0.05 imply that the null hypothesis is accepted, meaning that the assumption of even distributions between the two groups is satisfied, and distributions can be considered similar. This assures that the p-value obtained at the further step during the non-parametric test can be interpreted.

'Effect size' was measured to indicate the magnitude of the differences between the groups when there was no significant difference. For interpretation of the obtained values, the following guidelines (Cohen, 2013) were adopted: 0.0-0.05 = no effect, 0.1-0.3 = small effect ; 0.3-0.5 = moderate effect; 0.5 ≤ large effect.

$$Effect\ Size\,(r) = \frac{|Z|}{\sqrt{N}} \tag{1}$$

Where Z – Standardized Test statistic z; N – Sample size of the two groups considered.

Table 4.2 presented below depicts the group statistics for the five features of LPs grouped by LP type. This will assist in interpreting the result of the non-parametric test. The detailed hypotheses testing results are listed further in section 4.3.2.

Perceived Value and Loyalty		**N**	**Mean**	**Std. Deviation**	**Median**	**Std. Error Mean**
(1) Points usage	BCLP	110	3.433	0.878	3.500	0.084
	Trad. LP	96	3.457	0.816	3.500	0.083
(2) Timing of points accrual	BCLP	110	3.483	0.934	3.667	0.089
	Trad. LP	96	3.033	0.905	3.000	0.092
(3) Offering relevance	BCLP	110	3.271	1.099	3.500	0.105
	Trad. LP	96	3.002	0.966	3.000	0.099
(4) Points expiration	BCLP	110	3.776	1.048	4.000	0.100
	Trad. LP	96	3.233	1.100	3.000	0.112
(5) Points transferability	BCLP	110	3.641	1.072	3.750	0.102
	Trad. LP	96	3.245	1.066	3.250	0.109
Overall Loyalty	BCLP	110	3.573	0.954	3.667	0.091
	Trad. LP	96	2.705	0.985	3.000	0.101

TABLE 4.2 : GROUPS STATISTICS

	Levene's Test for Equality of Variances		Mann- Whitney U test			Effect size - r
	F	Sig.	U	Z	Asymp. Sig. (2-tailed)	
(1) Points usage	1.381	0.241	5233.000	-0.110	0.912	0.0077
(2) Timing of points accrual	0.740	0.391	3724.500	-3.652	0.000	0.2544
(3) Offering relevance	4.647	0.052	4447.000	-1.955	0.050	0.1362
(4) Points expiration	0.931	0.336	3708.500	-3.691	0.000	0.2572
(5) Points transferability	0.004	0.952	4068.000	-2.851	0.004	0.1986
Overall Loyalty	0.079	0.778	2774.500	-5.940	0.000	0.4138

TABLE 4.3 : RESULTS OF MANN-WHITNEY U TEST AND LEVENE'S TEST

4.3.2. Hypotheses testing and results

The first study examines the impact of blockchain-enabled LP design elements on customer value perception and program loyalty through answering the research question "How do blockchain-powered features of LP design influence customer value perception and loyalty towards an LP?". Therefore, the following five directional hypotheses for blockchain-enabled LP design elements and one for overall program loyalty were posed and tested:

$H_{Loyalty}$: Blockchain-enabled LP triggers higher level of loyalty than a Traditional LP.

$$H_{Loyalty0}: \quad \mu_{Group\ 1} = \mu_{Group\ 2} \tag{2}$$

$$H_{Loyalty1}: \quad \mu_{Group\ 1} \neq \mu_{Group\ 2} \tag{3}$$

There is a significant difference in scores of Overall Loyalty between Blockchain-enabled LP (M=3.57, SD=0.954, Mdn=3.677) and Traditional LP (M=2.70, SD=0.985, Mdn=3.000); U= 2774.500, p<0.001. The magnitude of the effect size is moderate (effect size = 0.4138).

Therefore, the null hypothesis $H_{Loyalty0}$ is rejected in favor of $H_{Loyalty1}$. Overall Loyalty for Blockchain-enabled LP (M=3.57, SD=0.953) is higher than Traditional LP (M=2.70, SD=0.985).

H_{11}: Higher number of available loyalty points redemption options triggers a higher level of perceived value and loyalty.

$$H_{110}: \quad \mu_{Group\ 1} = \mu_{Group\ 2} \tag{4}$$

$$H_{111}: \quad \mu_{Group\ 1} \neq \mu_{Group\ 2} \tag{5}$$

Results suggest that there is no significant difference in scores of points usage between Blockchain-enabled LP (M=3.43, SD=0.878, Mdn=3.500) and Traditional LP (M=3.45, SD=0.816, Mdn=3.500); U= 5233, p=0.912. The magnitude of the effect size is negligible (effect size = 0.0077).

The null hypothesis (H_{110}) is corroborated while alternative hypothesis (H_{111}) is rejected. $H_{loyalty}$ is also valid.

Therefore, a higher number of available loyalty points redemption options does not trigger a higher level of perceived value and loyalty.

H_{12}: Immediate loyalty points accrual triggers a higher level of perceived value and loyalty than a delayed one.

$$H_{120}: \quad \mu_{\text{Group 1}} = \mu_{\text{Group 2}} \tag{6}$$

$$H_{121}: \quad \mu_{\text{Group 1}} \neq \mu_{\text{Group 2}} \tag{7}$$

The obtained results suggest that there is a significant difference in scores of timings of points accrual between Blockchain-enabled LP (M=3.48, SD=0.933, Mdn=3.667) and Traditional LP (M=3.03, SD=0.905, Mdn=3.000); U= 3724.5, p<0.001. The magnitude of the effect size is slightly moderate (effect size = 0.2544).

The null hypothesis (H_{120}) is rejected in favor of alternative hypothesis H_{121}. $H_{loyalty}$ is also valid.

Therefore, Immediate loyalty points accrual triggers a higher level of customer perceived value and loyalty.

H_{13}: Personalized customer-tailored offers trigger a higher level of perceived value and loyalty than non-personalized generic offers.

$$H_{130}: \quad \mu_{\text{Group 1}} = \mu_{\text{Group 2}} \tag{8}$$

$$H_{131}: \quad \mu_{\text{Group 1}} \neq \mu_{\text{Group 2}} \tag{9}$$

The obtained results suggest that there is a significant difference in scores of offering relevance between Blockchain-enabled LP (M=3.27, SD=1.099, Mdn=3.500) and Traditional LP (M=3.00, SD=0.965, Mdn=3.000); U= 4447, p=0.050. The magnitude of the effect size is small (effect size = 0.1362).

The null hypothesis (H_{130}) is rejected in favor of alternative hypothesis H_{131}. $H_{loyalty}$ is also valid.

Therefore, personalized customer-tailored offers do trigger a higher level of perceived value and loyalty.

H_{14}: Loyalty points with no expiration date trigger a higher level of perceived value and loyalty than loyalty points with an expiration deadline.

$$H_{140}: \mu_{\text{Group 1}} = \mu_{\text{Group 2}} \tag{10}$$

$$H_{141}: \mu_{\text{Group 1}} \neq \mu_{\text{Group 2}} \tag{11}$$

There is a significant difference in scores of points expirations between Blockchain-enabled LP (M=3.77, SD=1.047, Mdn=4.000) and Traditional LP (M=3.23, SD=1.100, Mdn=3.000); U= 3708.5, $p<0.001$. The magnitude of the effect size is slightly moderate. (effect size = 0.2572).

The null hypothesis (H_{140}) is rejected in favor of the alternative hypothesis H_{141}. $H_{loyalty}$ is also valid.

Therefore, loyalty points with no expiration date trigger a higher level of customer perceived value and loyalty.

H_{15}: Loyalty points transferable to other peers trigger a higher level of perceived value and loyalty than non-transferable ones.

$$H_{150}: \mu_{\text{Group 1}} = \mu_{\text{Group 2}} \tag{12}$$

$$H_{151}: \mu_{\text{Group 1}} \neq \mu_{\text{Group 2}} \tag{13}$$

The obtained results suggest that there is a significant difference in scores of loyalty points transferability between Blockchain-enabled LP (M=3.64, SD=1.072, Mdn=3.750) and Traditional LP (M=3.24, SD=1.066, Mdn=3.250); U= 4068, $p=0.004$. The magnitude of the effect size is small (effect size = 0.1986).

The null hypothesis (H_{150}) is rejected in favor of alternative hypothesis H_{151}. $H_{loyalty}$ is also valid.

Therefore, loyalty points with no expiration date trigger a higher level of customer perceived value and loyalty.

4.4. Study 2 findings: Socio-economic factors and Program Loyalty

The second part of the research investigates the impact of socioeconomic factors on the customer attitudes towards the LP design with the blockchain-based features, hence program loyalty. A non-directional, two-tailed hypothesis is posed: H2: Socioeconomic factors will have an impact on the program loyalty towards the blockchain-based LP.

In order to test the hypothesis, a Two-way ANOVA test was performed to compare the mean scores of overall program loyalty for Blockchain-enabled LP group in three pairs of independent variables, namely, *Gender* Age*, *Gender* Employment*, *Gender* Income*. These variables were selected considering the relative importance of interpreting LPs' nature, the data obtained from the survey, and previous findings from the literature.

For the tests 95% of confidence interval was assumed. Levene's test of equality of error variances was performed to check whether the variances of each conditions are approximately equal or not. With Sig. value larger than 0.05, all variables were assumed with equal variance. Post-hoc comparisons, using the Tukey HSD test, were conducted to explore the differences in mean scores of groups within independent variables. F ratios were calculated by dividing the appropriate mean square between-groups by mean square within-groups.

4.4.1. Effects of Gender and Age

Survey respondents who answered questions related to a blockchain-enabled LP were organized into two groups according to their Age (Group 1: Below 35 years; Group 2: Above 35 years). Levene's test of equality of error variances suggested that the variance of the Program Loyalty is not equal across the groups (p>0.05), as depicted in Table 4.5. Table 4.4 which contains the descriptive statistics of Gender * Age and Customer Loyalty will help further to interpret the results of the hypothesis tests.

