8-10-2021

Defining, Measuring, And Managing Networked Customer Experience: A Multi-Method Study of Mobile Payment Applications in Retail Settings

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DEFINING, MEASURING, AND MANAGING NETWORKED CUSTOMER EXPERIENCE:

A MULTI-METHOD STUDY OF MOBILE PAYMENT APPLICATIONS IN RETAIL SETTINGS

BY

NANDINI NIM

A Dissertation Submitted in Partial Fulfillment of the Requirements for the Degree

Of

Doctor of Philosophy

In the Robinson College of Business

Of

Georgia State University

GEORGIA STATE UNIVERSITY
ROBINSON COLLEGE OF BUSINESS
2021

ACCEPTANCE

This dissertation was prepared under the direction of the *NANDINI NIM's* Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Business Administration in the J. Mack Robinson College of Business of Georgia State University.

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ABSTRACT

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NANDINI NIM

JULY 19TH, 2021

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This research introduces a new concept of *Networked Customer Experience* (NCX), where technologies mediate a customer's purchase journey, and their experiences are co-created and co-managed by the service provider and technology providers. We conduct 2×2×2 factorial experiments and manipulate NCX evaluation and attribution drivers – the brand value of service provider, use benefits of technology, and technology-service failures, for mobile payment applications in retail settings. As hypothesized, failures significantly impact the differential attribution mechanism among users with better evaluation for the service provider when use benefits are low. Also, we use unsupervised text classification to extract the dimension information from customer reviews for mobile payment apps and build a model that classifies the NCX dimensions with 55% macro-precision. With this multi-method research, we contribute to the marketing literature by providing a new perspective on technology-mediated customer experience. For practitioners, we provide useful insights for the Customer Experience Management (CXM) Strategy.

Keywords: technology-driven customer experience, customer experience management, mobile payments, mobile wallets, technology failure, text analysis, factorial experiments

ACKNOWLEDGEMENTS

I thank my mother, Veena, for showing me the value of education. As my role model and an independent woman, she gave me wings to fly and achieve my dreams. The continuous encouragement and love of my parents are my driving force to be a better person.

I am grateful to my remarkable mentor and advisor, Dr. V. Kumar (VK). He has played a key role in helping me grow as a researcher. His expertise, patience, motivation, and guidance have been instrumental in my Ph.D. journey. As I move to the next phase of my academic life, I will always look up to him for advice and intend to follow his philosophy of paying it forward.

I thank my dissertation committee members – Dr. Naveen Donthu (chair), Dr. Denish Shah, Dr. Yi Zhao, Dr. Kelly Hewett, and Dr. Agata Leszkiewicz. They have been incredibly supportive and guided me to shape this manuscript. Their feedback pushed me to think harder and helped me to grow as a researcher.

My wonderful support system at the Georgia State University – fellow Ph.D. students, colleagues, and staff – made my journey more fun, enjoyable, and meaningful. A few of them became good friends and family. Especially, I am forever grateful for the friendship and support of Dr. Anita Pansari, Dr. Avishek Lahiri, Dr. Ankit Anand, Dr. Brianna Paulich, Parag, Anamika, Sudhanshu, Baha, Divya, and Kiwoong. I also appreciate Dr. Amalesh Sharma and Amit Agarwal, who were an important part of my Ph.D. journey as colleagues and co-authors.

I thank my siblings, Monisha, Dhiraj, and Priya, and my dearest friend Bhoomika for keeping my spirits up and believing in me unconditionally. I am grateful to my husband's parents, Bhupesh and Ashok Mann, for their love and encouragement. It would have been a great joy of my life to share this achievement with my late grandparents – especially my grandfather, Lt. Shri Kundan Lal, who taught me the value of hard work and determination.

Finally, I thank my beloved husband, Vineet Mann, for his unwavering support, love, and belief in my abilities that constantly motivate me to be the best version of myself.

Thank you.

Nandini Nim

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INTRODUCTION AND MOTIVATION

Imagine a customer wants to book a stay with the Westin Hotel for a conference. The customer has two ways to book a stay. First, the direct channel, the customer can call the Westin property or use their website to book the stay. However, Westin's stay is a little costly, and the customer wants to get a better deal. There is a second way, which is indirect and growing in popularity. The customer can use a third-party mobile app or website, such as Groupon or Hotels.com, to book a discounted stay. Using a third-party technology, the customer gets an additional discount and cashback as well. When the customer arrives at the hotel, she/he uses the Groupon app to redeem the coupon. In the end, the customer had a pleasant stay at the conference and went back happy and satisfied. The customer gives a 5-star rating for his overall stay experience in a survey sent by Westin. However, the pre-purchase and purchase stages of the customer journey were managed mainly by a third party, Groupon, in this case. To generalize to other similar scenarios, both technology and service providers co-create and co-manage technology-mediated customer experiences at the front end of the customer journey. We define and study this phenomenon as Networked Customer Experience (NCX). By front-end, we imply that a customer can directly observe the involved parties in creating and managing NCX across one or more stages of a customer journey. Thus, the observation by customers and its consequences can vary across customers and situations.

Apart from a few big firms such as Walmart and Target, service providers often have limited capability to innovate new technologies. Thus, big and small tech firms provide technologies connecting both service providers and customers. For example, firms such as Amazon, Apple, and Facebook offer service providers and customers with payments, banking, and fulfillment solutions worldwide. One unique characteristic is that technologies connect customers to multiple service providers and cater to their varying needs. A service provider (such as Westin) can only provide and manage their customers' experience within their service environment. However, technology providers can observe customers over multiple journeys with multiple service providers across various service environments. Having said that, by no means we are inferring that technology providers (TP) are more important than service providers

(SP). It is just that the TP has a broader customer view. Consequentially, they get a better understanding of consumer behavior. Also, as customers extensively use third-party technologies across service providers, they are bound to develop brand and relationship equity with technology providers. Thus, customer-technology provider relationships and past experiences can impact how customers evaluate and attribute their good and bad experience with service providers. Moreover, there can be unintended experience evaluation and attribution among service providers, technology providers, and customers. Notably, in the situation of failures, customers may misattribute to the wrong party. For example, if a customer cannot redeem the Groupon deal at the Westin Hotel, to whom should she/he attribute the failure? Hence, in each service encounter over one or more stages of a customer journey, we must account for various drivers, such as brand and technology characteristics, to understand the resultant customer experiences.

The process of experience evaluation and attribution is dependent on internal and external factors. Internal factors can include customer goals and experience. External factors such as brand experience and employee support are the forces that can interact with both contextual and internal factors to create a service or product experience (Puccinelli et al., 2009). Thus, any negative deviation from expected results and goals leads to a negative evaluation of the experience. An element that is central to evaluation and attribution is *'Affect'*. Researchers have shown that customers' emotions and moods impact the evaluation of such deviations from the desired goal (Bagozzi, Gopinath, & Nyer, 1999). Also, emotions help customers to express their feelings, such as satisfaction, pleasure, and discontent that can arise due to multiple reasons during their journey (Palmer, 2010). Hence, firms use customer satisfaction and feedback surveys to understand experiences and their impact on marketing metrics such as brand equity, loyalty, and attrition (Steenkamp, De Jong, & Baumgartner, 2010). However, surveys can suffer from a lack of generalizability and self-selection of participants, leading to common-method bias (MacKenzie & Podsakoff, 2012).

Nowadays, firms can gather large quantities of customer data across a customer's journey using technologies, such as mobile apps and wearable devices. Such customer technologies, often provided by third parties, are intelligent and interactive[1] and enhance customer satisfaction via better personal and social experiences (Yim, Chu, & Sauer, 2017). For example, in a National Retail Foundation (2019) survey, 66% of respondents believed that their in-store shopping experience has improved because of shopping technologies such as self-checkout, mobile payments, and buying online and picking up in-store. For firms, they provide customer insights and operational efficiencies. Recently, Hoyer, Kroschke, Schmitt, Kraume, and Shankar (2020), Nam and Kannan (2020), and Kranzbühler, Kleijnen, and Verlegh (2019) have also highlighted the need to explore the dimensions and impact of such technology-mediated CX and the role of partner-owned (third-party) touchpoints on various customer and firm outcomes.

We address the need highlighted in the marketing literature by presenting a new perspective on the role of technology providers and service providers in co-creating and co-managing technology-mediated CX at the front end of the customer journey. We define this as a new concept called *Networked Customer Experience (NCX)* and answer three related questions:

1. What are the dimensions of Networked Customer Experience (NCX)?
2. How do customers attribute their experience evaluations among multiple parties who create NCX? What are the critical internal and external drivers of this attribution process to the firm?
3. How do customers evaluate their technology-mediated experiences? Can we rely on affective information throughout the various stages of a customer's journey to predict customer-related outcomes such as technology ratings or service satisfaction?

In this context of technology-driven CX, some researchers have discussed that CX can combine user, brand, product, and service experiences (Lemon & Verhoef, 2016). Some studies have also highlighted the role of customers in co-creating their experiences, focusing on failures and attributions (Collier & Barnes, 2015; Heidenreich, Wittkowski, Handrich, & Falk, 2015). However, very few studies have provided a new conceptual perspective or metric for CX for technology-mediated interactions (Lemon &

[1] Smart technologies can possess varying degree of artificial intelligence. That is smart technologies have learning abilities, temporal continuity, and proactivity in changing environment (Franklin and Grasser, 1996). The technologies inhabit digital environment, can assimilate vast amount of information, and carry out tasks with greater speed, efficiency, and accuracy (Kumar, Dixit, Javalgi, & Dass, 2016).

Verhoef, 2016; Verhoef et al., 2009). It is a difficult task because CX, as a measure, has various connotations, measurements, and standards across industries.

We explore NCX by adopting a hybrid perspective offered by Becker and Jaakkola (2020). The authors proposed two perspectives to understand CX- a response to managerial stimuli or a consumption process. In this research, we view customer technologies as managerial stimuli, where resultant customer experience can be assessed as a response to the stimuli and outcome of the consumption process.[2] Also, we set our research in a two-dimensional context. First, we focus on the retail industry as a substantive context because it has seen much disruption with the growth of customer technologies. The rise in omnichannel retail has created a need to adopt and integrate customer technologies, such as mobile apps, in providing and managing better CX across various touchpoints in a customer journey (Grewal, Noble, Roggeveen, & Nordfalt, 2020). Second, we use *mobile payment apps* as customer technology. Mobile payments app such as mobile wallet (Mwallet) is among the fastest-growing customer technologies worldwide. In NRF Consumer Survey (2019), mobile payment is one of the top three technologies used by customers in both online and offline retail purchases.

As smartphones become more integral to customers' lives, contactless mobile applications aim to replace physical wallets with digital wallets and cash and card payments with tokenized digital payments. The mobile payment app space (integrated with the fintech industry) is evolving fast due to stiff competition between multiple stakeholders. Banks and financial institutions (PayPal and Bank of America), Big-tech firms (Apple, Samsung, and Google), retailers (Walmart, Alibaba, and Amazon), new entrants (Paytm and WeChat) are competing to get the role of key orchestrator in the payment and retail ecosystems. Thus, there is considerable variability in mobile payment applications in terms of functions and integration. For example, some apps can provide a digital payment experience (Apple pay) while others can also provide access to m-commerce, savings & microfinance (Paytm in India). There are

[2] For example, augmented reality (AR) applications by Sephora and Ikea let consumers upend the physical and digital worlds to co-create product-brand experiences. A customer can visualize the furniture in their home before purchasing using Ikea AR mobile app. Similarly, customers can see how a cosmetic product would look on them without trying every product in their consideration set using AR mirrors in Sephora. Such customer technologies make the decision process easier and faster for consumers and help retailers with operational and marketing effectiveness.

various types of Mwallet which provide different functions and benefits. One categorization can be based on consumers' view, i.e., how consumers can use a mobile payment app, say person-to-person wallets (P2P) such as Venmo, business-to-consumer wallets (B2C) such as Apple Pay.[3]

We conduct a multi-method study to explore the concept of NCX in the context of customer technologies and multiple partners (See Figure 2.). In *Study 1*, we conceptually define and explore NCX using academic literature, industry reports, and managerial interviews. We draw on the 'Service Convenience' construct and present five dimensions of NCX- decision, access, transaction, benefits, and post-decision (Berry, Seiders, & Grewal, 2002). In *Study 2*, which consists of two parts, we conduct multi-method research to explore the internal and external factors in customer evaluation and attribution. Specifically, in *Study 2a*, we conduct a 2×2×2 factorial experiment to understand customer evaluation and attribution of NCX. We manipulate use-benefits salience of Mwallet technology, the brand value of service provider (retailer), and technology-service failure in a lab setting, and assess the impact of manipulated variables on the overall networked customer experience and attribution to multiple parties (retailers, technology provider, self). In *Study 2b*, we use unsupervised text classification to identify the NCX dimensions of customer evaluation and associated sentiments, particularly for Mwallet apps. Then we present the next steps to scale up this research to create an NCX metric and make CXM strategies.

This research contributes to the marketing literature by presenting a new perspective to understand evolving CX due to technological integration across different stages of the customer journey. We highlight that the role of the technology provider is central in technology-mediated interactions for customers to evaluate their experiences with a service provider embedded within a service environment. We introduce and explore this phenomenon as Networked Customer Experience. We posit that for front-end CX, the impact of technology providers should be considered when evaluating the customer experiences and their outcomes, such as attribution, satisfaction, and loyalty. We draw on the theoretical

[3] One of the most widely used differentiation is closed vs. semi-closed wallets. In closed wallet such as Amazon Pay and Kroger Pay, a user can transact within the wallet provider ecosystem only. This type of wallet is primarily developed and used by retailers. However, big retailers are now trying to expand their payment services to other retailers to develop a bigger ecosystem. In semi-closed wallet such as Alipay and Paytm, user can transact with merchants who have adopted the wallet ecosystem. (Source: Singh, R.; Article retrieved on May 19, 2020 from https://medium.com/@appsexpert/a-quick-guide-to-understand-mobile-wallets-and-mobile-payments-5dd932ffdee4)

foundations from the attribution and goal regulation theories to better understand technology-mediated CX and NCX mechanisms. Subsequently, we show that various brand and technology-related elements drive the customer evaluation and attribution of their experiences. Practitioners can leverage our study to fine-tune their Customer Experience Management (CXM) strategies. They can use multiple sources of data to understand their customers' evaluation of technology-mediated NCX. Our research makes a strong case for service providers (such as retailers) to include technology partners' contributions in the customer evaluation of the firm's NCX. With a better understanding of NCX, firms can develop streamlined and effective frontline and technology management strategies. Moreover, we prescribe firms to conduct NCX analysis across all partner-owned technology-driven touchpoints to understand the impact of technology integration on a firm's customer-centric outcomes.

RELATED LITERATURE

This paper draws from multiple strands of marketing literature. Table 1. highlights select studies related to CX, focusing on conceptualization and measurement and the literature on technology-driven marketing strategies. CX has been conceptualized and discussed from various perspectives – elements related to CX process, consumer behavior, and outcomes for consumers and organizations (Lemon & Verhoef, 2016), S-D logic and service logic to focus on service experience co-creation (Jaakkola, Helkkula, & Aarikka-Stenroos, 2015), static experience related to one touchpoint in time vs. dynamic evolution over time from consumer and organizational perspectives (Kranzbühler, Kleijnen, Morgan, & Teerling, 2018). Recently, in a review article, Becker and Jaakkola (2020) evaluated the existing literature in the area of CX and broadly classified the scope of the CX phenomenon as narrow (response to managerial stimuli) and broad (response to consumption process and resultant evaluations). The authors' central posit is to define CX as non-deliberate, spontaneous responses and reactions to stimuli. This broad definition can encompass different types of stimuli and customer responses (sensory, affective, cognitive, physical, and social-identity experiences) and focus on the touchpoints across different stages of a customer journey.

[Table 1. Here]

Although there is no universal definition and measure, researchers agree that customer experience is a multi-dimensional construct with five dimensions: sensory, affective, cognitive, physical, and social identity experiences (Schmitt, 1999; Verhoef et al., 2009). Firms can use customer reviews and feedback (user-generated data) to extract CX-related information from large datasets. Ordenes, Theodoulidis, Burton, Gruber, and Zaki (2014) extracted CX and feedback-related information via three value-creation elements – activities, resources, and context using a text-mining approach. Next, we divide the existing research into three areas – Technology-Driven Customer Experience, Customer Adoption and Evaluation of Technologies, and Partner-owned Touchpoints and Attribution. First, we explain the current state of research and elaborate on the connections with this study.

Technology-Driven Customer Experience

Customer technologies aim to provide benefits such as ease of search, buy, pay, and return products, thus higher convenience (Grewal et al., 2020). For example, convenience is the primary driver associated with the ease of use of mobile payment applications such as Apple Pay. As markets embrace technology-mediated customer journeys, we are bound to see changes in CX dimensions (Hoyer et al., 2020). All these stages of the customer journey (pre-purchase, purchase, and post-purchase) can integrate technology providers at the front-end (i.e., where customers can observe the brand and role of technology providers in co-creating and co-managing their experiences). Technologies provide access to various types of customer data, and with better analytics tools, we can mine for deeper customer insights. In the past few years, the field has increasingly debated the role of emotions vs. cognition in assessing CX related to technology adoption and usage (Huang & Rust, 2017; Kimes & Collier, 2015). The literature has shown that emotions vary with the strength of subjective experience, and we can observe variation in the magnitude of physiological response and the extent of bodily expressions (Bagozzi et al., 1999). Also, a strong positive emotional evaluation of CX can lead to customer engagement (Pansari & Kumar, 2017).

However, we need more research to explore the role of emotions as a driver of psychological and physical responses for technology-driven CX.

Customer Adoption and Evaluation of Technologies

The literature has shown that perceived ease of use and perceived usage are two critical drivers of technology adoption and usage (Venkatesh, Morris, Davis, & Davis, 2003; Venkatesh, Speier, & Morris, 2002). In terms of customer evaluation of technologies, it can be translated into convenience and perceived value (benefits). With more capabilities, technologies make daily activities easier for customers (Schatsky, Muraskin, & Gurumurthy, 2015), and over time with repeated learning, they become part of customers' digital selves (Belk, 2013). Although customers still desire human interaction in service encounters, they also appreciate the convenience, speed, and benefits of technologies (Kimes & Collier, 2015). Based on the level of involvement with technology and purchase decision, customers learn to delegate control to technologies in the purchase journey (Bitner, Brown, & Meuter, 2000).[4] Also, the level of involvement affects the degree and direction of affective evaluation of the associated experiences, such as happiness and frustration in a customer journey (Puccinelli et al., 2009). While evaluating any situation or experience, customers draw on environmental settings and cues (Hilken, de Ruyter, Chylinski, Mahr, & Keeling, 2017). For example, cues such as interface design, product quality, and brand value of service providers can impact customer evaluation. Also, as per appraisal theories, customers evaluate their service encounters via an appraisal of their personal goals, which can be utilitarian or hedonic (Roseman, 1991). Thus, if technology-related goals are met (goal congruence), customers would have positive evaluation of the service encounter. However, the adoption of technology and the resultant experience is driven by the service context and culture. Hence, we need more research across technologies and service contexts to explore and generalize the drivers of technology-driven CX at the front-end of the customer journey.

[4] For example, customers are increasingly utilizing low-involvement digital technologies, such as mobile payment applications, to make decisions or interact with retailers. However, for high involvement technologies such as AR and VR, customers are still learning to internalize the experience as part of the extended self.

Partner-owned Touchpoints and Attribution

Technology providers bring additional elements to evaluating service encounters where CX is co-created and co-managed – technology characteristics and technology evaluation environment (Hoyer et al., 2020). For example, the features and capabilities of technologies can impact the usage and outcomes of a service encounter. Lately, there is a significant increase in third-party or partner-owned touchpoints created by technologies in a customer journey (Nam & Kannan, 2020). Specifically, the retail industry is disrupted with technological integration (such as mobile apps), where both service providers and technology providers create value through convenience and relevance (Reinartz, Wiegand, & Imschloss, 2019). Usually, technology providers provide technology as a digitalized platform, such as Uber and Apple Pay. Service providers and customers benefit from network externalities via value co-creation (Ramaswamy & Ozcan, 2018a).[5] Network externalities mean that as more customers start using a third-party technology, say Apple Pay, it positively impacts service providers' adoption of the technology. Similarly, as more service providers integrate Apple Pay as their transaction and promotion partner, it positively impacts customers' adoption of the technology, leading to higher value for all the involved stakeholders.

Technology-driven CX brings out the notion of attribution to the center of CX measurement and management. Tax, McCutcheon, and Wilkinson (2013) defined three types of networks where the service provider or focal firm has different roles and power – customer coordinated, service-coordinator based, and firm-coordinated. Specifically, in a service coordinated environment, firms together take care of the service delivery. However, customers' attribution mechanisms may vary depending on the outcomes. If customers fail to achieve their goals (utilitarian and hedonic), the resultant attribution will depend on the service environment. The literature has shown that customers react differently to technology failures and self-induced failures (Collier, Breazeale, & White, 2017). For example, online customers blame

[5] For example, smart POS terminals provide payment mobility and intelligence to process customer habits and reward integration for service providers. For customers, Mwallets provides transaction convenience and rewards integration.

themselves more compared to offline customers in the case of service failures. The attribution theory brings out the impact of the locus of control in service encounters to explain the attribution mechanism. When there is an external locus of control, customers will attribute the failures to others rather than themselves. However, individual customers with an internal locus of control may take responsibility for technology usage and not attribute failures to service providers (Collier et al., 2017). This process can be complicated, given that technology and service providers bring multiple cues in service settings. Also, while a service provider can aim to manipulate the locus of control for customers, customer's experience with both technology and service providers can impact the appraisal of the failures and subsequent attribution.

Literature Gap

The integration of third-party-owned technologies has fundamentally changed consumers' search, purchase, and consumption of products and services. It has also impacted service providers by shifting some accountability and responsibility of customer experience management and creation to technology providers. However, there is not considerable focus on third-party providers' role in co-creating and co-managing the CX in the existing literature, particularly for technology-mediated experiences. Hence, there is a gap in the marketing literature to understand changes in CX with the rising technology-driven and partner-owned touchpoints. In this research, we adopt both views presented by Becker and Jaakkola (2020) and propose to observe technology as a managerial stimulus provided by the technology providers and incorporated into the experience by the focal firm or service provider, and the resultant technology-mediated experiences as a consumption process. Both perspectives provide us with the flexibility to evaluate technology-mediated interactions and consequent evaluation of CX from a customer point of view and their understanding of the service environment. We focus on the mechanism of evaluation and attribution of technology-mediated customer experience by customers among service providers, third-party technology providers, and customers.

Surveys, observations, interviews, and qualitative studies are used extensively to measure CX and related outcomes like satisfaction and feedback. However, with the availability of computing resources and diverse datasets, academicians and firms can now study the phenomenon of CX and NCX much broadly. Precisely, we can combine survey data with user-generated data – customer reviews of technologies, retailers, and chatter on social media platforms (Ordenes et al., 2014). In this research, we present a multi-method approach to define, measure, and manage NCX. Next, we elucidate the concept of Networked Customer Experience and outline its dimensions, drivers, and evaluation and attribution processes.

STUDY 1 - DEFINING NETWORKED CUSTOMER EXPERIENCE

Dimensions, Evaluation, and Attribution

As discussed earlier, we adopt a hybrid perspective on technological integration in service encounters. First, we posit that technologies can act as a stimulus for service providers, similar to price and brand logos (Brakus, Schmitt, & Zarantonello, 2009). In this case, CX can be studied as a response to this stimulus. Second, we acknowledge that technologies can bring together multiple stakeholders during a customer's journey, within or outside the service provider's control, as a part of the service ecosystem (Nam & Kannan, 2020). In this case, CX can be studied as customers' interpretation and evaluation and response towards technology-mediated and multi-party connected or networked interactions. Thus, Networked Customer Experience (NCX) can be explained as a dynamic interplay between a service provider and one or more technology providers to manage technology-mediated interactions for customers, focusing on convenience (Figure 1). Hence, we define *Networked Customer Experience* (NCX_i) as a customer *i's* experience (CX_i), which is,

(a) driven by customer technology or technologies (T)

(b) co-created or co-managed by a network of stakeholders- namely, service provider firm (SP) and one or more technology provider firms (TP_j)

(c) across one or more stages of the customer's journey (k) where technology is used to co-create or co-manage the experiences

(d) at the front-end of the customer journey, i.e., customers can observe the brands of service and technology provider firms

(e) primarily focused on creating convenience across stages for customers during a service encounter

Our definition of NCX is broad and captures service contexts where different technologies are integrated across different touchpoints in a customer journey. For example, in the decision or access stage, SP such as Macy's can add an Instagram shop or Facebook market as a TP, at transaction and benefits stage, it can incorporate Google Pay as a payment and promotion TP, and no technology integration for the support stage. Thus, in a customer journey, there can be many TPs integrated with one SP. Also, if only one TP is integrated at only one stage or NCX dimension, the resultant experience can still be conceptualized and measured as NCX. For example, a customer directly transacts with Macy's and only uses Google Pay to make payments without any benefits. Thus, we postulate that NCX_i is a function of the interaction of the service provider's and technology providers' CX across one or more stages of a customer's journey.

$$NCX_i = \sum_k CX_k \qquad \text{[Eq 1.1]}$$

$$CX_k = \sum_j CX\ (SP, TP_j), \text{ for a given stage k} \qquad \text{[Eq 1.2]}$$

where, for each customer, *i*; *j* is a particular technology provider firm in a technology-mediated interaction with a service provider (SP) at *k* stage(s) in a customer's journey. Thus, CX_k reflects the customer *i* experience with SP and technology provider *j* at a particular stage/touchpoint *k*. NCX_i is the summation of all the networked technology-mediated interactions by the service provider and *j* technology providers for a customer *i* over *k* stages in a journey. For example, a customer can use a mobile payment app (Google Pay-technology provider) at Macy's (service provider) to make payments (k=1) and earn cashback (k=2). Thus, Macy's customer uses technology at two stages of their customer journey. If Google Pay also integrates search capabilities for Macy's products within the app, we can say that a customer can also use the app for the search and decision-making stage (k=3).

[Figure 1. Here]

Comparing NCX with CX and Co-Branding

As we delve deeper into the conceptualization of NCX, we need to establish its difference from other related concepts such as CX and Co-branding. A key characteristic of NCX is the presence of third-party technology across one or more touchpoints of the customer journey with a service provider. Thus, in this study, we limit the scope of NCX within the purview of applications of customer technologies across touchpoints.[6]

While all the conceptualization and perspective of CX are relevant and applicable for understanding CX from customers' or organizations' perspectives, we still need to identify and conceptualize the dimensions for technology-driven multi-stakeholder created CX. The role of technology as a stimulus and its characteristics embedded in customer journey across one or more touchpoints. Hence, we need to merge two or more perspectives of CX and introduce attributes of technology and its impact on service elements such as quality and delivery as central determinants of NCX.

The 'source of technology' is one of the central premises in the concept of NCX. The source of technology, i.e., who provides the technology, directly impacts the evaluation and attribution of technology-mediated interactions. If the technology is provided by the service provider within its online and offline ecosystems exclusively, then NCX boils down to technology-enabled CX. For example, Amazon Pay and Walmart Pay are embedded within the closed ecosystems of Amazon and Walmart. Thus, CX of using these payment methods pertains to technology-related CX for these firms.[7] If a third-party technology provider manages the technology in an open or semi-open ecosystem, then the CX

[6] We discuss the generalizability of the concept of NCX to other contexts such as non-technology settings with two or more service providers co-creating and co-managing the customer experience at the end of this study.
[7] However, both firms are slowly opening their payment ecosystems to third-party service providers, such as small retailers, to generate better customer insights and scale their businesses.

transitions into NCX because customers can observe both technology and service providers in their journey.

For example, using Klarna to purchase a Nike product vs. buying directly from a Nike app, website, or store are two different customer journeys. In Figure 2., one can observe that across touchpoints, k (1 to 5) technology providers may or may not co-create the service experience that impacts the overall CX. The extent of co-created experience depends on the dimensions or touchpoints in which this experience is created, associated evaluation of the experience, and resultant outcomes. However, we consider Klarna as a technology app and not a service provider or retailer. This distinction is more nuanced and outside the scope of this paper. The partnership structure and the scope of services between two parties are important to identify as a technology or service provider. Suppose Klarna takes ownership of the Nike products and handles all the service-related elements within its service ecosystem. In that case, Klarna is the service provider which uses various technology-driven touchpoints. The resultant experience is technology-driven as Klarna does everything for a customer across different customer journey stages.[8]

Similarly, if Nike does all the things for customers via different technology integrated touchpoints, then the result CX is technology-driven CX for Nike. Technology-driven CX becomes a part of the entire CX for the customer. However, in the current context, Klarna integrates various brand offers on its app (personalized to customer tastes and preferences). It sends customers to the service provider's webpage to show how that customer journey progresses. However, the payment is still made via Klarna. Thus, for Nike, its CX is networked with the CX of Klarna for that customer journey.

