TOWARDS A DATA-DRIVEN UNDERSTANDING OF THE CUSTOMER EXPERIENCE GESTALT

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Abstract

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Towards A Data-Driven Understanding of the Customer Experience Gestalt

Customer experience (CE) has become a focal area of interest for both academics and managers, providing firms with a competitive edge over others in the “experience economy”. Despite the importance of CE and the many conceptual studies aiming to deliver a better understanding of it’s multidimensional and subjective nature, a gap exists in developing an empirically grounded understanding of this construct. Generally, CE has been mainly addressed through its antecedents (e.g., touchpoints) and outcomes (e.g., loyalty and satisfaction), while the CE phenomenon has often been treated as a black box. With recent advancements in data-driven technology ushered by what some call the fourth industrial revolution, methods involving artificial intelligence, big data analytics, conversational agents, and neuroscience show promise in providing marketers, and specifically service researchers the tools to explore and better understand complex constructs such as CE.

As a result, the objectives of this thesis are to develop a data-driven understanding of the CE phenomenon by incorporating three studies that: (i) Develop an experiential and sub-elemental data-driven CE framework (RAFTS) (Study1), (ii) develop and verify a data-driven method that examines customer feelings using conversational agents and storytelling (Study 2), and (iii) explore the dynamic interplay of the customer’s state-of-mind on recalled experiences and conversational data-driven agents (Study 3). The main contributions of this thesis are: (i) Provide service researchers with RAFTS that incorporates the customer journey and allows multiple data-driven collection and analysis methods (e.g., AI chatbots) to map experiential (realtime) data to a unified and semantically clear sub elemental CE framework, (ii) propose and verify conversational agents that use sentiment analysis as promising, novel, cost/resource-effective tools to be used in interviewing customers about their CE feelings, (iii) and establish that the customer’s state-of-mind does influence recalled experiences and feelings towards customer-facing conversational agents, thus highlighting the importance of designing human-friendly technologies capable of managing and adapting to the customer’s state-of-mind throughout customer service encounter.

While a holistic data-driven CE understanding is an ambitious endeavour, this thesis provides a path towards achieving this objective. A unified data-driven CE framework (RAFTS) enables researchers and managers to use similar units of analysis allowing them to “speak the same language” when measuring and analysing CE. This aids in further benchmarking CE across different contexts, industries, and cultures allowing for valuable insights that aid in progressing the conceptualisation of this construct. Moreover, the more data points captured with RAFTS across customer journey touchpoints, the more understanding can be achieved and thus more avenues for improving CE management. Furthermore, this thesis paves the way forward with conversational agents that can interview customers about their CE feelings, allowing both academics and researchers to improve scalability and resource/cost efficiency when collecting and examining CE feelings data. Lastly, this thesis highlights the importance of the human experience in the path of better understanding and examining holistic CE using data-driven methods. These methods should account for and manage customer feelings and their state-of-mind to mitigate negative CEs and as a result, a decline in satisfaction and loyalty. The thesis also provides an extensive future work agenda to continue this ambitious effort by the means of a CE archetype map that is broken down into four quadrants (service, customer, touchpoint, and human), each addressing an area of CE that aims at improving data-driven holistic CE understanding.

Declaration

I, Karim Sidaoui, declare that no portion of the work referred to in the thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning.

Copyright Statement

Dedication

As my doctoral journey comes to an end, a crescendo of frantic feelings of anxiety, frustration, fear of the unknown, guilt, and loneliness often intermixed with gratitude, excitement, happiness, empathy, and the unyielding conviction to face matters head on has made this a once in a lifetime character building experience for me.

To this end, I would like to start by thanking my supervisors Professor Jamie Burton (Professor of Marketing and Head of the MSM Division) and Dr. Matti Jaakkola (Senior Lecturer of Marketing). From their initial and ongoing trust in me, to their guidance and support every step of the way, I am endlessly grateful to have had them supervise my journey into academia. I have learned much from them and appreciate the extent of which they have opened countless opportunities for me by means of inclusion, recognition, encouragement, and freedom to explore. The prestigious Postgraduate Researcher of the Year 2021 for the faculty of Humanities award I received, stands as a testament of this support and guidance.

Furthermore, I would like to thank Professors Raymond Fisk, Anders Gustafson, Sertan Kabadayi, and Werner Kunz, as well as Drs Linda Alkire, and Paul Fombelle who have all been a source of mentorship, encouragement, support, and have made my doctoral journey even more exciting and memorable. I would also like to extend my thanks to Professor Heiner Evanschitzky and Dr Mohamed Zaki who served as my examiners.

Finally, I would like to dedicate this thesis to my family who have stood by me through it all. To my mother and father whom I ended up following in the academic journey, to my late grandfather who departed from this world before I could place this thesis next to his and see him smile, to my late grandmother who taught me the meaning of sacrifice, and to the rest who watch over me with love from beyond. I only hope I am making you all proud.

"This heart within me I can feel, and I judge that it exists. This world I can touch, and I likewise judge that it exists. There ends all my knowledge, and the rest is construction"

— Albert Camus

Chapter 1 - Introduction

The “experience economy” (Pine & Gilmore, 1998) highlights customer experience (CE) as a distinguishing factor in meeting customer expectations as a means to build customer loyalty (Klaus & Maklan, 2007). This “experience” economy has a significant effect on marketing, as Gilmore and Pine express citing Drucker (1973): "The aim of marketing is to make selling superfluous" and adding "the aim of experience is to make marketing superfluous." (2002, p. 5). Today’s companies are increasingly catching up in their awareness of the importance of CE – nondeliberate, spontaneous responses and reactions to offering-related stimuli embedded within a specific context – (Becker & Jaakkola, 2020), which is still considered a research "greenfield" (Lemon & Verhoef, 2016, p. 89). Not only is CE a critical research priority (Lemon & Verhoef, 2016), but from a managerial standpoint, it has the potential to drastically boost business performance (McIntyre & Virzi, 2018).