Gender	Age Group	Mean	Std. Deviation	N
Male	Age<35	3.091	0.990	11
	Age>=35	3.556	0.989	15
	Total	3.359	0.997	26
Female	Age<35	3.899	0.963	33
	Age>=35	3.471	0.887	51
	Total	3.639	0.936	84
Total	Age<35	3.697	1.021	44
	Age>=35	3.490	0.904	66
	Total	3.573	0.954	110

TABLE 4.4 : DESCRIPTIVE STATISTICS OF GENDER * AGE AND CUSTOMER LOYALTY

F	df1	df2	Sig.
0.387	3	106	0.763

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.
a. Design: Intercept + Gender + Age + Gender * Age

TABLE 4.5 : LEVENE'S TEST OF EQUALITY OF ERROR VARIANCES - PROGRAM LOYALTY

As depicted in Table 4.6, there was no significant main effect either by Gender (F(1,106)= 2.887, p=0.092) or Age (F(1,106)= 0.007, p=0.932) separately. However, interaction effect of Gender and Age (F(1,106)= 4.403, p=0.038) was tested statistically significant with a small effect size (partial eta squared = 0.04). More detailed report on every item is delivered further.

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	6.603	3	2.201	2.521	0.062	0.067
Intercept	946.805	1	946.805	1084.548	0.000	0.911
Gender	2.520	1	2.520	2.887	0.092	0.027
Age	0.006	1	0.006	0.007	0.932	0.000
Gender * Age	3.844	1	3.844	4.403	0.038	0.040
Error	92.538	106	0.873			
Total	1503.222	110				
Corrected Total	99.140	109				

a. R Squared = .067 (Adjusted R Squared = .040)

TABLE 4.6 : TESTS OF BETWEEN-SUBJECTS EFFECTS – GENDER, AGE

Main Effect of Gender

$$H_{Gender0}: \mu_{Male} = \mu_{Female} \tag{14}$$

$$H_{Gender1}: \text{not } H_{Gender0} \tag{15}$$

The analysis did not reveal a main effect of Gender, F(1, 106) = 2.887, MSe = 0.873, p = 0.092, α = 0.05 on program Loyalty - refer to Table 4.6 above. The magnitude of the difference in the means was small (partial eta squared = 0.027).

The null hypothesis ($H_{Gender0}$) is corroborated. Therefore, gender attribute demonstrated no impact on the program loyalty towards the blockchain-based LP.

Main effect of Age

$$H_{Age0}: \mu_{Below35} = \mu_{Over35} \tag{16}$$

$$H_{Age1}: \text{not } H_{Age0} \tag{17}$$

The analysis did not reveal a main effect of Age, F(1, 106) = 2.887, MSe = 0.873, p = 0.932, α = 0.05 on program Loyalty - refer to Table 4.6 above.- The magnitude of the differences in the means was very small (partial eta squared < 0.001).

The null hypothesis (H_{Age0}) is valid. Therefore, age attribute demonstrated no impact on the program loyalty towards the blockchain-based LP.

Interaction Effect of Gender and Age

$$H_{Gender*Age0} : \mu_{Male, Below35} - \mu_{Male, Over35} = \mu_{Female, Below35} - \mu_{Female, Over35} \tag{18}$$

$$H_{Gender*Age0} : \mu_{Male, Below35} - \mu_{Male, Over35} = \mu_{Female, Below35} - \mu_{Female, Over35} \quad (18)$$

$$H_{Gender*Age1} : \text{not } H_{Gender*Age0} \quad (19)$$

The analysis revealed an interaction of Gender and Age , $F(1, 106) = 2.887$, $MSe = 4.403$, $p = 0.038$, $\alpha = 0.05$ on program Loyalty - refer to Table 4.6 above. The magnitude of the difference in the mean was small (partial eta squared = 0.04).

The null hypothesis ($H_{Gender*Age0}$) is rejected in favour of the alternative hypothesis ($H_{Gender*Age1}$) Therefore, Gender and Age collectively has an interactional impact on the program loyalty towards the blockchain-based LP.

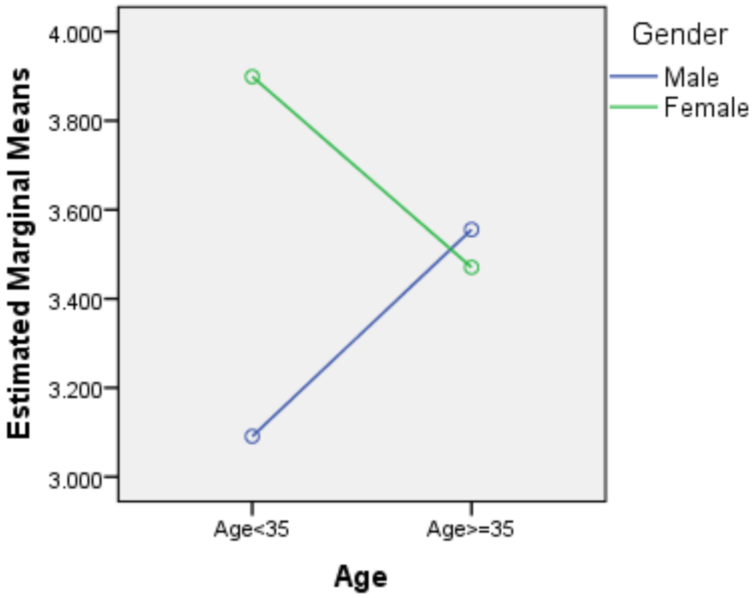

FIGURE 4.1 : ESTIMATED MARGINAL MEANS OF PROGRAM LOYALTY FOR GENDER AND AGE

Figure 4.1 and Table 4.4 depict the estimated marginal means of overall customer loyalty for gender and age attributes and visualize the variables' relationship. It is evident that elder people (above 35), both males and females, have a comparable level of overall customer loyalty ($M_{Male, Over35}$=3.556; $M_{Female, Over35}$=3.471). However, the dependency is opposite for the two genders with the decrease of the age: younger males have a lower level of overall customer loyalty ($M_{Male, Below35}$=3.091) while younger females, on the contrary, have higher ($M_{Female, Below35}$=3.899).

4.4.2. Effects of Gender and Employment Status

The subjects were divided into two groups according to their employment status (Group 1: Employed for wages; Group 2: Self-employed; Group 3: unemployed). Levene's Test of Equality of Error Variances (Table 4.9) suggested that the variance of the overall program loyalty is not equal across the groups (sig>0.05).

The results of a two-way ANOVA test for gender and employment status (Table 4.8) suggested that there was no significant main effect either by gender ($F(1,105)= 1.998$, $p=0.160$) or employment status ($F(2,105)= 0.133$, $p= 0.876$) observed independently. The interaction effect of gender and employment status ($F(1,105)= 0.818$, $p=0.368$) was also not statistically significant. Post-hoc comparison using the Tukey HSD test (Table 4.10) also confirmed that there were no interaction effects among the groups (sig>0.05). The magnitudes of the effect sizes were very small for the two variable and the interaction (partial eta squared = 0.019, 0.003, 0.008 respectively).

Table 4.7 which contains the descriptive statistics of gender * employment status and overall customer loyalty will help further to interpret the results of the hypothesis tests.

Gender	Employment	Mean	Std. Deviation	N
Male	Employed for wages	3.400	0.965	20
	Self Employed	3.222	1.186	6
	Total	3.359	0.997	26
Female	Employed for wages	3.532	0.889	52
	Self Employed	3.824	1.081	17
	Unemployed	3.800	0.933	15
	Total	3.639	0.936	84
Total	Employed for wages	3.495	0.906	72
	Self Employed	3.667	1.115	23
	Unemployed	3.800	0.933	15
	Total	3.573	0.954	110

Table 4.7 : Descriptive Statistics of Gender * Employment status and Program Loyalty

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	3.264	4	0.816	0.894	0.471	0.033
Intercept	724.149	1	724.149	793.059	0.000	0.883
Gender	1.825	1	1.825	1.998	0.160	0.019
Employment	0.243	2	0.121	0.133	0.876	0.003
Gender * Employment	0.747	1	0.747	0.818	0.368	0.008
Error	95.876	105	0.913			
Total	1,503.222	110				
Corrected Total	99.140	109				

TABLE 4.8 : TESTS OF BETWEEN-SUBJECTS EFFECTS- GENDER, EMPLOYMENT STATUS

F	df1	df2	Sig.
0.564	4	105	0.689

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.
a. Design: Intercept + Gender + Employment + Gender * Employment

TABLE 4.9 : LEVENE'S TEST OF EQUALITY OF ERROR VARIANCES - PROGRAM LOYALTY

(I) Emp	(J) Emp	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Employed for wages	Self Employed	-0.171	0.229	0.735	-0.715	0.373
	Unemployed	-0.305	0.271	0.502	-0.949	0.340
Self Employed	Employed for wages	0.171	0.229	0.735	-0.373	0.715
	Unemployed	-0.133	0.317	0.907	-0.887	0.621
Unemployed	Employed for wages	0.305	0.271	0.502	-0.340	0.949
	Self Employed	0.133	0.317	0.907	-0.621	0.887

TABLE 4.10 : POST HOC MULTIPLE MEAN COMPARISONS OF PROGRAM LOYALTY FOR EMPLOYMENT CATEGORIES – TUKEY HSD TEST

Main Effect of Employment Status

$$H_{Employment0}: \mu_{Employed\ for\ wages} = \mu_{Self\ Employed} = \mu_{Unemployed} \quad (20)$$

$$H_{Employment1}: \text{not } H_{Employment0} \quad (21)$$

Th analysis did not reveal a main effect of employment status on program loyalty, $F(2,105) = 0.133$, $MSe = 0.913$, $p = 0.876$, $\alpha = 0.05$ - refer to Table 4.8 above. The magnitude of the differences in the means was very small (partial eta squared = 0.003). Post hoc Multiple Mean Comparisons of program loyalty for employment status categories also confirm the same outcome.

The null hypothesis ($H_{Employment0}$), therefore, is valid.

Therefore, employment status has no impact on the overall program loyalty towards the blockchain-based LP.

Interaction Effect of Gender and Employment

$$H_{Gender*\ Employment\ 0}: \mu_{Male,\ Employed\ for\ wages} - \mu_{Male,\ Self\ Employed} - \mu_{Male,\ Unemployed} = \mu_{Female,\ Employed\ for\ wages} - \mu_{Female,\ Self\ Employed} - \mu_{Female,\ Unemployed} \quad (22)$$

$$H_{Gender*\ Employment\ 1}: \text{not } H_{Gender*\ Employment\ 0} \quad (23)$$

Analysis revealed no interaction effect of gender and employment status, $F(1, 105) = 0.818$, $MSe = 0.913$, $p = 0.368$, $\alpha = 0.05$ on overall program loyalty - refer to Table 4.8 above. The magnitude of the differences in the means was minimal (partial eta squared = 0.008). Post hoc Multiple Mean Comparisons of Program Loyalty for Employment categories confirm the same result.

The null hypothesis ($H_{Gender*\ Employment\ 0}$) is confirmed.