[Figure 2. Here]

Further, NCX is different from the Co-branding strategy that a firm may employ to increase its scope of the target market, leverage the benefits of another brand name, create more efficient bundles, increase sales, and positively impact its brand value and sales. Ramaswamy and Ozcan (2016) highlighted a

[8] Similarly, platforms such as Amazon or Zalando can be considered as TP if they are just providing platform to SPs in terms of access to target market, leading to NCX. However, if Amazon takes over the ownership from the SPs, then it becomes the SP for the customer leading to CX, not NCX.

similar perspective as brand value co-creation for digitalized platforms, where two or more enterprises create a nexus of co-creation platforms of engagement. The focus is on brand experience and brand capability ecosystems where value and outcomes may differ for stakeholders. However, in NCX, technology providers play a critical role in managing services for customers and service providers. As service providers integrate third-party technology, the focus is on the convenience that technology can bring for the customers, with a secondary emphasis on rewards and benefits and efficiency for themselves. As more customers and service providers use their technology, the network externalities help them reach more service providers and customers. Also, brand value co-creation is a relatively narrower perspective. NCX covers the role of technology characteristics and what functions it can perform throughout a customer's journey, which is a broader way to look at CX. Next, we discuss the tole of technology as a stimulus and how it can impact CX from customers' and service providers' perspectives.

Application of term 'Networked'

The term *networked* implies that the service provider firm has created a service-technology network with one or more technology provider firms to create seamless and convenient customer experiences across various service settings. However, in our context, it does not imply or infer network orchestration. Network orchestration is the process of assembling and managing an inter-organizational network to achieve a collective goal, in which the other network members accept the role.[9] In literature related to social media, the term 'network' has also been used to represent connections among users and the strength of their relationships (Kane, Alavi, Labianca, & Borgatti, 2014). However, we use this term to represent a group or system of interconnected stakeholders and technologies in our context.

From the customer journey's point of view, we are implying that networked customer experience can arise because of one or more of the following conditions: customer coordination, service coordination, and firm coordination. Customers choose the technologies they want to employ at one or more

[9] For a detailed introduction on this topic readers can refer to study by Perks, Kowalkowski, Witell, and Gustafsson (2017).

touchpoints in the customer journey in customer coordination. Hence, they coordinate their network, which co-creates value for them. For example, a customer can order food delivery from Doordash, where they can pay via Google Pay, food is prepared by the restaurant (SP), delivered by Doordash, and any support-related activities are also handled Doordash. Let us assume SP has also integrated a third-party augmented reality TP to help customers decide what food to order. However, all the technology is primarily adopted and managed by customers, and they coordinate their own actions. In the previous example of Klarna, consider adding other technologies across different touchpoints. A customer can buy from Amazon via Klarna, and Amazon is a TP for other small and large manufacturers and service providers. Hence, there are two TPs and one SP who create NCX. This type of coordination can be explored as service coordination. Essentially, a partner coordinates the various service elements for customers across their journey. The last one is firm coordinated networks. The focal firm or SP in our research explores different technologies and integrates various technologies (developed in-house or third-party) to manage a customer's journey. A good example can be Amazon and Walmart who add more technologies to create better customer experiences across different touchpoints.

From our perspective, we are focusing on networks that are either customer coordinated or service coordinated and bring opportunities for third-party technology providers to co-create and co-manage customer experiences. Thus, we differ from the traditional understanding of networks and focus more on the technology providers firms that can create a network with customers and service providers across one or more stages of the customer journey. Next, we focus on technology characteristics to understand the impact of the stimulus, service provider characteristics, and technology provider characteristics in the process of NCX evaluation and attribution.

Technology as a Stimulus: Benefits and Source

The characteristics of a stimulus can impact a customer's initial response and their evaluation of experiences Becker and Jaakkola (2020). For example, in AR apps, the customer responses are oriented more towards the sensory and physical components. In contrast, mobile payment apps are oriented more toward cognitive responses of making payments and managing rewards. Irrespective of the type of response to stimuli, convenience is at the core of all technology-mediated interactions. A part of this convenience encompasses greater access and control that customers can get during service encounters (Meuter, Ostrom, Roundtree, & Bitner, 2000).[10] However, the customer usage of technologies in service encounters also depends on the salience of usage benefits. It reflects what and how much benefits customers can enjoy by adopting and using technologies in service encounters. Apart from the tangible benefits such as coupons, cashback, rewards, and savings, there can be intangible benefits of technologies. For example, new customer technologies such as AR, VR, intelligent assistants, and chatbots (also known as smart technologies) provide much more than just convenience. Such technologies are intelligent and interactive[11] and enhance customer outcomes via personalized offers and experiences by learning from consumer behavior and context-specific information (Yim et al., 2017). Thus, technologies can vary in terms of their level of convenience and benefits to customers and the service provider.

For service providers, technologies help decide their strategic position between standardization vs. personalization, replace or augment service personnel, and facilitate thinking or feeling (Huang & Rust, 2017; Rust & Huang, 2014). A key consideration in deciding and aligning towards the chosen strategic position is the source of technology. Technology acts as a managerial stimulus and connects multiple stakeholders. Therefore, service providers must have complete or partial control over the stimulus, controlling customer data and leveraging insights for personalized marketing strategies (Pancras & Sudhir, 2007). This control gets diluted with the infusion of third-party technologies and gives rise to partner-owned touchpoints in service encounters. Next, we focus on the roles of service providers, technology providers, and customers in the co-creation and management of NCX.

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[10] For example, with mobile commerce applications, customers can search for products at their own pace. Customer technologies, such as mobile apps, are becoming part of daily lives across different functions. For example, mobile payment apps such as Paytm in India provide customers with banking services apart from the capability to pay for products across retailers. The Paytm app also has a dedicated m-commerce platform for customers to redeem reward points.

[11] Smart technologies can possess varying degree of artificial intelligence. That is smart technologies have learning abilities, temporal continuity, and proactivity in changing environment (Franklin and Grasser, 1996). The technologies inhabit digital environment, can assimilate vast amount of information, and carry out tasks with greater speed, efficiency, and accuracy (Kumar et al., 2016).

Stakeholders in Networked Customer Experience

Service Provider (SP). A service provider, such as a retailer, is a central actor who fulfills the customer demands for products or services via different digital and physical channels. The primary role of SPs is to ensure that customers can meet their goals efficiently and effectively. Usually, SPs strategize for various marketing activities such as prices, supply-chain and logistics, communications, payment and transactions, after-sale services. With technological infusion to marketing activities, SPs need to integrate various customer technologies across touchpoints in a service encounter. Thus, in addition, technologies are important for SPs. Few large SPs, such as Walmart, leverage their human and technical capabilities, resources, and industry experience to develop in-house technologies. The aim is to integrate the value chain activities and create data-driven competitive advantages. However, most SPs adopt third-party technologies to create better customer experiences, bringing TPs into the customer journeys and experiences. Hence, both SP and TP need to align their CXM strategies to provide seamless experiences to customers.

Technology Provider (TP). In technology-mediated interactions, value co-creation depends on the continuous interactions between customers, technology providers, and service providers. This phenomenon has been studied as digitalized interactive platforms (DIP) by Ramaswamy and Ozcan (2018a). The role of technology providers is to enhance the value of the offering for all the stakeholders (customers and service providers) via DIPs. Technology providers collect information and provide insights to other stakeholders. These insights can be further used to create personalized and strategic marketing strategies for both customers and firms (Huang & Rust, 2017). Many technology firms, also known as platforms (incumbents and startups), provide technologies to service providers and customers. Unlike SPs, TPs usually observe customers across multiple service encounters with multiple SPs and collect data. It helps them to understand customer needs better and create a personalized offering.

Customers. The role of customers in technology-mediated interactions is to co-create the experiences with SP and TP. The experience of co-creation and its outcomes is a function of customer goals.

Customers adopt technologies to fulfill either utilitarian or hedonic goals (Botti & McGill, 2011; Bridges & Florsheim, 2008).[12] A utilitarian goal will encompass the perception of time and effort saving if a customer decides to adopt and use the technology for any activity during a purchase journey. A hedonic goal would lead to a perception of enhanced core benefits of service encounters via technology-mediated fun or sensorial benefits. For example, in AR apps, the fun and excitement of changing reality add value to the overall purchase journey. Apart from goals, customers vary in their affluence towards technology adoption and usage, impacting their interaction with SPs and TPs.[13] Next, we deliberate on the dimension of NCX.

Dimensions of Networked Customer Experience

Technology-infused service encounters and service designs are more oriented towards the experience-oriented nature of service and service delivery (Bitner et al., 2000). At the core of service delivery is that technology creates or increases the value proposition for users. To further analyze this, we draw from the concept of 'Service Convenience' presented by Berry et al. (2002), which is further derived from the economic utility theory to conceptualize the key dimensions of NCX (Brown, 1989). This concept is related to the consumer's time and effort perceptions of buying or using a service which is explained as non-monetary costs a consumer incur, willingly or unwillingly, during a service encounter. There are five dimensions in the service convenience - decision, access, transaction, benefits, and post-benefit (these dimensions can be mapped onto a customer journey as different stages as well). Authors have deliberated on how service convenience is linked to above mentioned five dimensions across various stages of a customer journey. We adapt these dimensions to understand how technology creates convenience-related benefits for users across multiple touchpoints in technology-driven service settings (see Figure 2). While

[12] In some cases, the adoption of technology might be necessary for the customer to consume the service provider's offering. For example, an online retailer may only accept PayPal payments. In such cases, the adoption of technology can become the part of utilitarian goal along with the other utilitarian and hedonic benefits of a technology.

[13] The phenomenon of customer co-creation is widely researched in the context of new product development (Heidenreich et al., 2015; O'Hern & Rindfleisch, 2017). From the customer experience point of view, there is limited literature that focus on experience co-creation (Jaakkola et al., 2015; Payne, Storbacka, & Frow, 2008), and few with a focus on technology (Åkesson, Edvardsson, & Tronvoll, 2014; Ramaswamy & Ozcan, 2018b). In this research, we do not primarily focus on the customer-related drivers of co-creation of experience. However, we use the reasoning behind customer's adoption of technologies to motivate and understand the drivers of NCX.

these five dimensions cover any technology-service settings, there can be distinct sub-components depending on the service setting and technology type (Grewal et al., 2020).

1. Decision- In this component, the customer's focus is on how easy it is to use technology to decide and start a networked service encounter and enable higher control over the purchase journey. In other words, how easily customers can manage their performance during the co-creation of their technology-driven service experience if they decide to use the technology. Asking customers to perform some tasks using self-serving technologies (SSTs) can be complicated because they may not perceive technology as worthy. For example, if a customer decides to use self-checkout at a retail store, she may find that using this technology can create a cognitive burden to perform the task correctly. This perception can further solidify if that customer sees long waiting queues and observe other customers struggling in the process (Berry et al., 2002; Colwell, Aung, Kanetkar, & Holden, 2008). It can result in decision inconvenience and bad experiences during a service encounter. As many consumers decide to use technologies at one or more touchpoints in anticipation of convenience related to journey and rewards, the decision is an important technology-integrated touchpoint for service providers. However, this touchpoint is challenging to manage and assess for its contribution. For example, a customer's decision to use the Klarna app[14] to purchase a Nike product compared to the Nike website or store may depend on the technologies' ability to provide transaction and payment-related convenience and benefits. On the contrary, a customer may like to purchase from Klarna's ecosystem to integrate its purchases from various services. Thus, a customer's affinity to using a technology with a service provider may or may not be observed. However, it can impact the service provider NCX score due to integrated technology-driven CX.
2. Access- The convenience in this stage focuses on the customers' actions required to initiate service delivery. This type of convenience positively pushes customers to self-perform certain activities as it

[14] Bell, A. (2019). "Klarna is a financial technology company that aims to change the way consumers pay for products online. It offers a "buy now, pay later" service that allows online shoppers to purchase from major retailers without paying upfront. Consumers can pay for their purchases in four interest-fee installments charged every two weeks, or pay the entire amount within 30 days." Article retrieved on June 4, 2021 from https://www.investopedia.com/articles/personal-finance/121316/how-klarna-lets-you-pay-later-no-interest.asp.

reduces dependence on service providers. Technologies can further reduce the reliance on service providers and put more accountability on technology providers to optimize customer actions and decisions and provide a better experience. For example, the speed and ease of using Mwallet at checkouts can impact customers' payment habits in the long run. Moreover, Mwallet providers need to ensure that technology provides easy access and facilitates the initiation of the customer journey for the user. The user experience with the technology itself plays a critical role in creating a service experience for this touchpoint. In the case of mobile apps and websites, the user interface (such as navigation panel, color scheme, app version), technical requirements, and compatibility with other technologies are a few of the key drivers of Access convenience. This touchpoint acts as a filter for customers to assess the ease of use and usability of the technology as a whole.

3. Transaction- The convenience focus at this stage is on the actual payment and transaction phase. Payment is the least rewarding act for customers and contributes to the high cart abandonment rate. New payment technologies aim to reduce inconvenience by consolidating rewards and payments in one mobile app across different retail channels and partners. Similarly, self-checkout systems provide higher convenience by speedy checkouts. However, the efficiency of these technologies can vary, and customers may not perceive higher convenience associated with transactions. Customer inertia for existing payment habits is the main driver behind their goal development and achievement for new technologies and NCX score. Also, speedy and seamless transactions and payment might be the key reason why some customers stay with a service provider. The fintech space becomes more challenging as banks, financial institutions, and neo-banks provide rewards and incentives to customers for using their cards, websites, or payment apps. Also, service providers embrace these fintech solutions to remove frictions from their payment processes and provide higher convenience to customers.
4. Benefit- The benefit convenience focuses on the core and peripheral benefits of using technology during a service encounter. In the case of technology-mediated service encounters, apart from the greater convenience (time and effort), there can be add-on tangible benefits in the form of loyalty

rewards. New sensory experiences can lead to fun and excitement as benefits, as in AR or VR apps (Grewal et al., 2020). At this stage, customers try to maximize their hedonic value in service encounters integrated with third-party technologies. For apps such as Klarna, customers get discounts or more affordable payment arrangements with specific service providers. Also, being a member, they are entitled to cashback and rewards with Klarna. Many retail tech and fintech firms are crafting solutions to make customers adopt new technologies and create ecosystem-level benefits. Also, service providers are experimenting with creating additional value-driven rewards for themselves and their customers. This touchpoint is very sensitive to customer evaluation and attribution of the NCX. Customers are goal-driven, and rewards are one of the key goals associated with technology usage. If those goals are not met, the inability to get the rewards might overturn the seamless experience and convenience associated with the decision, access, and transaction.

5. Support- This component focuses on the customers' need for support related to after-purchase services, benefits, repair, maintenance, exchange, and return of products. It is similar to the 'Post-Benefit' dimension of the Service Convenience scale, which focuses on time and effort expenditure on reinitiating contact with a service provider after the benefits stage. However, the critical difference is that the initiation may be moderated via a technology provider. In technology-mediated service encounters, a customer can use technology to initiate communication and eventually enter a conversation. It may provide faster access and short post-service time for users and service providers, thus creating greater support convenience. Service providers can focus on service failures and recovery, which can be subsumed into the previous four components of NCX. However, the role of technology providers can be prominent if the transaction is majorly mediated via technology, and the service provider's role is limited to fulfillment services. Consider a situation where a customer bought a Nike shoe via Klarna, and she needs to return it. Since the transaction was financed via the Klarna app and shipped via Nike, the customer does not clearly understand how to initiate the return. She goes to the Nike store and tries to return the shoe. While the Nike employee is willing to take back the shoe and issue a return, he cannot find the credit card through which the payment was made. The

customer called Klarna customer care and figures that the payment was completed via a temporary virtual card issued in her name. She will have to initiate the return process via Klarna, and it can take some time. Ultimately, she decided to make a return in the Nike Balance card, although she did not want to buy another Nike shoe. Such support-related experiences bring down the NCX by lowering the overall convenience of the technology during service encounters.

As we use the concept of service convenience in the context of technology-mediated interactions, not all the components may apply in every service encounter. The applicability of each component will depend on the characteristics of technology and the stage of the customer journey. For example, for Mwallet, access, transaction, and benefit convenience make the most sense. However, for AR apps, decision and access convenience may matter the most. Also, the characteristic of experience associated with each touchpoint will vary with industry, technology, and the relationship between service and technology providers. Our focus is to throw light on the role of actors in a networked environment and the need to conceptualize and measure co-created and co-managed customer experiences in technology-mediated interactions by highlighting the roles of service providers and technology providers.

Drivers of Customer Evaluation, Attribution, and Outcomes of NCX

Evaluation. As per appraisal theories, events such as service encounters are appraised with respect to a personal goal (Roseman, 1991). Thus, goal relevance and goal congruence can result in a stronger emotional evaluation and interpretation of subjective experiences (Lazarus, 1991). In this regard, we believe that the role of affect is central in the evaluation process. [15] In cognitive processing and evaluation, we posit that customers would consciously identify the role of technology as a stimulus and the accountability of the technology providers in co-creating and co-managing the networked experiences (Stephens & Gwinner, 1998).[16] Thus, the impact of the service provider's activities would not take a

[15] Affect is a broad category that consists of three components- moods, emotions, and attitudes (Bagozzi et al., 1999). Moods are non-intentional, while attitudes are evaluative judgments. Usually, emotions have an object or referent. In the case of NCX, the service provider takes the role of a referent.

[16] For the evaluation, it is necessary for the customer to be aware and recognize the technology providers role and brand in the service encounter.

central role in the evaluation process. In affective processing and evaluation, a customer would actively identify the role of the service provider because of the environmental embedding and proximity to experience creation and management (Bustamante & Rubio, 2017; Rose, Clark, Samouel, & Hair, 2012).[17] We do not assert that the customer evaluation process in NCX as cognitive or affective is mutually exclusive. Instead, each customer would have components of both these evaluations. However, we assert that the degree to which one type of evaluation would take precedence over other would depend on three factors – the level of involvement in the service encounter, the level of involvement with the technology, and learning from previous experiences (Puccinelli et al., 2009).

Involvement in a service encounter pertains to the level of resources (monetary and non-monetary) a customer is willing to expend to achieve their goals (Mattila, 1999). High involvement in service encounters would make customers take a more calculated and rational approach to the experience evaluation than the low-involvement service encounters (Solomon, Surprenant, Czepiel, & Gutman, 1985). In such situations, a customer would also use brand-related cues to make informed decisions. The level of involvement with the technology pertains to the resources (time and effort) a customer is willing to spend on leveraging technologies to get tangible and intangible benefits such as convenience, discounts, or fun (Schatsky et al., 2015). For example, customers are increasingly using low-involvement digital technologies, such as mobile payment applications, to make decisions or interact with service providers. Thus, low involvement technologies would help in reducing cognitive load for activities during a purchase journey. Learning from their previous technology-mediated experiences would help customers identify the resources required to leverage technologies during service encounters (Balaji & Roy, 2017). Also, it will provide an anchor into the nature of the evaluation process needed in different situations. For example, if the technology has worked well in the past with service providers, a customer may have learned not to put much onus on the technology providers. It is possible because technology has worked

[17] Here readers should note that we are focusing on the evaluation process itself, which can only be observed in the customer behavior and outcomes. So, if a customer conducts the cognitive evaluation, she/he would assign substantial weightage to the role of technology and technology provider in the creation and management of NCX. However, in emotional evaluation, she/he would assign more weight to the experience with the service provider and its store in the creation and management of NCX. This evaluation process would lead to differential scores on individual CX measures and other outcomes such as satisfaction and repurchase intentions.

for them seamlessly, and there were no issues with the technology usage for customers. Hence, the evaluation process will be driven by environmental elements such as service providers' store layout or mobile app interface. However, suppose a customer had to face adverse outcomes from technology-mediated interactions. In that case, they will have to invest cognitive resources to assess the contribution of technology during the service encounters.

Attribution. The attribution mechanism is primarily defined by the environmental embedding of the customer's purchase journey and past experiences with technology and other stakeholders. As per the situated cognition perspective, customers process information related to service encounters within the embedded environment rather than abstract activity (Hilken et al., 2017). A successful service encounter would not create much of a difference in the attribution process as customers do not spend many resources assessing the roles of stakeholders and technologies. However, we can expect things to change drastically during technology-service failures. A failure of any kind can negatively impact customer behavior and firm performance if not managed at the right time (Hess Jr, Ganesan, & Klein, 2003). For example, a personnel service failure can lead to customer dissatisfaction, impact customer engagement negatively, and sometimes leads to customer attrition (Dabholkar & Spaid, 2012). An important consideration during the technology-mediated interactions in offline and online contexts is how customers process the failures.

In the case of SSTs such as mobile apps, customers choose to control and co-create their service encounters with the help of technologies, retailers, and technology providers. However, this can complicate the processing of technology failures if customers do not have the proper attribution mechanism. In some cases, the research has shown that customers take the onus of failures because they self-select themselves into using the technology (Dabholkar & Spaid, 2012; Yen, Gwinner, & Su, 2004). In some situations, customers may attribute failures to the service provider irrespective of the source of technology failure. In this case, the immediate environment, the service provider's store (digital or physical), is used as a cue to make any attributions. Also, if the technology itself has worked well in the past for customers, this attribution would be more pronounced and create a higher negative impact

(Meuter et al., 2000). According to the cue utilization theory, customers use brand names to evaluate the quality of products and create attribution mechanisms (Rao & Monroe, 1988). Thus, the brand equity of the service provider and technology provider can impact the attribution mechanism.

Outcomes. The impact of service encounter failures on customer usage of technology and other customer metrics for firms would vary in intensity and outcome. For example, if the benefits salience of technology is high, and customers cannot use those benefits, it might lead to technology abandonment, cart abandonment, or service provider abandonment. Thus, apart from co-creating value during service encounters, both technology providers and service providers need to manage failures tactfully to avoid adverse outcomes for all the stakeholders. This fuels the need to understand the resultant experience as NCX and manage NCX with co-created strategies and efficient use of technologies.

An Approach towards Development of NCX Measure

As defined earlier, NCX_i is the summation of all the networked technology-mediated interactions by the service provider and *j* technology providers for a customer *i* over *k* stages in a journey. However, the relevance and importance of each stage defined as five dimensions of NCX would vary across service contexts. For example, for 'Buy Now Pay Later' Apps such as Klarna or Affirm, the decision to enter a purchase journey with a particular service provider may depend on the benefits provided by the technology provider. However, technology may focus only on one or more touchpoints such as access, transaction, and others for some service contexts. As described in this study, the touchpoints are action-oriented, where a customer engages with the service provider aided by technology. Since we are dealing with subjective actions conceptualized as touchpoints, we need to approach the measurement of NCX from a multi-method and leverage different types of data across a customer's journey. We propose a metric with three dynamic components – dimension extraction, dimension importance, and weighted NCX score. Next, we explain these three dimensions:

1. Measuring NCX – Firms should first focus on the relevant items to their service context and capture the combined effects and outcomes for them and their technology providers. As we adapt the concept

of service convenience to NCX, the first step can be to look at how convenience can be captured across the dimension of service where technology is integrated. Also, a service provider can specifically ask its customers to rate the experience of using technology within its service setting – similar to current satisfaction and customer feedback surveys.

2. Dimension Extraction – This component focuses on identifying the NCX dimensions where a technology provider actively co-creates or co-manages the experience with the service provider. This exercise should be based on both the customer journey and the contractual relationship between the service provider and technology provider. Notably, a significant focus is on the customer journey – what customers feel and think about their experience of using technology by a technology provider *j* during their encounter with the service provider. Given the advancement in data analytics and broader access to customer data, we can observe the customer focus on NCX dimensions. User-generated content (data) in the form of customer ratings and reviews for a technology provider on various social media and third-party platforms and their own complaints and support teams' communications with customers to identify the incidences of technology-driven customer interactions. Also, this would contain the market information as opposed to just one customer evaluation. The market information can adjust the NCX score by discounting or appraising the role of technology provider and technology-driven CX.
3. Dimension Assessment – The user-generated content is an excellent source for exploratory analysis of a given technology and its usefulness and convenience. However, the extent to which technology impacts a customer's overall experience would differ across technology characteristics (type of technology, level of interactivity and intelligence), customer characteristics (orientation towards technology, previous experience), and service context (online, offline). Hence, a good deal of effort needs to be put in dynamically assessing the relative importance of various technology-driven touchpoints. A possible approach is to assess the importance of touchpoints econometrically. Both service providers and technology providers can undertake this activity at their end. However, technology providers can better view a customer's activities with multiple service providers than a

service provider. For example, Groupon knows I purchased coupons for what kind of service providers, for how much, how frequent, and how I redeemed the benefits, how many returns were made, and why, among other things). By leveraging social media and publicly available information for similar technologies, service providers can calculate the weights to understand better the importance of touchpoints in creating a networked customer experience score. Also, they can build a robust econometric model at the customer level by retrieving their customer data from the technology providers across different touchpoints in a customer journey.

The final step in understanding the NCX is to create a weighted NCX score that identifies the role of the technology provider in a service encounter. The weights or the coefficients from the dimension assessment can provide relative importance for different touchpoints or NCX dimensions. Existing customer experience and service convenience scales can be adapted to the service context to create a repository of items to measure technology-driven CX for service providers and technology providers. A service provider can identify the pain points for customers and better manage the experience based on this score. Next, in Study 2, we explore the approach mentioned above.

STUDY 2 – NETWORKED CUSTOMER EXPERIENCE AND CUSTOMER EVALUATION OF MOBILE PAYMENT APPLICATION (APP) EXPERIENCE

Research Setting

We anchor our study in a two-dimensional context. First, we use mobile payment apps (such as Mwallet) as customer technology. Traditionally, digital payments via debit and credit cards have been used extensively in the purchase phase of a customer journey. Mwallet provides a new and integrated way of making payments, redeeming rewards, and storing coupons (Kumar, Nim, & Sharma, 2017). The level of involvement with Mwallet is usually low, with a varying level of interactivity and intelligence. Mwallet services can be provided by a retailer (SP) such as Walmart Pay or a third-party such as Apple Pay (TP). Lately, there have been many activities in the fintech industry from different stakeholders for payment options. Banks and financial institutions are actively trying to fight off competition from service and TPs for customer financial technologies such as Mwallet (Capgemini & BNPParibas, 2017).

Second, we anchor our service context in retail settings. With the rise of omnichannel retail, there is increasing integration of technologies across different touchpoints in a customer journey. Specifically, there is an increase in technology-driven behavioral activities such as buy online and pickup in-store (BOPIS) and NFC or QR-based contactless payments. Besides, during the COVID-19 pandemic, contactless payments have boosted both customer and retailer adoption of Mwallet across the world.[18] This makes the research setting exciting and relevant for both academicians and practitioners.

Initial Exploratory Evidence

The research has shown that in the case of self-service technologies (SSTs), there can be substantial differences between managers' and customers' perspectives (Kimes & Collier, 2015). We explore any substantial differences in the industry evaluation and customer evaluation of Mwallet as a customer technology, embedded across retail stores, both offline and online. The underlying idea is to find model-free evidence that highlights any disassociation between the viewpoints of customers and managers with respect to CX. There are two ways to understand the Mwallet experience evaluation by customers. First, select a representative sample of users (multiple Mwallet applications) and conduct a survey-based study to understand the aggregate evaluation and the associated features of evaluation. However, this is time-consuming and poses challenges in terms of sampling. It is challenging to collect a representative sample for multiple Mwallet applications spread across different parts of the world. The second way is the use the available aggregate measures from both industry and customers. This information is available in mobile application ratings across Google, Apple, and other operating system platforms from customers. These user ratings are a self-reported measure for experience evaluation and outcomes for customers. The literature has shown that online ratings and reviews are usually biased as they represent the most extreme

[18] Xiao, Y. and Chorzempa, M. (2020) Article retrieved on June 12th , 2020 from https://www.weforum.org/agenda/2020/05/digital-payments-cash-and-covid-19-pandemics/.

views (Schoenmueller, Netzer, & Stahl, 2020). Therefore, we use these ratings only as an indicator or overall evaluation of experience rather than an absolute measure. Similarly, the industry evaluation of customer technologies varies across evaluators. For example, we can find ratings and reviews by opinion leaders (usually industry analysts and technology experts). Sometimes, industry aggregators also publish their white papers, reports, and tracker studies that consolidate multiple information to provide such aggregate measures.