Simultaneously, advancements in data-driven technologies such as artificial intelligence (AI) and machine learning have paved the way for extracting and potentially improving CE (e.g., Bolton et al., 2018; Ordenes et al., 2014; Sidaoui et al., 2020). For instance, customer-facing technologies such as chatbots are reported to exhibit an average annual growth of 400% by 2024 and are estimated to handle 90% of banking customer interactions by 2022 (*Juniper Research*, 2020). Such technologies commonly leverage AI, which by market value is estimated to reach 36.62% of compound annual growth rate within a forecast period of 7 years, reaching USD 190.6 billion by 2025. Some marketing scholars have even referred to this growth and potential as the fourth industrial revolution (e.g., Maynard, 2015; Syam & Sharma, 2018).

Keeping this technological growth in mind, CE has also recently witnessed several academic attempts at progressing the field conceptually (e.g., Becker & Jaakkola, 2020; Bolton et al., 2018; De Keyser et al., 2020; Lemon & Verhoef, 2016; McColl-Kennedy et al., 2019). While these studies have significantly contributed to the conceptualization of CE, empirical studies have remained scattered in the manner in which they measure and extract CE (Kawaf & Tagg, 2017). As a result, a major opportunity lies in leveraging the recent advancements in data-driven technologies such as the internet of things, augmented/virtual/mixed reality, and conversational agents to provide more empirical insights into the constituents of CE using AI analytics such as data/text mining and other machine learning algorithms (Hoyer et al., 2020; Humphreys & Wang, 2018). Thus, this thesis examines how CE could be further explored and examined using technology to inform theory and practice. More specifically, how data-driven technology could be used to build up the CE phenomenon from it's constituent elements (e.g., feelings and thoughts), enabling a more holistic human experience understanding of the concept.

To achieve this, the thesis is structured as follows. First, the key theories and concepts are reviewed in section 1.1. This includes a review of what CE is, how it has been approached theoretically, and traditional ways in which it is measured (sections 1.1.1 – 1.1.3). Next, a review of the potential of using a data-driven approach to build up the understanding of holistic CE via the customer journey is portrayed (sections 1.1.4 – 1.1.7). These review sections help set the stage to highlight the research gaps (section 1.2) and develop the research programme and objectives (section 1.3).

Next, chapters 2, 3, and 4 include the studies that aim at addressing: (i) the development of a data-driven CE framework (Study 1), (ii) developing and verifying a data-driven method that leverages this framework to extract CE data (Study 2), (iii) explore the dynamic interplay of the customer's state-of-mind and feelings when encountering such methods and their role on their experience (Study 3). Finally, chapter 5 concludes with a discussion on the contributions, limitations, and future research agenda that emerge from the work conducted in this thesis.

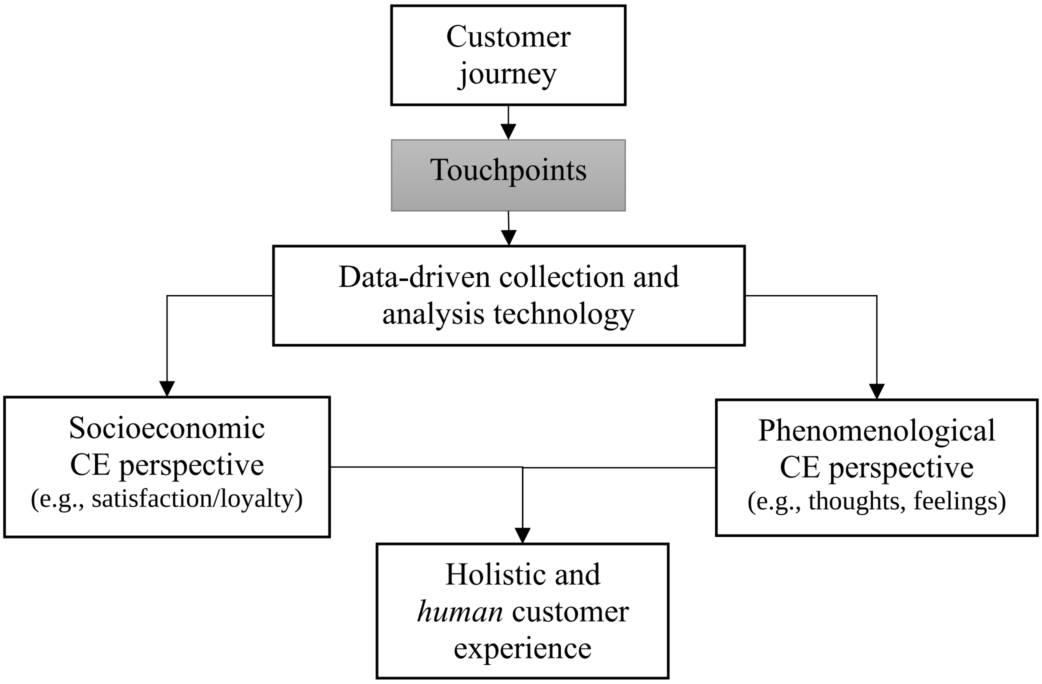
What follows is a review of the key theories and theoretical concepts that aid in developing the research gaps of this thesis.

1.1 Key theories and theoretical concepts

CE is not a new notion, and some of its key facets (e.g., dimensionality, outcomes, and antecedents) have been studied through the customer journey – a customer's experience as a result of their interaction with the firm's touchpoints at different stages of their purchase journey – over the last 50 years (Lemon & Verhoef, 2016). Its experiential aspects have been explored since the 1900s via concepts like consumption experience (Holbrook & Hirschman, 1982). As such, there have been multiple ways in which CE has been depicted in business research in general, and service research in particular. CE originates from psychological constructs, mainly subjective experience, which makes studying it from a business discipline challenging due to its multidimensional, holistic, and subjective nature (McColl-Kennedy et al., 2015; Schmitt, 1999a). However, this has not hindered the development of scales such as EXQ, inspired by the service quality scale SERVQUAL, that aim to measure CE (Klaus & Maklan, 2012; Parasuraman et al., 1988). While the scales seem to effectively measure CE as an outcome, they neglect to measure it as a subjective phenomenon – a 'lived' experiential "state of consciousness with a variety of symbolic meanings, hedonic responses, and esthetic criteria" (Holbrook & Hirschman, 1982, p. 132; Klaus & Maklan, 2012).

As such, CE is conceptualised in many ways and as a result of its subjective and multidimensional nature extends into other service research concepts (e.g., customer engagement and transformative service research) (McColl-Kennedy et al., 2019). A thorough understanding of how CE is conceptualized as well as how it links to other related concepts is portrayed in Figure 1 and discussed in the next section.