Therefore, gender and employment status collectively have no interactional impact on the program loyalty towards the blockchain-based LP.

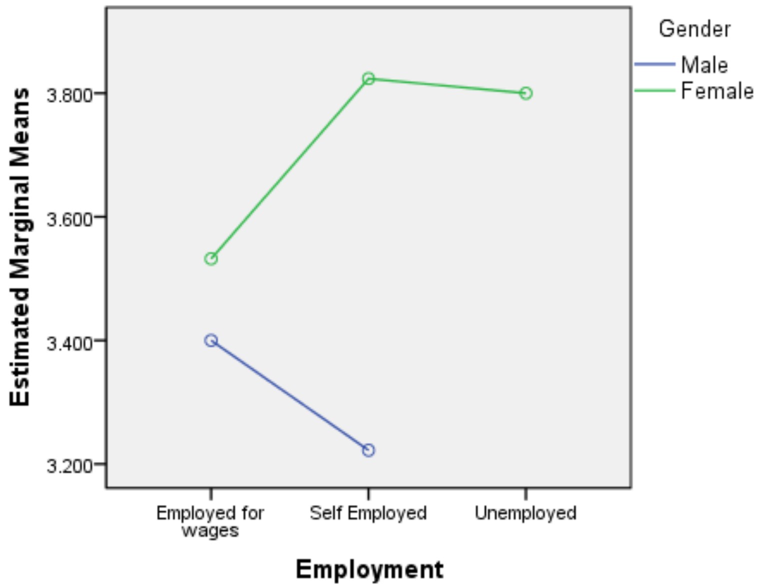

FIGURE 4.2 : ESTIMATED MARGINAL MEANS OF CUSTOMER LOYALTY FOR GENDER AND EMPLOYMENT STATUS

Figure 4.2 and Table 4.7 plot the estimated marginal means of overall customer loyalty for gender and employment status attributes and visualize the variables' relationship. Gap in overall program loyalty scores for males and females who are employed for wages is much smaller ($M_{Male,Employed\ for\ wages}$=3.400 against $M_{Female,Employed\ for\ wages}$=3.532 respectively) than between the self-employed respondents: self-employed females tend to demonstrate much higher program loyalty rate ($M_{Female,\ Self\text{-}Employed}$=3.820) than self-employed men ($M_{Male,Self\text{-}Employed}$ =3.222). Unemployed, females in turn, have similar level of loyalty as self-employed females ($M_{Female,\ Unemployed}$=3.800) In the study sample unemployed males were not represented.

4.4.3. Effects of Gender and Income Level

The survey respondents were divided into three groups according to their income level (Group 1: Below € 30,000; Group 2: € 31,000 – € 60,000; Group 3: € 61,000 or more). Levene's Test of Equality of Error Variances (Table 4.12) revealed that the variance of the Program Loyalty is not equal across the groups (p>0.05).

The outcomes Two-way ANOVA Test (Table 4.13) revealed that there was no significant main effect either by gender ($F(1,102) = 1.382$, $p=0.243$) or income level ($F(2,102) = 1.223$, $p=0.299$) separately. However, the interaction effect of Gender and Income level ($F(2,102) = 2.938$, $p=0.050$) was tested statistically significant with a moderate effect size (partial eta Squared = 0.64). Post hoc Multiple Mean Comparisons of Program Loyalty for Income categories (Table 4.14) indicated that the mean score for Below € 30,000 group (M = 3.879 , SD= 0.820) was significantly different from € 31,000 – € 60,000 group (M = 3.365 , SD= 1.020).

Gender	Income	Mean	Std. Deviation	N
Male	Below € 30,000	3.111	0.839	3
	€ 31,000 – € 60,000	3.026	0.947	13
	€ 61,000 or more	3.867	0.971	10
	Total	3.359	0.997	26
Female	Below € 30,000	3.956	0.791	30
	€ 31,000 – € 60,000	3.517	1.030	29
	€ 61,000 or more	3.391	0.941	23
	Total	3.642	0.944	82
Total	Below € 30,000	3.879	0.820	33
	€ 31,000 – € 60,000	3.365	1.020	42
	€ 61,000 or more	3.535	0.961	33
	Total	3.574	0.960	108

TABLE 4.11 : DESCRIPTIVE STATISTICS OF GENDER * INCOME LEVEL AND PROGRAM LOYALTY

F	df1	df2	Sig.
0.536	5	102	0.749

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.
a. Design: Intercept + Gender + Income + Gender * Income

TABLE 4.12 : LEVENE'S TEST OF EQUALITY OF ERROR VARIANCES - PROGRAM LOYALTY

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	10.637	5	2.127	2.466	0.038	0.108
Intercept	700.592	1	700.592	812.118	0.000	0.888
Gender	1.192	1	1.192	1.382	0.243	0.013
Income	2.110	2	1.055	1.223	0.299	0.023
Gender * Income	5.069	2	2.534	2.938	0.050	0.064
Error	87.993	102	0.863			
Total	1478.222	108				
Corrected Total	98.630	107				

a. R Squared = .108 (Adjusted R Squared = .064)

TABLE 4.13 : TESTS OF BETWEEN-SUBJECTS EFFECTS- GENDER, INCOME

(I) Emp	(J) Emp	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Below € 30,000	€ 31,000 – € 60,000	0.514	0.216	0.047	0.000	1.028
	€ 61,000 or more	0.343	0.229	0.294	-0.200	0.887
€ 31,000 – € 60,000	Below € 30,000	-0.514	0.216	0.047	-1.028	0.000
	€ 61,000 or more	-0.170	0.216	0.711	-0.684	0.344
€ 61,000 or more	Below € 30,000	-0.343	0.229	0.294	-0.887	0.200
	€ 31,000 – € 60,000	0.170	0.216	0.711	-0.344	0.684

TABLE 4.14 : POST HOC MULTIPLE MEAN COMPARISONS OF PROGRAM LOYALTY FOR INCOME CATEGORIES – TUKEY HSD TEST

Main Effect of Income Level

$$H_{\text{Income } 0}: \mu_{\text{Below € 30,000}} = \mu_{\text{€ 31,000 – € 60,000}} = \mu_{\text{€ 61,000 or more}} \quad (24)$$

$$H_{\text{Income } 1}: \text{not } H_{\text{Incomet } 0} \quad (25)$$

The analysis did not reveal a main effect of Income, F(2, 102) = 1.223, MSe = 0.863, p = 0.299, α = 0.05 on program Loyalty - refer to Table 4.13 above. The magnitude of the differences in the means was small (partial eta squared = 0.023). Post hoc Multiple Mean Comparisons of Program Loyalty for Income categories also confirm the same.

The null hypothesis ($H_{\text{Income } 0}$) is corroborated, while the alternative hypothesis ($H_{\text{Income } 1}$), in turn, is rejected.

Therefore, Income has no impact on the program loyalty towards the blockchain-based LP.

Interaction Effect of Gender and Income

$$H_{Gender^{*}\ Income\ 0}:\ \mu_{Male,\ Below\ €\ 30,000} - \mu_{Male,\ €\ 31,000-€\ 60,000} - \mu_{Male,\ €\ 61,000\ or\ more} = \mu_{Female,\ Below\ €\ 30,000} - \mu_{Female,\ €\ 31,000-€\ 60,000} - \mu_{Female,\ €\ 61,000\ or\ more} \quad (26)$$

$$H_{Gender^{*}\ Income\ 1}:\ \text{not}\ H_{Gender^{*}\ Income\ 0} \quad (27)$$

The analysis revealed an interaction of gender and income level, $F(2, 102) = 2.938$, $MSe = 0.863$, $p = 0.050$, $\alpha = 0.05$ on program Loyalty - refer to Table 4.13 above. The magnitude of the differences in the means was moderate (partial eta squared = 0.064). Post hoc Multiple Mean Comparisons of Program Loyalty for Age categories also confirms the same.

Th null hypothesis ($H_{Gender^{*}\ Incomet\ 0}$) is rejected in favour of the alternative hypothesis ($H_{Gender^{*}\ Incomet\ 1}$).

Therefore, gender and income collectively has an interactional impact on the program loyalty towards the blockchain-based LP.

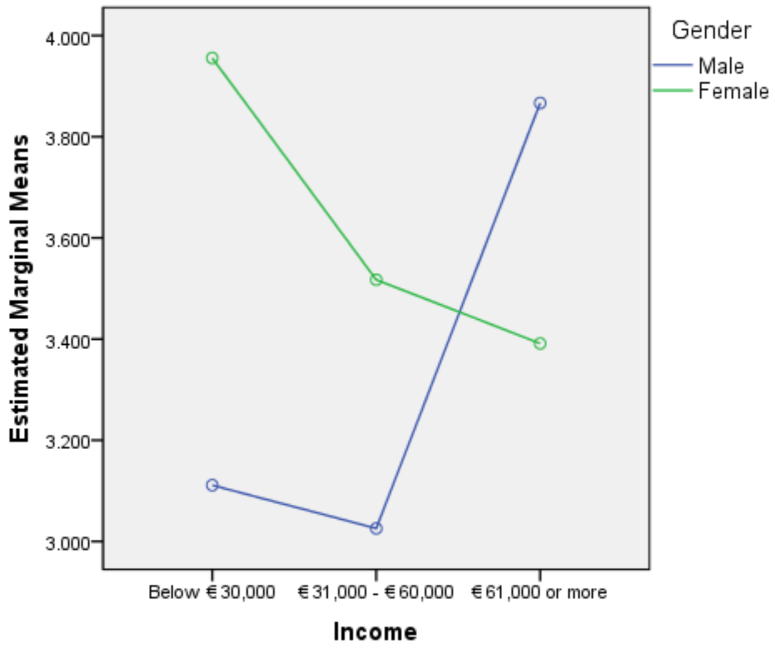

FIGURE 4.3: ESTIMATED MARGINAL MEANS OF PROGRAM LOYALTY FOR GENDER AND INCOME LEVEL

Figure 4.3 and Table 4.11 represent the estimated marginal means of overall customer loyalty toward the blockchian-enabled LP for gender and income attributes and visualizes the variables' relationship. The scores for program loyalty for male and female genders are changing with the increment of the income. Males with a smaller income show a lower level of program loyalty ($M_{Male,\ Below\ €\ 30,000}=3.111$ $M_{Male,\ €\ 31,000-€\ 60,000}=3.026$), while females show a higher level of program loyalty in the same income categories ($M_{Female,\ Below\ €\ 30,000}=3.956$ $M_{Female\ €\ 31,000-€\ 60,000}=3.517$). This situation turns around in the upper-income category. Males scored the higher level of program loyalty ($M_{Male,\ €\ 61,000\ or\ more}$=3.867) while females' declined ($M_{Female,\ €\ 61,000\ or\ more}$=3.391). By looking at the plot, we can articulate that further investigation is needed to explore this dynamic relationship with Gender and Income towards overall program loyalty.