We collect a small dataset on 25 leading Mwallets across the world. A few of these wallets are Paytm, Venmo, Apple Pay, CashApp, among others.[19] For industry evaluation, we use the information provided by Pymnts.com. They provide scores and ranking on four components of mobile payment apps- loyalty, features, channels, and authentication.[20] We collect customer ratings across Google Play Store and Apple Store and information such as country availability, payment channels (online, in-store), and other aspects from multiple sources. The details for the dataset are provided in Table 2.

[Table 2. here]

Simple correlation analysis and multiple regression analysis show that aggregate customer ratings and industry evaluation ratings do not have a strong relationship. The average customer ratings (across Google Play Store and Apple Store) have a low correlation with any of the four components or the overall score provided by pymnts.com (between 0.06 and 0.18, see Table 2). Similarly, regressing four components or the overall score provided by pymnts.com on average customer ratings yield multiple R^2 = 0.05. Although the sample size is small and may not be representative of the population, this analysis indicates that there may be a discrepancy between industry evaluation and customer evaluation of Mwallet experience as technology. To understand this discrepancy in detail, we further examine the CX, focusing on the evaluation process in two parts – NCX Score and Dimensions Extraction.

[19] For some wallets such as Apple Pay and Amazon Pay, there are no separate mobile applications. Amazon Pay is embedded within Amazon digital infrastructure. Similarly, Apple Pay is embedded within Apple products (iPhone, iPad). To get aggerate user rating for these applications/embedded applications we used other third-party opinion and review websites)

[20] Data retrieved on March 17th, 2020 from https://www.pymnts.com/mobile-wallet-apps/

Study 2a – Measuring Networked Customer Experience for Service Encounters with Mobile Payments

Key Drivers of Networked Customer Experience and Hypotheses

Based on our previous discussion, there can be multiple drivers of NCX stemming from technology characteristics and benefits, service environment, and stakeholders' characteristics. This research focuses on three critical drivers of NCX evaluation and attribution based on the attribution theories, appraisal theories, cue-utilization theory, and situated cognition perspective.

First, we believe that the key distinction in the evaluation and attribution of NCX score from CX itself comes from the outcome of the application of technology in the service encounter. For example, if a customer cannot use Mwallet successfully to purchase a product, at that point, they would decide the onus of the failure.[21] Most of the customers would not enter the evaluation process to assess the contribution of SP and TP when everything goes well. However, a technology-service failure would activate a node in the evaluation process to distinguish between the role of SP and TP in the experience evaluation. The evaluation of experiences pushes customers to actively and cognitively assess their environment and embedded stimuli (Hilken et al., 2017). In the case of no failure, customers will not need to identify and evaluate SP's and TP's role in the experience. Identifying and appraising the role of TP and SP together in that environment would help customers find or create experience evaluation anchors that would lead to different scores for SP and TP compared to the standalone CX scores. Hence, we hypothesize:

H1: A technology-service failure would activate a differential evaluation and attribution of NCX.

Second, the *salience of use benefits* (technology attributes and benefits) impacts when customers use technologies to fulfill any kind of goal. For example, Mwallets provide cashback and discounts, meaning that a customer can get additional benefit-related convenience along with transaction convenience by using Mwallet. A high (low) salience would give a higher (lower) push towards usage and goal creation in

[21] Not being able to use a technology can happen for multiple reasons. For example, customers may find it challenging to operate or use a technology, there can be a system failure at the TPs end, or there can be integration problem at SPs end. In our context, we are focused on problems at TP or SP system.

technology-mediated interactions. Thus, if a customer is aware that discount or cashback is substantially high, the resultant negative evaluation would also be stronger when there is any kind of technology-service failure. Using the goal congruence theory (Bagozzi et al., 1999; Coote, Price, & Ackfeldt, 2004), we know that any goal incongruence may lead to a negative evaluation of technology-mediated interactions in service encounters. Conversely, if use-benefits salience is low, a customer might not create concrete technology-related goals and have fewer expectations from technology integration in a service encounter. Thus, they will spend less emotional and cognitive resources on the evaluation process. Hence, we hypothesize:

H2: A higher (lower) use-salience of benefits of technology would lead to a higher (lower) NCX score:

a) if the is no technology-service failure

b) lower (higher) NCX score if there is technology-service failure

According to appraisal theories, customers would compare their actual state with the desired state with respect to goal relevance and congruence (Johnson & Stewart, 2005). To make sense of their technology-mediated interactions and evaluations, customers would investigate the locus of control among all the stakeholders, namely SP and TP. In terms of attribution, in low benefit salience conditions (no cashback or discount), customers may be indifferent or positive towards the role of SPs as they do not expect any benefits from the application of technology. However, in such cases, customers may shield SPs from the negative outcomes of technology-service failures. For example, inexperienced customers or ones who had similar failure experiences in the past would evaluate SP more positively related to TP as they would take a cue from their immediate service environment to evaluate and attribute NCX. In the immediate environment, failure of technology would stand out while SP's service environment would be assessed more positively than the TP. Also, in high benefit salience conditions, customers are mindful of additional benefits that TP brings to the service encounter and would more likely attribute more to TP. Hence, we hypothesize:

H3: A low (high) salience of use benefits of technology would lead to:

a) higher NCX evaluation for the service provider if there is technology-service failure

b) overall a lower (higher) attribution score for the technology provider

Third, we posit that the *brand value of SP would also impact the evaluation and attribution of NCX.* According to the cue utilization theory, customers use brand names to evaluate the quality of products and create attribution mechanisms (Rao & Monroe, 1988). A higher brand value generates higher trust in the brand and quality of products and services. For example, a high (low) trust in the brand of the source of technology can lead to a higher (lower) evaluation of NCX for TP. Similar arguments can be made for SPs. Hence, we hypothesize,

H4: A low (high) brand value of technology and service providers would lead to:

a) higher NCX evaluation for both service provider and technology providers if there is no technology-service failure.

In the case of failure, high trust in the TP brand can shield the firm from negative evaluations and attributions. Thus, customers may focus more on the SP's environment, capabilities, and management strategies in the case of failures. Conversely, the brand value of SP can shield them from the lower NCX evaluation and attribution when a technology-service failure occurs. This effect may be further impacted by how many benefits are provided to the customer. Hence, we do not hypothesize for the direction and attribution of NCX evaluation with respect to the brand value of service and technology providers.

Next, we adapt and test the applicability of Service Convenience to measure the NCX using a survey. Then, we use the tested scale in a laboratory experiment to explore the drivers of NCX and attribution, as discussed.

Adapting Service Convenience Scale to Measure NCX

We primarily adapted the SERVCON scale developed by Seiders, Voss, Godfrey, and Grewal (2007) and Colwell et al. (2008) to measure NCX across touchpoints – decision, access, transaction, benefits, and support. Both these scales have identified a list of 17 items in the context of retailing and personal internet and telephone services. We pooled the list of items to generate 22 items that are valid in the context of co-created and co-managed service encounters. We also theoretically argued with two independent researchers to explore the context-scale-item combinations along with solid empirical support. Consequentially, based on the theoretical support and reliability analysis (to measure each item's contribution towards a dimension), we dropped five items. We recruited participants from CloudResearch Consumer Panel (formerly known as MTurk Prime Panels) to validate the scale.

We asked respondents to recall a service encounter during the scale testing where they used Mwallet to make a purchase. We asked them to identify the TP and SP for their encounter. During the survey, the respondents first shared their perception of SP and then TP. After each dimension, they were also asked to allocate 100 points on a constant-sum scale to both SP and TP (based on the contribution of their experience on that dimension). To provide an anchor, we briefly explained the meaning of dimensions to respondents. Also, we performed CFA for the overall satisfaction scale Colwell et al. (2008), personal innovativeness scale (Agarwal & Prasad, 1998), and technology involvement scale (Seiders et al., 2007), which is later used as a dependent variable and observed heterogeneity controls in the experiments.

Participant Recruitment

We recruited participants on CloudResearch Panels for remuneration to test our adapted service convenience scale to measure NCX. We targeted to recruit approximately 100 respondents to test the adapted NCX scale. In total, 715 respondents showed interest in our survey, 370 gave us consent and cleared eligibility criteria (18 years and above, Mwallet user in past three months). However, the professional survey takers are known to have shown multiple biases, from acquiescence bias and straight-lining to provide inaccurate data. Therefore, to delineate the good quality data, we further filtered the data on three quality checks – reverse coded survey items, attention check questions, and qualitative examination of open-ended questions (See Appendix 1A). This resulted in a final sample size of 95 respondents.

Results

[Table 3. Here]

The final list of items, along with the results from CFA, is presented in Table 3. CFI_{SP} = 0.988, CFI_{TP} = 0.987, $SRMR_{SP}$ = 0.053 and $SRMR_{TP}$ = 0.062 suggests an overall good fit for adapting SERVCON scale to NCX context. For all dimensions, Cronbach's $\propto$ values (for ordered ordinal data) range between 0.901 to 0.976, indicating high reliability and internal consistency. The factor loading of all the items is above 0.81. Also, the average variance extracted (AVE) > 0.74 for all the factors, indicating high convergent validity. We see similar results for overall satisfaction. However, personal innovativeness and technology involvement scales, together, do not perform well on RMSEA and SRMR, and values are close to 0.10. All other model fit indices are under acceptable ranges. We decided not to combine these two scales to account for unobserved heterogeneity and use them separately.

Laboratory Experiment Design and Procedure

In this part, we explore the impact of drivers of NCX (as identified in Study 1) and advance towards building a composite NCX score for technology-driven CX. We aim to highlight how mobile payment apps can create a networked CX for SPs and TPs by identifying the unique dimensions and creating a weighted NCX score. This study uses a 2 (Brand value of SP: high, low) × 2 (Brand value of TP: high, low) × 2 (Salience of Use Benefits: high, low) × 2 (Technology-Service Failure: Yes, No) between-subjects design. This type of experimental design is known as symmetrical factorial design (2^3 factorial design), where each factor has the same number of levels (Street & Burgess, 2007, p. 24). Thus, we have a total of 8 manipulations or treatment conditions.

In this study, we do not manipulate the source of technology as one of the drivers. We only focus on mobile payment apps provided by a third-party TP, such as Google Pay, Venmo, and Apple Pay. On the other hand, apps such as Amazon Pay and Walmart Pay are retailer apps that are embedded in retailers' ecosystems. As discussed earlier, if the source of technology is the SP itself, then the resultant CX is the technology-driven CX of the SP rather than it being an NCX. Also, we do not manipulate the TP's brand value as there is unobserved heterogeneity in a customer's decision to adopt a particular brand of Mwallet. For example, Apple Pay's adoption is an organic decision for iPhone and other Apple product users, while non-iPhone users can not adopt Apple Pay. On the other hand, iPhone users can adopt Venmo and CashApp, if needed. To limit the study's scope, we do not manipulate the brand value of the TP. Instead, we use one of the widely used brands/providers of Mwallet (Google Pay) to integrate mobile payments in our experimental context. However, we do control for the brand value of TP in the analysis.

Measures

Independent or Treatment Factors

Brand Value of Service Provider (SP) – We manipulate SPs' brand value to uncover the differences in the NCX evaluation and resultant attribution of NCX between the SP and TP. We have two combinations of brand value conditions: High SP vs. Low SP. For SPs, we focus on department stores such as Neiman Marcus and Ross Stores as our context because it is one aspect of customer's life where the involvement varies, and customers actively look to get rewards and benefits. In short, the involvement with the task varies across service encounters, but customer goals for technology-driven interactions would not vary across the service encounters. To manipulate the SP's brand value, we induce the brand value connotations by giving the participant a Neiman Marcus vs. Ross Stores store. Neiman Marcus is widely considered a high-end retailer vs. Ross Stores as a low-end retailer based on its product, price, and brand assortments.

Salience of Use Benefits (UB) – A high (low) salience of use benefits for mobile payment apps in terms of convenience and rewards would be directly associated with a stronger (weaker) customer's goal to get all the benefits. Thus, the resultant evaluation of their interaction with an SP using a mobile payment app would be affected by the salience of benefits provided by a mobile payment app. We randomly assign participants to two conditions: High Use Benefits Salience (HUBS) vs. Low Use Benefits Salience (LUBS). In the HUBS condition, the communication to participants highlights convenience and security as key benefits and makes the additional discount (digit rewards) associated with Mwallet usage salient. While in the LUBS condition, the communication was given to participants only highlights convenience and security as key benefits.

Technology-Service Failures vs. No Failures – After the customer in the scenario makes her purchase decision, we manipulate the outcome of using a mobile payment app to pay for the products and get additional rewards as payment success and failure. In the case of failure, the customer still completes the transaction with the retailer using a credit card in this situation. However, we consider that as a technology-service failure.

Thus, there are a total of 8 combinations of conditions in our 2×2×2 between-subjects design. The description of scenarios is in Appendix 1.

<u>Group 1 – No Technology Failures</u>

(C1) HUBS -- High SP, **(C2)** HUBS -- Low SP, **(C3)** LUBS -- High SP, **(C4)** LUBS -- Low SP

<u>Group 2 – With Technology Failures</u>

(C5) HUBS -- High SP, **(C6)** HUBS -- Low SP, **(C7)** LUBS -- High SP, **(C8)** LUBS -- Low SP

Pretest for Manipulation Validation

In our pretest manipulation validation, a group of 82 undergraduate students from a large Southeastern public university took a survey to elucidate their perception of different brands of service providers (retailers). We sent out the survey to 125 students in exchange for extra credit on their final score. Out of 125, we got responses from 82 participants. The sample had 40 males and 41 females (1 participant chose not to disclose the gender). 71 participants come from the 18-24 years age group, 10 belong to the 25-34 years age group, and one participant from the above 55 years age group. We randomly assigned the participants to the above-mentioned experimental conditions. However, the aim was to check if the participants are cognizant of the manipulations or not.

1. *Service Provider Manipulation* – 63 out of 82 participants (76.83%) correctly recalled Neiman Marcus or Ross Stores as their SP. In addition, we asked their perceptions about the brand value of six retailers – Bloomingdale, Macy's, JC Penney, Marshalls, Neiman Marcus, and Ross Stores. The goal was to determine the average perception of these SP brands to corroborate the evidence from the popular press. We used a five-point Likert Scale to get participant ratings. Neiman Marcus was rated

significantly higher on brand equity perception as compared to Ross Stores [$M_{\text{Neiman Marcus}}$ = 4.19, $M_{\text{Ross Stores}}$ = 2.89, Mann-Whitney U = 1568.00, p-value = <0.00, N=53][22]. Thus, we decided to use both Neiman Marcus and Ross Stores as our High SP and Low SP brands for SP manipulation. However, we amplified the brand names by highlighting them in bold fonts to make them more salient to participants.

2. *Salience of Use Benefits Manipulation* – We presented two combinations of rewards and general benefits to the participants. The only difference was that in Combination A, we gave an explicit digit reward as '7% Cashback' vs. no digit reward in Combination B. 79 out of 82 participants selected Combination A to be a more beneficial combination of benefits. This signifies that we can use Combination A as HUBS manipulation and Combination B as LUBS.
3. *Technology-Service Failure Manipulation* – We manipulated the outcome of using a Mwallet at the payment terminal in the form of payment success and failure. To assess the cognizance of the outcome, we asked the participants to recall this outcome at a later stage. Once the scenario ended, they could not go back to refresh their memory. 76 out of 82 participants correctly recalled their payment outcome. Hence, we decided to keep our manipulation intact for the experiment.

Apart from three manipulations, we also asked our participants to rate the top five Mwallet Apps in the US market – Google Pay, Apple Pay, Cash App, Venmo, PayPal. Apple Pay rated highest on brand equity perception while Google Pay was the lowest-rated brand [$M_{\text{Apple Pay}}$ = 4.66, $M_{\text{Google Pay}}$ = 3.60, Mann-Whitney U = 411.00, p-value = <0.00, N=63][23]. In the experiment, we decided to use Google Pay as a TP rather than Apple Pay because, unlike Apple Pay, anyone can download and use Google Pay on their smartphone. Hence, it provides a wider reach to the general population. Also, we do not intend to manipulate the brand value of the TP.

[22] The t-test generated a statistic of 4.44 with p-value = 0.00006. However, a Likert scale generates non-normal data, we applied a non-parametric test Mann Whitney U or Mann Whitney Wilcoxon test to test the difference between the average perceptions of all the brands. Our final sample size after dropping the 'Not Applicable' data is 53.

[23] Our final sample size after dropping the 'Not Applicable' sample size is 63.

Dependent Variable

This study focuses on NCX drivers and develops a composite score for a technology-driven service encounter. We ask participants to assume if the presented scenario had happened with them and then express the degree of their agreeableness with the presented statements related to NCX dimensions, overall satisfaction, attribution of experience, and other control variables. In the first outcome, we focus on the customer score on NCX dimensions described in previous studies. We measure a customer's experience on the NCX dimension using a post-scenario survey. We calculate the NCX score for each customer as follows:

$$NCX_i = \sum_{i,j} \frac{\overline{NCX}_{SP_{i,j}}}{\overline{NCX}_{TP_{i,j}}} \times n_j \qquad \text{[Eq.2]}$$

where,

for each customer $\boldsymbol{i}$, for $\overline{NCX}_{SP_{i,j}}$ is the average score for the retailer (Nieman Marcus or Ross Stores) across all survey items in each $\boldsymbol{j}$ – dimension of NCX (decision, access, transaction, benefits, and support), $\overline{NCX}_{TP_{i,j}}$ is the average score for TP (Google Pay) across all survey items in j – dimension of NCX, and $\boldsymbol{n_j}$ is the number of survey items in each dimension. Our Likert scale measures 1 as strongly agree and 5 as strongly disagree. We reverse-coded it for the analysis. Thus, a score of 1 for $\frac{\overline{NCX}_{SP_{i,j}}}{\overline{NCX}_{TP_{i,j}}}$ means that for the participant, both parties (retailer and TP) contributed equally to the NCX. An NCX score > 1 means that SP contributed more to the NCX. Consequentially, a lower score means the TP contributed more to the NCX. For decision, access, and transaction dimensions n_j = 4, for benefits n_j = 3, and for support n_j = 2. For a perfectly balanced NCX, this NCX score for a customer *i* will be 17. If this score is greater than 17, SP is creating more NCX than TP and vice-a-versa.

This operationalization of NCX takes care of any non-response due to the respondent's perception of no applicability. Since we are calculating an average score, it does not consider the no response items in the numerator and denominator, gives the average score on a scale of 1 to 5 yet. As those scores are not added to the NCX score but n_j contain that item-level information, thus creating a weighted average score. Also, using a proportion of SP and TP scores allows us to bring out the relative assessment of both parties (SP and TP) for a particular dimension or touchpoint in a customer journey. It also allows us to incorporate more than one TP in the denominator across different dimensions of a customer journey. For example, if a customer uses Groupon to book a stay at Westin hotel and Google Pay to make payments, there are two TPs across NCX dimensions. However, we can incorporate each TP based on its contribution to NCX at a particular NCX dimension without changing the score of other dimensions. SP can look at the aggregate score to have a general idea of its contribution to NCX compared to all TPs or break it down for each dimension and then assess its role.

Control Variables

We control for observed heterogeneity among respondents via many variables. First, we use age as a (demographic) control variable. We expect that younger participants would have a higher usage of Mwallet as a technology. We also control for the gender of participants. Second, we use scores on respondent's Personal Innovativeness with technologies (INN) and involvement with technologies (INV) to control for orientation towards technology in general. INN with technology measures individual perception regarding adopting information technology (IT) related products by users. Since Mwallet apps are driven by IT and its adoption is highly subjective among consumers, we believe this scale can capture heterogeneity among respondents.

Similarly, involvement with technology measures respondent involvement with a particular set of technology. We believe higher involvement can lead to differential evaluation and attribution mechanisms among respondents as well. In general, both these constructs would lead to differential attitudes towards the Mwallet usage and response to our experiment. We also control for participants whom themselves use any mobile payment or Mwallet app. Among users, we should observe a better understanding of the technology usage and benefits. For those, who do not have any experience using the Mwallet app, we briefly introduce them to Mwallet technology and how the customers can use it. The purpose was to highlight the benefits and use of technology and avoid any biased responses. Lastly, we control respondents' ratings for SP (Neiman Marcus vs. Ross Stores) and TP (Google Pay). We expect an inherent effect of how much a respondent values the TP relative to SP while evaluating and attributing their technology-mediated experience.

Power Analysis and Sample Size Selection for Main Experiment

A power of 0.80 is considered to be satisfactory in behavioral factorial design experiments (Brysbaert, 2019). Based on our power analysis (β), to achieve a power of $(1-\beta) = 0.85$, Type-1 error level, $\alpha = 0.05$ for a hypothesized small effect size, $f = 0.15$, we need $n = 401$ to identify the interaction effect of two or more independent variables (see Table 4). There are two conditions to be met. First, there must be a minimum of 49 observations in each treatment condition (C1 to C8), and for each treatment or factor in our experiment, we need at least 100 observations. Thus, we aimed to get a sample of $n = 550$ for our eight treatment conditions before cleaning the data for incomplete or unusable responses.

[Table 4. Here]

Data and Results

Data and Manipulation Check – We recruited 672 participants from CloudResearch Prime Panel (formerly known as MTurk Prime). As an attention check, we asked participants to choose the color 'orange' among a list of four colors at the midpoint of the survey. Four participants failed the attention check question that has been used as an instrumental manipulation check (IMC), leaving N = 668. Based on a stricter manipulation check, only 341 respondents correctly recalled their treatment condition. The recent literature has highlighted the redundancy or strictness of verbal manipulation checks, specifically for scenario-based experiments (Hauser, Ellsworth, & Gonzalez, 2018). Such manipulation checks themselves can act as interventions that can initiate new processes. With virtual lab experiments, participants take multiple surveys every day, multi-tasking between many platforms and going on about their lives. In such scenarios, the key question is the attention they give to the given task. Also, dropping participants based on the manipulation checks can lead to biased results (Aronow, Baron, & Pinson, 2019). Hence, we conduct our analysis on N=668. The descriptive details of the sample for each condition are given in Table 5.

[Table 5. Here]

Quality Check for Non-Response Bias and Duration – We further checked our sample for non-response bias and duration for each response. The respondents had the option to not respond to any statements related to NCX or other demographic questions. It has been observed that uninterested participants choose not to respond to questions and finish the survey as soon as possible to earn the remuneration. We removed any participant for non-response bias based on two conditions – more than ten non-responses on statements and invariability (straight-lined as 5 or 1 for all responses – checked against the assigned treatment) in the given responses. More than ten non-responses mean that they have not provided information on more than 50% of the statements. On a closer check, these respondents are the ones who either took a lot of time or less than ideal time to finish the survey. We removed 26 respondents based on the non-response bias. Second, we investigated the time that each respondent took to complete the survey. We removed any response that was less than 5 minutes or more than 30 minutes.[24] This time limit is based on our pretest with two novice survey takers and two expert survey takers. We expect that these participants have not read the survey thoroughly or finish in one sitting, leading to the omission of important information or extinction of the given treatment. Based on both these conditions, our final sample size is 558. [25]

Orthogonality and Normality – In factorial designs with more than one between-subject independent variable, as group sizes become unequal, the assumption of homogeneity of variance breaks down. It means that there is overlapping variance, which can be attributed to more than one source. As a result, we

[24] Based on the distribution of time taken to finish the survey, the average time is approximately 14 minutes, we limit our sample size to respondents who take approximately double the time to read and fill the survey. Also, in terms of platform surveys, if a respondent is taking more than average of the stipulated time, there is a high chance that they are filling multiple surveys on the same on different platform, or simply they are multitasking. In both these cases, it dilutes the impact of our manipulations. Given that respondents were not allowed to go back to the assigned treatment at the time of answering the questions, we decided to not include such participants in our final sample.
[25] N=297 after removing all the observations which did not pass the strict manipulation checks and data quality check.

see an increased Type 1 error and inflated $\alpha -$ level (Tabachnick, Fidell, & Ullman, 2007). As evident in Table 6, we also have unequal group sizes and unbalanced factorial design. We followed random assignment to remove any underlying participant-level biases, but we do not control the completion of the survey and the quality of responses which led to the differences in sample sizes across eight treatment conditions. We can observe different distributions for age, gender, and mean value of the NCX score and different sample sizes.

The Levene test for homogeneity of variance [$F(7,550) = 3.54$, $p < 0.00$] indicates that the assumption of homogeneity is violated in our dataset. The Shapiro-Wilk test for normality of data across each group is violated with a p-value < 0.05 for all treatment combinations except one. In Figure 3, we can observe that the NCX score is significantly right-skewed with $s = 1.38$ and $k = 6.92$. We also conducted a Kruskal Wallis test to see if the distributions are identical within each factor irrespective of normality. For the failure treatment group, KW chi-square = 26.616, $p<0.00$, indicating a significant difference between the failure treatment groups. However, we do not find the same result for brand value (KW chi-square = 0.0149, $p = 0.90$ and use benefits treatment (KW chi-square = 0.20, $p = 0.65$). The boxplot for each treatment factor in Figure 4 shows that the distribution is dominantly skewed for technology-service failures and looks somewhat similar for brand value and use benefits treatment conditions.

[Figure 3. Here]

[Figure 4. Here]

Hence, we conducted a log transformation to address the skewness of the NCX variable (See Figure 4). We calculate the transformed score as $\log_{10}$ (NCX). Levene Test for homogeneity of variance [$F(7,550) = 2.03$, $p = 0.05$] indicates the assumption is met with the transformed NCX. However, with the transformed NCX as the dependent variable, there is a considerable reduction in skewness (from 1.38 to -0.57) but not in kurtosis (from 6.92 to 5.74). Factorial ANOVA analysis assumes that the dependent variable approximates a multivariate normal distribution and has homoscedastic error variances across the group. Also, other regression assumptions of independent and identical observations and no or low multicollinearity are applicable. In case of violation of these assumptions, it is better to use Generalized

Linear Models (GLM) to account for non-parametric assumptions.[26] Hence, we estimate the following model using GLM with a Gamma distribution.

$$\mathrm{NCX_i} = \beta_0 + \beta_1 \times \mathrm{BV_i} + \beta_2 \times \mathrm{UB_i} + \beta_3\ \mathrm{FAIL_i} + \beta_4 \times \mathrm{BV_i} \times \mathrm{UB_i} + \beta_5 \times \mathrm{BV_i} \times \mathrm{FAIL_i} + \beta_6 \times \mathrm{UB_i} \times \mathrm{FAIL_i} + \beta_7 \times \mathrm{BV_i} \times \mathrm{UB_i} \times \mathrm{FAIl_i} + \beta_8 \times \mathrm{Age_i} + \beta_9 \times \mathrm{Gender_i} + \beta_{10} \times \mathrm{USER_i} + \beta_{11} \times \mathrm{INN_i} + \beta_{12} \times \mathrm{INV_i} + \beta_{13} \times \mathrm{BENM_i} + \beta_{14} \times \mathrm{BERS_i} + \beta_{15} \times \mathrm{BEGP_i} + \varepsilon_i \qquad \text{[Eq.3]}$$

where,

BV is the fixed factor for Brand Value dummy coded as 0=low for Ross Stores and 1=high for Neiman Marcus treatment conditions; β_1 is the main effect of BV

UB is the fixed factor for Use-Benefits dummy coded as 0= no digit rewards and 1=digit rewards treatment conditions; β_2 is the main effect of UB

FAIL is the fixed factor for Technology-Service Failures dummy coded as 0= no failure and 1=payment failure; β_3 is the main effect of Fail

$\beta_4\ to\ \beta_7$ represent the second-order and third-order interaction effects of BV, UB, and FAIL

$\beta_8\ and\ \beta_9$ represent the effects of control variables Age and Gender, respectively.

β_{10} is the dummy coded control variable to represent is the respondent is a Mwallet User (=1) or not (=0)

$\beta_{11}\ and\ \beta_{12}$ represent the effects of control variables personal innovativeness (INN) with technology and involvement with technology (INV), respectively.

$\beta_{13}\ to\ \beta_{15}$ represent the control variable effects of brand value for Neiman Marcus (BENM), Ross Stores (BERS), and Google Pay (BEGP), respectively.

Results and Discussion

We use the Gamma distribution because our NCX variable is strictly positive and has a right skew, and this distribution can handle such data. The model for *NCX* as dependent variable [Null deviance (dof =557) = 67.361, Residual deviance (dof=542) = 59.504; AIC = 3508.8] shows that the main effect of Fail is positive and significant (β_{FAIL} = 4.09, p<0.001), positive and significant effect of UB (β_{UB} = 1.94, p =

[26] A factorial ANOVA analysis on the transformed NCX score yields significant main effects of use benefits [$F(1,542) = 6.72$; p = 0.009; η^2 = 0.0012], technology-service failure [$F(1,542) = 16.94$; p < 0.00; $\eta^2 = 0.042$], marginally significant interaction effect of use benefits × technology-service failure [$F(1,542) = 5.85$; p < 0.00; $\eta^2 = 0.015$], and brand value for Google Pay [$F(1,542) = 20.99$; p < 0.00; $\eta^2 = 0.03$]. However, the distribution now has a left skew with a kurtosis of 5.74.