Figure 1. Key theoretical concept relationships



1.1.1 Defining customer experience

In 1970, futurist Alvin Toffler predicted that value offers of industries would transcend their core output from goods and services to experiences, igniting an era of "super-industrialism the very foundation ... of the post-service economy" (1970, p. 120). Thus, CE was conceived in the process of striving to enhance and study value in services (Babin et al., 1994). The concept of value was defined by Porter (1985, p. 85) as "the amount buyers are willing to pay for what a firm provides them" and gained traction from theories like Schumpeter's theory of economic development (1934) (Bazhal, 2017). Socio-industrial conceptualizations shifted profit-driven purposefulness of industrial enterprises to producers of goods, services (Drucker, 1950, p. 68) and "customers" (Drucker, 1954, p. 37).

By the turn of the twentieth century, value creation was also referred to as dominant logic (Prahalad & Bettis, 1986) by analysts (Miller, 2016) and remains to this day, "a corporation's raison d'être, the ultimate measure by which it is judged" (Hindle, 2008, p. 201).

In the early 2000s, various socio-economic concepts appeared bearing a service and customer focus such as 1) service-dominant logic (SDL) which approaches dominant logic from a service perspective (Vargo & Lusch, 2004), 2) value co-creation which emphasizes the interaction between the customer and service provider to create value (Grönroos, 2008, 2011; Payne et al., 2008; Prahalad & Ramaswamy, 2004a, 2004b; Vargo, 2008; Vargo & Lusch, 2004, 2006), and 3) the "experience economy" coined by Pine & Gilmore (1998). Such customer-centric business and marketing value outlooks led the way to concepts like customer-dominant logic (CDL) (Heinonen & Strandvik, 2015), which in turn has pivoted CEs into becoming a significant driving concern of marketing strategy in organizations and conclude the era of feature-focused marketing (Schmitt, 1999a).

CE is generally defined as the direct or indirect interaction with a set of market actors involving experiential elements such as thoughts, feelings, sensations, activities, and relations (Lemon & Verhoef, 2016; Schmitt, 1999b). However, it has also been defined very broadly as “life itself” Csikszentmihalyi (1991, p. 192) or, more recently as “nondeliberate, spontaneous responses and reactions to offering-related stimuli embedded within a specific context” (Becker & Jaakkola, 2020; De Keyser et al., 2020, p. 2). Table 1 portrays an exhaustive list of CE definitions. Definitions used either introspectively phenomenological (7 definitions), value-driven socio-economic (10 definitions), or a combination of both (8 definitions) approaches in their construction. In the last decade or so, conceptualizations that account for both theoretical lenses have dominated. While this significant trend is promising, a more comprehensive CE definition utilizing both the socio-economic and phenomenological lenses yet accommodating service and customer-centric approaches is more encompassing.

A review of previous CE definitions enables the development of a refined and exhaustive definition, which acknowledges both phenomenological (e.g., Holbrook & Hirschman, 1982) and socio-economic (e.g., McColl-Kennedy et al., 2015) approaches, as well as its holistic and multi-layered gestalt elements (e.g., Schmitt, 1999b) affected by context and temporality (e.g., Kranzbühler et al., 2018; Ordenes et al., 2014; Palmer, 2010). Thus, drawing from the review, the following CE definition is put forward:

A customer's multifaceted subjective, dynamic, and holistic mental state journey, resulting from direct or indirect service-in/extrinsic touchpoint interactions stimulating a customer's thoughts, feelings, senses, activities, and relations, thereby co-creating value from their current or temporal recollections of service encounter experiences.

1.1.2 Theoretical approaches to customer experience

With a definition that accounts for the socioeconomic and phenomenological perspectives, it is imperative to understand how both these perspectives aid in the depiction of CE as a notion that was conceived in the process of striving to enhance and study value in services (Babin et al., 1994). However, CE at its core, has been derived from the study of human experience through psychology, neuroscience, and even philosophy. This section provides an overview of the phenomenological and socio-economic theoretical approaches often employed in the study of CE (e.g., Holbrook & Hirschman, 1982; Lemon & Verhoef, 2016; McColl-Kennedy et al., 2015; Schmitt, 1999a). For both phenomenological and socio-economic approaches, service- and customer-centric lenses could be adopted to derive a holistic understanding of CE.

Table 1. Customer Experience Definitions

Reference	Definition	Theoretical Approach
Holbrook and Hirschman (1982, p. 132)	"a phenomenon directed toward the pursuit of fantasies, feelings, and fun."	Phenomenology
Thompson, Locander, and Pollio (1989, p. 136)	"is conceptualized as a dynamic process in which certain events become figural (stand out) in the individual's life-world while others recede into ground."	Phenomenology
Carbone and Haeckel (1994, p. 18)	"The aggregate and cumulative customer perception created during the process of learning about, acquiring, using, maintaining, and (sometimes) disposing of a product or service."	Socio-Economic
Otto and Ritchie (1996, p. 166)	"described as the subjective mental state felt by participants"	Phenomenology
Pine and Gilmore (1998, pp. 97–99)	"Experiences are inherently personal, existing only in the mind of an individual who has been engaged on an emotional, physical, intellectual, or even spiritual level"	Both
O'Sullivan and Spangler (1998, p. 5)	"a state of being physically, mentally, socially, and spiritually, or emotionally engaged"	Phenomenology
Schmitt (1999b, p. 57)	"Experiences occur as a result of encountering, undergoing or living through things. Experiences provide sensory, emotional, cognitive, behavioural, and relational values that replace functional values."	Phenomenology
Gupta and Vajic (2000, p. 35)	"Any sensation or knowledge acquisition resulting from a person's participation in daily activities"	Socio-Economic
Lewis and Chambers (2000, p. 46)	"the total outcome to the customer from the combination of environment, goods and services purchased"	Socio-Economic
Shaw and Ivans (2002, p. 6)	"The customer experience is a blend of a company's physical performance and the emotions evoked, intuitively measured against customer expectations across all moments of contact"	Socio-Economic
Poulsson and Kale (2004, p. 270)	"an engaging act of co-creation between a provider and a consumer wherein the consumer perceives value in the encounter and in the subsequent memory of that encounter."	Both
Prahalad and Ramaswamy (2004a, p. 16)	"The co-creation of value through personalized interactions that are meaningful and sensitive to a specific consumer"	Socio-Economic
Johnston and Clark (2005, p. 8)	The service experience is the customer's direct experience of the service process and concerns the way the customer is dealt with by the service provider.	Socio-Economic
Gentile et al. (2007, p. 397)	"a set of interactions between a customer and a product, a company, or part of Customer its organization, which provoke a reaction. This experience is strictly personal and implies the customer's involvement at response different levels (rational, emotional, sensorial, physical and spiritual).	Both
Meyer and Schwager (2007, p. 118)	"the internal and subjective response customers have to any direct or indirect contact with a company."	Socio-Economic
Grundey (2008, p. 138)	"a subjective episode in the construction/transformation of the individual, with however, an emphasis on the emotions and senses lived during the immersion at the expense of the cognitive dimension."	Phenomenology
Sundbo and Hagedorn-Rasmussen's (2008, p. 83)	"a mental journey that leaves the customer with memories of having performed something special, having learned something or just having fun"	Socio-Economic
Ghose (2009, p. 180)	"the user's interpretation of his or her total interaction with the brand"	Socio-Economic