4.5. Study 3 findings: Twitter Data Analysis

To answer a third research question, "How do Twitter users perceive a blockchain-based LP compared to a traditional LP?" A Term-Document matrix was drawn up as well as semantic analysis of Twitter data was performed.

Appendix 3 contains the complete code of Term-Document Matrix creation, most frequent terms plot creation, and sentiment analysis for both types of analyzed LPs.

4.5.1. Term-Document Matrix and Top Frequent Terms

The term-document matrix represents a table containing the terms and frequency of their usage in corpus. For building up a matrix the function *TermDocumentMatrix* was used. Table 4.15 depicts firsts 20 most frequent terms for Miles&More (traditional LP) and KrisPay/Kris+ (blockchain-based LP) respectively. The available amount of data for Miles&More is more than 4 times larger than for KrisPay/Kris+ due to the longer observed period of time. Hence, frequency of terms is proportional.

Data extraction peculiarities and the fact that for the Miles&More program, the tweets mentioning the official LP account were extracted, while for KrisPay, only hashtags were used appeared to impact the results. The high frequency of appearance of such words as "please," "help", "thanks" testifies that users utilize Twitter as yet another channel to reach out to the program to get support on specific topics related to it. KrisPay, on the contrary, does not have an official account represented in Twitter, meaning that rather than addressing their requests, users tend to share news and opinions on the program. Remarkable for this study that the word "blockchain" is ranked 7 in the most frequently used terms rating, which indicates that users are interested in innovations related to LPs and actively discuss them online. Further analysis will concern the sentiment analysis of tweets that were extracted for both LPs.

Miles&More		KrisPay	
Terms	**Freq**	**Terms**	**Freq**
miles	991	krisflyer	921
can	439	miles	325
flight	250	singapore	298
card	241	singaporeairlines	254
lufthansa	240	airlines	223
fur	232	krispay	138
meilen	203	blockchain	105
service	201	travel	94
get	200	points	69
account	197	wallet	65
please	196	class	63
now	175	status	58
help	171	werbung	58
thanks	156	business	57
app	155	members	55
just	153	unserem	54
status	152	digital	50
credit	144	get	49
website	137	sia	49
flights	135	new	46

TABLE 4.15: TERM-DOCUMENT MATRIX

4.5.2. Twitter Data Sentiment Analysis

Implementing NRC Emotion lexicon, the *get_nrc_sentiment* function analysed sentiments of words occurring in every tweet and categorized them according to eight distinctive emotions (anger, fear, anticipation, trust, surprise, sadness, joy, and disgust) and two sentiments: negative and positive (Mohammad & Turney, 2013). Emotional connotation of words in every tweet can be viewed as table, having sentiments as columns and tweets as rows:

	anger	anticipation	disgust	fear	joy	sadness	surprise	trust	negative	positive
1	0	0	0	0	1	0	0	0	0	1
2	0	0	0	0	0	0	0	0	0	0
3	1	0	1	0	0	0	0	0	2	0
4	0	0	0	0	0	0	0	1	0	1
5	0	0	0	1	0	1	0	0	1	0
6	0	0	0	0	0	0	0	1	0	1

The data in the columns can be accessed, and tweets identified with every emotion can be retrieved. For instance, words retrieved from the following tweets were considered as having an angry sentiment (examples are randomly selected for every LP):

Miles&More:

[174] "Horrible customer experience. Account suspended for no reason, 60 minutes on phone—no help. Time 2 move to a diff airline!"
[222] " I love the service of lufthansa . its changed for the better now. I hate the miles and more program. it is too rigid.sanjiv"
[256] " I only had bad experiences with them, avoid them"
[342] " why to cheat people when you cannot even keep your promise of refunds"

KrisPay:

[17] "In the Gold #KrisFlyer lounge. Bedlam as usual - crowded, no seats. Angry customers, dunno why this lounge is 1/4 the size of the #silverKris lounge?!"
[49] "Still waiting for a reply from on this one:\n #KrisFlyer #Redemption #tickets #complaint "
[52] "Another shity #flight, thank you #singaporeair. Why a #gold member should sit at the last row near the toilet? What have I done wrong? Flying too often? #krisflyer #gold are not getting any priory. "
[53] "I've been trying to buy tickets from #Krisflyer using mix of miles+cash, for 3 hours now. Being shown \"just a moment...\" Called helpdesk, told to change computer, browser. Did both can't access either on Chrome or Edge. And they say \"nothing is wrong on our end Sir\""

Same actions can be performed for every emotion. Aggregate results for Miles&More and KrisPay programs are plotted in Figures 4.4 and Figure 4.5 respectively.

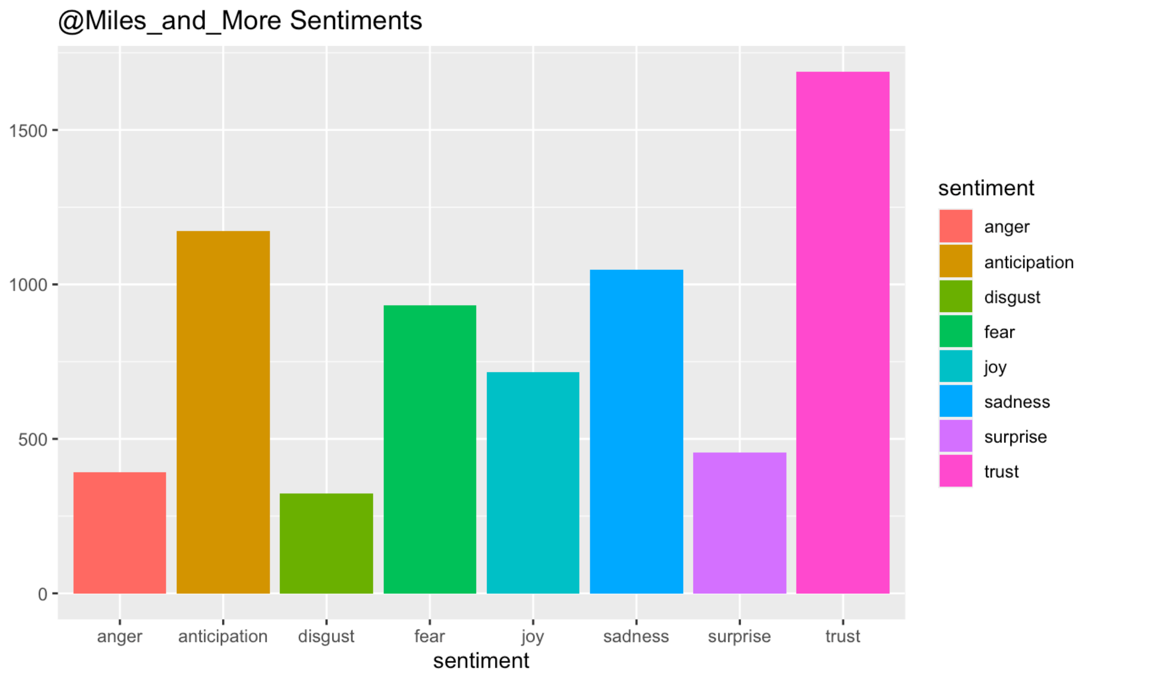

FIGURE 4.4: TWEETS SENTIMENTS FOR MILES&MORE PROGRAM EMPLOYING NRC EMOTION LEXICON

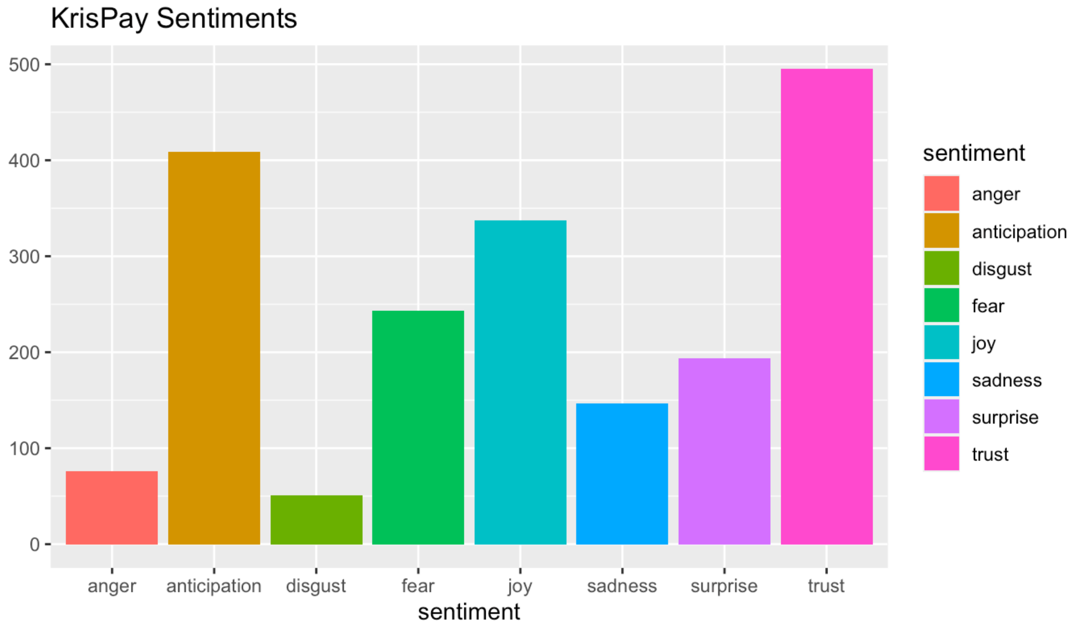

FIGURE 4.5: TWEETS SENTIMENTS FOR KRISPAY PROGRAM EMPLOYING NRC EMOTION LEXICON

Visual inspection reveals that positive emotions such as trust and anticipation are prevalent sentiments for both types of LPs. “Joy” was ranked third for KrisPay, while “sadness” landed at third place for Miles&More. To be able to more precisely assess the results, the relative values are needed in line with absolute. To see the exact relative breakdown of tweets having words with a particular emotional dimension for every program, the following bar graphs were plotted: Figure 4.6 and Figure 4.7, respectively, for Miles&More and KrisPay programs.