0.03), negative and significant effect of brand value of Google Pay ($\beta_{BEGP} = -1.32$, $p < 0.001$) and a marginally significant and negative effect of interaction between Fail and UB ($\beta_{UB \times FAIL} = -2.52$, $p = 0.06$).

However, the model with *transformed NCX* performed much better on the AIC criteria [Null deviance (dof =557) = 9.987, Residual deviance (dof=542) = 9.081; AIC = -468.65]. We also see a similar pattern – the main effect of Fail is positive and significant ($\beta_{FAIL} = 0.103$, $p<0.001$), there is positive and significant effect of UB ($\beta_{UB} = 0.067$, $p = 0.007$), and a negative and significant effect of brand value of Google Pay ($\beta_{BEGP} = -0.031$, $p < 0.001$). Also, we observe a significant effect of interaction between UB × Fail treatment conditions ($\beta_{UB \times FAIL} = -0.086$, $p = 0.015$). Results for both models are given in Table 6.

[Table 6. Here]

We can observe a significant presence of outliers in the data across box plots, histograms, and residual analysis for both NCX and $\log_{10}$ (NCX). Residual analysis of GLM models is presented in Figure 5. Both the models have Shapiro-Wilk, W = 0.974, $p<0.001$ (for NCX) and W= 0.907, $p<0.001$ (for transformed NCX), indicating that the outliers may be causing significant problems in the estimates. The mean for the residuals GLM for NCX is -0.0349 and Std. Dev is 0.650. The outliers (outside two std. deviation range) for NCX are presented in Figure 6. In total, there are 33 outliers which are approximately 6% of the entire data set.

[Figure 5. Here]

[Figure 6. Here]

[Figure 7. Here]

After removing outliers, we see few changes in the distribution of NCX (See Figure 7). Specifically, for $\log_{10}$(NCX), the distribution is closer to symmetry, yet there is high kurtosis value = 3.46 and an acceptable skewness value = -0.022. The model for NCX as dependent variable [Null deviance (dof =524) = 39.972, Residual deviance (dof=509) = 33.458; AIC = 3041.5] shows that the main effect of FAIL is positive and significant ($\beta_{FAIL} = 4.22$, $p<0.001$), a positive and significant main effect of UB ($\beta_{UB} = 1.91$, $p = 0.007$), negative and significant effect of brand value of Google Pay ($\beta_{BEGP} = -1.07$, $p < 0.001$), and positive and significant effect brand value of Ross Stores ($\beta_{BEGP} = 0.47$, $p = 0.015$). Also, the interaction effect of FAIL and UB is significant and negative ($\beta_{UB\times FAIL} = -2.99$, $p = 0.006$).

However, the model with transformed NCX perform much better on the AIC criteria [Null deviance (dof =524) = 5.13, Residual deviance (dof=509) = 4.36; AIC = -783.4]. We also see the similar pattern of main effects for main effect of FAIL is positive and significant ($\beta_{FAIL} = 0.10$, $p<0.001$), a positive and significant main effect of UB ($\beta_{UB} = 0.06$, $p = 0.002$), a negative and significant effect of brand value of Google Pay ($\beta_{BEGP} = -0.026$, $p <0.001$), and positive effect of brand value of Ross Stores ($\beta_{BERS} = 0.01$, $p = 0.032$). Also, we observe a significant effect of interaction between UB × Fail treatment conditions ($\beta_{UB\times FAIL} = -0.084$, $p = 0.002$). The net effect of FAIL on NCX score across levels of UB can be presented as ($\beta_3 + \beta_6 |UB$). When UB = 0, the net effect of failure is β_3 which is 0.106, and when UB = 1, the net effect of failure is $\beta_3 + \beta_6$, which is 0.022 (0.106-0.084). Similarly, the net effect of UB on NCX score across levels of FAIL can be presented as ($\beta_2 + \beta_6|FAIL$). When FAIL = 0, the net effect of use-benefits on NCX is β_2, which is 0.059, and when FAIL = 1, the net effect of use-benefits on NCX is $\beta_2 + \beta_6$, which is -0.025 (0.059-0.084). In addition, we observe a marginally significant effect of INN ($\beta_{INN} = -0.010$, $p = 0.09$). The results for both models are given in Table 7. The interaction plots for FAIL, UB, and BV are given in Figure 8.

[Table 7. Here]

[Figure 8. Here]

Since the interaction between UB × FAIL is significant, we further investigated the simple slope analysis to understand the source of interaction. For all the interactions, we observe cross-over effects; that's why it is not surprising to see insignificant main effects for UB and BV in the main effects models. The results for simple slope analysis are given in Table 8. We can observe that the effect of FAIL for BV = 0 and UB = 0 is 0.0192 ($p<0.001$) and BV =1 and UB = 0 is 0.020 ($p<0.001$) are significant. For UB, the source of significant effect is BV = 0 and FAIL = 0 with an estimate of 0.06 ($p = 0.002$) and BV = 1 and FAIL = 0 with an estimate of 0.021 ($p = 0.048$).

[Table 8. Here]

The results from GLM analysis for NCX reveal that failure significantly affects the NCX score. Thus, failure induces a differential evaluation among respondents (we do not test for the relative brand value of TP). However, we observe that the NCX score (SP/TP) is higher in the failure treatment conditions. In general, respondents are evaluating SP more favorably than TP during technology-service failures irrespective of the brand value of SP. But the brand value of Google Pay as a control variable has a consistent significant and negative impact on the NCX score. It signifies that else being equal, when TP is rated higher on brand value (on a scale of 1 to 5), then the overall NCX score is lower, implying better evaluation for TP than SP. Thus, we find partial support for H1, with better evaluation for SP than TP, after controlling TP's brand value.

Overall, we observe a significant positive impact of Use-Benefit (supporting H2a) and a significant impact of its interaction with Failure. A 7% cashback increasing the overall NCX score indicates that respondents are evaluating NCX more positively when there are substantial benefits in the form of cashback. However, in the case of failure, the positive impact on NCX is more for low UB than high UB, hence leading to a negative interaction effect on NCX (supporting H2b). Perhaps, respondents link the inability to get the benefits more with TP than with SP when UB is low compared to when UB is high. With low UB, respondents do not have specific technology-related goals that were unfulfilled. Hence, they evaluated SP better than TP when the failure happened. However, in high UB, with specific technology-related goals, respondents evaluated their experience in the given service setting and utilized cues to create a relatively lower NCX score. All the simple slopes for Failure conditions are significant apart from when BV and UB are high. Perhaps, the change in NCX due to failure is not significant when the SP has high brand value, and the Use-Benefits of Mwallet are also high.

MANOVA Analysis for NCX Evaluation – With NCX as a composite score of all the dimensions, we cannot trace the key source of difference in the evaluation and attribution between SP and TP. Hence, we conducted a MANOVA analysis for each dimension (Decision, Access, Transaction, Benefits, and Support) as dependent variables (untransformed). The specification for each dimension is still the proportion of the average score of SP to the average TP score. We can observe that the significant effects are mostly observed in the transaction dimension (Adj-R^2 = 0.137). For Transaction, we observe a significant main effect of FAIL (β_{FAIL} = -0.421 , p=0.03), a negative and significant effect of brand value of Google Pay (β_{BEGP} = -0.169, p <0.001), and a positive and significant effect of Age (β_{Age} = 0.007, p = 0.021). Also, age has a positive and significant impact on transaction NCX, implying that older respondents evaluate SP more positively than TP while paying using Mwallet. Lastly, INV has a positive and significant impact on transaction (β_{USER} = 0.148, p = 0.014). For Benefits, we observe a marginally significant main effect of FAIL (β_{FAIL} = -0.244, p =0.075), a negative and significant effect of brand value of Google Pay (β_{BEGP} = -0.068, p = 0.043), and a negative and marginally significant effect of Mwallet User (β_{USER} = -0.128, p = 0.061). The results are presented in Table 9.

[Table 9. Here]

From the MANOVA analysis, we trace the source of variation in NCX to the transaction dimension. Like GLM analysis for consolidated NCX, we see a significant negative effect of Failure=0, implying that when failure happens, the NCX score increases by 0.421 for transaction and 0.244 for benefits, ceteris paribus. Google Pay brand value has a significant negative impact on NCX, implying that the higher the brand value perception of TP, the lower the NCX evaluation for SP. Also, the impact of Mwallet User as a control variable is negative and significant, indicating that respondents who have experience with Mwallet do not evaluate SP more favorably than TP and bring down the overall NCX score, ceteris paribus. This makes logical sense since Google Pay as technology is primarily a payment tool along with the capability to receive personalized discounts and cashback. Thus, experience with technology can provide TP with a larger share of the NCX than SP. However, we do not find a significant impact of UB or BV or their two-way interaction with Failure. Further, with higher involvement in technologies like Mwallet, users learn from their experience and create evaluation mechanisms. Thus, a higher INV score leads to a higher NCX score for the transaction dimension (a better evaluation for SP than TP, ceteris paribus).

Attribution as Dependent Variable

In the second outcome, we focus directly on attribution as a dependent variable. One of the critical questions of this research is understanding how customers attribute the resultant experience between three actors – SP, TP, and customer. From the managerial perspective, the attribution likelihood can be informative in understanding consumer behavior concerning technology-mediated interactions and failures. Consequentially, both SPs and TPs can create better customer experience management strategies for NCX.

Attribution Scores between SP and TP – We measure the attribution between the SP and TP across all the treatment conditions. For each actor, we use three items on a five-point Likert scale (see Appendix A2, pg. XX), asking whether that actor (e.g., SP) is reason to interact with the other actor (e.g., TP). Also, we ask respondents to attribute their overall experience between SP and TP. This is fundamentally different from the NCX evaluation scores, where respondents evaluated their experience across different dimensions. The focus is on how the respondents attribute the experience (whether good or bad). The average score on three items is the attribution score for that actor. We observe scores for both SP and TP by each respondent as:

$$\mathrm{Att}_{i,a}^{t} = \begin{cases} \overline{\mathrm{SP}_{i,j}^{t}}, \text{where } 1 \le \mathrm{SP}_{i,j}^{t} \le 5 \\ \overline{\mathrm{TP}_{i,j}^{t}}, \text{where } 1 \le \mathrm{TP}_{i,j}^{t} \le 5 \end{cases} \qquad \text{[Eq.4]}$$

where,

i is the customer, ***a*** is the actor (SP or TP), ***j*** is the survey item, and ***t*** is the treatment condition (1 to 8). Since a respondent is answering for both actors at the same time, there will be a correlation between errors of $\mathrm{Att}_{i,SP}$ and $\mathrm{Att}_{i,TP}$. Hence, the measurement model 1 can be represented as:

$$\mathrm{Y}_{i,a} = \mathrm{Att}_{i,a} = \begin{bmatrix} \mathrm{Att}_{1,SP} & \mathrm{Att}_{1,TP} \\ \vdots & \vdots \\ \mathrm{Att}_{n,SP} & \mathrm{Att}_{n,TP} \end{bmatrix} = \begin{bmatrix} 1 & \mathrm{BV}_1 & \mathrm{UB}_1 & \mathrm{FAIL}_i \\ \vdots & \vdots & \vdots & \vdots \\ 1 & \mathrm{BV}_n & \mathrm{UB}_n & \mathrm{FAIL}_n \end{bmatrix} \times \begin{bmatrix} \beta_{0,SP} & \beta_{0,TP} \\ \beta_{1,SP} & \beta_{1,TP} \\ \beta_{2,SP} & \beta_{2,TP} \\ \beta_{3,SP} & \beta_{3,TP} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,SP} & \varepsilon_{1,TP} \\ \vdots & \vdots \\ \varepsilon_{n,SP} & \varepsilon_{n,TP} \end{bmatrix}$$

[Eq.5]

where, ***i*** is the customer, and ***a*** is the actor (SP or TP). BV is the dummy variable for the brand value of the SP (0=low or Ross Stores, 1=high or Neiman Marcus). UB is the dummy variable for use benefit salience (0=low, 1=high). FAIL is the dummy variable for technology service failure (0=No, 1=Yes). We also add control variables include age, gender, innovativeness with technology, and involvement with technology to account for observed heterogeneity.

Results and Discussion – We ran a MANOVA analysis for attribution scores and find a marginally significant main effect of UB for Att_{TP} ($\beta_{UB=0}$ = -0.449, p = 0.057), supporting H3b, and no significant effect for Att_{SP} . In both DVs, INV (involvement) has a positive and significant impact on attribution [β_{INV} for Att_{TP} = 0.483, p<0.001; β_{INV} for Att_{SP} = 0.480, p<0.001]. For Att_{SP}, BERS has a significant and negative impact (β_{BERS} = -0.132, p = 0.017). We do not find any other IV or control variables to have a significant impact on the attribution scores.[27] The results are presented in Table 10.

[Table 10. Here]

We do not find the main or interaction effects of failure on the attribution scores for both parties in NCX. However, a negative and marginally significant effect of UB for TP indicates that more benefits (such as cashback) lead to increased attribution of the resultant experience to TP but not to SP. Hence, respondents are clearly relating the benefits of technology to TP and not SP, irrespective of their evaluation of the resultant NCX. Interestingly, we observe a very high, positive, and significant impact of respondent's involvement with technology on attribution scores. With everything else constant, higher involvement with technology increases the attribution scores for both TP and SP. Respondents with higher involvement would better understand the distinction between roles and responsibilities of various actors involved in NCX. These respondents are likely to be experienced in using different types of technologies. They know that the creation and evaluation of NCX take active efforts from all parties, including the customer. Thus, greater involvement is with technologies helps them evaluate more cognitively than emotionally and attribute to all the involved parties. Lastly, there is a negative effect of

[27] A non-parametric MANOVA for AttSP and AttTP with BV, UB, and Fail as fixed factors shows only significant main effect of UB (Wald Type Statistic = 9.626, p = 0.008, Modified ANOVA Type Statistic = 12.286, p = 0.005).

the brand value of Ross Stores on the Attribution of SP, implying that a low brand value SP gets a lesser share of attribution as compared to TP, ceteris paribus.

Satisfaction as an Outcome of NCX

Third, we measure overall satisfaction with a technology-driven service encounter. The literature has shown that satisfaction with a brand/firm is one of the many important strategic outcomes of customer experience (Lemon & Verhoef, 2016). We create a proportion of average satisfaction scores for retailers and TPs on four statements mentioned in Appendix 2B. Note, participants had an option not to give scores on items that did not apply to the context. This ensures that the average score for that dimension incorporates the information that the item is not applicable. This analysis introduces a mediated-moderation model with Use-benefits and Brand value as IVs, NCX as a mediator and Failure as a moderator, and Satisfaction as DV.

A higher CX score should positively relate to satisfaction. Also, satisfaction has been used as a proxy for customer experience measurement in the past few decades. We posit that satisfaction is an outcome of NCX. In our scenario, a failure to make payment via Google Pay might lead to a lower NCX score for TP or a higher score for SP. However, how much failure impacts the relationship between NCX and satisfaction would be a valuable tool for CXM strategy for SP and TP. Hence, we measure if NCX mediates the impact of BV and UB on Satisfaction (SAT) and whether this impact changes with the presence of failure as a moderator between BV, UB, and NCX. Our DV for this analysis is the $\log_{10}(\text{Avg Sat}_{SP} / \text{Avg Sat}_{TP})$, and the NCX measure is $\log_{10}(\text{NCX})$.[28] The conceptual model is presented in Figure 10.

[Figure 10. Here]

Results and Discussion

For Brand Value – Like the GLM model, in the first equation (BV→NCX), we see that BV has no impact on NCX, and only the brand value of Google Pay has a negative and significant effect on NCX

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[28] [28] Note that NCX is a log-transformed variable while our independent variables are not. Hence, all the interpretation is in percentage change in the DV. So. Exp(0.067) = 1.06929, which is equal to 6.9% increase in the DV.

[β_{BEGP} = -0.0293, $p < 0.001$], FAIL has a significant positive effect on NCX [(β_{FAIL} = 0.0631, p = 0.003], and no significant moderation effect [$\beta_{BV\times FAIL}$ = -0.0245, p = 0.324]. Also, the control variable INN has a marginally significant and negative effect on NCX [(β_{INN} = -0.0134, p = 0.092]. In the second equation (BV→NCX→SAT), NCX have a significant direct and positive effect on satisfaction [(β_{NCX} = 0.4697, p < 0.00] and INV has a marginally significant and positive effect on SAT [(β_{INV} = 0.017, p = 0.080]. While we observe that NCX positively impacts SAT, we do not find any significant role of SPs brand value. Interestingly, we can see that respondents' overall orientation towards new technologies positively impacts NCX. It indicates that experience is driven by trial and openness to new technologies. Also, we see that involvement in technologies like Mwallets has a positive impact on SAT. It indicates that satisfaction is focused on the usage and integration of technologies in daily lives.

For Use-Benefits – In the first equation (UB→NCX), there is a significant and positive impact on NCX (as seen in the earlier models) [β_{UB} = 0.0516, p = 0.0020], FAIL has a significant and positive effect on NCX [(β_{FAIL} = 0.0815, p < 0.00], and significant and negative moderation effect [$\beta_{UB\times FAIL}$ = -0.0656, p = 0.0088]. On further analysis, we can observe that the moderation effect is positive for non-failure conditions [$\beta_{UB\times FAIL=0}$ = 0.0516, p = 0.002] and negative for failure conditions [$\beta_{UB\times FAIL=1}$ = -0.014, p = 0.4364]. Thus, with higher benefits and no technology failure conditions, respondents evaluate SP more positively than TP. However, when use benefits are high and technology fails, it can negatively impact NCX. Respondents may be evaluating TP more favorably than SP because they cannot utilize the benefits provided by the technology within the SP's environment. This can be further corroborated by the significant and negative impact of the brand value of Google Pay on NCX [β_{BEGP} = -0.0324, p < 0.00].

In the second equation (UB→NCX→SAT), NCX have a significant direct and positive effect on satisfaction [(β_{NCX} = 0.480, p < 0.001]. However, the direct effect of use-benefits on satisfaction is negative and significant [β_{UB} = -0.043, p = 0.002]. We also see a marginal positive effect of respondent's technology involvement on satisfaction [(β_{INV} = 0.017, p = 0.079]. It indicates that respondents can differentiate between their experience and satisfaction scores when it comes to technology-driven CX. Using Mwallet with SP and getting high use benefits more the SP's score relative to TP's score. This effect is significant conditional on the failure of the payment. One possible explanation of this contradictory effect is that NCX is a composite measure across all dimensions, and benefit is just one part. However, they may also understand that TP and not SP provide benefits; therefore, there is a reduction in SAT scores. This highlights that NCX and satisfaction are two different measures that use-benefits does not impact in the same manner. Given that nothing else went wrong with SP, and the customer was the first-time user of Mwallet, they are shielding SP more than TP. Also, in the experiment, we did not manipulate the outcome for the service encounter after the Mwallet payment failure. The customer was able to complete the purchase using a credit card. Neither did we manipulate the service provider's reaction to payment failure. With such manipulations, we may not see such contradictory effects of UB on satisfaction. The results for both models are given in Table 11.

[Table 11. Here]

Post-hoc Analysis[29]

We delved into the behavior of Mwallet users when exposed to failure to better understand the evaluation and attribution mechanisms in NCX. Respondents (both users and non-users of Mpayment apps) in the failure treatment condition have significantly higher NCX and Overall Satisfaction scores than the respondents in the non-failure conditions. Thus, in the process of cognitively appraising the failure as an event, respondents are critically examining the role of SP and TP. Further, Among the Mpayment users, we can observe the increase in NCX score is significantly higher for respondents with no prior failure experience [$\overline{NCX_{Exp}} = 17.82$, $\overline{NCX_{No\ Exp}} = 19.56$, p = 0.05]. It indicates that customers apply their learning from past experiences and adjust their anchors for the cognitive appraisal process to evaluate and attribute events such as failures. Hence, in the long run, SPs need to manage better their

[29] We also looked at the attribution behavior from the perspective of the onus of failure incidence. Particularly, we asked respondents in the failure treatment condition to tell us who is responsible for the failure. The majority of the participants (212 out of 273) attributed to one party (SP, TP, or customer). However, 49 participants attributed it to two parties and 12 to all three parties. We find no significant differences between the respondents' attribution mechanism from one party to two-party attribution using a multivariate logit model. We find that the odds ratio increases exponentially for lower BV and lower UB conditions from one party to three-party attribution. However, the likelihood ratio test is insignificant [χ^2 = 7.527, dof = 8. Sig.= .481].

CXM strategies to deal with such NCX failures across one or more dimensions. We see similar results for Satisfaction scores. However, among the Mpayment users, there is no significant increase in the scores among respondents with no prior failure experience [$\overline{SAT_{Exp}} = 5.03$, $\overline{SAT_{No\ Exp}} = 5.26$, p = 0.33]. This indicates that the anchors for the cognitive appraisal for events like failures impact experience evaluation and satisfaction differently among technology users, particularly for failures.

[Figures 11a, 11b, 11c. Here]

[Figures 12a, 12b, 12c. Here]

Conclusion

This experiment is the first step in exploring the drivers of NCX in service encounters. With this study, we conclude that NCX as a measure can exhibit differential patterns under failure and no-failure, and use benefits can impact the pattern to a certain extent. However, we do not find the role of brand value to be significant in such a situation. Hence, we do not find support for H4 in either direction. The interaction plots show the right directional effects. However, simple effects are significant.

The interaction effect of failure and use-benefits is significant for the consolidated measure of NCX, but it is not substantial when we break the score for each dimension. More interestingly, the attribution score for TP is impacted by the UB. With 7% cashback, the average attribution score for TP increases by 0.45, thus making the role of TP more dominant. Also, UB directly impacts the satisfaction score (SP/TP) by reducing the proportion. Therefore, irrespective of payment failure via Mwallet, respondents differentiate between the source of benefits when it comes to satisfaction. We do not see a similar effect for NCX evaluation, where UB positively impacts NCX, i.e., 7% cashback increases the NCX score by 6.9%.[30] However, when a respondent is getting 7% cashback and failure happens, it reduces the NCX score by 8.24%. Overall, we can conclude failure itself won't hurt the SP, but when there are substantial and tangible benefits involved with technology usage, it takes away some portion of the SP's NCX score.

[30] Note that NCX is a log-transformed variable while our independent variables are not. Hence, all the interpretation is in percentage change in the DV. So. Exp(0.067) = 1.06929, which is equal to 6.9% increase in the DV.

Also, higher customer involvement with technologies is good for both SP and TP. Technologies bring convenience for customers across one or more dimensions of NCX. The next step would be to explore other drivers of NCX, such as failure experience, experience with the technology, and product category, to see how customers evaluate and attribute their experiences across different technologies and different service contexts.

Contribution

Contribution to Academia

Our study provides a direction to the marketing field on the attribution mechanisms in technology-mediated interactions. There has been a consistent call in our field to develop more practical and contextual customer experience measures. Recently, many studies have posited that customer technologies such as AR, VR, mobile apps, etc., are fundamentally changing the nature of customer experience. However, we need to leverage existing theories and develop new concepts to understand the changing nature of CX. Our research contributes to the theoretical foundation of CX literature by showing how customers change their process of evaluation of CX while interacting with customer technologies provided or managed by third parties. First, we conceptually define a new construct of Networked Customer Experience (NCX) using multiple streams of literature. Our focus is on showing how firms (both technology and service providers) can operationalize, measure, and manage their technology-driven co-managed CX. Evaluating a product with technology-mediated interactions can directly impact customer intentions of technology usage, brand evaluations for service and technology providers, and attribution of successes and failures. We employ various theories such as cue utilization, goal congruence, and incongruence to explore the impact of a widely used customer technology on the experience.

Notably, we contribute to the services marketing literature on the effects of new technologies on consumer and firm behaviors. Mwallet is low involvement and non-interactive technology, where a customer enters NCX evaluation when something goes wrong. As seen in this study, failure triggers the node to evaluate service providers and technology providers differentially. As customers adopt and become habitual users of Mwallet, they can identify the unique benefits as a critical determinant of their payment and benefit-related experience. And the role of other service environment cues can take a secondary place in the evaluation and attribution process. However, failures can bring many more elements to the primary evaluation and attribution process. This phenomenon applies to all the service providers that co-create service encounters across one or more dimensions. We call for more research on this co-creation phenomenon and identify other elements related to service providers, technology providers, technology characteristics, customers, and service environment that can lead to differential NCX evaluation and attribution mechanisms.

Contribution to Practice

Practitioners (technology and service providers) can use this research to understand how consumers evaluate their experiences of their new customer technology more holistically. Technology adoption and abandonment has been a critical issue for mobile-based customer technologies. By using the critical technology-related factors, firms can further improve on product design and capabilities. Firms can benefit from this research in two more ways- understanding NCX attribution, which can help in designing better frontline strategies, and designing strategies to educate customers on interaction ownership and attribution processes.

Different technologies across or more dimensions of the customer journey can come together and create a networked customer experience for firms. However, they can analyze and effectively separate these touchpoints based on technology integration to create focused CXM strategies. For example, one of the key outcomes of technology integration is the management of failures. We find, to an extent, customers would shield service providers. However, this process of shielding goes down considerably when the use-benefits provided by the technology are high. Thus, a technology provider that offers greater benefits may not be attributed more in the case of failure than the service provider. In such cases, if a customer has a specific goal related to benefits by using Mwallet, it can lead to dissatisfaction with the overall service encounter. If a service provider focuses on such situations, they may want to invest in staff training to handle such failures both technically and behaviorally.

Managers can account for heterogeneity among their customers concerning general technology adoption and usage as we find that older respondents shield service providers more than the younger ones. However, technologies are quickly adopted and widely used by younger generations. Therefore, service providers and technology providers should focus on adopting and using technologies like Mwallets together. A consorted effort can lead to a better-customized promotion strategy and actions to manage support associated with any technology-service failure.

Limitations and Future Research

The conceptualization of NCX as adapted from the Service Convenience scale has its merits. First, it puts 'convenience' at the core of this technology-driven CX. Second, it maps the dimensions of service convenience to a customer's journey. However, there can be other conceptualizations of NCX. One can look at NCX from the lens of emotions and cognition and develop an NCX scale that can be applied to other technologies. Also, future research can look at NCX from the lens of CX dimensions, as summarized by Becker and Jaakkola (2020), and develop a broader measure of NCX.

The operationalization of NCX as a proportion of SP and TP scores has one limitation. The NCX score can increase or decrease because of a change in the numerator (SP) or denominator (TP), or both. However, we are only assessing the overall effect. If the score increases, that means SP is better evaluated by the customer and vice-a-versa. However, how much change is happening for both parties simultaneously can't be assessed in the current operationalization. Suppose SP needs to break down the impact for each stakeholder across one or more NCX dimensions. In that case, one possible operationalization is to use percentage contribution to each dimension of NCX from the SP's perspective. Alternatively, one can use actual scores and use econometric models such as seemingly unrelated regression (SUR) to estimate the effect of each driver or independent variable on the NCX score across one or more dimensions. Future research can explore further other operationalizations of NCX.

We provide a way to design a composite metric for NCX by using multiple methods and data sources. A composite metric like NCX requires corroboration across technologies, service contexts, and consumption situations. Specifically, how much importance to give to technology would depend on its inclusion across dimensions of the customer journey. As we find, Mwallet significantly contributes to NCX only for the transaction and benefits dimension. However, we do not directly manipulate decision, access, and support-related dimensions in this study. For apps like Klarna and Affirm, decision and support may be equally or more crucial as transaction and benefits. Thus, future research can look into:

- applying the concept of NCX across different types of technologies, such as AR devices, Alexa, and Klarna, cater to different customer journey dimensions.
- Also, technologies themselves can be inherently different in terms of their emotional and cognitive appeal. For example, Alexa as a digital assistant is more interactive hence contains more emotional content than a Mwallet. Thus, future research can investigate different technologies and their impact on NCX evaluation and attribution.
- The relative importance of the brand value of service and technology provider can be manipulated or studied in the firm-level dataset to assess the impact on NCX evaluation and attribution. Alternatively, it is possible that brand value is a stable metric (over time) and its impact may not show up in a cross-sectional experiment. This aspect can be studied using longitudinal experimental design or firm data.
- The outcomes of technology-service failures, such as cart abandonment, and the resultant CXM strategy by service providers, such as technical support, can be manipulated to understand the attribution process better.
- One of the critical drivers of NCX can be the channel or service context – online, offline, vs. hybrid. The literature has shown that consumer behavior differs in online service encounters. Future research can explore how NCX evaluation and attribution differ across these contexts.