Reference	Definition	Theoretical Approach
Tynan and McKechnie (2009, p. 508)	"an extended range of value from sensory, emotional, functional/utilitarian, relational, social, informational, novelty and utopian sources"	Both
Verhoef et al. (2009, p. 32)	"the customer experience construct is holistic in nature and involves the customer's cognitive, affective, emotional, social and physical responses to the retailer. This experience is created not only by those elements which the retailer can control (e.g., service interface, retail atmosphere, assortment, price), but also by elements that are outside of the retailer's control (e.g., influence of others, purpose of shopping)."	Both
Walter et al. (2010, pp. 238–239)	"a customer experience is defined as the customer's direct and indirect experience of the service process, the organisation, the facilities and how the customer interacts with the service firm's representatives and other customers. These in turn create the customer's cognitive, emotional and behavioural responses and leave the customer with memories about the experience."	Both
Lemke et al. (2011, p. 848)	"the customer's subjective response to the holistic direct and indirect encounter with the firm, including but not necessarily limited to the communication encounter, the service encounter and the consumption encounter."	Both
De Keyser et al. (2015, p. 1)	"is comprised of the cognitive, emotional, physical, sensorial, and social elements that mark the customer's direct or indirect interaction with a (set of) market actor(s)"	Both
McColl-Kennedy et al. (2015, p. 432)	"is a dynamic phenomenon, emerging during various phases of the customer journey, including, for example, search, purchase, consumption and after-sale encounters, typically involving multiple channels and multiple touch points."	Socio-Economic
Becker & Jaakkola (2020)	nondeliberate, spontaneous responses and reactions to offering-related stimuli embedded within a specific context	Phenomenology

Phenomenological approaches

While CE is considered the *root* of customer value (Babin et al., 1994; De Keyser et al., 2015, p. 27), underlying this notion is subjective experience that modern philosophers attribute to phenomenal consciousness. This concept has not reached complete consensus but could be generally divided into four mental states (perceptual experiences, bodily sensations, felt emotions, and felt moods) (Sytsma & Machery, 2010). Neuro-psychologically, specific brain areas interact with experiences we undergo in our daily lives, creating *perceived immediate experience* acquired via direct interaction with our environment (Csikszentmihalyi, 1991, p. 212; Schmitt, 1999a). These experiences are made up of simplified properties, such as a colour or taste, and are called *qualia* (Buck, 1993, p. 491); subjective and unobservable phenomena producing what Marston et al. describe as "a holistic gestalt of polyvalent perceptions, including feelings, cognitions, behaviors, and intuitions" (1998, p. 18). CE inherits these characteristics, making its observations and measurements challenging, thus requiring "introspective or phenomenological" holistic approaches (Pekala & Levine, 1981, p. 31). Phenomenology, or more specifically existential-phenomenology, "seeks to describe experience as it emerges in some context(s) or … as it is lived" (Thompson et al., 1989, p. 135). Therefore, as Csikszentmihalyi alludes, experience envelopes us and "is not just one of the dimensions of life, it is life itself" (1991, p. 192). Similar descriptions have been attributed to CE as well, such as: "customer experience isn't a choice, there's always an experience whether you want to manage it or not" (Walden, 2017, p. 33).

CE has been studied since the early 1900s and Holbrook & Hirschman provide one of the earliest widely acclaimed attempts to tackle consumption experience by approaching it using an input-process-output system (2006; 1982). These approaches focus on defining CE through a conscious awareness of experience based on the experience embodiment theory (Tsai, 2005). This is done by identifying contexts in "human experience, such as thinking, feeling, knowing, imagining, and remembering" (Thompson et al., 1989, p. 136). This perspective enables a study of experience using both psychology and neurobiology, allowing the measurement of *extrinsic* behaviour and providing *introspective* and reflective phenomenological reporting, which results in a broader, more holistic study of experience (Buxbaum, 2016, p. 7; Holbrook & Hirschman, 1982, p. 137). The extrinsic and introspective perspectives could be contrasted with service- and customer-centric lenses respectively, wherein a service provider could design their servicescape based on the behaviour (output) of its customers without considering what they are experiencing at the human level (Bitner, 1992).

Considering an introspective approach highlights the importance of context, temporality (Kranzbühler et al., 2018; Palmer, 2010), and the distinctions between stand-alone, perceived, and intersubjective experience (Gillespie & Cornish, 2010). A stand-alone experience describes the phenomenon as it happens while the perception of an experience is a recollection, and generates a *point-of-view* that is occurring during different points in time resulting from stimulus and memory recollection, if available (Buxbaum, 2016, p. 63; Hellén & Gummerus, 2013). Therefore, an *attitude* toward an experience may change over time since it also depends on the memorability of that experience (Palmer, 2010, p. 199). Moreover, when businesses ask their customers what they experienced, they are adopting a customer-centric lens considering the unit of that analysis to be a temporally sensitive perceived experience, which, when spanned across different subjects, generates an intersubjective perspective (one shared between multiple customers) of what these customers experienced during a service encounter (Gillespie & Cornish, 2010).