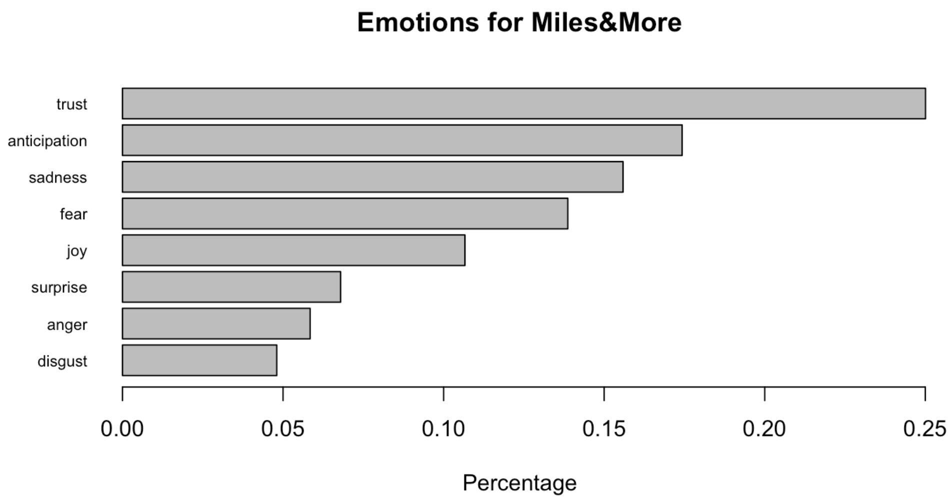

FIGURE 4.6: TWEETS SENTIMENTS FOR MILES&MORE PROGRAM IN %

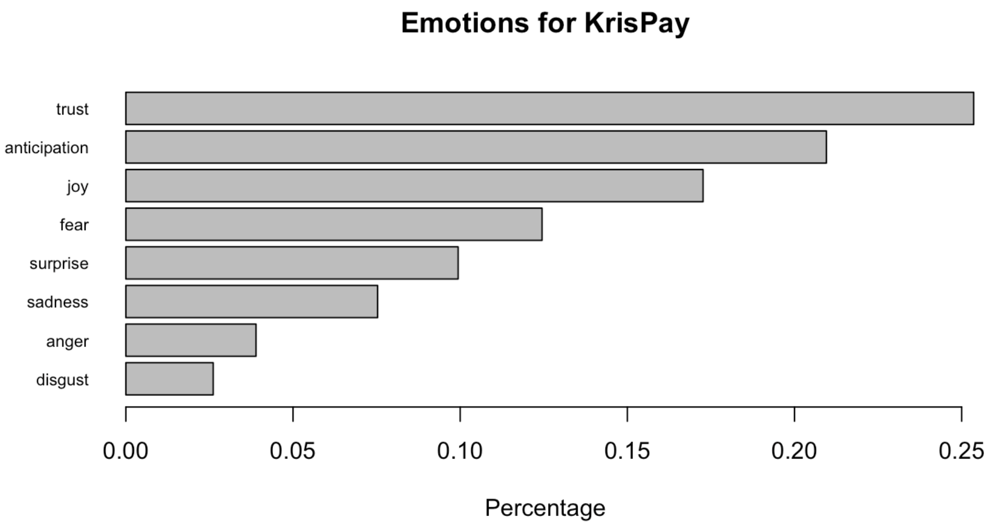

FIGURE 4.7: TWEETS SENTIMENTS FOR KRISPAY PROGRAM IN %

The obtained findings show that the KrisPay program demonstrated a lower level of negatively connotated emotions, such as anger, disgust, fear, and sadness (3.9%, 2.5%, 12.3%, 7.6%) compared to Miles&More (5.9%, 4.9%, 13.9%, 15.7%). Likewise, such positive emotions as trust, joy, anticipation and surprise demonstrated to be more prevalent in KrisPay's sample (25.5%, 17.3%, 20.9%, 9.9%) in comparison with Miles &More (25%, 10.6%, 17.4%, 6.7%).

Further, using a different function get_sentiment() from the "syuzhet" package, a sentiment score was calculated for every particular tweet within two sets. Afterward, using an assigned score, the emotions were segregated to define if tweets generally have positive, negative, or neutral valence. The results are represented in Table 4.16 in absolute values as well as relative. According to the results, KrisPay has more than 6% less negative tweets, 5% fewer neutral tweets, and more than 11% more positive tweets compared to Miles&More. The outcomes of both sentiment analysis sub-studies conclude that Twitter users were more favorable to KrisPay (blockchain-enabled LP) than to Miles&More (traditional tier-based LP). Nonetheless, a generalization that users are more positive towards a blockchain-enabled loyalty solution has to be made very cautiously as the sentiment analysis of Twitter data has a number of severe limitations, which will be discussed in the next chapter.

Sentiment	Miles&More, abs.	Miles&More, %	KrisPay, abs.	KrisPay, %
Negative	1077	26,14	187	19,91
Neutral	1415	34,34	276	29,39
Positive	1628	39,51	476	50,69
Total	4120	100,00	939	100,00

TABLE 4.16 : TRIVALENT SENTIMENTS BREAKDOWN OF TWEETS PER LP TYPE

5. DISCUSSION AND CONCLUSION

The final chapter contains a conclusion and discussion of the findings of this study in comparison with the existing literature on the topics, implications for key stakeholders, limitations, and propositions for further research.

5.1. Discussion

The main focus of the Study 1 was to examine the effects of blockchain-enabled design of LP and its’ particular five features on the customer values perception and loyalty toward such LP. The initial expectation was that blockchain-enabled features will trigger higher level of perceived value split across three groups: economic utility, psychological self-fulfilment and social interaction (Kreis and Mafael, 2014; Wang et al., 2018, 2019a, 2019b).

The conducted correlation analysis between LP design attributes and overall program loyalty illustrated significant findings regarding the relative importance of blockchain-powered LP design attributes separately. 'Points usage' feature of a blockchain-enabled LP (loyalty points can be used to make day-to-day purchases at any of the partnering merchants) and 'Offering relevance' (user receives personalized offers, based on the previous shopping preference) were perceived to have strong positive relationships with overall program loyalty throughout all market segments. While 'Timing of points accrual’ (earned points are credited to user account immediately in real-time), 'Points expiration’ (loyalty points have no expiration date), and 'Points transferability' (loyalty points can be transferred to other users) were deemed important in certain market segments. Findings are summarised in Table 5.1. Additionally, relationships calculated for the same attributes on Traditional LPs demonstrated negative values towards overall program loyalty.

Hypothesis		Effect on Perceived value and Program Loyalty
Perceived value	**Program Loyalty**	
	$H_{Loyalty}$	Moderately significan difference
H_{11} (Points usage)		Not significant difference
H_{12} (Timing of points accrual)		Moderately significant difference
H_{13} (Offering relevance)		Small significant difference
H_{14} (Points expiration)		Moderately significant difference
H_{15} (Points transferability)		Small significant difference

TABLE 5.1 : SUMMARY OF HYPOTHESES TESTING FOR STUDY 1

Among the considered LP design features explored in this research, four features, namely, 'Timing of points accrual,' 'Offering relevance,' 'Points expiration, and 'Points transferability,' did trigger a significantly higher level of perceived value and resulting program loyalty towards a blockchain-enabled LP design compared to a traditional LP, while the only 'Points usage' attribute did not. However, the possibility for a customer to redeem the points within the extensive partner network is one of the main advantages offered by the blockchain LPs (Deloitte, 2016), and it would be logical to assume this factor to have an impact on value perception and loyalty. The explanation for the results may lie in the design of the survey and a way it was conducted (refer to Q4-Q5 in Appendix 4). First of all, the survey question for a traditional LP was designed in the way that in line with such redemption options as “buy merchandise at the Airline’s online shop (various categories of goods)” and “buy flights/upgrades at Airline”, which were shared across both LP types, “get discounts for selected services (from travel category: hotels, car rentals)” option was offered. It is possible that this option sounded good enough for the majority of the respondents because the way it was described was specific enough. Moreover, this is what most of the LP users are used to in LPs. Secondly, survey respondents were segregated into two independent groups, and each of them answered only to questions related to one LP type; hence they could not see the options offered by the other LP. Consequently, they had nothing to compare an offered option with to define what option would be preferable for them. If the question was designed in a different manner (shorter, more focused, and specific about the conditions of points usage), the obtained results could have been different.

Currently available academic assessment of the impact of blockchain application on LPs, customer value perception, and resulting loyalty is deficient due to the novelty of the phenomena. Therefore findings of this research cannot be directly compared to the outcomes of the existing studies. Wang et al. (2018, 2019a, 2019b) pioneered in the field. Their exploratory studies dug into how the key natures of a blockchain-enabled design (such as real-time exchange, multi-partner network, peer-to-peer exchange, and security of the exchange) respond to various customer needs (guided by SDT-based motivations of economy, autonomy, competence, and relatedness) and how eventually they impact customer perceived value. Their research did not have a purpose of comparing it with a traditional LP design, unlike this study. The studies of Wang et al. (2018, 2019a, 2019b) established the following interconnections: (1) real-time exchange technique contributes to perceived economic utility and psychological self-fulfillment. This nature of a blockchain-based design can be comparable (partially thought) to the outcomes of current research. Testing hypothesis H_{12} concluded that such feature as instant points accrual triggered a higher level of perceived value and loyalty in blockchain-enabled LP users than users of a traditional LP. (2) Multi brands exchange nature of blockchain contributes to the perceived economic utility and psychological self-fulfillment. The current study's findings suggested that "Loyalty points can be used to make day-to-day purchases at any of the partnering merchants to pay the purchase price in full or partially" feature did not trigger a higher level of perceived value and loyalty compared to a traditional LP (H_{11}). The possible reasons that lead to such results are mentioned previously. (3) Peer-to-peer exchange nature of blockchain-based LP contributes to psychological self-fulfillment and social interaction. This point can be compared (again partially) with the fifth feature explored within this study ("Loyalty points can be transferred to another user", H_{15}), which triggered a small but significant difference in perceived value and loyalty in blockchain-enabled design compared to a traditional LP design. (4) "Secure, traceable and fraud-proof: preventing double-spending or any fraud, abuse of the transactions" (Wang et al., 2019a, p.4571; Wang et al., 2019b, p.407) - this nature of blockchain-based LP design contributes to the perceived economic utility and social interaction. The current study did not include a feature that would be compared to this nature; therefore outcomes cannot be compared in any dimension.