We establish NCX as a concept centered around customer technologies that bring together service providers and third-party technology providers in a service encounter. With the rising popularity of ecosystems and platforms, we would see increased co-created and co-managed customer experiences. Application of this concept of NCX for ecosystems would be appropriate and challenging to operationalize.

Further, the logical question is whether it can be extended to a non-technology context and aligned with Co-branding literature. Suppose two service providers co-create and co-manage customer experience at the front-end of the customer journey (customers can observe the brands of both service providers and their role in creating the customer experience). Would that be considered a networked customer experience? One of the defining features of NCX is that technology enables partner-driven touchpoints, but customers have a choice to adopt third-party technology. For example, a customer can choose to use Groupon over hotels.com or Apple Pay over Google Pay. From the SP's perspective, different technology partners can add value to all stakeholders at a partner-driven touchpoint. However, in two or more SPs, customers may not have much say in SPs' choice. For example, if Westin hotel decides to co-create some experience with Starbucks only, a customer is bound to that co-created experience.

Nonetheless, all the mechanisms related to use-benefits, brand value, and failure would still apply. However, customer choice or customer-driven networked experience would not be the fundamental premise. In such cases, future research can look into unique drivers related to customer characteristics and service providers' characteristics to better understand the NCX evaluation and attribution. Also, related methodological issues can be explored further in future research.

Next, we introduce Study 2B, focusing on extracting NCX dimensions-related information from user-generated content and highlighting how it can be used to develop a robust NCX metric.

Study 2B – Understanding Customer Evaluation of Technology-mediated Interactions with Mwallet using Text Analysis

Customer Ratings and Reviews as a Measure of Experience

A user generates content as ratings and reviews for products, services, and experiences. These ratings and reviews act as a signal of product or service quality to other customers and a source of feedback to service and technology providers (Sridhar & Srinivasan, 2012). They are also leveraged to understand the anchors of the customer evaluation process and outcomes. For example, the content of reviews in terms of topics discussed and emotions expressed can be leveraged to understand better the customer evaluation of technology-mediated interactions (Chakraborty, Kim, & Sudhir, 2019). For mobile apps as a technology, customers can express their views on the characteristics of technology and the support by the technology provider. It is challenging to delineate the role of technology characteristics and technology provider characteristics in the expressed reviews and ratings. However, we can find out how much importance a customer puts on technology and technology provider's characteristics in creating technology-driven service experiences. Moreover, we can extract the expressed emotions from the reviews and ratings to understand the relative strength of technology characteristics in customer evaluation.

Take an example of the following customer review about Google Pay wallet: *"Thanks for adding an option for loyalty cards storage. Could you please add editable fields for the cards like Notes or something where you would be able to save PIN-codes and other info about your cards. Also most cards look the same (except for well-known global brands like Adidas). Hope they will have the design of physical ones in the future. Or at least add an option to change colors."* In this review, a customer expresses delight that the technology provider has added loyalty card storage characteristics to the wallet. From the first sentence, we can observe a positive tone. The customer also highlights features in the technology that can be useful and provide a better experience. In the context of NCX, this feature can be related to both access and benefits dimensions. At the same time, a positive sentiment highlights that the customer is happy with the technology and provides constructive feedback to the technology provider. However, the review is silent on the role of service providers during the interactions. The focus of most reviews and ratings in the case of technology-mediated interactions is to understand the role of the technology itself. Thus, app ratings and reviews provide a useful setting to delineate the role of technology characteristics in understanding the evaluation of technology-mediated interactions.

Surveys and interviews are alternatives to customer ratings and reviews to understand the importance of the technology characteristics in service settings. While surveys and interviews can be used to understand NCX drivers, the sample size is often a limitation. With a relatively small sample size, we can provide exploratory insights into the role of technology characteristics and NCX dimensions. However, we can use the power of user-generated content on multiple social media platforms, firm webpages, and other third-party platforms to study the same phenomenon in a scalable manner. Also, we focus on customer insights into the evaluation process of customers by approximating the role of affect via sentiment information from the text. Thus, we adopt a text analysis approach to understand the content and evaluation of customer experiences with Mwallet as customer technology.

Text Analysis Approach for Gaining Insights

We use machine learning-based text analysis approaches to gain insights from the unstructured review data. Over the last decade, research in marketing has leveraged text analysis in a variety of settings. For example, it can help us identify the valence of sentiment for a document (tweet, review, blog) that reflects customer evaluation (Homburg, Ehm, & Artz, 2015). Few studies have used unsupervised Latent Dirichlet Allocation (LDA) models at the document or sentence level to identify the major topics from the text (Mankad, Han, Goh, & Gavirneni, 2016). However, very few studies use aspect-based text analysis. Such models are much useful as they can consolidate dimension or topic level information with the sentiment information and provide a deeper view of customer feedback and evaluation. However, this task is challenging if we use a lexicon-based approach due to scalability, time consumption, and poor performance on sentiment categorization (difficult to process sentiment negation or sarcasm). With deep learning methods such as neural networks, researchers can overcome these limitations and construct a scalable model (Chakraborty et al., 2019).

We use aspect-based sentiment analysis to identify the key topics of importance in customer evaluation and the associated sentiments. Aspect-based sentiment analysis combines topic modeling and sentiment analysis. In this NLP analysis, we take a document d (a customer review for Mwallet) as an input and identify the various aspects or attributes $k \in K$, where K is the full set of attributes (five dimensions of NCX- decision, access, transaction, benefits, and support). Then, we associate a sentiment score s with k. Each sentence in a document can be associated with more than one attribute/aspect, k. However, the final classification is based on the highest probability.

Consequently, we assume that the aspect/attribute level sentiment score for each review is the average of the sentiment scores of all sentences within a document that mentions that attribute. If an attribute is not mentioned in any of the review sentences, we treat it as missing. We introduce the steps in Aspect-based Sentiment Analysis and associated methods in Figure 13. This study focuses on extracting the aspects via text modeling and classification techniques and does not focus on sentiment analysis. Next, we discuss the characteristics of our dataset.

[Figure 13. Here]

Data

We collect ratings and reviews for multiple Mwallet applications from Google Play Store (Android Store). This data is collected using APIs from a third-party data aggregator and insight generation firm.[31] Initially, we could extract reviews, ratings, and other metadata for around 25 Mwallet applications from Google Play Store, from July 1, 2019 to July 2, 2020. Thus, we have year-long data on customer ratings and reviews. Across 25 Mwallet applications, the range for numbers of reviews is broad, between 53 to 7711. In sum, we have about 89,986 Google Play Store reviews to conduct text analysis.[32]

[31] 42matters.com gives paid programmatic access to mobile data for Android and iOS apps. It includes meta-data, insights and audiences on Google Play, Apple App store, and for Tencent MyApps and Amazon Store in some cases.
[32] In our dataset, we do not have data for embedded wallets such as Walmart Pay, as they are no standalone apps. However, the customer experience information for these embedded functional Mwallet can be collected from multiple social media platforms. For example, from Twitter, we can search for #WalmartPay or #ApplePay to get user reviews and responses. While being an imperfect measure, it can still allow to incorporate text data for technology-mediated interactions for service provider owned wallets. At this stage, we do not incorporate this information in our analysis.

Descriptive Analysis and Results

Table 12 presents the descriptive analysis of the rating and review dataset for 19 Mwallet apps from Google Play Store. To represent the Mwallet application accurately in text analysis, we need to ensure enough reviews for each app in the dataset. Hence, we decided to drop six Mwallet apps with less than 500 reviews from our analysis. In our data, average customer ratings are distributed as U-shape across a five-point Likert scale from 1 being worse to 5 being excellent. This departs from the actual rating distribution of most of these mobile apps, which are positively skewed towards 4 or 5. For example, the Paytm app has 7,738,518 ratings on Google Play Store with a positive skew towards 4 & 5. However, in our dataset, we have 4683 total ratings and reviews with the highest concentration of 1 & 5. The reason behind this disparity is that we have ratings that are only associated with reviews. We do not observe standalone ratings in our dataset. This provides us with useful research setting to observe customer evaluations at both extremes and the insights from text data.

[Table 12. Here]

The average rating across all the apps is 2.50, with a standard deviation of 1.57. It highlights that customer evaluation is more towards the scale's negative spectrum with substantial differences across different apps. Thus, we can further explore the drivers of these differences across apps, such as the brand effects, type of Mwallet, the user interface of the app, and the rating environment of users. Further, on average, there are 18.30 words in a review across all the Mwallet apps. The range varies from 1 to 429. We removed reviews with one word because it is challenging to identify any aspect. It will not affect the results systematically because it still has a balanced representation of different types of Mwallets, which is an essential characteristic of technology usage and evaluation.

Results of App-level Aspect Based Sentiment Analysis

We qualitatively analyze the results of the aspect-based sentiment analysis on each app using the mobile app industry classification (See Appendix B2). As per the summary statistics, for most aspects/categories, the proportion of negative sentiments is higher. Only a few Mwallets, such as Paytm and Google Pay, have a balanced proportion of negative and positive sentiments across all the aspects. This analysis highlights that technology characteristics such as user interface and UX might be a prominent driver of the customer evaluation of Mwallet-driven service experiences. However, other factors are related to technology usage and service experiences that are not covered in this analysis. For example, rewards which is a key characteristic of Mwallet technology, are not discussed in this analysis. Hence, we need to conduct customer-level aspect-based sentiment analysis to uncover the underlying and more meaningful topics in customer reviews.

Unsupervised Topic Modeling

Our research context is unique as we apply the service convenience concept to define and measure NCX. Thus, there is no existing training data with established keywords for each dimension. Also, our context of NCX and its dimensions are unique. Therefore, in this research, first, we conduct unsupervised topic modeling on the data to identify the key aspects without an inclination towards the dimension of NCX. This approach is useful and less time-consuming for exploratory research, but there is no established way to assess the classifier's efficiency.

For extraction of an aspect, we use an attention-based classifier instead of LDA or LSA. We employ Contrastive Attention (CAt)[33] based on Radial Basis Functions (RBF) for aspect extraction.[34] CAt only requires in-domain word embeddings and part-of-speech tagging to extract an aspect from the text data (Tulkens & Van Cranenburgh, 2020). In the first iteration, we could extract five topics that we can loosely link to access, transaction, benefits, and support dimensions of NCX (See Appendix 2A). However, the model does not delineate between words or tags among the underlying dimensions. One of the possible reasons is that our context is unique, and we need to create our tags. Hence, we developed our dictionary of keywords using popular press and inputs from academic experts.

[33] To learn more about Contrastive Attention, please refer at https://towardsdatascience.com/understanding-contrastive-learning-d5b19fd96607.
[34] Radial Basis Function (RBF) is real value function whose value depends only on the distance from origin or a center point. In classification models, an input vector is processed by multiple Radial basis function neurons, with varying weights, and the sum total of the neurons produce a value of similarity. If input vectors match the training data, they will have a high similarity value. Alternatively, if they do not match the training data, they will not be assigned a high similarity value. Comparing similarity values with different classifications of data allows for non-linear classification. Source: https://deepai.org/machine-learning-glossary-and-terms/radial-basis-function, Article accessed on June 20, 2021.

Dictionary Development and Testing

We developed a dictionary of keywords or tags associated with each dimension of NCX. The keywords are generated via two sources. First, we use the industry reports to inform our initial understanding of a keyword and dimension association. We used our subjective evaluation to categorize the words into NCX dimensions. Second, we use the high-frequency words from our customer reviews to add to the dictionary. From a list of more than 1000 high-frequency words, finally, we use 261 words in our dictionary. These keywords were chosen in two steps. First, we consolidated the words that were closely related or had verb or noun connotations. For example, retailer/retailers or discount/discounts are put as one root word retailer and discount.[35] At the end of this exercise, we generated a list of 278 keywords. Note that in this dictionary, we do not classify the keywords into the decision dimension of NCX. The decision to use a Mwallet is a latent construct, and we do not observe it in the users' behavior in our dataset. We only observe customer behavior and reaction once they have used a Mwallet to purchase at some service provider (retailer) store. While this dimension is critical, it is out of the scope within our research to classify for this dimension.

To validate the list of keywords and associated dimensions, we tested our dictionary with academic experts. We reached out to academicians who qualified for one or both of the following criteria. First, they need to be subject matter experts in technology-driven customer experiences or customer relationship management areas. Second, they can be experts in machine learning models and have experience in text analysis. From a list of 31 experts, we initially reached out to 12 academicians. Due to unavailability, we recruited one more expert at a later stage. We divided the dictionary into six versions and recruited two experts for each version. With the list of keywords, we sent a detailed list of instructions and explained the project. Notably, we highlighted the definitions of each NCX dimension and gave an example in the context of Mwallets as a technology. Also, to avoid confusion, we asked the

[35] This process is similar to lemmatization, i.e., derivational words have similar meanings, and for text analysis, we do not need all the words of a family. Hence, car, cars, car's, cars' all become car (a root word). Stemming and lemmatization is a pre-processing stage of machine learning-based text analysis. For more information of stemming and lemmatization process readers can look at Srinidhi, S. (2020) retrieved on April 19, 2021 from https://towardsdatascience.com/lemmatization-in-natural-language-processing-nlp-and-machine-learning-a4416f69a7b6.

experts to classify each word into one NCX dimension. Thus, two experts and two researchers classified each keyword into the NCX dimension before we finalized the dictionary.

The average correct classification rate is 85.25% (237 words). Hence, out of 278 words, our experts raised issues with the classification of 41 words. The nature of these issues was either a suggestion to reclassify a word into another NCX dimension (28 words) or an inability to classify in only one dimension (13 words). We discussed our motivations for classifying each conflicted keyword with experts and resolved the discrepancies by dropping 14 words from our list. We retained the initial classification of 19 words and reclassified 9 words. Also, we added two new words as suggested by one of the experts. Thus, our final dictionary has 264 keywords classified into five dimensions of NCX.

Further, this exercise highlighted that we need to break down the benefits dimension of NCX into two sub-dimensions. The first is related to general benefits associated with Mwallets, such as convenience, security, ease of use, and tangible rewards. We name this dimension as 'rewards benefits'. The second sub-dimension is about the activities and places where a customer can use Mwallet, thus collating all daily activities in one app. We name this dimension as 'place benefits'. The list of final keywords is given in Table 13.

[Table 13. Here]

Results of Customer-level Aspect Based Sentiment Analysis

As described previously, we can assign each customer review (d_i) to one or many NCX dimensions (k_j) and then calculate the sentiment(s) for each review. First, we break down each review into standalone sentences. Then, we collate the probability scores of each sentence belonging to one of the five dimensions of NCX. The assignment with maximum probability is the end-state classification of the review to a topic. It allows exploring the possibility of a sentence belonging to more than one dimension. The final assignment of a review to a category depends on all the sentences rather than just one key sentence. For example, consider a review for Google Pay, *"it works just fine but then when i go to try to use it to pay it doesnt do anything so this app isnt very useful when i still have to go back out to my car to* *get my card".* The algorithm considers it as a single sentence and assigns it to the access and transactions dimensions. However, consider the other review for Google Pay, *"The app is really comfortable but sometimes i cant pay the first time. How can i solve this issue".* This sentence would be broken into two sentences: s1 – "*The app is really comfortable but sometimes i cant pay the first time",* and s2 – *"How can i solve this issue".* Both these sentences are analyzed separately. The s1 is assigned to access or transaction dimension and s2 is assigned to support dimension. Finally, we assign one or more aspects to each review based on the maximum probability of each sentence. In the previous example, the review would be assigned to two aspects – access/transaction and support.

Sentence Tagging for Precision Measure

To estimate the precision of our dictionary-based tagging and classifier, we tagged some portion of our reviews to create a training dataset. In our dataset, there are 89,986 reviews which are broken up into 297,783 sentences. We tagged approximately 5% of these sentences based on our keywords in the dictionary. The objective is to test the precision of our dictionary and aspect extraction model. Since we do not observe the decision of users to use Mwallets, we are focusing on the rest four dimensions of NCX. The model does not clearly distinguish between access and transaction as separate dimensions. Therefore, we combine these two dimensions at this stage for any analysis. Similarly, we combine both benefits-related dimensions into one aspect. Lastly, in the training dataset, many sentences do not belong to any of the four categories but express a general opinion or action. We labeled these sentences under the 'General' category.

Further, we only use few unique and discrepant keywords under each dimension to ensure that the classifier can understand the context and create the right word embeddings. After five iterations, the combination of keywords that we used in the analysis is as follows:

Access/Transaction: account, connection, network, call, amount, balance, payment, invoice, topup, recharge, bill, card, otp, receipt, transaction, transfer

Benefits: booking, cashback, coupons

Support: care, help, solution, support, service, agent, complaint, feedback, suggestion

General: recommend, experience, app

The overall classification accuracy is 0.55, which is good considering that we don't have training data and a list of keywords (word embeddings). The micro-precision (weighted accuracy measure for each category) is also 0.55. and the macro-precision (unweighted accuracy measure) is 0.52. The classification results are given in Table 14.

[Table 14. Here]

Discussion and Conclusion

In Study 2a, we created a weighted NCX score where the weights were based on the number of items (statements) used to calculate the total score for NCX dimensions. However, this approach is not very scientific but may work well in some contexts. To remedy this, in Study 2b, we highlight the power of unstructured data in the form of Mwallet app reviews to derive weights more scientifically. The first step is to extract the classification from the text and map it to NCX dimensions. This step enables us to capture two types of information. First, how technology interacts with its users' purchase experiences that occur with relatively high frequency – including the dimensions of NCX and in how many different scenarios users deploy a particular technology. Second, we can aggregate market information across different brands and products to further understand the customer experience with technology-driven interactions.

With higher computing and data handling power, SPs and TPs can now assess the aspect-based sentiment analysis information per their goals and objectives. The key is to create a robust training dataset around their technology and industry context. For example, we focused on Mwallet apps as a technology. However, the dictionary and keywords may differ across intelligent technologies, such as Amazon Alexa or Google Home. Also, the integration of technology across various touchpoints would vary across technology characteristics and service contexts. Hence, we build a keyword dictionary for Mwallet technology across service contexts to better understand the application of the concept of 'convenience' in NCX.

The main challenge at this stage is to identify unique keywords for each dimension. Usually, touchpoints across a customer's journey overlap in terms of characteristics and service. For example, we need to know when a transaction phase starts – in the checkout queue or when making a payment. Any subjectivity or overlap between keywords reduces the classification accuracy of the model. We reached out to twelve marketing professors (some content experts and some method experts) to address the subjectivity and researcher bias. However, in the current model, we still see overlap between access and transaction dimensions. Conceptually, these two dimensions overlap, and users may find it challenging to identify the targeted dimension. For example, if something is wrong with the handset itself, it may disrupt the access to deploy Mwallet while making a transaction. However, users may construe it as a transaction failure. Similar issues are bound to exist across all NCX dimensions.

Next, we use a simple approach of Contrastive Attention (Tulkens & Van Cranenburgh, 2020) for the classification algorithm. While this approach is relatively new, it allows us to create a training dataset with a reduced processing load. Methods such as Latent Dirichlet Analysis (LDA), Latent Semantic Analysis (LSA), and other hybrid models are widely used for unsupervised text modeling. Such approaches rely on syntactic features in the dataset and complex neural networks. CAt employs an attention vector to boost the performance of the model and make the results more interpretable. For example, this method automatically assigns labels to sentences, unlike the other approaches where researchers need to decide on labels manually. With a more enriched keyword dictionary and reduced overlap between dimensions, there is a scope to increase the overall performance of our model from 0.55 to 0.70, which is a good fit for such subjective classifications. Also, we can generalize it to other technology-service contexts.

Limitations and Future Research

The current study is the first step to build a classification model for Mwallet apps on NCX dimensions. At this stage, our primary goal is to explore the possibility of utilizing machine learning and extract meaningful information for NCX. However, below are few limitations of this study:

1. We need to update the model with clearer keywords. Thus, the next step is to adopt a semi-supervised or supervised approach to topic classification. We plan to train 10% of the data on topic classification using the dimensions of NCX. Then we feed that data in the model to classify remaining reviews until we hit a high precision, the recall, and F1-score (Pavlinek & Podgorelec, 2017).[36]
2. Usually, review datasets are messy, which leads to substantially small sample size for modeling. We also had to remove many reviews from our analysis based on non-English language, symbols, and fewer words. Thus, we plan to collect more data that can help us better uncover the underlying pattern in the data.
3. In the current version of Mwallet as a technology, we omit Mwallets operated under closed ecosystems, such as Apple Pay, Amazon Pay, and Walmart Pay. While it is only possible to get similar data via companies, we can include social media reviews of these wallets to give more breadth to our model. Although, even in that case, we cannot build an econometric model to have them in the weight's information.
4. We plan to incorporate review data for AR, VR, and other financial apps that are mainstream customer technologies and can be assessed on the dimensions of NCX.
5. The dataset used for text analysis is one year long for different Mwallet providers across the world. There can be country or technology-level effects that may systematically affect the users and their experience evaluation. A text classification model is not suited to handle such situations. This kind of observed and unobserved heterogeneity can be captured in econometric models. Thus, we plan to conduct a user-level econometric analysis to derive the weights for each dimension for the NCX score and use it to create a weighted NCX score.

[36] Precision refers to the percentage of texts the classifier tagged correctly out of the total number of texts it predicted for each topic. Recall refers to the percentage of texts the model predicted for each topic out of the total number of texts it should have predicted for that topic. F1 score refer to the average of both precision and recall (Source: https://monkeylearn.com/blog/introduction-to-topic-modeling/ , accessed on June 20, 2021

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TABLES AND FIGURES

Table 1: Select Literature on Customer Experience and Digital Technologies in Marketing

Select Studies with Focus on Conceptualization and Measurement of CX and CXM				
Study	**Methodology**	**Focus**	**Theoretical Underpinnings**	**Key Contribution**
Becker and Jaakkola (J. of the Academy of Marketing Science, 2020)	Systematic Literature Review and Metatheoretical Analysis	To develop a set of fundamental premises of CX. Compare the across research streams and integrate.	CX as a response to consumption process (broad scope and interpretive) CX as a response to managerial stimuli (narrow scope and positivist)	CX should be defined as non-deliberate, spontaneous responses and reactions to particular stimuli. Stimuli reside within and outside firm-controlled touchpoints. Firms cannot create the CX, but they can monitor, design, and manage various stimuli that affect such experiences.
Lemon and Verhoef (J. of Marketing, 2016)	Systematic Literature Review and Future Research Directions	Examining existing definitions and conceptualizations of CX as a construct and provide a historical perspective.	Customer Satisfaction, Brand Experience, Service Quality, Customer Delight, Customer Feedback – Net Promoter Score, Customer Effort Score; Customer Experience Ecosystem	Highlighted need to study CX in digital environments across multiple touchpoints stages. No robust measurement approached to evaluate all aspects of CX across the customer journey. How can brands exert more control over partner-owned touchpoints? Effects of different touchpoints on CX.
Ordenes, Theoduolidis, Burton, Gruber, and Zaki (J. of Service Research, 2014)	Empirical Article	Text mining to enable automatic extraction of information from textual data to assess the impact of interactive service processes on CX.	Elements of Customer Experience, Three value creation elements – activities, resources, and context (ARC).	Open learning model to account for changing contests and service domains in understanding customer feedback experiences.
Tax, McCutcheon, and Wilkinson (J. of Service Research, 2013)	Conceptual Article	Concept of Service Delivery Network (SDN) in Customer Journey	Transactional vs. Relational Goals of Customers	Highlights role of complementary service providers in creating service experience. Attribution of Success and Failures in SDN. Who should take the lead role in SDN?
Verhoef, Lemon, Parsuraman, Roggeveen, Tsiros, and Schlesinger (J. of Retailing, 2009)	Conceptual Article	Determinants of CX with a focus on the dynamic view. Five aspects: social environment, service interface, retail brand, CX dynamics, and CX management strategies.	Conceptualization of CX that captures cognitive evaluations, affective responses and encompasses physical and social components.	Setting up the research agenda for the role of social environment, self-serving technologies, and the store brand.

Puccinelli, Goodstein, Grewal, Price, Raghubir, and Stewart (J. of Retailing, 2009)	Systematic Literature Review and Future Research Directions	Customer Experience Management in Retailing by understanding the buying process	Goals, Schemas, and Information processing; Memory; Involvement; Attitudes; Affect; Atmospherics, and Consumer Attributions and Choices.	Highlighting the need to understand better consumer behavior in order to measure and manage CX.
Select Studies focusing on Digital Technologies and its Impact on Marketing Strategy				
Study	**Methodology**	**Focus**	**Theoretical Underpinnings**	**Key Contribution**
Hoyer, Kroschke, Schmitt, Kraume, and Shankar (J. of Interactive Marketing, 2020)	Conceptual Article	Impact of new technologies on the stages of the customer journey	Impact on the type of customer experience (cognitive, sensory/emotional, social).	Typology of new technologies powered by AI and conceptual framework with potential moderators for the customer journey and experiential value.
Nam and Kannan (J. of International Marketing, 2020)	Conceptual Article	Cross-cultural and socioeconomic differences in the customer journeys because of digital technologies and digital media.	Adoption, usage, and interactions of technology-driven touchpoints, Hofstede's cultural dimensions	Focus on evolving customer interactions with technology-driven touchpoints – firm-owned, partner-owned, and social-touch points.
Ramaswamy and Ozcan (J. of Marketing, 2018)	Conceptual Article	Role of interactive system-environments where two or more organizing actors drive creation.	Broader view of value creation, functional relations, brand value co-creation, and ecosystems.	Offering as evolving digitalized networked arrangements of artifacts, persons, processes, interfaces, referred to as Digitalized Interactive Platform (DIP).
Huang and Rust (J. of the Academy of Marketing Science, 2017)	Conceptual Article	Technology-focused service strategy based on the customer attributes, CLV, technology type, and data.	Technology use for standardization vs. personalization; Role of thinking and feeling	Typology and positioning map with technology as a central driver of a service strategy.
Ramaswamy and Ozcan (International J. of Research in Marketing, 2016)	Conceptual Article	Brand engagement platform is at the intersection of experiential co-creators (e.g., customers and employees) and co-creational enterprises (marketing offerings or managing network relations)	Brand value co-creation in joint agencial experiential creation (Starbucks and Apple) on digital brand engagement platforms.	Strengthen the idea of a network of partners managing the entire or part of customer experience (though customer experience is broader than just brand-related value and experience).
Meuter, Ostrom, Roundtree, and Bitner (J. of Marketing, 2000)	Empirical Article	Customer interactions with technology-based self-service delivery options.	Critical incident categories and sources of satisfaction and dissatisfaction with SSTs and relationship to customer attributions.	Highlighted the importance of technology-driven service encounters.
This Study	Conceptual and Multi-Method Empirical Study	Focus on defining and measuring technology driven CX created and co-managed by a network of service providers and technology providers in the context of mobile apps and retail settings	Using the concept of service convenience as a central motivation to define touchpoints and service context for technology driven CX. Using latent structure in unstructured text to understand the importance of	Introducing a concept of Networked Customer Experience – driven by technology and co-created and co-managed by a network of partners. Identifying key items for measuring NCX and uncovering the mechanism behind

	technology-driven touchpoints in a customer's journey. Identifying causal links between brand value, customer goals, and service outcomes on the co-created and co-managed technology-driven CX.	customer attribution of NCX among partners.