Socio-economic approaches

In contrast to the phenomenological approaches to CE, socio-economic approaches identify the interplay of service and customer co-created experience within socio-economic constructs (Grönroos, 2008; Prahalad & Ramaswamy, 2004b; Vargo & Lusch, 2006). Service logic and value co-creation emphasize the interaction between the customer and a service provider to create value (Payne et al., 2008; Prahalad & Ramaswamy, 2004a; Vargo, 2008), and the notion of the *experience economy* shifts the focus from value co-creation to value perception by the customer (Pine & Gilmore, 1998). Furthermore, literature that emphasizes the importance of customer-centricity (Heinonen & Strandvik, 2015) champions CE as the major driving concern of marketing strategy in feature-focused marketing (Schmitt, 1999b).

With CE and value being tightly interwoven into what has been described as the marketing trinity (CE, engagement, and value) (De Keyser et al., 2015), these concepts have been regarded from both service and customer-centric lenses (Heinonen et al., 2010; Lemon & Verhoef, 2016; Payne et al., 2008). To illustrate this point, we look at Holbrook's (2006, p. 715) work, citing Abbott (1955), portraying how customers driven by extrinsic utilitarian objectives do so in pursuit of intrinsic *hedonistic* experiences. This perspective becomes less polarized when one focuses on the interaction occurring between service and customer in a value co-creation paradigm. Such an interaction takes into account *hedonistic* (Palmer, 2010) values "that replace functional" ones (Schmitt, 1999b, p. 57) while remaining within the boundaries of what a service provider has control over, relying on its points of contact with the customer to generate both experience and value (Gentile et al., 2007; Grewal et al., 2009; Gummesson, 2008).

Approach Complementarity

As discussed above, CE has developed from a strongly attributed philosophical and neuropsychological experience concept into a socio-economic phenomenon that shaped the history of consumer business over the past decades. The phenomenological and socio-economic approaches to CE appear complementary, since CE not only resides within the experiences that are facilitated or orchestrated by the service provider, but also depends on the subjective phenomenological nature of that customer's experience within and beyond the service provider's interfaces (Grönroos, 2008, 2011; Holbrook, 2006; Schmitt, 1999a; Vargo & Lusch, 2008). The customer's state of mind, for example, affects the level of perceived value and benefits from being acknowledged when studying CE.

Combining both the service and the customer-centric phenomenological approaches would yield an enhanced empathetic *human* understanding by which services would observe intersubjective experiences, thereby supplementing their observable outcome-focused service-centric measures and establishing a deeper connection with their customers' lived experience (Fisk et al., 2020). At the same time, it would incentivize service providers to develop technology-ready frameworks and tools to assist them in monitoring the dynamic nature of CE; to manage and even predict them effectively in real-time. To achieve this, the next section highlights how CE is measured traditionally, followed by how a data-driven approach could be a promising means of doing so.

1.1.3 Traditional ways of measuring customer experience

Positive CE has predominantly been associated with service quality and excellence (Parasuraman et al., 1985; Wirtz & Zeithaml, 2018). These evaluations of service have suggested that CE in firms needs to be managed. As a result, terms like 'customer experience management' and ‘total customer experience’ have emerged to approach CE measurement and analysis managerially. CE management is defined as “the process of strategically managing a customer’s entire experience with a product or company” (Schmit, 2003, p. 17). Total CE, on the other hand, is defined as “a totally positive, engaging, enduring, and socially fulfilling physical and emotional customer experience across all major levels of one's consumption chain and one that is brought about by a distinct market offering that calls for active interaction between consumers and providers” (Mascarenhas et al., 2006, p. 399). Contrastingly, some authors argue that these terms add nothing new to our understanding of CE within marketing and aid in diluting its meaning (Palmer, 2010).

Generally, since the 1970s, the measurement of CE has been attributed to its outcomes such as loyalty and satisfaction (Lemon & Verhoef, 2016). Another approach to measuring CE was inspired by the multi-item service quality scale SERVQUAL and was dubbed EXQ (Klaus & Maklan, 2012; Parasuraman et al., 1988). While the EXQ scale addresses CE contextuality and temporal customer journey stages (pre, mid, and post), it, like most of the aforementioned measurement approaches to CE, neglect the customer-centric human phenomenon (Fisk et al., 2020; Kuppelwieser & Klaus, 2020). Some studies have attempted to include the CE elements (e.g., cognitive and emotional) in their measurements of CE outcomes (e.g., loyalty). Yet, the focus remains on these outcomes or antecedents, and the experience phenomenon itself is, in most cases, not the focal aspect of the study (e.g., Brun et al., 2017). In sum, the varying methods of measuring CE from simple single-item scales such as the Net Promotor Score to relatively more in-depth CE element measures (e.g., Gentile et al., 2007) create major inconsistencies in systematically assessing holistic CE (Keiningham et al., 2007).