The outcomes of Study 2 reveal that the selected socioeconomic factors, gender, age, employment, and income, individually do not significantly impact the overall customer loyalty towards a program with Blockchain-enabled LP design features. However, interaction effects in gender* age and gender* income indicate that potential market segments with multiple tiers for demographic variations are present which draws the path for further research. Findings for Study 2 are summarized in Table 4.18. There are factual and impartial findings in this research's threefold analysis, which was conducted using the data collected via a structured online survey. However, it is prudent to discuss the dynamics of the data set before reaching out for unrealistic conclusions. Since the research topic itself demands the representation of dynamic market segments to be explored, it is unavoidable to eliminate all the biases of market research similar to this. It is observed that demographic biases are present throughout the data set, particularly in gender, age, employment, region of residence, which led to unrealistic and/or partial findings in the analysis. Therefore, it is highlighted that the results presented in this chapter can be viewed as subjective and should be treated carefully.

Variable / Interactions of variables	**Effect on Program Loyalty**
Gender	Not significant difference
Age	Not significant difference
Employment	Not significant difference
Income	Not significant difference
Gender* Age	Significant difference
Gender* Employment	Not significant difference
Gender* Income	Significant difference

TABLE 5.2 : SUMMARY OF HYPOTHESIS TESTING FOR STUDY 2

Results of sentiment analysis of Twitter data for Study 3 indicated that users were more favorable to KrisPay program than to Miles&More. First of all, the number of tweets related to KrisPay which had positive sentiment was higher. Secondly, KrisPay entailed a more significant number of words with positive emotional coloring and less negatively connotated words (segregation according to NRC Emotion lexicon). Nonetheless, the conclusion that Twitter users are more favorable to a blockchain-based LP than a traditional LP would be premature. The reason for that is that data obtained from Twitter and the analysis method have a number of serious limitations. At first, using hashtags (#) or account mentions (@) to collect data from Twitter does not guarantee that all of the collected tweets will contain user opinions toward LPs: there will be a lot of news and retweets of this news, which cannot be viewed as user impressions of a certain LP. Besides, the semantic analysis method used for this study cannot define sarcasm, meaning that messages having positively connotated words but in a general negative sense would still be recognized as positive tweets. For example, tweet "I had to wait for miles to be credited to my account for almost two months! What a fantastic service!" which is meant sarcastically would be categorized as a positive, which is obviously wrong and would lead to inaccuracies in the statistics. Eventually, not all positive tweets toward KrisPay are positive due to the fact that this LP is blockchain-based. And another way around, not all negative tweets toward Miles&More are negative due to the fact that this LP is not blockchain-backed.

5.2. Contribution to knowledge

This study contributes to a scarce knowledge about blockchain application for LPs and how blockchain-enabled features of an LP design impact customer perceived value and attitudinal aspect of customer loyalty. The ability to measure the perceived value of blockchain-enabled LPs provides researchers and managers with a better capacity to study the implications of BCT application to loyalty management.

5.3. Limitations

This study utilized only one prototype design of a blockchain-enabled LP, including five distinctive features that were backed by the real-world existing airline LPs. LP design and the way it is employed and communicated to an end-user may vary dramatically. Simultaneously, LP design is an important factor that influences the value creation (Kumar & Shah, 2004). Therefore further enhancing the prototype design needs to be continued by future researches. More features of a blockchain-backed LP can be explored and compliment the prototype design.

Future studies also need to explore the impact of blockchain-enabled LP design on a more diverse customer segment across various industries and regions to measure the effect of blockchain application for loyalty management more comprehensively. The sample used for this study was limited, and the representativeness of the sample can be enhanced to get a better overview of different market segments.

Furthermore, it is worth mentioning that features 4 and 5 of the traditional LP design examined in this study (expiration of points and points non-transferability) can be exposed to customers even within blockchain-enabled LPs. It is also worth mentioning that non-expiring and transferable points that give an advantage to LP in a customer's eyes are organic to a blockchain-powered LP design but always stay at the LP owner's discretion and may be revoked depending on the company's goals and marketing strategy (Deloitte, 2016).

5.4. Implications for relevant stakeholders

If an existing LP gets backed by blockchain technology at some point, visually customer might not even notice the change. Although the extended functionality and the additional value that upgraded LP will bring to a user will not be left unnoticed.

Although this study digs into the customer perceptions of a blockchain-based LP, the real target audience is LP owners / Brands. This paper serves as quantitative proof of the positive impact of blockchain application to LPs on customer perceived value. A large body of prior research indicated that LP might be effective only if it contributes to a customer value perception, which in turn results in customer loyalty (Yi & Jeon, 2003). And customer loyalty, in turn resulting in profitability, is an ultimate goal of every business that strives for market advantage. Therefore, this thesis helps decision-makers evaluate the impact of blockchain technology applications when switching their customer LPs to blockchain-backed LPs or launching new ones.

5.5. Future research

To deliver value to the users, blockchain-based LP should match its' design elements to the users' individual motives. Driving motives underlay the LP participative behaviors (Kreis & Mafael, 2014). Therefore future research can include one more variable, "customer motives" into the equation to see how the underpinning customer movies influence the value perception of certain blockchain-enabled LP design elements and how this impacts the perceived customer value.

LP implementation by itself does not directly lead to behavioural loyalty (Henderson et al., 2011) as well as customer value perception of an LP does not automatically convert into brand loyalty (Dowling & Unlies, 1997). Customers tend to derive value from the LP itself rather than from a core product of the LP owner, which means that customers may be loyal to an LP and maybe not loyal to a brand (Yi & Jeon, 2003). This is a critical question for an LP owner since brand loyalty is a foundation stone the final goal of implementing an LP at all. Research in this thesis only aimed to investigate the impact of blockchain-enabled design on loyalty toward LP, while the impact of LP loyalty on brand loyalty has to be examined further. Therefore proposition for future research includes an investigation of how blockchain-enabled features of an LP impact brand loyalty. For this, researchers may want to study the more specific LP designs and not only abstractly defined ones, and even better, real-world examples.

One part of this research was dedicated to examining how blockchain-enabled features of LP influence customer value perception. According to this research methodology, a value perception measurement definition was split across three groups: economic utility, psychological self-fulfillment, and social interaction (Kreis and Mafael, 2014; Wang et al., 2018, 2019a, 2019b). The impact of 5 defined features of blockchain-powered LP design on overall value perception and loyalty was established. However, the exact interconnections between features and each of three groups of value perception dimensions remained out of scope. This leaves room for further researchers to investigate the phenomena.

Major study of this research (Study 1) focused on specific features of a blockchain-based design, but only five features were considered. There can be near interminable ways to design an LP and combine all the elements together. More blockchain-powered features can be identified and studied in prospective researches. For instance, the fact that in a typical blockchain LP scenario, there is no minimum limit of points that customers should collect for getting a reward. Example: "collect 5000 miles and get a free flight". In a blockchain-based design, users can redeem any amount of points right after the points were credited to their account. By do doing so, they can pay for their purchase either partially or in full. There is no obligation to collect a certain amount of points to get any reward.

5.6. Conclusion

As an existing body of theoretical knowledge states and some of the practical researches confirm (including this study), blockchain technology holds the potential to effectively oust the outmoded systems that underpin most of nowadays points/miles-based traditional LPs. Furthermore, this study affirms that features of an LP design powered by blockchain technology trigger a higher level of customer perceived value and result in stronger customer loyalty toward an LP with such features in comparison with a traditional LP. It puts one more fact in the base of knowledge regarding the blockchain application in incentive management that industry decision-makers may want to consider when planning their companies' strategies. On the one hand, the nascent state of blockchain adoption for LPs provides merchants with a tremendous opportunity to grasp the value of the innovation and shape the future of customer loyalty management. And on the other hand, it brings pioneers challenges accompanied by a certain level of uncertainty and risk that they might need to examine closely.

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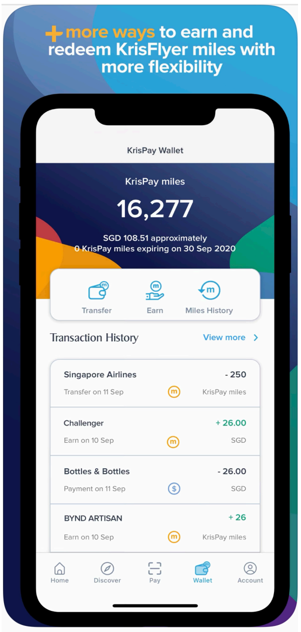
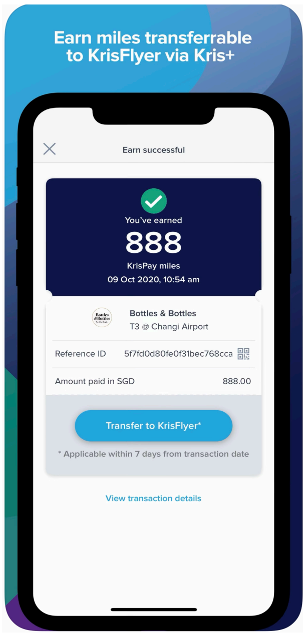
APPENDICES

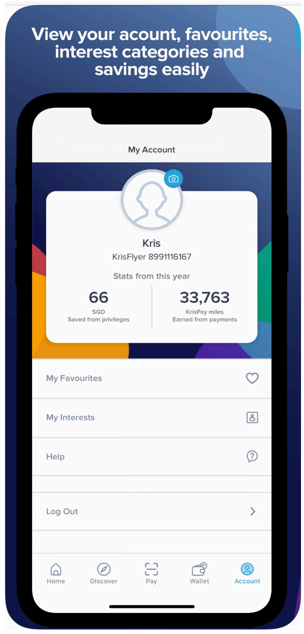
Appendix 1: Customer experience with Kris+ mobile app

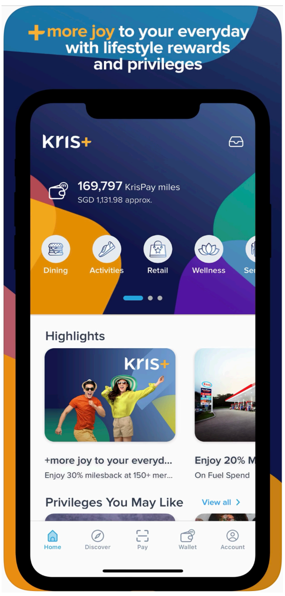
Source: Kris+ by Singapore Airlines Mobile App, 2021

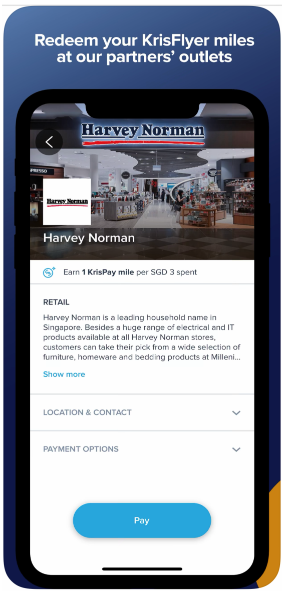
1. Home page: rewards, privileges and partners nearby or explored by categories
2. Reward page: offer of one of the merchants that can be redeemed in store by scanning a QR code at the cashier
3. Map: Privileges can be explored on map to locate closest relevant offerings
4. KrisPay wallet: various flexible ways to earn and redeem KrisPay miles
5. KrisPay miles transfer from KrisFlyer. Within first 7 days miles can be credited back.
6. Account overview: provides overview of available points, user favourites and interests

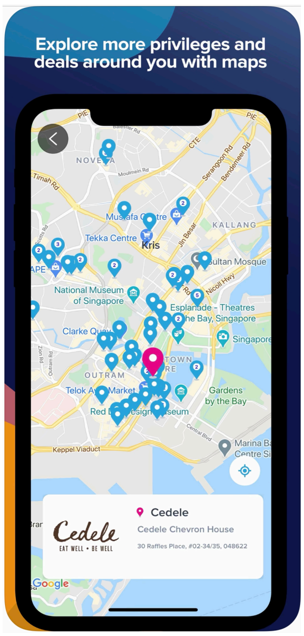












Appendix 2: Survey Full Text

Introduction page:

Hello,

My name is Elena Petrozhitskaya; I am an MBA student at Modul University Vienna.