Table 2: Correlation Industry Evaluation vs. Customer Evaluation of Customer Experience: Initial Exploratory Evidence

Scores from Pymnts.com = Industry Evaluation

	OS	L	F	C	A	IND	EXP	IND_EXP	DEV	LEARN	PS	RATE
Overall Score	1.000											
Loyalty	0.314**	1.000										
Features	0.835***	0.006	1.000									
Channels	0.248	-0.122	0.148	1.000								
Authentication	0.629***	0.121	0.267*	-0.150	1.000							
Industry	-0.084	-0.010	0.102	0.338**	-0.520***	1.000						
Wallet related Experience	0.149	-0.056	0.101	0.217	0.094	0.082	1.000					
Industry Experience	0.105	0.127	-0.075	-0.504***	0.545***	-0.502***	-0.159	1.000				
Developed Country	-0.002	0.239	-0.145	-0.206	0.175	-0.066	-0.032	0.282*	1.000			
Learning	0.007	0.006	-0.111	0.188	0.072	0.020	0.725***	-0.175	-0.020	1.000		
Payment Segment	0.093	0.219	0.170	0.124	-0.258	0.107	-0.031	-0.305*	-0.150	0.044	1.000	
Average Rating	**0.179**	**0.060**	**0.086**	**0.140**	**0.151**	-0.069	0.070	-0.001	0.107	0.096	0.098	1.000

Ratings from Google Play and App Store = Customer Evaluation

Variable Definition and Source

Variable	Full Name	Description or Source
OS	Overall Score	Pymnts.com Ranking
L	Loyalty	Pymnts.com Ranking
F	Features	Pymnts.com Ranking
C	Channels	Pymnts.com Ranking
A	Authentication	Pymnts.com Ranking
IND	Industry	Payment =1; 0=Otherwise
EXP	Wallet Related Experience	Mobile Wallet Related Experience; Number of years in this industry from the popular press
IND_EXP	Industry Experience	Total Experience of the Parent Company; Company Websites and Popular press
DEV	Developed Country or not	Whether the parent location is a developed country or not; based on World Bank categories
LEARN	Learning	Calculated as different between 2020 and launch year
PS	Payment Segment	Business segments; All = 1; B2C, B2B, C2C = 0
RATE	Average Rating of Apps	Average of the App Store and Google Play store rating

*** significant at <0.001, ** significant at 0.05, * significant at 0.10

Table 3*:* Results from Confirmatory Factor Analysis for NCX (Adapted ServCon), Overall Satisfaction, and Personal Innovativeness with Technology, N=95

NCX Dimension and Measurement Items[1]	CFA Model Statistics[2]		Factor Loadings[3] Retailer --- Technology Provider
	CFI (TLI)	RMSEA (SRMR)	
(A) Decision ($\propto_{SP} = 0.933$, and AVE $= 0.781$ | ($\propto_{TP} = 0.914$, and AVE $= 0.764$)	0.988	0.00 (0.053)	
(1) Let me know of the exact cost or special offers before I made the purchase.	(0.985)	--- 0.00	0.856 --- 0.867
(2) Information I received made it easy for me to choose what to buy.	---	(0.062)	0.867 --- 0.839
(3) It was easy to get the information I needed to decide which product to buy.	0.987		0.896 --- 0.950
(4) It took minimal time to get the information needed.	(0.983)		0.916 --- 0.834
(B) Access ($\propto_{SP} = 0.938$, and AVE $= 0.812$ | ($\propto_{TP} = 0.909$, and AVE $= 0.741$)			
(5) Was accessible through various ways (email, telephone, chat, in-person).			0.908 --- 0.826
(6) It was easy for me to contact the retailer/technology provider.			0.912 --- 0.934
(7) It did not take much time to reach the retailer/ technology provider.			0.926 --- 0.869
(8) It is easy for me to contact an employee, if required.			0.857 --- 0.809
(C) Transaction ($\propto_{SP} = 0.976$, and AVE $= 0.914$ | ($\propto_{TP} = 0.976$, and AVE $= 0.921$)			
(9) I did not have to make much of an effort to pay for the product.			0.927 --- 0.955
(10) Made it easy to conclude my purchase.			0.967 --- 0.977
(11) I found it easy to complete my purchase.			0.977 ---0.991
(12) Helped me to quickly complete my purchase.			0.953 --- 0.913
(D) Benefits ($\propto_{SP} = 0.901$, and AVE $= 0.758$ | ($\propto_{TP} = 0.960$, and AVE $= 0.892$)			
(13) I was able to get the rewards from the purchase with little effort.			0.921 --- 0.929
(14) Solved my rewards-related needs without creating other problems.			0.874 --- 0.986
(15) The time required to receive the benefits (such as loyalty rewards or cashback) was reasonable.			0.813 --- 0.917
(E)Support ($\propto_{SP} = 0.975$, and AVE $= 0.954$ | ($\propto_{TP} = 0.940$, and AVE $= 0.888$)			
(16) Resolved my problem quickly.			0.94 --- 0.939
(17) Made it easy for me to resolve my problem.			1.012 --- 0.945
(F) Satisfaction ($\propto_{SP} = 0.946$, and AVE $= 0.825$ | ($\propto_{TP} = 0.936$, and AVE $= 0.789$)	0.998	0.04 (0.023)	
(1) Overall, I am satisfied with my retailer/technology provider.	(0.993)	---	0.993 --- 0.939
(2) Shopping was a delightful experience.	---	0.00 (0.01)	0.877 --- 0.895
(3) My encounter was better than expected.	1.00		0.818 --- 0.806
(4) As a result of my interaction, I was Satisfied.	(1.00)		0.936 --- 0.909
(G) Personal Innovativeness with Technologies ($\propto = 0.894$, and AVE $= 0.742$)	0.98	0.07 (0.07)	
(1) If I heard about a new technology, I would look for ways to experiment with it.	(0.95)		0.823
(2) Among my family and peers, I am usually the first to try out new technologies.			0.780
(3) I like to experiment with new technologies.			0.944
(H) Involvement with Technologies ($\propto = 0.851$, and AVE $= 0.670$)			
(4) Technologies like mobile payment apps are important to me.			0.881
(5) Technologies like mobile payment apps make it easier to conduct my day-to-day purchase activities.			0.809
(6) I feel comfortable in using technologies in my daily life.			0.760

1. Measured on Likert Scale with NA Option**:** Completely Agree—Agree—Neither Agree nor Disagree—Disagree—Completely Disagree—Not Applicable
2. For good fit – CFI and TLI should be closer to 1; RMSEA and SRMR should be closer to 0.
3. The first number is the factor loading for the retailer or service provider, and the second number is the factor loading for the technology provider.

Table 4*: 2×2×2 Factorial Design to Measure the Impact of Use Benefits Salience, Brand Value of Service Providers, and Technology Failures on NCX*

Group 1 – No Technology-Service Failure (G1) (*q3*)		
Use Benefit Salience	**Brand Value of Service Provider**	
	High SP	Low SP
High Use Benefit Salience (HUBS) (Convenience, Security, and Digit Rewards)	**C1** N=57 M_{age}=51.37 75.43% female Mpayment Users = 34 Average NCX = 16.65 (SD = 5.42) Average Satisfaction = 3.96 (SD = 1.24)	**C2** N=66 M_{age}=40.90 68.70% female Mpayment Users = 47 Average NCX = 16.36 (SD = 3.27) Average Satisfaction = 3.92 (SD = 0.84)
Low Use Benefit Salience (LUBS) (Convenience, Security, and General Rewards)	**C3** N=64 M_{age}=48.46 66.66% female Mpayment Users = 46 Average NCX = 16.23 (SD = 5.15) Average Satisfaction = 4.22 (SD = 1.57)	**C4** N=70 M_{age}=41.11 67.14% female Mpayment Users = 48 Average NCX = 15.02 (SD = 4.74) Average Satisfaction = 4.25 (SD = 1.55)
Group 2 – With Technology-Service Failure (G2) (*q3*)		
Use Benefit Salience	**Brand Value of Service Provider**	
	High SP	Low SP
High Use Benefit Salience (HUBS) (Convenience, Security, and Digit Rewards)	**C5** N=82 M_{age}=49.83 78.04% female Mpayment Users = 54 Average NCX = 18.41 (SD = 7.20) Average Satisfaction = 4.61 (SD = 2.52)	**C6** N=75 M_{age}=41.74 64.17% female Mpayment Users = 45 Average NCX = 18.97 (SD = 7.82) Average Satisfaction = 4.45 (SD = 2.27)
Low Use Benefit Salience (LUBS) (Convenience, Security, and General Rewards)	**C7** N=71 M_{age}=50.91 60.56% female Mpayment Users = 52 Average NCX = 18.92 (SD = 6.54) Average Satisfaction = 5.72 (SD = 4.93)	**C8** N=73 M_{age}=43.57 64.00% female Mpayment Users = 44 Average NCX = 19.40 (SD = 6.63) Average Satisfaction = 5.11 (SD = 3.28)

Table 5: Power Analysis and Sample Size Calculation for 2×2×2 Full Factorial Design

Effect Size, f		Desired Power (1-β)				
		0.75	**0.80**	**0.85**	**0.90**	**0.95**
Small Effect Size	0.10	696	787	900	1053	1302
	0.15	311	351	401	469	580
Medium Effect Size	0.20	176	199	227	265	327
	0.25	114	128	146	171	210
	0.30	80	90	102	119	147
Large Effect Size	0.35	59	67	76	88	109
	0.40	46	52	59	68	84

This table is created using G*Power (Version 3.1.9.7) using ANOVA: Fixed Effects, Main Effects, and Interactions Statistical test with F-Test Family.
Type of Power Analysis: Compute required sample size – given ∝ (error probability as 0.05), power, and effect size.
Numerator df=1 [q1 (2-1), q2 (2-1), and q3 (2-1)] and Number of Groups = 8 (2×2×2)

Table 6: Results from Generalized Linear Model Analysis for NCX

Model Variable	**NCX**				**Log Transformed NCX**			
	Main Effects Model		Interaction Effects Model		Main Effects Model		Interaction Effects Model	
	Estimate (β)	p-value	Estimate (β)	p-value	Estimate (β)	p-value	Estimate (β)	p-value
Intercept	**18.931*** **	<0.001	**18.35*** **	<0.000	**1.269*** **	<0.001	**1.252*** **	<0.00
Brand Value (BV)	-0.087	0.861	0.812	0.363	-0.003	0.811	0.026	0.290
Use Benefits (UB)	0.715	0.144	**1.942** **	0.03	0.017	0.174	**0.067** **	0.007
Failure (FAIL)	**2.270*** **	<0.001	**4.089** **	<0.000	**0.049*** **	<0.001	**0.103*** **	<0.000
BV × UB	-	-	-0.594	0.654	-	-	-0.033	0.367
BV × FAIL	-	-	-1.778	0.194	-	-	-0.046	0.194
UB × FAIL	-	-	**-2.525** **	0.066	-	-	**-0.086** **	0.015
BV × UB × FAIL	-	-	1.072	0.583	-	-	0.045	0.372
Age	0.011	0.454	0.009	0.504	0.000	0.816	0.000	0.894
Gender	-0.084	0.873	-0.044	0.9322	0.006	0.660	0.007	0.593
Mwallet User (USER)	0.082	0.873	0.077	0.880	0.007	0.570	0.007	0.583
Innovativeness with technology (INN)	-0.418	0.177	-0.410	0.190	-0.012	0.116	-0.012	0.134
Involvement with technology (INV)	0.345	0.254	0.346	0.255	0.009	0.232	0.009	0.246
Brand Equity for Neiman Marcus (BENM)	0.015	0.960	-0.015	0.961	-0.000	0.939	-0.001	0.838
Brand Equity for Ross Stores (BERS)	0.363	0.139	0.390	0.113	**0.005** **	0.426	0.006	0.351
Brand Equity for Google Pay (BEGP)	**-1.257*** **	<0.001	**-1.322*** **	<0.000	**-0.030*** **	<0.001	**-0.032*** **	<0.000
N	558		558		558		558	
AIC	3507.3		3508.8		-468.92		-468.65	

Table 7: Results from Generalized Linear Model Analysis for NCX after removing Outliers

Model Variable	**NCX**				**Log Transformed NCX**			
	Main Effects Model		Interaction Effects Model		Main Effects Model		Interaction Effects Model	
	Estimate (β)	p-value	Estimate (β)	p-value	Estimate (β)	p-value	Estimate (β)	p-value
Intercept	**17.456*** **	<0.001	**16.978*** **	<0.001	**1.238*** **	<0.001	**1.221*** **	<0.001
Brand Value (BV)	-0.430	0.285	0.349	0.623	-0.010	0.3198	0.014	0.476
Use Benefits (UB)	0.490	0.210	**1.915** **	0.007	0.0130	0.1910	**0.059** **	0.002
Failure (FAIL)	**2.241*** **	<0.001	**4.218*** **	<0.001	**0.0524*** **	<0.001	**0.106*** **	<0.001
BV × UB	-	-	-0.420	0.690	-	-	-0.017	0.530
BV × FAIL	-	-	-1.444	0.185	-	-	-0.038	0.161
UB × FAIL	-	-	**-2.990** **	0.006	-	-	**-0.084** **	0.002
BV × UB × FAIL	-	-	0.736	0.635	-	-	0.024	0.538
Age	0.013	0.271	0.010	0.404	0.000	0.441	0.000	0.607
Gender	0.241	0.566	0.340	0.414	0.007	0.480	0.005	0.638
Mwallet User (USER)	0.362	0.381	0.368	0.369	0.009	0.379	0.010	0.351
Innovativeness with technology (INN)	-0.370	0.135	-0.362	0.143	**-0.011***	0.084	**-0.010***	0.094
Involvement with technology (INV)	0.249	0.300	0.217	0.365	0.005	0.349	0.005	0.408
Brand Equity for Neiman Marcus (BENM)	-0.024	0.923	-0.069	0.780	-0.001	0.846	-0.002	0.705
Brand Equity for Ross Stores (BERS)	**0.450** **	0.022	**0.474** **	0.015	**0.010** **	0.049	**0.010** **	0.032
Brand Equity for Google Pay (BEGP)	**-1.012**	<0.001	**-1.075*** **	<0.001	-0.0240	<0.001	**-0.026*** **	<0.001
N	525		525		525		525	
AIC	3047.7		3041.5		-775.48		-783.40	

Table 8: Simple Effects Analysis for Brand Value, Use-Benefits, and Failure for $\log_{10}$(NCX)

Factor	Interaction	Test-Statistic	P-value
Failure	BV = 0, UB = 0	0.1064***	<0.000
	BV = 1, UB = 0	0.0676***	<0.000
	BV = 0, UB = 1	0.0220	0.2744
	BV = 1, UB = 1	0.0075	0.7102
Use-Benefits	BV = 0, FAIL = 0	0.0590**	0.0020
	BV = 1, FAIL = 0	0.0414**	0.0484
	BV = 0, FAIL= 1	-0.0253	0.2003
	BV = 1, FAIL = 1	-0.0187	0.3317
Brand Value of SP	UB = 0, FAIL = 0	0.0138	0.4765
	UB = 1, FAIL = 0	-0.0039	0.8523
	UB = 0, FAIL = 1	-0.0249	0.2139
	UB = 1, FAIL = 1	-0.0184	0.3456

Table 9*:* MANOVA Results for NCX (Tests of Between Subjects Effects and Parameter Estimates

IVs	Decision	Access	Transaction	Benefits	Support
Intercept	**1.081*** (<0.001)**	**1.039*** (<0.001)**	**1.067*** (0.002)**	**1.366*** (<0.001)**	**1.418*** (<0.001)**
Brand Value (BV=0)	-0.040 (0.633)	-0.018 (0.887)	0.088 (0.589)	-0.138 (0.232)	-0.021 (0.869)
Use Benefits (UB=0)	-0.026 (0.762)	-0.060 (0.610)	-0.181 (0.269)	-0.114 (0.327)	-0.116 (0.359)
Failure (FAIL=0)	-0.106 (0.289)	-0.15 (0.917)	**-0.421** (0.030)**	**-0.244* (0.075)**	-0.131 (0.378)
BV × UB	-0.001 (0.992)	0.000 (0.998)	0.245 (0.294)	0.260 (0.115)	0.153 (0.394)
BV × FAIL	0.127 (0.334)	0.002 (0.993)	0.070 (0.784)	0.189 (0.295)	0.076 (0.698)
UB × FAIL	0.029 (0.835)	-0.053 (0.784)	0.214 (0.423)	0.102 (0.587)	0.230 (0.263)
BV × UB × FAIL	-0.040 (0.831)	0.108 (0.682)	-0.399 (0.276)	-0.118 (0.647)	-0.193 (0.491)
Age	**0.003* (0.088)**	**0.005** (0.020)**	**0.007** (0.021)**	0.003 (0.146)	0.002 (0.353)
Gender	-0.045 (0.369)	-0.022 (0.753)	0.079 (0.414)	0.005 (0.944)	0.028 (0.710)
Mwallet User	0.005 (0.915)	0.014 (0.843)	-0.045 (0.639)	**-0.128* (0.061)**	-0.001 (0.989)
INN	-0.031 (0.339)	-0.008 (0.861)	-0.080 (0.201)	-0.18 (0.690)	-0.024 (0.614)
INV	-0.007 (0.817)	-0.010 (0.815)	**0.148** (0.014)**	0.039 (0.354)	0.033 (0.470)
BENM	0.003 (0.914)	-0.023 (0.537)	0.058 (0.250)	0.013 (0.710)	**-0.102** (0.009)**
BERS	0.023 (0.294)	0.047 (0.128)	0.055 (0.191)	0.012 (0.685)	0.000 (0.997)
BEGP	-0.028 (0.294)	**-0.061* (0.075)**	**-0.169** (<0.001)**	**-0.068* (0.043)**	-0.021 (0.560)
Corrected Model	F=1.058 (0.396)	F=1.045 (0.409)	**F=3.973*** (<0.001)**	F=1.499 (0.105)	F=0.968 (0.490)
Adjusted R^2	0.003	0.002	0.137	0.026	-0.002

Results are for bootstrapped errors with 1000 bootstraps for N=283. Many observations were dropped if the proportion of a dimension did not have a score or is 0. Figures in brackets are the p-value for an estimate.

Table 10*:* MANOVA Results for Attribution

IVs	Attribution to Retailer	Attribution to Google Pay
Intercept	**2.120*** (<0.001)**	**1.599*** (<0.001)**
Brand Value (BV=0)	-0.111 (0.598)	-0.012 (0.956)
Use Benefits (UB=0)	**-0.384** (0.044)**	**-0.431** (0.035)**
Failure (FAIL=0)	-0.078 (0.746)	-0.031 (0.909)
BV × UB	0.274 (0.334)	-0.039 (0.885)
BV × FAIL	0.345 (0.340)	0.214 (0.551)
UB × FAIL	0.467 (0.164)	0.372 (0.291)
BV × UB × FAIL	-0.460 (0.338)	-0.165 (0.734)
Age	0.004 (0.253)	0.005 (0.218)
Gender	0.160 (0.194)	-0.145 (0.253)
Mwallet User	-0.108 (0.380)	0.028 (0.819)
INN	-0.048 (0.575)	-0.049 (0.530)
INV	**0.467*** (<0.001)**	**0.469*** (<0.001)**
BENM	0.048 (0.549)	0.026 (0.710)
BERS	**-0.131** (0.019)**	-0.036 (0.549)
BEGP	-0.013 (0.844)	0.029 (0.642)
Corrected Model	F=7.265*** (<0.001)	F=7.219*** (<0.001)
Adjusted R^2	0.214	0.213

Results are for bootstrapped errors with 1000 bootstraps for N=346. Many observations were dropped if it did not have a score or is 0.

Table 11: Moderated Mediation Regression Results for NCX as Mediator and Satisfaction as Moderator

IVs	Equation 1: BV→NCX (Mod=Fail)	Equation 2: NCX→SAT	Equation 1: UB→NCX (Mod=Fail)	Equation 2: NCX→SAT
	F (HC0) = 5.6742 p = 0.0000	F (HC0) = 6.7367 p = 0.0000	F (HC0) = 5.9784 p = 0.0000	F (HC0) = 7.4609 p = 0.0000
Constant	**β= 1.2716***** **(0.0000)**	**β= 1.0835***** **(0.0000)**	**β= 1.2982***** **(0.0000)**	**β= 1.0778***** **(0.0000)**
BV	β= 0.0085 (0.6321)	β= 0.0051 (0.7275)	-	-
UB	-	-	**β= 0.0516**** **(0.0020)**	**β= -0.0431**** **(0.0024)**
NCX	-	**β= 0.4697***** **(0.0000)**	-	**β= 0.4786** **(<0.001)**
Fail	**β= 0.0631***** **(0.003)**	**-**	**β= 0.0815***** **(0.0000)**	**-**
IV × Fail	β= -0.0245 (0.3240)	**-**	**β= -0.0656***** **(0.0088)**	**-**
BENM	β= 0.0001 (0.9904)	β= -0.0083 (0.3977)	β= -0.0004 (0.9512)	β= -0.0072 (0.4631)
BERS	β= 0.0050 (0.4418)	β= -0.0057 (0.4622)	β= 0.0062 (0.3515)	β= -0.060 (0.4447)
BEGP	**β= -0.0293***** **(<0.001)**	β= 0.0021 (0.8462)	**β= -0.0324***** **(<0.001)**	β= 0.0041 (0.6961)
INN	**β= -0.0134*** **(0.0920)**	β= -0.0102 (0.3589)	β= -0.0116 (0.1364)	β= -0.0092 (0.3979)
INV	β= 0.0107 (0.1400)	**β= 0.0170*** **(0.0808)**	β= 0.0092 (0.2001)	**β= 0.0170*** **(0.0794)**
Age	β= 0.0001 (0.7089)	β= -0.0001 (0.8627)	β= 0.0001 (0.8072)	β= 0.0000 (0.9532)
Gender	β= 0.0088 (0.5418)	β= -0.0232 (0.1317)	β= 0.0083 (0.5638)	β= -0.0192 (0.2046)
R^2	0.087	0.1666	0.098	0.1797
Direct Effect	BV→SAT: 0.0051, p = 0.7275		UB→SAT: -0.0431, p-value = 0.0024	
Moderation Effect	F (1,547) =0.9744, p = 0.324		F (1,547) = 6.9054, p =0.0088 Effect p-value Fail = No 0.0516 0.0020 Fail = Yes -0.0140 0.4364	
Conditional Indirect Effects	Effect BootLCI BootUCI Fail = No 0.0040 -0.0123 0.0210 Fail = Yes -0.0075 -0.0259 0.0100		Effect BootLCI BootUCI Fail = No 0.0247 0.0103 0.0436 Fail = Yes -0.0067 -0.0265 0.0107	

Table 12: Summary Statistics for Reviews and Rating Data from Google Play Store

Mwallet App	No. of Reviews	Average No. of Words in the Review	Average Rating	S.Dev of Ratings
Airtel Thanks	5603	29.13	1.45	1.04
Alipay	927	11.24	1.91	1.46
BigPay	1478	14.20	3.61	1.72
BoostPay	2921	18.25	2.06	1.47
CashApp	4977	26.09	2.38	1.67
Freecharge	5083	12.26	2.75	1.79
Google Pay	4446	17.65	3.45	1.71
Mobikwik	6638	15.56	2.62	1.83
PayZapp	6772	15.84	2.25	1.63
Paypal	6493	16.85	3.43	1.75
Paytm	4683	21.71	2.44	1.67
PhonePe	4348	22.24	2.62	1.69
Pockets	2843	12.89	2.14	1.64
RBC	595	19.71	1.45	1.00
Samsung Pay	4037	16.54	3.88	1.60
TMW	1378	20.99	1.48	1.23
TouchnGo	2166	20.61	2.18	1.47
Venmo	4359	19.34	3.10	1.79
Vodafone M-pesa	6819	16.70	2.26	1.66

Table 13: Dictionary of Keywords Used for Text Classification

Decision	Access	Transaction	Rewards Benefits	Place Benefits	Support
	ability	activity	benefits	bus	action
	access	amount	bonus	booking	agent
	Account	authentication	cashback	car	answer
	activation	authorization	cashless	deliver	assistance
	App	balance	choice	family	bot
	application	barcode	coupon	flight	caller
	atm	bill	deals	games	care
	auto	billing	discount	gas	chat
	banks	bills	ease	grocery	checking
	biometric	bitcoin	expiry	hotel	complaint
	broadband	business	finance	house	concern
	bugs	card	instant	insurance	conversation
	button	cash	loyalty	lunch	delay
	camera	cashier	members	mall	dispute
	cell	charges	membership	menu	email
	channels	checkout	offers	movie	employees
	computer	code	premium	parking	executive
	connection	confirmation	privacy	passport	explanation
	connectivity	contactless	promocodes	petrol	feedback
	coverage	crashes	promotion	rent	fix
	crash	credit	protection	ride	fraud
	data	debit	rebate	transport	future
	description	deduction	redemption	travel	garbage
	design	deposit	reminders		help
	desktop	detection	rewards		helpline
	developer	error	risk		human
	device	exchange	safety		mail
	display	face	savings		management
	download	failure	security		manners
	energy	fees	self		matter
	errors	function	simple		mistake
	features	funds	speed		notice
	fingerprint	glitch	supercash		operator
	handset	identity	utility		pain
	hotspot	loan	validity		queries
	information	machine	value		rating
	instructions	merchant	vouchers		reason
	interface	message			refund
	internet	otp			reply
	language	pack			representative
	layout	password			request
	link	pattern			response
	location	payment			review
	Lock	penalty			robot
	login	performance			satisfaction
	mobile	permission			scam
	network	pin			scammer
	pc/computer	price			screenshot
	phone	processing			service
	playstore	proof			solution
	policy	providers			staff
	recognition	purchases			suggestion
	register	rate			support
	registration	receipt			team
	screen	recharge			waiting
	server	reload			
	setup	retailers			
	shop	scanner			
	signal	seamless			
	smartphone	seller			
	software	sign			
	storage	sms			
	system	store			
	tech	tap			
	technology	text			
	terms	ticket			
	touch	topup			
	tracking	transaction			
	uninstall	transfer			
	update	vendor			
	usage	verification			
	version	visa			

	video	wallet wallets warning withdraw

Table 14: Classification Measures for Unsupervised Learning Model with Contrastive Attention Classifier

Dimension	Precision	Recall	F1 score	N
Access/Transaction	0.61	0.69	0.65	2665
Benefits	0.46	0.40	0.43	1158
Support	0.51	0.55	0.53	784
General	0.52	0.41	0.46	1573
Overall Accuracy	0.55	-	-	6180
Overall Micro-Average	0.55	0.55	0.55	6180
Overall Macro-Average	0.52	0.52	0.52	6180
Weighted Average	0.54	0.55	0.54	6180

Figure 1*: Conceptualization of Networked Customer Experience*

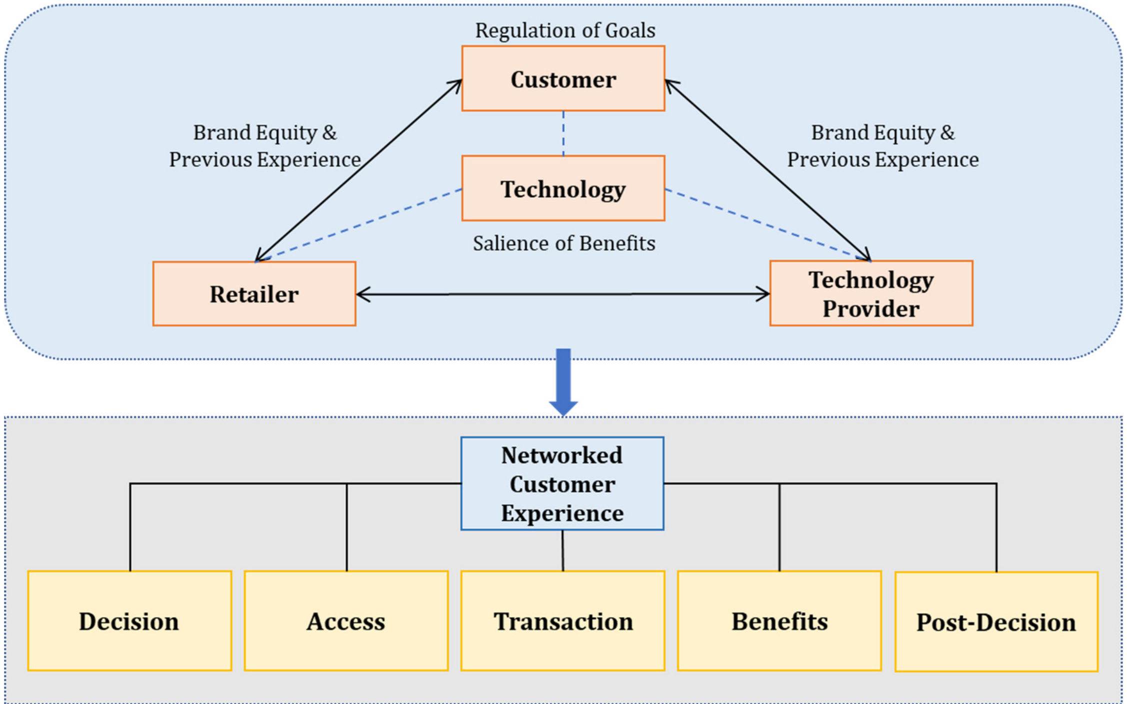


Figure 2*:* Illustration of Networked Customer Experience: Klarna App and Nike

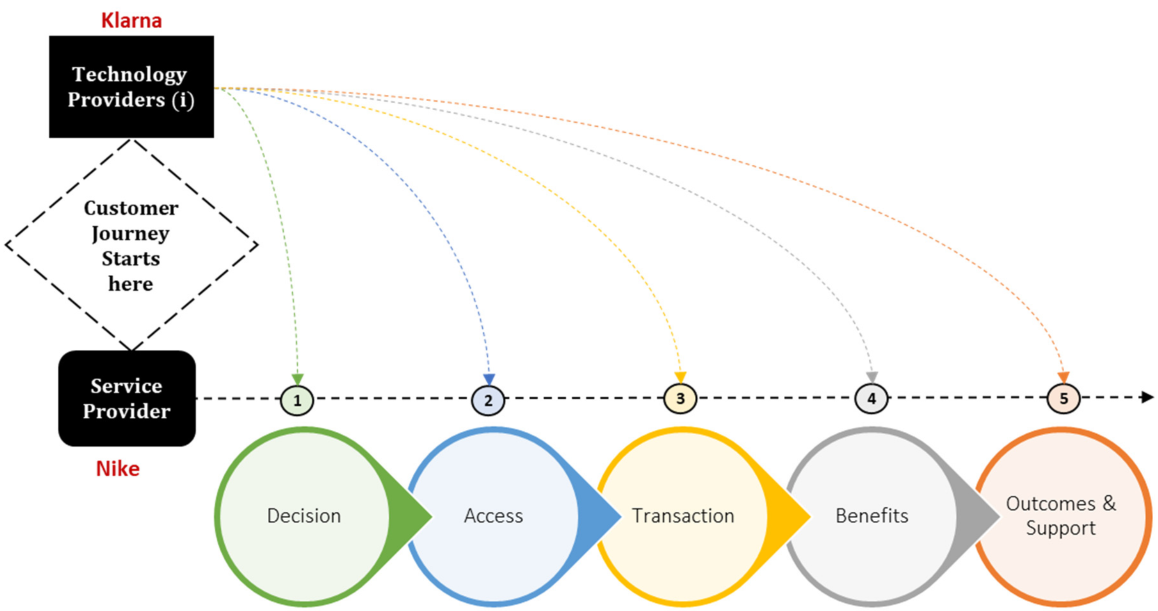


Figure 3: Distribution for NCX and Log_{10}(NCX)