1.1.4 The potential of a data-driven approach

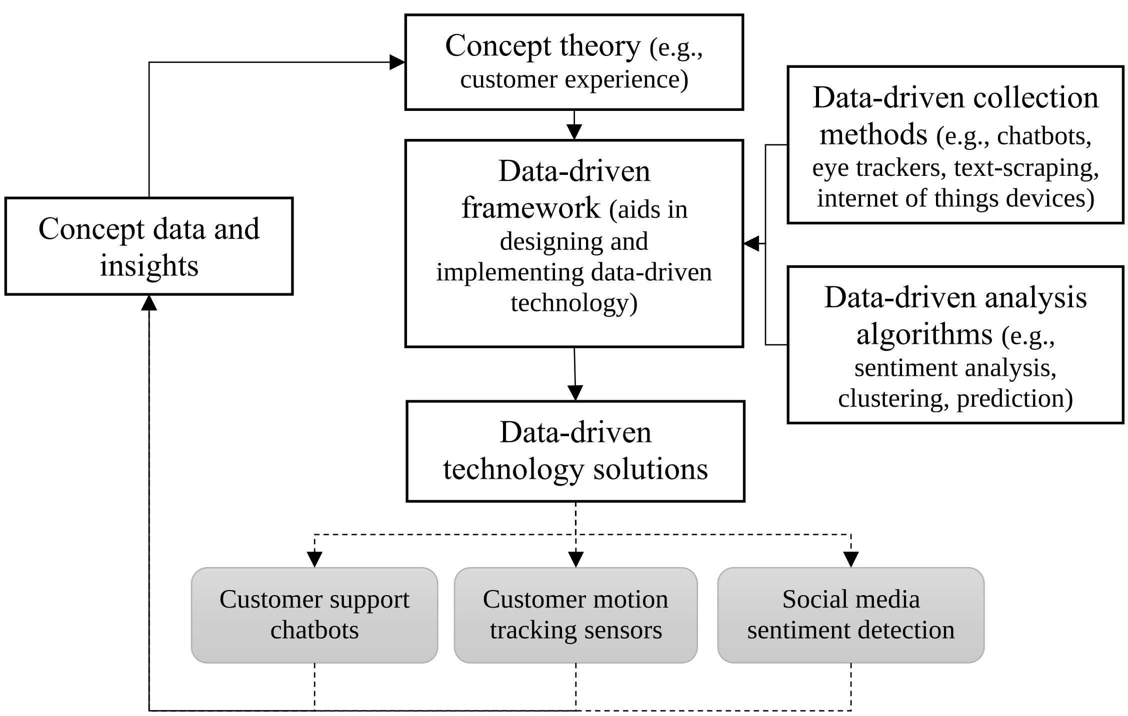
In addition to the inconsistencies in CE measurement, a systematic literature review conducted in the first study of this thesis finds 53 empirical studies involving CE elements across two major repositories without a timeframe constraint. This not only suggests a lack of empirical studies using CE elements, but also an evident gap in not addressing the measurement of CE as a phenomenon. This is not to say that the traditional approaches of CE measurement are not without their value and insights, however many of these methods choose to either measure the antecedents or outcomes of CE or attempt to measure it inconsistently (Kawaf & Tagg, 2017). The result of which leads to the fragmentation of the CE concept, measurement inconsistency, a non-holistic approach to measuring a subjective and holistic construct, and a lack of empirical grounding to aid in further developing and understanding this complex and subjective construct (Lemon & Verhoef, 2016; Palmer, 2010).

While the idea of using a (big) data-driven approach to CE management is not novel (e.g., Holmlund et al., 2020), the inclusion of the phenomenological elements of CE is. These ideas stem from measuring as many aspects of CE as possible and attempting to build a better understanding of the concept. In computer science, this approach is often referred to as the divide-and-conquer paradigm, which breaks down a complex problem into simpler ones using recursion, and proceeds to merge the result of each into the originating solution (Cormen, 2009). Naturally, such a method is and has been used in parallel computing and big data analysis for some time now, and the potential for using it to address holistic CE measurement provides a promising way forward (Dean & Ghemawat, 2008). Thus, in a similar manner in which scientists broke down the constituents of matter into molecules, atoms, and quarks, a similar deconstruction exercise could be applied to the CE phenomenon.

Applying this divide-and-conquer paradigm to the measurements of the CE elements could yield more insights into not only these individual constituents, but also, when reconstructed, a better understanding of the concept as a whole. This exercise would entail going beyond the conceptualizations of each experiential element (e.g., thoughts and feelings) and delve into the empirical measurement and exploration, breaking these elements down further. Once each element and its respective sub-elements are identified, methods for each could be explored and further verified. The result of which makes up the building blocks for a data-driven framework where the methods help build up sub-elemental meaning, which in turn aids in developing an understanding of the constituent experiential elements and the CE phenomenon.

Figure 2 portrays a view of how a data-driven approach could aid in improving the understanding of complex constructs such as CE.

Figure 2. A bottom-up data-driven approach



Note: Dotted lines signify solutions and insights not limited to the ones available in the figure

When combining data-driven collection methods that act as interfaces for data collection with analysis algorithms, data-driven technology solutions could be designed and implemented based on a framework developed for a specific concept (e.g., CE). This is portrayed in Figure 2. Using the abovementioned divide-and-conquer paradigm (discussed in detail in the research programme section), a CE data-driven framework would aid in: (i) Collation of the experiential elements making up the CE phenomenon, (ii) identification of any sub-elements within these major elements, (iii) disambiguation and semantic grouping of these elements to enable data-driven methods to reliably extract experiential data pertaining to these sub-elements, and (iv) provision of a way forward by identifying appropriate methods to measure and analyse each of these sub-elements. This results in the development of data-driven technology solutions that can produce varying amounts of data and insights, that in turn, abductively feed theory (Figure 2).

The advantages of using a data-driven approach to better understand CE are many and include: (i) the utilisation of (big) data that could otherwise go unused by companies (e.g., unstructured data like images and video), (ii) the analysis of both structured and unstructured data types such as text, audio, video, and images, (iii) realtime data collection and analysis, (iv) multidisciplinary data-driven methods (e.g., experiential data and insights could be processed from social media, neuroscience, or live conversational agents), (v) scalability and deployment efficiency (e.g., data-driven methods such as chatbots could be deployed across multiple countries, in different languages, and interact with many customers at once), (vi) leverage artificial intelligence for natural language processing, analysis and prediction (i.e., using machine learning, deep learning, and neural networks), (vii) ability to utilise many data sources (e.g., social media data, biofeedback sensors, customer heatmaps, as well as traditional CE measurements), and lastly (viii) could result in less costs and resource utilisation as scalability and adoption increases (Huang & Rust, 2018; Humphreys & Wang, 2018; Ma & Sun, 2020; Ordenes & Zhang, 2019; Zaki et al., 2021).

1.1.5 Building up a data-driven understanding of customer experience

The previous section establishes the potential of a data-driven approach to understanding complex concepts such as CE. This section on the other hands explores further the potential of how such a data-driven approach can be used to do so. Table 2 highlights how this data-driven approach could be applied via different conceptualization layers and their respective disciplines. An ontological reasoning for this approach will be discussed in a later section, however since CE is phenomenological in nature, building a data-driven understanding of it would span multiple conceptualization layers and as such, disciplines. Starting from the bottom layer of Table 2, a theoretical and empirical foundation to understanding the different elements of CE can be established from disciplines studying the individual, such as psychology and neuroscience (Lim, 2018). To attain experiential data, on the other hand, requires an interface between the individual and a data-driven method. As such, the human-computer interaction discipline could be a prime example of establishing this link while leveraging hardware and software to do so (Picard, 1999). With experiential (big) data in hand, algorithms including AI and natural language processing can be used for such analyses within data science (Siegert et al., 2012). Finally, this analysis, coupled with applied marketing and consumer behaviour use-cases and theories, could be turned into valuable insights from a business context (e.g., Ordenes et al., 2014; Sidaoui et al., 2020).