As a part of my thesis research, I am conducting a survey that explores customer perceptions of blockchain-enabled loyalty programs. I investigate how blockchain-powered features of a loyalty program influence customers' value perception. By completing this survey, you will be of great help to me.

The completion of this survey will take you approximately 5-10 minutes.

In the following survey, you will be introduced to an Airline Loyalty Program. Participation in such a Loyalty Program is free of charge. You will need to imagine yourself being a customer of this Loyalty Program. Further, 5 different features will be described to you, and you will be asked to provide your personal evaluation of each feature. Please note that first 4 features have the same evaluation scale; the 5th differs.

Your participation in this study is voluntary. Your survey responses will be strictly confidential, and all results will be reported only in the aggregate form. If you have questions about the survey, please contact me by email at: 1802007@modul.ac.at

Thank you very much for your time and support; it is highly appreciated!
Please start the survey now by pressing the "Next" button below

Kind regards, Elena

Question 1:

* Are you a user of ANY Loyalty Program (e.g., Jö, Payback, Miles&More, IKEA Family...etc.)

- Yes
- No

Question 2 (answered if answer to Question 1="Yes", if "No" - skipped):

* How many Loyalty Programs are you subscribed to (approx.)?

- 1-4
- 5-9
- 10-14
- 15 and more

Question 3:

* Please randomly select either (1) or (2), this will assign you to one of the groups, and you will further get specific questions designated to this group.

- 1
- 2

Question 4 (group 1 - BC-based LPs):

Feature 1: Redemption of loyalty miles

Now you will be presented with five different features of one Loyalty Program and will be asked to evaluate your attitude toward each of them.

Imagine that you, as a customer, fly with the Airline or shop at partner merchants (e.g., dining, retail, wellness, activities, services).
For every such transaction, you accumulate loyalty points(miles) that you can later use to

- make day-to-day purchases at any of the partnering merchants to pay the purchase price in full or partially
- buy merchandise at the Airline's online shop (various categories of goods)
- buy flights/upgrades at Airline

Please express your attitude to such redemption options on a 5-point scale (1= strongly disagree; 5 = strongly agree).
Having this feature...

Question 5 (group 2 - traditional LPs):

Feature 1: Redemption of loyalty miles

Now you will be presented with five different features of a Loyalty Program and will be asked to evaluate your attitude toward each of them.

Imagine that you, as a customer, fly with the Airline or shop at partner merchants (in various categories). For every such transaction, you accumulate loyalty points(miles) that you can later use to:

- get discounts for selected services (from travel category: hotels, car rentals)
- buy merchandise at the Airline's online shop (various categories of goods)
- buy flights/upgrades at Airline

Please express your attitude to such redemption options on 5 point scale (1 = strongly disagree; 5 = strongly agree).
Having this feature...

Question 6 (group 1 - BC-based LPs):

Feature 2: immediate points accrual

Once you have purchased a flight ticket at the Airline or made a purchase at partner merchants, loyalty miles are credited to your account immediately in real-time without a delay of several weeks.

Please express your attitude on 5 star scale (1= strongly disagree; 5 = strongly agree).
Having this feature...

Question 7 (group 2 - traditional LPs):

Feature 2: delayed points accrual

Once you have purchased a flight ticket at the Airline or made a purchase at partner merchants, the loyalty miles are credited to your account with a delay of several weeks.

Please express your attitude on 5 star scale (1= strongly disagree; 5 = strongly agree).
Having this feature...

Question 8 (group 1 - BC-based LPs):

Feature 3: relevant offers

Once you have accumulated enough loyalty miles, you can spend them at partner merchants to pay part of the purchase price or the full price. The merchants have a variety of different offers. You can browse all offers available for all other users and receive personalized, relevant offers based on your previous shopping preferences.

Please express your attitude on 5-point scale (1= strongly disagree; 5 = strongly agree).
Having this feature...

Question 9 (group 2 - traditional LPs):

Feature 3: generic partner offers

Once you have accumulated enough loyalty miles, you can spend them at partner merchants by getting a discount for selected services (travel-related, such as car rental, hotel booking) or purchasing merchandise at Airline's online shop. The offers that you receive are not personalized and are the same as for all other users.

Please express your attitude on a 5-point scale (1= strongly disagree; 5 = strongly agree).
Having this feature...

Question 10 (group 1 - BC-based LPs):

Feature 4: no expiration of Loyalty Miles

Once you have accumulated loyalty miles, they have no expiration date and can be used whenever you want.

Please express your attitude on a 5-point scale (1= strongly disagree; 5 = strongly agree).
Having this feature...

Question 11 (group 2 - traditional LPs):

Feature 4: Loyalty Miles expiration

Once you have accumulated loyalty miles, they expire after three years, and unused miles cannot be spent after that.

Please express your attitude on a 5-point scale (1= strongly disagree; 5 = strongly agree).
Having this feature...

Question 12 (group 1 - BC-based LPs):

Feature 5: Points transferability

You have the possibility to manage your loyalty miles at your own discretion, they act as your digital asset. For example, you can transfer them to other users of the Loyalty Program.

Please express your attitude on a 5-point scale (1= strongly disagree; 5 = strongly agree).
Having this feature...

Question 13; Feature 5 (group 2 - traditional LPs):

Feature 5: no transferability of Loyalty Miles

You have the possibility to manage your loyalty miles if you want to redeem them, but you cannot transfer them to other users of the Loyalty Program.

Please express your attitude on a 5-point scale (1= strongly disagree; 5 = strongly agree).
Having this feature...

Question 14:

Program Loyalty

Please express your overall attitude toward the presented Loyalty Program on a 5-point scale (1= strongly disagree; 5 = strongly agree)

Question 15:

* Now tell a bit more about yourself.

You are...

- Male
- Female
- Diverse

Question 16:

* Your age group is...

- Below 18
- 18-24
- 25-34
- 35-44
- 45-54
- Above 54

Question 17:

* Your education level is...

- PhD
- Masters
- Bachelor
- Secondary
- Primary

Question 18:

* Your employment status is...

- Employed for wages
- Self-employed
- Out of work and looking for work
- Out of work but not currently looking for work
- A homemaker
- A student
- Military
- Retired

Question 19:

Your income (yearly, gross) is...

- Up to € 11,000
- € 11,000 up to € 18,000
- € 18,000 up to € 31,000
- € 31,000 up to € 60,000
- € 60,000 up to € 90,000
- 90,000 up to € 1,000,000
- more than € 1,000,000

Question 20:

* Your region of residence is...

- Western Europe
- Central and Eastern Europe
- Asia
- Africa
- Mediterranean & Middle East
- Americas