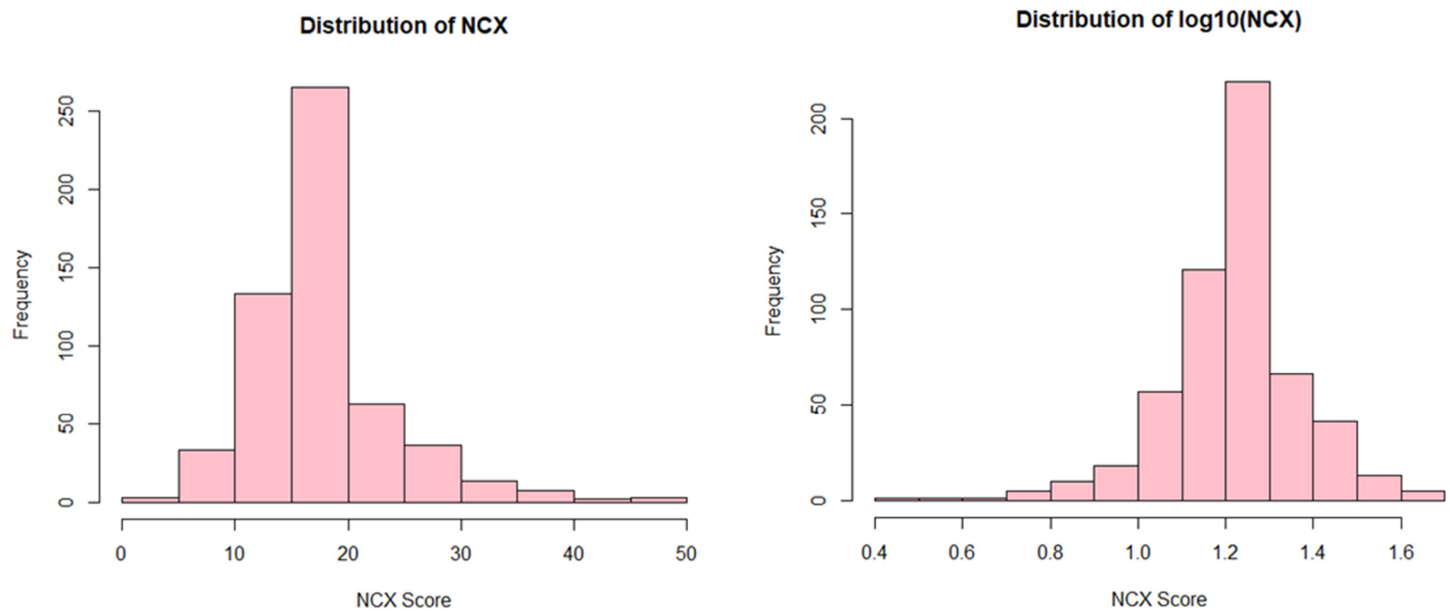
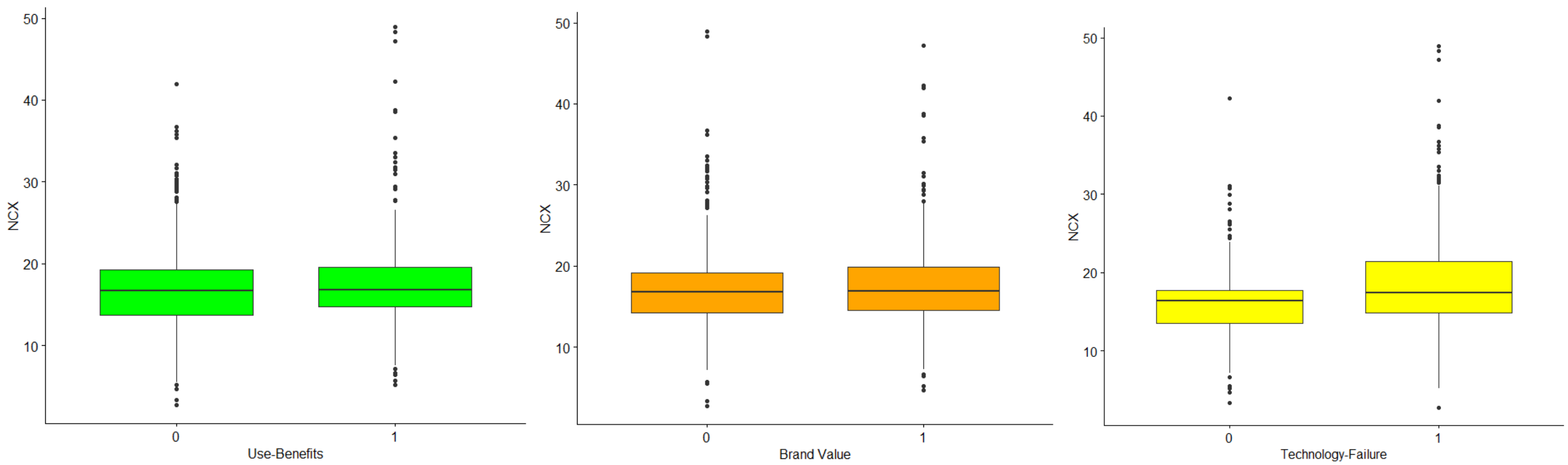


Figure 4: Boxplots for NCX Data Grouped by Treatment Factors

Untransformed NCX



Log-transformed of NCX

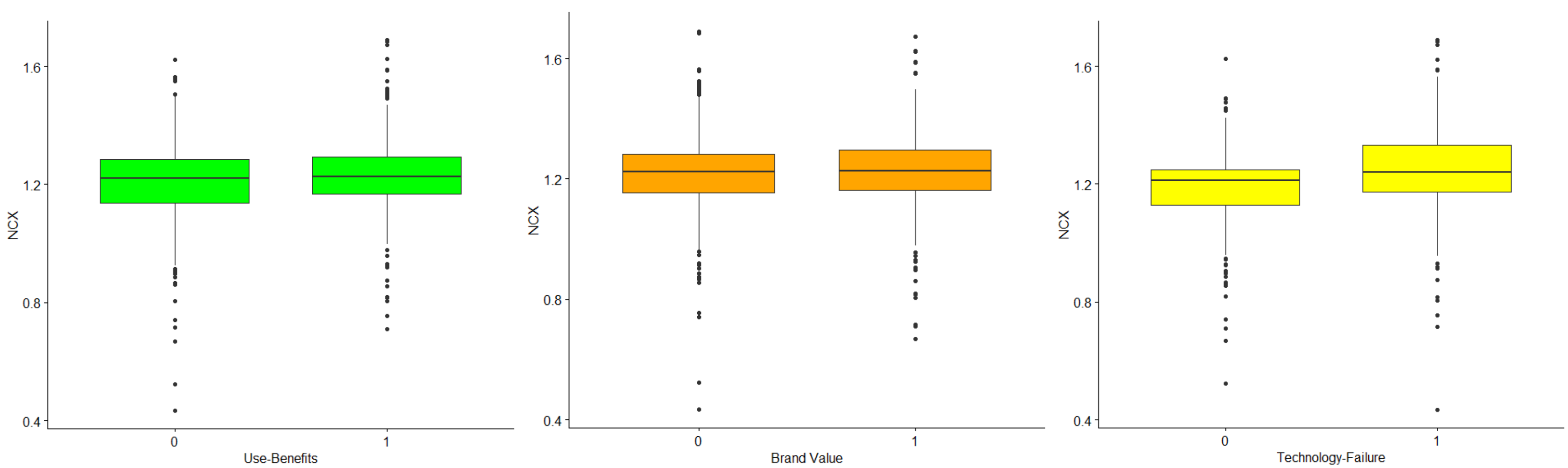
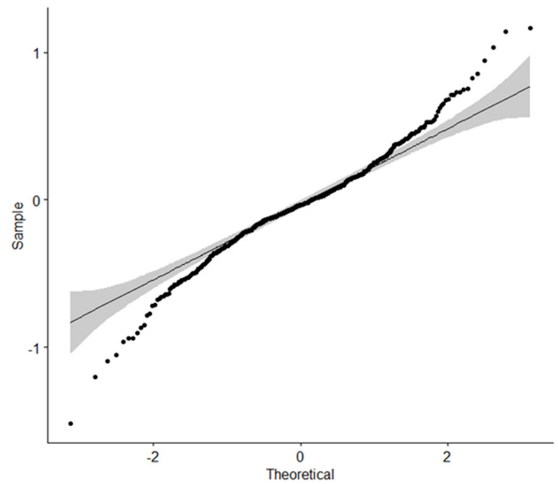
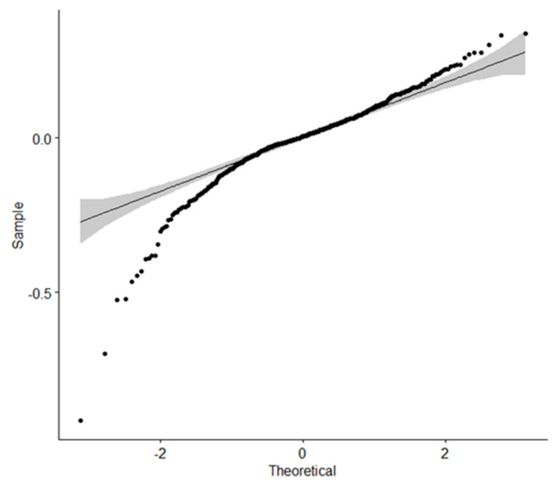


Figure 5: Residual Analysis from GLM



NCX as Dependent Variable



Log_{10}(NCX) as Dependent Variable

Figure 6: Outlier Analysis for NCX as Dependent Variable

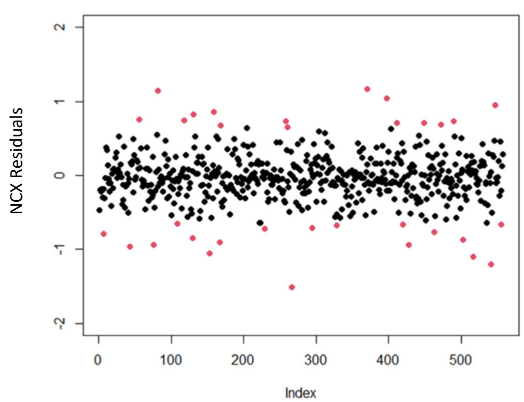


Figure 7: Distribution for NCX and Log_{10}(NCX) after removing outliers

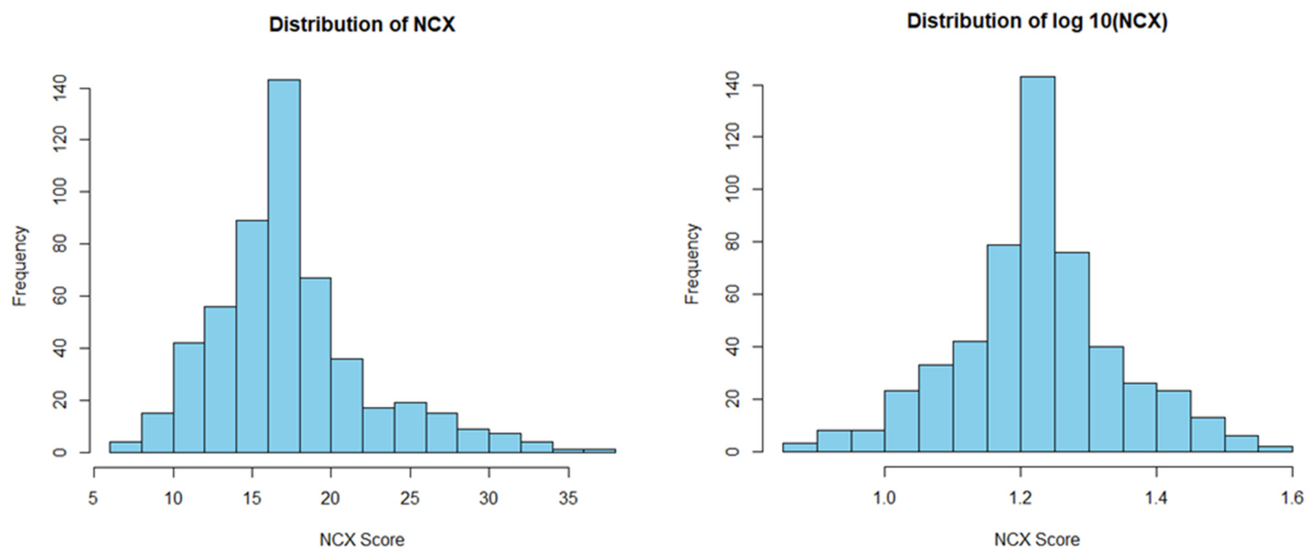
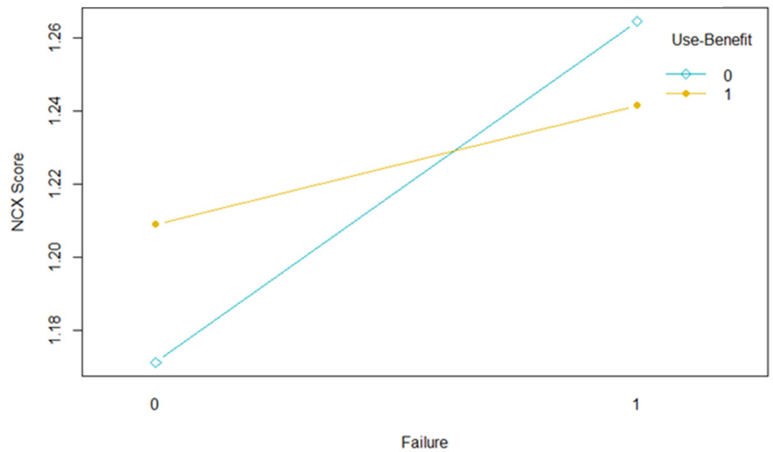
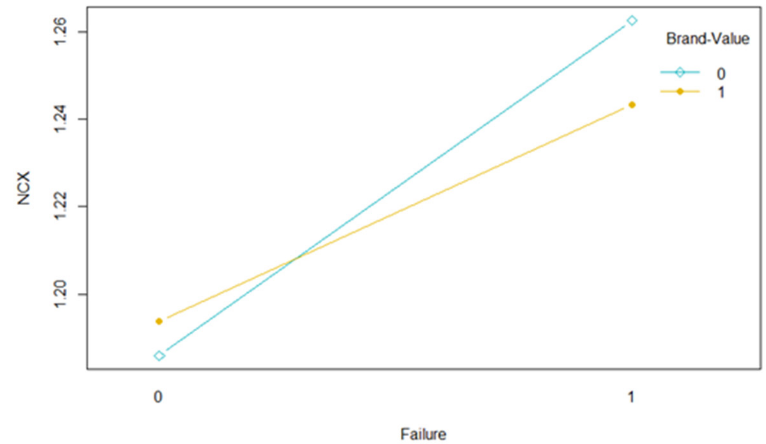


Figure 8*:* Interaction Plots for Use-Benefit, Failure, and Brand Value

a. Interaction Plot of Failure and Use Benefit



b. Interaction Plot of Failure and Brand Value



c. Interaction Plot of Use Benefit and Brand Value

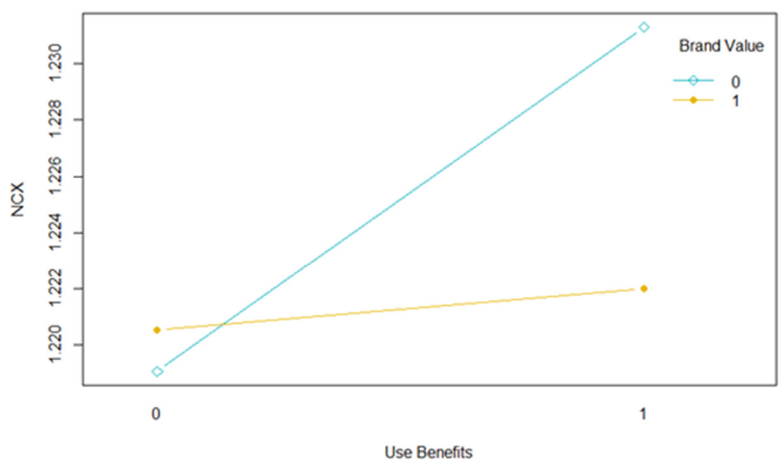
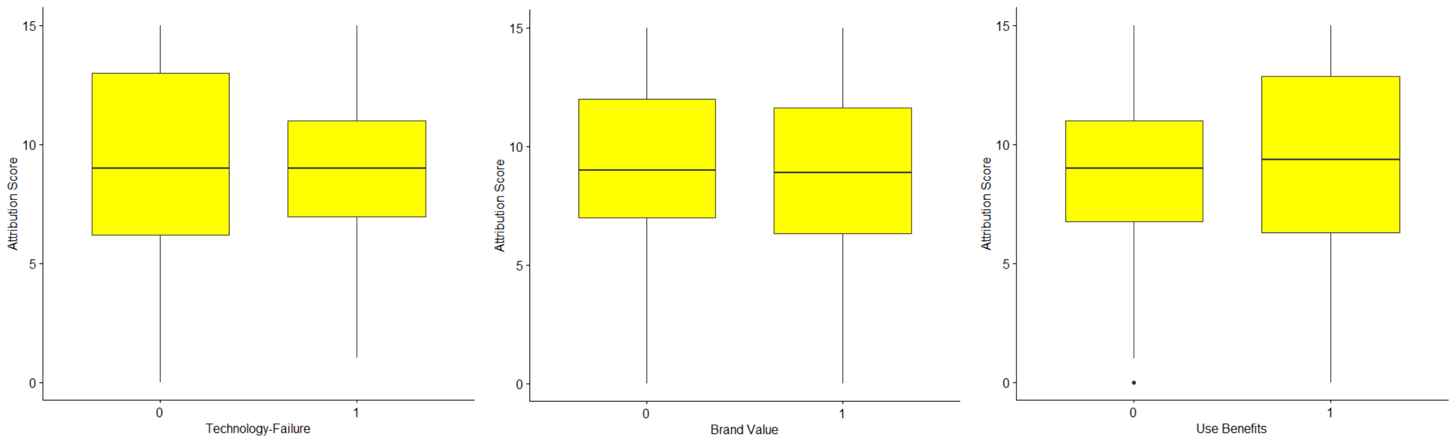


Figure 9: Boxplots for Attribution Model

For Service Provider



For Technology Provider

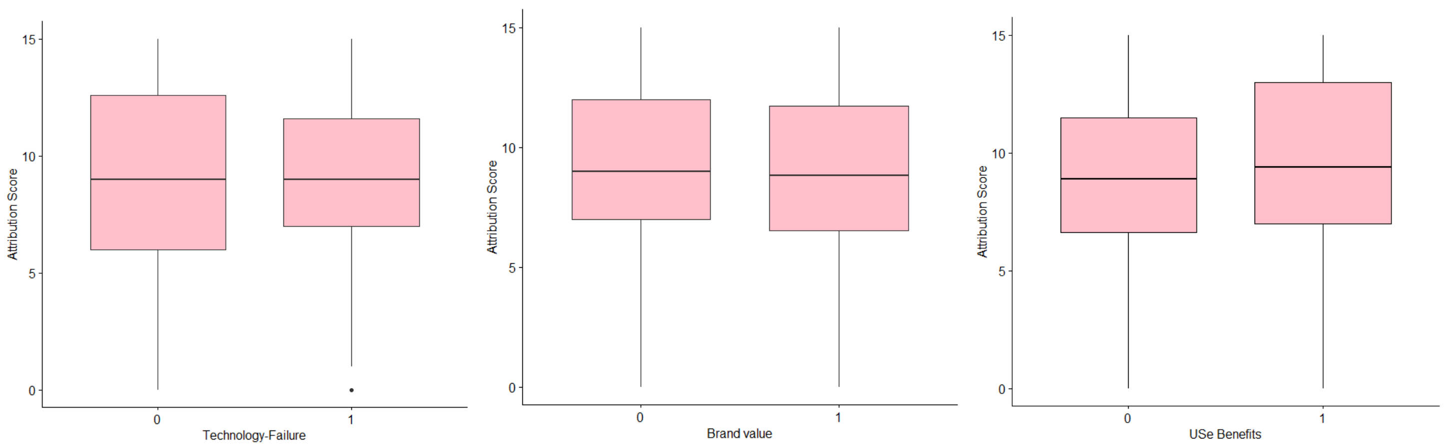


Figure 10: Conceptual Model for the Impact of NCX on Satisfaction

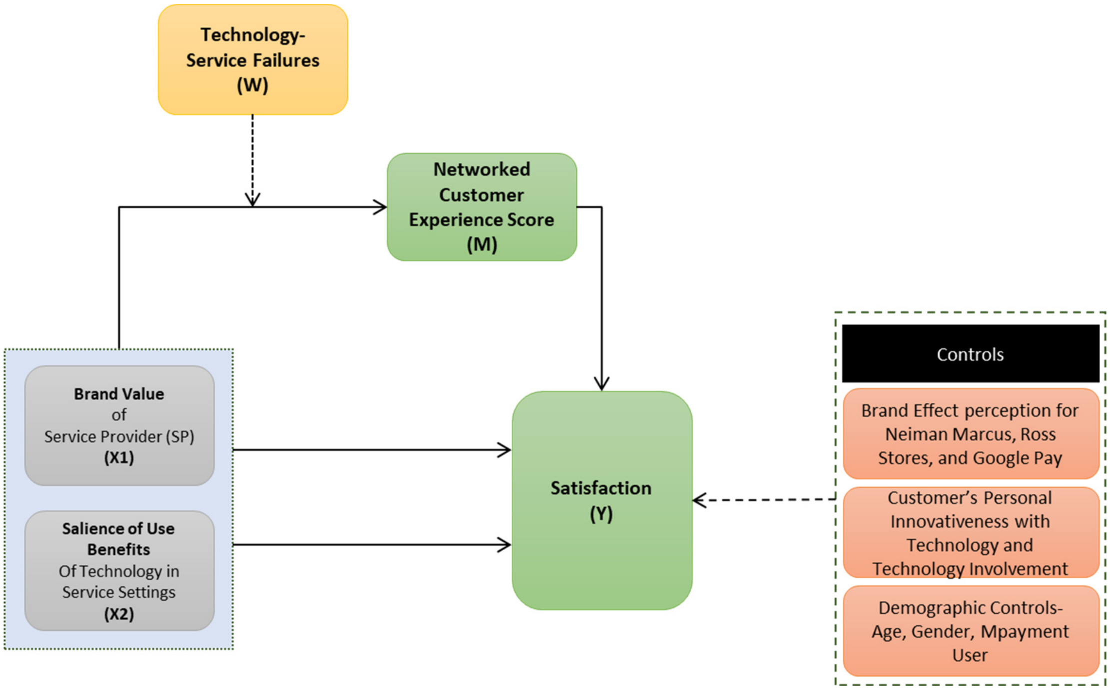


Figure 11: Post-hoc Analysis – NCX Scores for Mpayment Users vs. Non-users

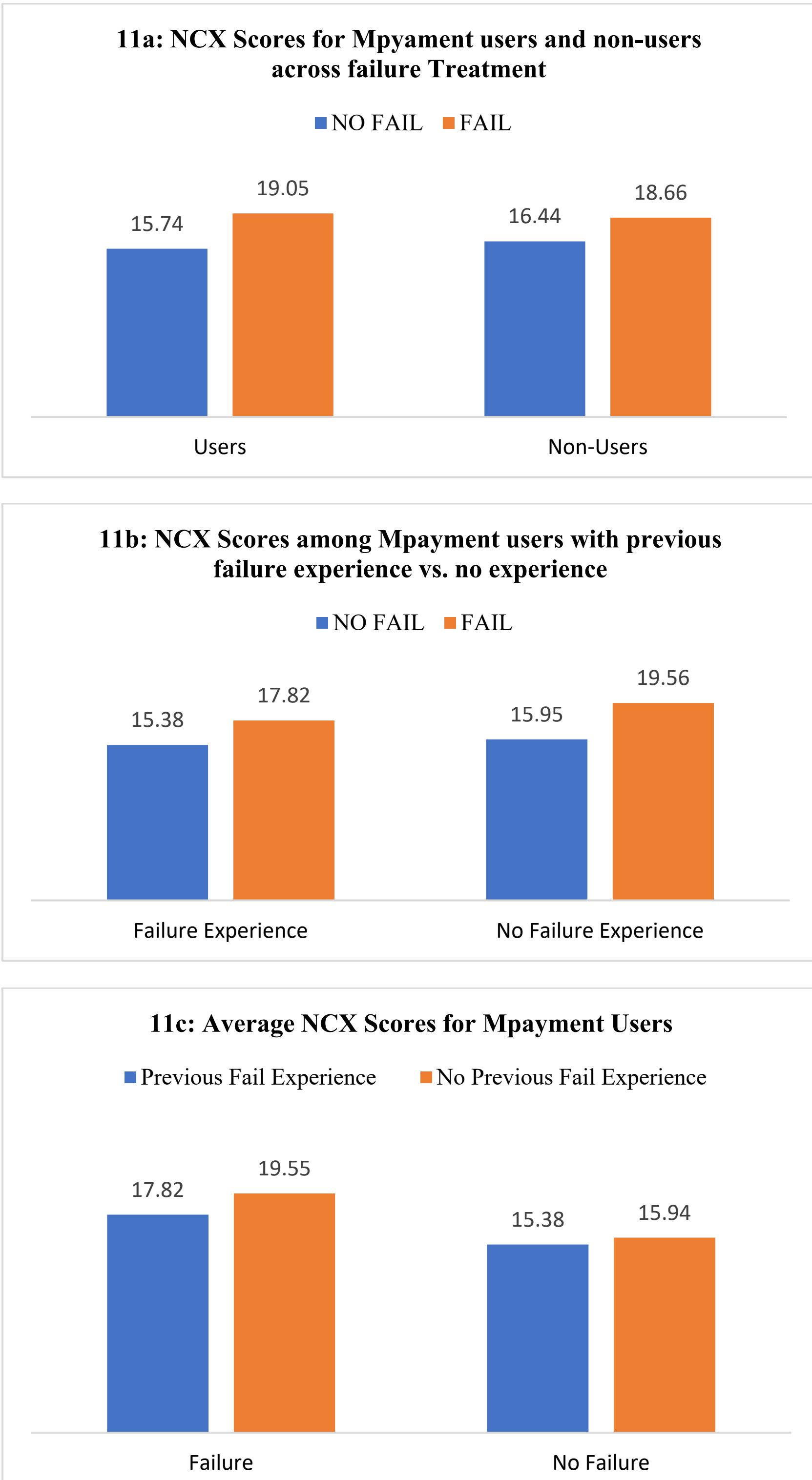


Figure 12: Post-hoc Analysis - Satisfcation Scores for Mpayment Users vs. Non-users