Table 2. Data-driven experiential approach to understanding CE

Layer	Disciplines	Selected citations
Applied	Marketing and consumer behaviour	(e.g., Kronrod et al., 2017; Ordenes et al., 2014; Sidaoui et al., 2020; Verhulst et al., 2019)
Algorithm	Data science and artificial intelligence	(e.g., Ma & Sun, 2020; Siegert et al., 2012; Sokolova & Lapalme, 2009)
Interface	Human-computer interaction	(e.g., Ahn & Picard, 2014; Lake et al., 2017; Picard, 1999)
Theoretical	Psychology and neuroscience	(e.g., Fox, 2018; Lerner, 2004; Lim, 2018; Sytsma & Machery, 2010)

Establishing a data-driven framework for the CE phenomenon is just an initial milestone; without the appropriate respective methods, an empirical build-up of a holistic CE understanding is not possible. Thus, the next question that needs addressing is what possible methods are available to extract and measure each experiential (sub)element? Even more specifically, which methods are more efficient for specific contexts? For instance, in a situation where a customer has been serviced by a restaurant. What are appropriate methods to evaluate the customer's experience during and then after the service encounter? Moreover, which methods would be best suited for this task in relation to the customer's interaction with a waiter for example, as opposed to other touchpoints such as a self-service encounter? This thesis provides a way forward in addressing these questions. However, it is essential to differentiate between two kinds of measurements. The first relates to the introspective methods of measuring experiences, while the second relates to direct measurements (Holbrook & Hirschman, 1982).

Utilizing the theoretical approaches discussed in the previous section, we can make out that experiences are an ongoing process of living (Csikszentmihalyi, 1991). As a result, individuals undergoing an experience formulate a perceived subjective and customer-intrinsic attitude towards it (Palmer, 2010). In other words, what one recalls about an experience at a given point in time. However, due to how our consciousness works, customers might experience aspects of a service they are not aware of (Lerner, 2004). As a result, an experience can stem from intrinsic (i.e., psychosomatic and physiological) and extrinsic (i.e., environmental stimuli) elements that make up the global holistic experience, termed ‘syncretic cognition’ (Buck, 1993, p. 496). Moreover, another aspect to consider is whether these methods are actively capturing (i.e., directly interacting) or passively measuring (i.e., indirectly without customers interacting) experiential data. The following subsections will shed some light on introspective and measured methods that can be applied actively or passively.

Active methods

When it comes to identifying active introspective methods suited to extract perceived experiences, we leverage a mechanism humans have used throughout history: Storytelling and narrative inquiry, which corresponds to research methods such as interviews (Connelly & Clandinin, 1990). Some claim, these methods are far superior in capturing subjective constructs such as CE, and provide a mechanism in which experiential elements (e.g., thoughts and feelings) could be exchanged in studying critical events occurring within a specific context (Carù & Cova, 2003; Holbrook & Hirschman, 1982; Webster, 2007). While human-to-human interviews are validated methods, they are also more resource and time-consuming, and so, a promising technology such as chatbots paired with AI and sentiment analysis could be used (e.g., Sidaoui et al., 2020). Thus, equipping chatbots with the correct experiential-element detection algorithms and validating them while emphasising effective anthropomorphic communication, is a scalable and promising approach to automate the capturing of experiential elements within recalled experiences (Van Pinxteren et al., 2020).

On the other hand, active CE measurements could comprise interdisciplinary methods from neuroscience for instance. Such methods are also referred to as neuromarketing and could consist of electroencephalography (EEG) and skin conductance approaches to measure the body's reactions to undergoing an experience (Lim, 2018). In conjunction with activity trackers and biorhythm sensors, an Internet of Things ecosystem of methods could be established to measure psychosomatic and physiological signals encompassing a customer's reactions to an experience (Ray, 2018). Even simple activity tracking could aid in gaining behavioural insights pertaining to experiences similar to Disney's Magicbands (Borkowski et al., 2016).

Passive methods

When it comes to passive methods, artifacts of recalled experience could be data-mined using natural language processing and sentiment analysis for instance (Humphreys & Wang, 2018). This could be in the form of customers introspectively expressing their feelings or reviewing a service they have experienced. This method has been the most adopted thus far with many studies using social media text analysis to extract insights into customer opinions and experiences (e.g., Mahr et al., 2019; Ordenes et al., 2017; Ordenes & Zhang, 2019; Park et al., 2020). The downside to these methods is they make pursuing missing data consequential to a holistic understanding difficult. In other words, if a customer expresses angry feelings towards a particular company resource (e.g., a waiter), that still does not mean that they had an overall negative experience (Sidaoui et al., 2020).

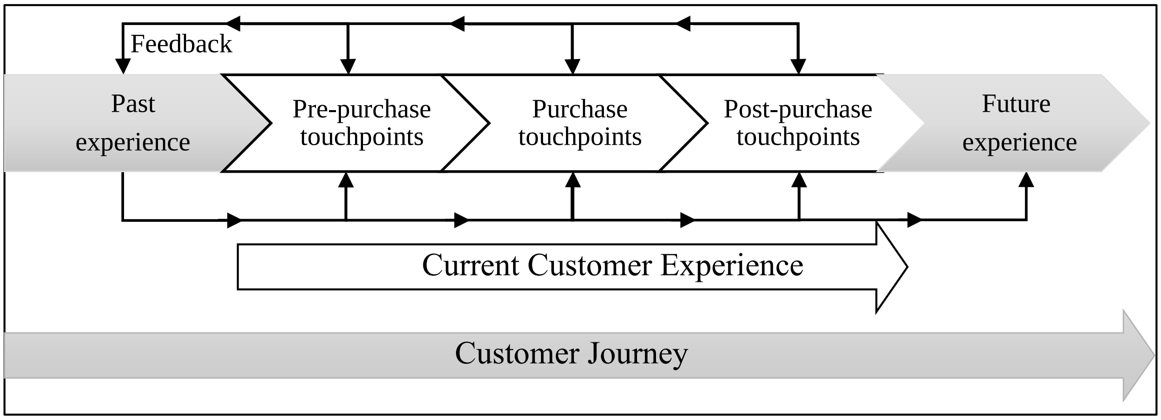
Passive yet measured approaches, on the other hand, could leverage heatmaps, CCTV, facial gesture recognition, and eye-tracking to monitor customer behaviour and movement as a result of their experience (Fombelle et al., 2020; Otterbring et al., 2016; Ray, 2018). While controversial, facial recognition studies geared at uncovering customer emotions have been developed using deep learning AI algorithms across different touchpoints within a retail context (Generosi et al., 2018). Additionally, data mining and business intelligence analysis of customer relationship data in companies (e.g., customer profile analysis and relationship network) could also be an avenue to measure the relationship-specific experiential elements and behaviours of customers (Al- Mudimigh et al., 2009).