Appendix 3: Twitter data Analysis R code

```
#install required packages and libraries
install.packages("academictwitteR")
install.packages("tm")
install.packages("RColorBrewer")
install.packages("httpuv")
install.packages("openssl")
install.packages("syuzhet")
install.packages("ggplot2")

library("academictwitteR")
library("tm")
library("RColorBrewer")
library("httpuv")
library("openssl")
library("syuzhet")
library("ggplot2")

#OAuth 2.0 Bearer Token authentication; bearer_token masked
bearer_token <- "XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX"

##########################################################################

#MILES&MORE ANALYSIS (TRADITIONAL LP)
#retrieve mentions of @Miles_and_More for the specified timeframe
MilesAndMore <- get_mentions_tweets("@Miles_and_More", "2009-02-01T00:00:00Z",
"T01:00:00Z", bearer_token, data_path = "/Users/elenapetrozhitskaya/Documents/Education/
MBA Modul/Thesis/Blockchain loyalty programs/Twitter/Tweets.json")
MilesAndMore_text <- MilesAndMore["text"]

#creation of corpus from collection of text files
MilesAndMore_corpus <- Corpus(VectorSource(MilesAndMore_text))
MilesAndMore_corpus <- tm_map(MilesAndMore_corpus, content_transformer(function(x)
iconv(x, to='UTF-8-MAC',sub='byte')))

#corpus clean up
MilesAndMore_corpus <- sapply(MilesAndMore_corpus,function(row) iconv(row, "latin1",
"ASCII", sub=""))

sample <- MilesAndMore_corpus
sum1 <- gsub("(RT|via)((?:\\b\\W*@\\w+)+)","",sample)
sum2 <- gsub("http[^[:blank:]]+","", sum1)
sum3 <- gsub("@\\w+","",sum2)
sum4 <- gsub("[[:punct:]]"," ", sum3)
sum5 <- gsub("[^[:alnum:]]", " ", sum4)
sum6 <- gsub("RT ","", sum5)

corpus <- Corpus(VectorSource(sum6))
clean.tweets<- tm_map(corpus , content_transformer(tolower))
clean.tweets<- tm_map(clean.tweets, removeWords, stopwords("english"))
clean.tweets<- tm_map(clean.tweets, removeWords, stopwords("german"))
clean.tweets<- tm_map(clean.tweets, removeNumbers)
clean.tweets<- tm_map(clean.tweets, stripWhitespace)
myStopwords <- c(setdiff(stopwords('english'), c("r", "big")),"amp")
clean.tweets<- tm_map(clean.tweets, removeWords, myStopwords)
```

```
#create term-document matrix
mam <- TermDocumentMatrix(clean.tweets)
mam <- as.matrix(mam)
mam <- sort(rowSums(mam),decreasing=TRUE)
mam <- data.frame(word = names(mam),freq=mam)
head(mam, 50)

#plot top 20 frequent terms
barplot(mam[1:20,]$freq, las = 2, names.arg = mam[1:20,]$word, col ="blue", main ="Most fre-
quent terms @Miles_and_More", ylab = "Word frequencies")

###########################################################################
#SENTIMENT ANALYSIS Miles&More
#extract tweets and remove undesirable symbols
MilesAndMore <- get_mentions_tweets("@Miles_and_More", "2009-02-01T00:00:00Z",
"2021-05-21T01:00:00Z", bearer_token, data_path = "/Users/elenapetrozhitskaya/Documents/
Education/MBA Modul/Thesis/Blockchain loyalty programs/Twitter/Tweets.json")
head(MilesAndMore$text)
tweetsmm <- MilesAndMore
sum_1_mm <- gsub("http[^[:blank:]]+","",tweetsmm$text)
sum_2_mm <- gsub("(RT|via)((?:\\b\\W*@\\w+)+)","",sum_1_mm)
sum_3_mm <- gsub("@\\w+","",sum_2_mm)

wordmm <- as.vector(sum_3_mm)
emotion <- get_nrc_sentiment(wordmm)
emotion2 <- cbind(sum_3_mm, emotion)
head(emotion2)

 anger anticipation disgust fear joy sadness surprise trust negative positive
1   0   0   0   0   0   0   0   1   0   1
2   0   0   0   0   0   0   0   0   0   0
3   0   0   0   0   0   0   0   0   0   0
4   0   0   0   0   1   0   0   0   0   1
5   0   0   0   1   0   1   0   0   1   0
6   0   0   0   0   0   0   0   0   0   0


sent.value <- get_sentiment(wordmm)

category <- ifelse(sent.value < 0, "Negative", ifelse(sent.value > 0, "Positive", "Neutral"))
table(category)

category
Negative  Neutral Positive
    1077     1415     1628

#carry out sentiment mining using the get_nrc_sentiment()function, after change the result from
a list to a data frame and transpose it
resmm <- get_nrc_sentiment(as.character(sum_3_mm))
res1mm <- data.frame(t(resmm))

#calculate the column sums across rows for each level of a grouping variable. Also add the
name to columns and rows for the future data frame
new_resmm <- data.frame(rowSums(res1mm))
names(new_resmm)[1] <- "count"
new_resmm <- cbind("sentiment" = rownames(new_resmm), new_resmm)
rownames(new_resmm) <- NULL
```

```
#plot nrc sentiments absolute values
qplot(sentiment, data= new_resmm[1:8,], weight=count, geom="bar",fill=sentiment)
+ggtitle("@Miles_and_More Sentiments")
qplot(sentiment, data= new_resmm[9:10,], weight=count, geom="bar",fill=sentiment)
+ggtitle("@Miles_and_More Sentiments")

#plot nrc sentiments % values
barplot(sort(colSums(prop.table(resmm[, 1:8]))), horiz = TRUE, cex.names = 0.7, las = 1, main
= "Emotions for Miles&More", xlab="Percentage")
##########################################################################

#KRISPAY ANALYSIS (BLOCKCHAIN LP)

#retrieve all tweets by hashtags #KrisPay OR #KrisFlyer for the specified timeframe
KrisPay <- get_all_tweets("#KrisPay OR #KrisFlyer", "2018-07-24T00:00:00Z",
"2021-05-21T00:00:00Z", bearer_token)
KrisPay_text <- KrisPay["text"]

#creation of corpus from collection of text files
KrisPay_corpus <- Corpus(VectorSource(KrisPay_text))
KrisPay_corpus <- tm_map(KrisPay_corpus, content_transformer(function(x) iconv(x, to='UTF-
8-MAC',sub='byte')))

KrisPay_corpus <- sapply(KrisPay_corpus,function(row) iconv(row, "latin1", "ASCII", sub=""))

#corpus clean up
sample <- KrisPay_corpus
sum1 <- gsub("(RT|via)((?:\\b\\W*@\\w+)+)","",sample)
sum2 <- gsub("http[^[:blank:]]+","", sum1)
sum3 <- gsub("@\\w+","",sum2)
sum4 <- gsub("[[:punct:]]"," ", sum3)
sum5 <- gsub("[^[:alnum:]]", " ", sum4)
sum6 <- gsub("RT ","", sum5)
corpus <- Corpus(VectorSource(sum6))
clean.tweets<- tm_map(corpus , content_transformer(tolower))
clean.tweets<- tm_map(clean.tweets, removeWords, stopwords("english"))
clean.tweets<- tm_map(clean.tweets, removeWords, stopwords("german"))
clean.tweets<- tm_map(clean.tweets, removeNumbers)
clean.tweets<- tm_map(clean.tweets, stripWhitespace)

#create term-document matrix
kp <- TermDocumentMatrix(clean.tweets)
kp <- as.matrix(kp)
kp <- sort(rowSums(kp),decreasing=TRUE)
kp <- data.frame(word = names(kp),freq=kp)
head(kp, 50)

#plot top 20 frequent terms
barplot(kp[1:20,]$freq, las = 2, names.arg = kp[1:20,]$word, col ="blue", main ="Most frequent
terms #KrisPay", ylab = "Word frequencies")

##########################################################################
#SENTIMENT ANALYSIS KrisPay

KrisPay <- get_all_tweets("#KrisPay OR #KrisFlyer", "2018-07-24T00:00:00Z",
"2021-05-21T00:00:00Z", bearer_token)
tweetskp <- KrisPay
```

```
head(tweetskp$text)

sum_1_kp <- gsub("http[^[:blank:]]+","",tweetskp$text)
sum_2_kp <- gsub("(RT|via)((?:\\b\\W*@\\w+)+)","",sum_1_kp)
sum_3_kp <- gsub("@\\w+","",sum_2_kp)

wordkp <- as.vector(sum_3_kp)
emotionkp <- get_nrc_sentiment(wordkp)
emotion2kp <- cbind(sum_1_3, emotionkp)
head(emotion2kp)

  anger anticipation disgust fear joy sadness surprise trust negative positive
1     0            0       0    0   0       0        0     0        0        0
2     0            0       0    1   0       1        0     0        1        1
3     0            0       0    1   0       1        0     0        1        1
4     0            0       0    1   0       1        0     0        1        1
5     0            0       0    1   0       1        0     0        1        1
6     0            0       0    1   0       1        0     0        1        2

sent.value <- get_sentiment(wordkp)

category <- ifelse(sent.value < 0, "Negative", ifelse(sent.value > 0, "Positive", "Neutral"))
table(category)

category
Negative  Neutral Positive
     187      276      476

#carry out sentiment mining using the get_nrc_sentiment()function, after change the result from
a list to a data frame and transpose it
reskp <- get_nrc_sentiment(as.character(sum_3_kp))
res1kp<-data.frame(t(reskp))

#calculate the column sums across rows for each level of a grouping variable. Also add the
name to columns and rows for the future data frame
new_reskp <- data.frame(rowSums(res1kp))
names(new_reskp)[1] <- "count"
new_res <- cbind("sentiment" = rownames(new_reskp), new_reskp)
rownames(new_reskp) <- NULL

#plot sentiments
qplot(sentiment, data=new_reskp[1:8,], weight=count, geom="bar",fill=sentiment)
+ggtitle("#KrisPay Sentiments")
qplot(sentiment, data=new_reskp[9:10,], weight=count, geom="bar",fill=sentiment)
+ggtitle("#KrisPay Sentiments")

#plot nrc sentiments % values
barplot(sort(colSums(prop.table(resmm[, 1:8]))), horiz = TRUE, cex.names = 0.7, las = 1, main
= "Emotions for Miles&More", xlab="Percentage")
```

Appendix 4: Study 1 and 2 sample description

	BCLP		Trad. LP		Total	
	Count	**N %**	**Count**	**N %**	**Count**	**N %**
Gender						
Male	26	23.6%	36	37.5%	62	30.1%
Female	84	76.4%	60	62.5%	144	69.9%
Age Group						
Below18	0	0.0%	0	0.0%	0	0.0%
18-24	5	4.5%	3	3.1%	8	3.9%
25-34	39	35.5%	45	46.9%	84	40.8%
35-44	55	50.0%	31	32.3%	86	41.7%
45-54	9	8.2%	13	13.5%	22	10.7%
Above 54	2	1.8%	4	4.2%	6	2.9%
Education Level						
Primary	0	0.0%	0	0.0%	0	0.0%
Secondary	2	1.8%	3	3.1%	5	2.4%
Bachelor	23	20.9%	29	30.2%	52	25.2%
Masters	77	70.0%	58	60.4%	135	65.5%
PhD	8	7.3%	6	6.3%	14	6.8%
Employment Status						
Employed for wages	72	65.5%	66	68.8%	138	67.0%
Self-employed	23	20.9%	15	15.6%	38	18.4%
Out of work and looking for work	3	2.7%	4	4.2%	7	3.4%
Out of work but not currently looking for work	3	2.7%	2	2.1%	5	2.4%
A homemaker	3	2.7%	4	4.2%	7	3.4%
A student	5	4.5%	4	4.2%	9	4.4%
Retired	1	0.9%	1	1.0%	2	1.0%
Income Level						
Up to € 11,000	10	9.3%	9	9.6%	19	9.4%
€ 11,000 up to € 18,000	9	8.3%	9	9.6%	18	8.9%
€ 18,000 up to € 31,000	14	13.0%	6	6.4%	20	9.9%
€ 31,000 up to € 60,000	42	38.9%	36	38.3%	78	38.6%
€ 60,000 up to € 90,000	21	19.4%	19	20.2%	40	19.8%
90,000 up to € 1,000,000	12	11.1%	14	14.9%	26	12.9%

More than € 1,000,000	0	0.0%	1	1.1%	1	0.5%
Region of Residence						
Western Europe	54	50.0%	43	44.8%	97	47.5%
Central and Eastern Europe	49	45.4%	50	52.1%	99	48.5%
Asia	0	0.0%	2	2.1%	2	1.1%
Africa	0	0.0%	0	0.0%	0	0.0%
Mediterranean & Middle East	0	0.0%	0	0.0%	0	0.0%
Americas	5	4.6%	1	1.0%	6	2.9%
LP's Total	110	100.0%	96	100.0%	206	100.00%