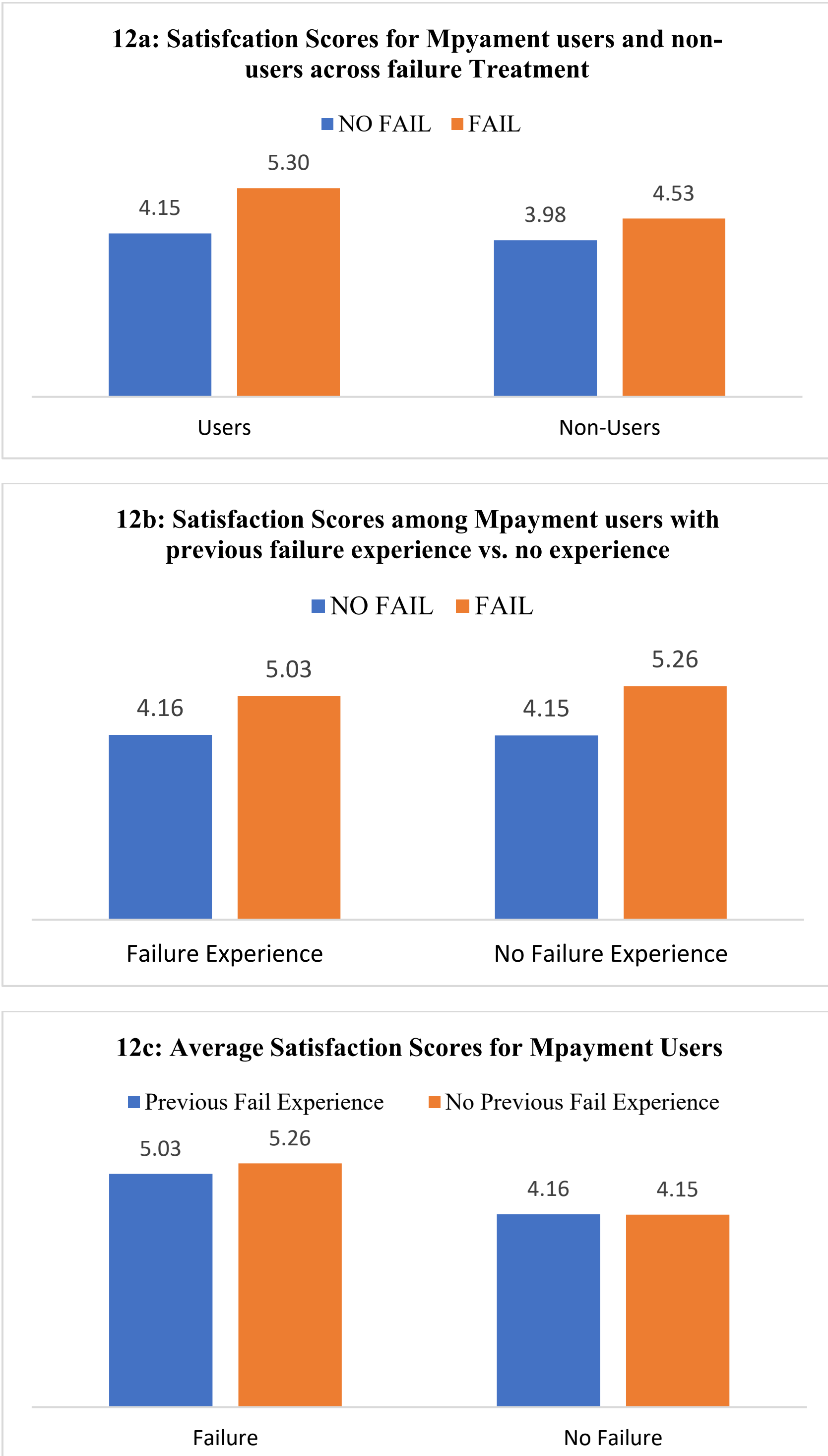


Figure 13: Aspect-Based Sentiment Analysis Approach

Step 1

Aspect Detection

Classify sentences to major attributes

Three methods:

Unsupervised Topic Modeling (LDA)- Results are subjective *(This Study)*

Semi-supervised- Use 20% (can vary) of the data to create your own tags and then classigy remaining dataset

Supervised (Multi-label Classification)- Researchers have to create a large set of annotated data based on the research setting *(Next Study)*

Step 2 *(Next Study)*

Sentiment Scoring

For each sentence in a review, map attributes to sentiment score

Methods to conduct Sentiment Analysis for detected Aspects in Step 1:

Lexicon-based approach- Use the number of positive and negative words

Machine learning approach- Support Vector Machines, Naive Bayes, Logistic Rgeression, and Classification Trees

Deep Neural Networks- Convolutional Neural Networks (CNN), Recurrent Neural Network (RNN), Long short-term memory (LSTM), Hybrid

APPENDIX 1 – STUDY 2A

1A. Confirmatory Factor Analysis

To delineate the good quality data, we further filtered the data on three quality checks – reverse coded survey items, attention check questions, and qualitative examination of open-ended questions. Out of 370 respondents, only 197 provided us with the complete information on all the scale items. Out of 197, we dropped 15 respondents because they did not provide us with the name of the service provider or technology providers of their evaluated encounter. Out of 182 respondents, 35 provided us the made-up Mwallet provider name or retailer name just to finish the survey, and 30 failed the attention check question. Out of the remaining 117 respondents, only 95 clearly marked the reverse coded items showing that they read the items and scale while answering all the questions.

Following is the complete list of scale items that were used in the Confirmatory Factor Analysis:

Table 1A.1 Scale Items for Confirmatory Factor Analysis

Scale Items Used	Scale Items Dropped
NCX Scale adapted from Service Convenience for both SP and TP	
Decision Let me know of the exact cost or special offers before I made the purchase. Information I received made it easy for me to choose what to buy. It was easy to get the information I needed to decide which product to buy. It took minimal time to get the information needed.	Helped me to make up my mind about what I wanted to buy. Information I received was clear and easy to understand.
Access Was accessible through various ways (email, telephone, chat, in-person). It was easy for me to contact the retailer. It did not take much time to reach the retailer. It is easy for me to contact an employee, if required.	Was available when I needed to reach them.
Transaction I did not have to make much of an effort to pay for the product. Made it easy to conclude my purchase. I found it easy to complete my purchase. Helped me to quickly complete my purchase.	There were no problems to deal with during the payment phase that added to the purchase time. When I have questions about my transaction, my retailer is able to resolve my transaction and payment-related questions.
Benefits	

I was able to get the rewards from the purchase with little effort. Solved my rewards-related needs without creating other problems. The time required to receive the benefits (such as loyalty rewards or cashback) was reasonable. *Support* Resolved my problem quickly. Made it easy for me to resolve my problem.	
Overall Satisfaction Scale	
Overall, I am satisfied with my technology provider. Shopping was a delightful experience. My encounter was better than expected. As a result of my interaction, I was Satisfied.	My impression of the interaction with me was unfavorable. I would be very unhappy to shop again at this retailer.
Personal Innovativeness Scale	
If I heard about a new technology, I would look for ways to experiment with it. Among my family and peers, I am usually the first to try out new technologies. I like to experiment with new technologies.	In general, I am hesitant to try out new technologies.
Technology Involvement Scale	
Technologies like mobile payment apps are important to me. Technologies like mobile payment apps make it easier to conduct my day-to-day purchase activities. I feel comfortable in using technologies in my daily life.	

1B. NCX Operationalization

We have 17 items across five dimensions of NCX, measured on a Likert scale of 1 to 5 (Completely disagree to Completely Agree). A higher score for SP or TP indicates that the respondent believes more in that party (SP or TP) creating the experience relating to that item within a dimension.

Actual Score – TP is scoring better than SP

	Decision	Access	Transaction	Benefits	Support
Average Score for Service Provider,	2.09	2.97	1.98	3.00	3.78
Average Score for Technology Provider	1.93	3.62	3.31	3.40	3.61
Avg. SP/ Avg. TP	1.082	0.820	0.598	0.882	1.047
No. of Items, n_j	4	4	4	3	2
(Avg. SP/ Avg TP) × n_j	4.328	3.28	2.392	2.624	2.09
NCX Score	14.73				

Conceptually Balanced Score – TP and SP are scoring equally

	Decision	Access	Transaction	Benefits	Support
Average Score for Service Provider,	3	4	3	2	1
Average Score for Technology Provider	3	4	3	2	1
Avg. SP/ Avg. TP	1	1	1	1	1
No. of Items, n_j	4	4	4	3	2
(Avg. SP/ Avg TP) × n_j	4	4	3	3	2

Actual Score – TP is scoring better than SP

	Decision	Access	Transaction	Benefits	Support
Average Score for Service Provider,	2.98	3.35	3.58	3.27	3.11
Average Score for Technology Provider	2.75	2.87	3.09	3.28	2.91
Avg. SP/ Avg. TP	1.083	1.167	1.158	0.9969	1.068
No. of Items, n_j	4	4	4	3	2
(Avg. SP/ Avg TP) × n_j	4.334	4.668	4.632	2.990	2.137
NCX Score	18.761				

If this ratio of (Avg. SP/ Avg. TP) increases, it would be either because of increased evaluation for SP or lower evaluation for TP. In either case, we are interested in the relative evaluation of SP and TP and how it impacts overall NCX score.

1C. Experimental Manipulation

You will read a scenario depicting a customer's situation using a mobile payment app, such as Apple Pay or Google Pay, to purchase at a retail store. We ask you to read the scenario with full attention as you would be asked to answer a few questions. You will not be able to go back to the scenario once you start answering the questions.

Manipulations

While going over her email inbox, Skyla noticed an email from Google Pay. The first line highlights that Google Pay is one of the most widely used mobile wallets in the US. It can be used to pay for purchases at retail stores or transfer funds between family and friends.

The digital ad focuses on the convenience and security offered by Google Pay in making payments. The email also highlighted a list of retailers where she can use the app to make payments. Moreover, next to each retailer's logo, a percentage discount was highlighted, ranging from 5% to 15%. Skyla quickly scanned through the digital ad and thought it is easy and cool to use smartphones to pay for things and earn rewards. Therefore, she downloaded the app and vows to use it the next time to pay.

Manipulation for q1

After few days, Skyla wanted to buy a new handbag for her personal use. She did some research related to prices and stores near her that carry some products of her liking. She decided to go to a

[High SP – C1, C3, C5, & C7]: Neiman Marcus

[Low SP – C2, C4, C6, & C8]: Ross Stores

These stores are near her home, and the customer reviews are also satisfactory. She entered the store and felt a little overwhelmed with so many different types of products. Just then, a smiling employee approached her and asked if she needed help. She asked for the aisle that carries handbags and, after getting the answer moves towards it. In the aisle, she takes some time to evaluate some alternatives and looks up online to see if she can find the same product at a lower price. After her due diligence, she makes her choice and moves towards the checkout counter. After waiting for 2-3 minutes in the queue, it's her turn to checkout.

Manipulation for q2

[HUBS – C1, C2, C5, and C6]: At the payment terminal, she notices small signage for Google Pay. She recalls the email ad she saw a few days ago and quickly pulled out her phone to check if she could get any additional rewards using Google Pay. She can earn a 7% cashback in her Google Pay account to her delight.

[LUBS – C3, C4, C7, and C8]: At the payment terminal, she notices small signage for Google Pay. She recalls the email ad she saw a few days ago and quickly pulled out her phone to check if she could get any additional rewards using Google Pay. She realizes there are no additional rewards if she uses Google Pay at this retail store. However, she thinks about using the app since the phone is in her hand already.

Manipulation for q3

[No Payment Failure – C1, C2, C3, and C4]: She brings the phone near the payment terminal and authenticates the payment using her fingerprint. Within a few seconds, she hears a click sound and sees a successful payment sign on the terminal. The transaction gets recorded in her mobile wallet, and she exits the store with great delight.

[Payment Failure – C5, C6, C7, and C8]: She brings the phone near the payment terminal and authenticates the payment using her fingerprint. After waiting a few seconds, she hears a two-beep sound sees a (!) symbol indicating that payment was unsuccessful on the terminal. The employee at the checkout counter asks her to try again, but the same thing happens. She then takes out her wallet from her pocket uses her card to make the payment. As she exits, she is still wondering why her mobile payment was not accepted.

1D. NCX Survey

Manipulation Check Questions

Q1) On a scale of 1 to 5, where 1 represents low brand value, and 5 represent high brand value, please rate the following brands:

***Retailer**: Neiman Marcus—Ross Stores*

Q2) Control Question: On a scale of 1 to 5, where 1 represents low brand value, and 5 represent high brand value, please rate the following brand:

***Technology Provider/Mwallet**: Google Pay*

Q3) Which of the following combinations of features is more beneficial to Mwallet uses and benefits for customers like you?

Combination A	Combination B
Faster and Convenient	Faster and Convenient
7% Cashback in Mwallet account	No Cashback in Mwallet account
Ability to pay for purchases at retail stores	Ability to pay for purchases at retail stores
Transfer of funds between family and friends	Transfer of funds between family and friends
More secure transactions	More secure transactions
Better Privacy Policies	Better Privacy Policies

- Combination A
- Combination B
- Both are same

Q4) What happened when Skyla tried to make payment at the checkout counter?

- Mwallet Payment Failed (represent technology-service failure manipulation)
- Mwallet Payment processed successfully (represent no technology-service failure)

Q5) Control Question: Where did Skyla go to buy a handbag?

- Neiman Marcus
- Ross Stores
- Bloomingdale
- Marshalls

Survey Instrument for Networked Customer Experience

Based on the scenario, please answer the following questions on Skyla's behalf. We ask you to consider yourself in place of Skyla and tell us how you would feel about your interaction with the retailer and technology provider.

Rating on a Scale of 1 (Completely Agree) to 5 (Completely Disagree). If you feel that you can't answer any of these sentences for the retailer or technology provider, you can choose NA.

1. Decision to Start the Journey

Items	Retailer	Technology Provider
Let Skyla know of the exact cost or special offers before she made the purchase.		
Information Skyla received made it easy for her to choose what to buy.		
It was easy to get the information Skyla needed to decide which product to buy.		
It took minimal time for Skyla to get the information needed.		

2. Access to the product or service

Items	Retailer	Technology Provider
Was accessible through various ways (email, telephone, chat, in-person).		
It was easy for Skyla to contact the retailer/technology provider.		
It did not take much time for Skyla to reach the retailer/technology provider.		
It is easy for Skyla to contact an employee, if required.		

3. Transaction and Payments

Items	Retailer	Technology Provider
Skyla did not have to make much of an effort to pay for the product.		
Made it easy to conclude Skyla’s purchase.		
Skyla found it easy to complete her purchase.		
Helped Skyla to quickly complete her purchase.		

4. Benefits

Items	Retailer	Technology Provider
Skyla was able to get the rewards from the purchase with little effort.		
Solved Skyla’s rewards-related needs without creating other problems.		
The time required to receive the benefits for Skyla (such as loyalty rewards or cashback) was reasonable.		

5. Support

Items	Retailer	Technology Provider
Resolved Skyla’s problem quickly.		
Made it easy for Skyla to resolve her problem.		

6. Overall Satisfaction

Items	Retailer	Technology Provider
Overall, Skyla should satisfied with retailer/technology provider.		
Shopping was a delightful experience for Skyla.		

Skyla's encounter was better than expected.	
As a result of interaction, Skyla was Satisfied.	

7. Attribution of Experience

Items	Retailer	Technology Provider
Played a major role in creating Skyla's purchase experience.		
Skyla decided to purchase from this retailer because of the benefits provided by the technology provider.		NA
This retailer impacted Skyla's choice of technology provider or Mwallet app while making a purchase.		NA
Skyla decided to use this Mwallet app because of the benefits provided by the retailer.	NA	
This technology provider or Mwallet app impacted Skyla's choice of retailer while making a purchase.	NA	

8. Attribution of Experience during Technology-Service Failure (Only for respondents who are assigned to conditions C5 to C8).

Who do you think is responsible for the technology service failure and its outcome?	
Technology App provider because the app did not work when Skyla was trying to pay for her handbag.	
Retailer because their system did not work for Skyla to use Mwallet app to make payment.	
Skyla herself because she did not know enough about the technology and how to use it to make purchases.	
Any other, please explain	

Individual Heterogeneity (Innovativeness and Involvement with Technology)

Rating on a Scale of 1 (Completely Agree) to 5 (Completely Disagree).

Items
If I heard about a new technology, I would look for ways to experiment with it.
Among my family and peers, I am usually the first to try out new technologies.
I like to experiment with new technologies.
Technologies like mobile payment apps are important to me.
Technologies like mobile payment apps make it easier to conduct my day-to-day purchase activities.
I feel comfortable in using technologies in my daily life.

Mobile Wallet Usage

1. Do you use any mobile payment or Mwallet app?
   - Yes (go to next question)
   - No (skip to end of the block)
2. Please list your preferred Mwallets (at max three) that you use.
   - Option 1
   - Option 2
   - Option 3
3. On average, how frequently you use these Mwallets to make purchases? If you do not use more than one Mwallet, please select NA.

	Daily	Multiple times in a Week	Once a Week	Once a Month	NA
Option 1					
Option 2					
Option 3					

4. Why do you prefer to use Mwallets over other payment methods? (Select all that apply)

Ease of Payments (e.g., integrated with loyalty benefits and faster payments)
Rewards such as Discounts and Cashbacks
More Secure
Others

5. Would you ever download and use a new Mwallet app instead of your preferred Mwallets to get a specific reward from a retailer? For example, using Venmo instead of Google Pay at Whole Foods to get an additional 5% cashback.

Definitely Yes—Probably Yes—Maybe—Probably No—Definitely No

6. Would you switch between your preferred Mwallets to get a specific discount from a retailer? For example, using Venmo at Whole Foods and Google Pay at Trader Joe's.

Definitely Yes—Probably Yes—Maybe—Probably No—Definitely No

7. For which purchase activities do you typically use Mwallets? (Select all that apply)

Utility Payments (e.g., electricity, gas, and internet, etc.)
Restaurants
Groceries
Clothing & Accessories
Education
Insurance
Travel & Transit
Others (please specify)

8. Where do you frequently use Mwallets?

In-store

Online
Both equally

Demographic Information

1. Please indicate your age using the dropdown menu.

18 to 70+ years

2. Please indicate your marital status.

Single
Married
Committed or With Partner
Do not want to answer

3. Please indicate your highest completed education.

No Formal Education
High School Degree
Bachelors Degree
Masters Degree
Doctorate Degree
Professional Degree (e.g., Charted Accountant, Actuarial Science)

4. Current Occupation

Allow participants to answer anything (create a dropdown)

5. Annual Household Income

Not Applicable
Less than $25,000
$25,000 to $50,000
$50,001 to $75,000

Above $75,001 to $100,000
Above $100,000

6. Gender

Male
Female
Do not wish to answer

Applicable for candidates who answered Yes to Q1 in the Mobile Wallet Usage section.

Would you be interested in taking part in a 15 to 20 minutes interview regarding your experience of using mobile payments apps or Mwallets? If selected for the interview, you would be compensated with a $10 visa gift card.

- Yes, Please share your email address
- No

APPENDIX 2 – STUDY 2B

2A. Aspect-based Sentiment Analysis for Mwallet App

Table 2A.1 Proportion of Negative Sentiments for the Identified Aspects across Mwallets

Mwallet App	Advertising	Connectivity	Device Compatibility	Notification & Alerts	Pricing & Payments	Privacy	Resource Usage	SignUp & Login	Update	User Interface & UX	General Feedback
Airtel Thanks	0.673	0.744	0.695	0.731	0.703	0.664	0.759	0.601	0.698	0.766	0.906
Alipay	1.000	1.000	0.962	0.786	0.738	0.885	0.808	0.719	0.648	0.819	0.837
BigPay	0.720	0.638	-	0.239	0.410	1.000	0.378	0.352	0.750	0.329	0.605
BoostPay	0.641	0.702	0.813	0.678	0.514	0.883	0.689	0.641	0.701	0.541	0.505
CashApp	0.636	0.687	0.758	0.585	0.648	0.690	0.752	0.672	0.625	0.565	0.696
Freecharge	0.576	0.678	0.695	0.690	0.579	0.690	0.820	0.721	0.622	0.512	0.737
Google Pay	0.502	0.427	0.690	0.372	0.466	0.694	0.599	0.434	0.563	0.530	0.615
Mobikwik	0.445	0.761	0.536	0.712	0.656	0.745	0.755	0.643	0.733	0.538	0.805
PayZapp	0.731	0.693	0.722	0.782	0.667	0.672	0.724	0.738	0.765	0.715	0.864
Paypal	0.292	0.682	0.644	0.608	0.505	0.796	0.717	0.617	0.545	0.399	0.638
Paytm	0.447	0.632	0.640	0.739	0.641	0.685	0.680	0.715	0.755	0.758	0.774
PhonePe	0.541	0.554	0.850	0.687	0.642	0.672	0.698	0.675	0.664	0.591	0.789
Pockets	0.479	0.663	0.720	0.703	0.610	0.805	0.705	0.717	0.689	0.682	0.787
RBC	-	0.586	0.773	0.769	0.740	0.701	0.638	0.752	0.571	0.746	0.956
Samsung Pay	0.614	0.570	0.589	0.545	0.347	0.643	0.619	0.372	0.631	0.396	0.562
TMW	0.517	0.750	0.813	0.842	0.522	-	0.637	0.676	0.693	0.407	0.838
TouchnGo	0.876	0.847	0.951	0.534	0.700	0.638	0.590	0.734	0.725	0.773	0.944
Venmo	0.481	0.641	0.580	0.717	0.437	0.675	0.728	0.621	0.655	0.351	0.525
Vodafone M-Pesa	0.806	0.688	0.762	0.756	0.676	0.682	0.760	0.671	0.763	0.727	0.852

In this analysis, the aspects/attributes are taken from the well-defined and accepted mobile app industry.

2B. Results from Unsupervised Topic Modeling

LDA results for aspect detection via unsupervised topic modeling are presented in the table below. We follow the standard topic modeling approach. Before the LDA analysis, the data was cleaned by stemming, lemmatization, stop word removal, and non-Ascii characters.

Based on our understanding of the subject area, we have given the titles to the topics. If we were to link the results with the dimension of NCX, we could say that Topic0 and Topic4 are associated with the access dimension. The words in both topics highlight how the app provides or hinders easy access to make payments and earn benefits. Topic1 and Topic 2 highlights two dimensions- transaction and benefits. However, Topic2 has more benefit convenience-related words. The topic3 is associated with support convenience. It majorly covers the customer service-related dimensions. Overall, the results from unsupervised topic modeling are sufficient to connect the NCX dimensions with the fundamental aspects/topics/attributes of Mwallet users' evaluation.

Table 2B.1 Results from Topic Modeling using CAt

Topic	Details
Topic0 *Recharge-related*	'0.085*"recharg" + 0.071*"bill" + 0.069*"month" + 0.059*"error" + 0.048*"amount" + 0.042*"plan" + 0.035*"detail" + 0.027*"pack" + 0.022*"tri" + 0.019*"date" + 0.015*"show" + 0.015*"kyc" + 0.013*"rs" + 0.012*"prepay" + 0.011*"postpaid" + 0.010*"till" + 0.010*"method" + 0.010*"valid" + 0.009*"etc" + 0.009*"sorri" + 0.008*"facil" + 0.008*"oper" + 0.007*"voda" + 0.007*"limit" + 0.006*"discount" + 0.006*"jio" + 0.006*"yesterday" + 0.006*"hang" + 0.006*"rupe" + 0.005*"electr" + 0.005*"morn" + 0.005*"wrost" + 0.005*"post" + 0.004*"msg" + 0.004*"lock" + 0.004*"lockdown" + 0.004*"offic" + 0.004*"cell" + 0.003*"dollar" + 0.003*"consum" + 0.003*"august" + 0.003*"cheater" + 0.003*"march" + 0.003*"rent" + 0.003*"car" + 0.003*"document" + 0.003*"uninstal" + 0.003*"lol" + 0.003*"explan" + 0.003*"cheat"'),
Topic1 *Money-related*	'0.247*"app" + 0.067*"money" + 0.053*"card" + 0.047*"account" + 0.031*"bank" + 0.026*"phone" + 0.023*"day" + 0.020*"pay" + 0.020*"option" + 0.020*"wallet" + 0.015*"payment" + 0.015*"way" + 0.014*"balanc" + 0.013*"thing" + 0.013*"cash" + 0.012*"use" + 0.011*"peopl" + 0.010*"friend" + 0.009*"point" + 0.009*"noth" + 0.008*"system" + 0.007*"access" + 0.007*"inform" + 0.007*"debit" + 0.006*"reason" + 0.006*"anyth" + 0.006*"store" + 0.006*"secur" + 0.006*"fund" + 0.006*"need" + 0.005*"everyth" + 0.005*"reward" + 0.005*"someon" + 0.005*"person" + 0.005*"today" + 0.005*"code" + 0.005*"verif" + 0.004*"process" + 0.004*"place" + 0.004*"charg" + 0.004*"busi" + 0.004*"famili" + 0.004*"time" + 0.004*"someth" + 0.004*"fraud" + 0.003*"useless" + 0.003*"anyon" + 0.003*"life" + 0.003*"info" + 0.003*"name"'
Topic2 *Benefit-related*	'0.068*"transact" + 0.065*"payment" + 0.048*"experi" + 0.042*"applic" + 0.034*"star" + 0.032*"user" + 0.030*"thank" + 0.028*"easi" + 0.026*"offer" + 0.025*"transfer" + 0.024*"credit" + 0.023*"featur" + 0.021*"cashback" + 0.014*"conveni" + 0.014*"histori" + 0.010*"ewallet" + 0.010*"rat" + 0.010*"tng" + 0.009*"interfac" + 0.009*"other" + 0.008*"upi" + 0.008*"fast" + 0.008*"kind" + 0.008*"voucher" + 0.007*"alway" + 0.007*"onlin" + 0.007*"type" + 0.006*"button" + 0.006*"reload" + 0.006*"hdfc" + 0.005*"bite" + 0.005*"touch" + 0.005*"appl" + 0.005*"rate" + 0.005*"simpl" + 0.005*"order" + 0.005*"hope" + 0.005*"benefit" + 0.004*"open" + 0.004*"job" + 0.004*"statement" + 0.004*"merchant" + 0.004*"mode" + 0.004*"suggest" + 0.004*"fact" + 0.004*"receipt" + 0.003*"platform" + 0.003*"gift" + 0.003*"wait" + 0.003*"machin"'

Topic3 *Customer service-related*	'0.103*"servic" + 0.080*"custom" + 0.070*"issu" + 0.064*"number" + 0.028*"care" + 0.026*"call" + 0.024*"support" + 0.020*"day" + 0.020*"messag" + 0.016*"respons" + 0.015*"team" + 0.014*"compani" + 0.014*"email" + 0.014*"help" + 0.011*"week" + 0.010*"hour" + 0.010*"request" + 0.010*"complaint" + 0.009*"otp" + 0.009*"password" + 0.009*"pin" + 0.008*"sms" + 0.008*"provid" + 0.007*"solut" + 0.007*"ca" + 0.007*"repli" + 0.006*"login" + 0.006*"ticket" + 0.006*"toll" + 0.006*"end" + 0.006*"guy" + 0.006*"mail" + 0.005*"id" + 0.005*"contact" + 0.005*"min" + 0.004*"tune" + 0.004*"case" + 0.004*"execut" + 0.004*"link" + 0.004*"log" + 0.004*"caller" + 0.004*"address" + 0.004*"permiss" + 0.004*"suck" + 0.004*"voic" + 0.003*"answer" + 0.003*"action" + 0.003*"chat" + 0.003*"concern" + 0.003*"queri"'
Topic4 *Network/Data-related*	'0.112*"time" + 0.095*"network" + 0.045*"problem" + 0.036*"data" + 0.034*"speed" + 0.028*"internet" + 0.021*"connect" + 0.020*"updat" + 0.019*"work" + 0.018*"year" + 0.016*"sim" + 0.015*"lot" + 0.014*"screen" + 0.011*"phone" + 0.008*"page" + 0.008*"version" + 0.008*"jio" + 0.008*"devic" + 0.008*"wast" + 0.007*"area" + 0.007*"home" + 0.007*"fee" + 0.007*"mobil" + 0.007*"minut" + 0.007*"notif" + 0.006*"nice" + 0.006*"develop" + 0.006*"purchas" + 0.006*"usag" + 0.006*"bug" + 0.005*"everytim" + 0.005*"function" + 0.005*"net" + 0.005*"fix" + 0.005*"someth" + 0.004*"load" + 0.004*"qualiti" + 0.004*"check" + 0.004*"improv" + 0.004*"review" + 0.004*"game" + 0.004*"app" + 0.004*"india" + 0.004*"keep" + 0.004*"idea" + 0.004*"download" + 0.004*"ui" + 0.004*"android" + 0.004*"play" + 0.003*"class"