So far, the previous sections have portrayed the different theoretical approaches to CE, as well as the potential of using a data-driven approach to build up this understanding via a layered conceptualization and use of various active and passive approaches (Table 2). As has also been discussed, a data-driven approach would need a framework to aid in the design and implementation of such technologies (Figure 2). However, CE is bound by the customer journey and it is therefore important to incorporate this journey in a potential data-driven approach (Lemon & Verhoef, 2016).

1.1.6 Incorporating the customer journey

Touchpoints engage the customer's cognition, emotions, and behaviours in a multidimensional and subjective manner (Hollebeek, 2011; Mollen & Wilson, 2010; Vivek et al., 2012). The term 'engagement' has been used since the 17th century; in the context of this thesis, it is: "a psychological state that occurs by virtue of interactive, cocreative customer experiences with a focal agent/object (e.g., a brand) in focal service relationships." (Brodie et al., 2011, p. 260). Thus, the collective stimulus generated from engaging with service touchpoints, influences the experience within the customer journey (Becker & Jaakkola, 2020). As such, the customer journey forms the bounding box of CEs occurring from the customer's engagement with the servicescape environment (Bitner, 1992).

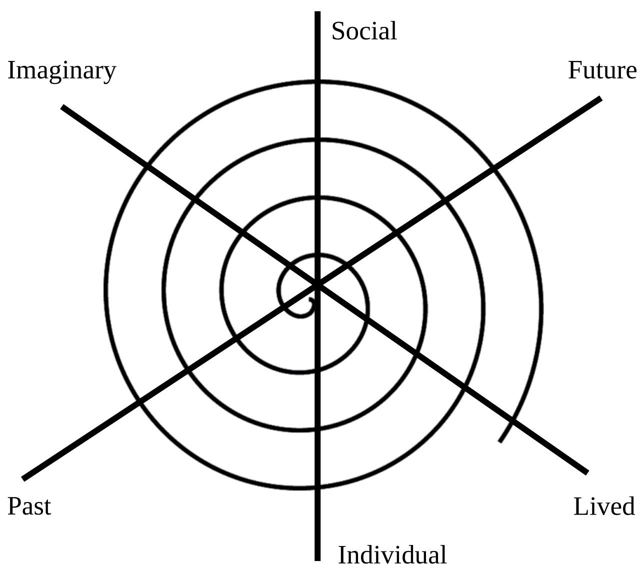
Figure 3. Customer experience throughout the customer journey



Source: Adapted from Lemon & Verhoef (2016, p. 77)

This results in a feedback loop or a "hermeneutic spiral" where past CEs occurring within the customer journey would impact future lived or expected ones both on the individual and social levels (Figure 3 and Figure 4) (Helkkula et al., 2012, p. 63; Lemon & Verhoef, 2016).

Figure 4. Hermeneutic spiral of a customer experience



Source: Adapted from Helkkula et al. (2012, p. 63)

It also echoes the view of CE being "lived," and as a result, being influenced by not only previous experiences, but also elements derived from the individual's self (e.g., expectations and emotions) and the external environments (e.g., societal norms and values) (Csikszentmihalyi, 1991; Thompson et al., 1989).

In sum, past experiences not only influence the overall perceived service quality, but also future experiences via touchpoint engagement throughout the customer journey (Lemon & Verhoef, 2016; Parasuraman et al., 1985). This logic works well when the context of studying a CE is within the domains of the firm and its touchpoints. However, as has been established so far, CE is not just multidimensional and subjective, but is phenomenologically rooted and an ongoing lived process (Csikszentmihalyi, 1991; McColl-Kennedy et al., 2019). So, the question remains, could there be other factors that influence CE outside of the service context? For example, a customer's dining experience could be influenced by them merely being symptomatic of a headache or even having engaged in an argument with their significant other before the dining experience. Such external factors lie outside the realm of what a service is expected to provide via its touchpoints; however, they still have a chance to impact the CE (Lipkin, 2016). While some might argue that these external stimuli consequences are outside the scope of what a firm is expected to address in their CE design, this notion creates a divide between the core concept of firms co-creating value together with their customers (Anderson et al., 2013).

As a result of such external factors and stimuli, a truly holistic data-driven CE understanding can only be achieved by viewing CE as a human phenomenological experience taking into consideration, for example, the customer's state-of-mind as they start a service encounter for instance.

1.1.7 Achieving holistic customer experience

The human experience approach to CE could accommodate these external factors and take into account an individual's state of mind. Transformative service research has been defined as “the integration of consumer and service research that centres on creating uplifting changes and improvements in the well-being of consumer entities: individuals (consumers and employees), communities and the ecosystem.” (Anderson et al., 2011, p. 3). This definition delegates a certain amount of responsibility towards the well-being of the customers to the service and its frontline employees (Rosenbaum, 2015). Thus, for services to more strongly adopt a value co-creation approach, they need to not only manage but also evaluate the external stimuli affecting their customer’s well-being and, ultimately, their CE.

For firms to achieve this, CE needs to be addressed not only within the customer journey but also, more holistically, throughout the human experiences of their customers (Fisk et al., 2020). This means leveraging an empathetic approach to not only customers, but also towards firm resources and touchpoints interacting with customers (e.g., employees and technologies such as chatbots) (Bove, 2019; Huang et al., 2019). Adopting such an (empathetic) approach would require a deeper understanding of the experiential elements at play during a CE (e.g., cognitive, emotional, and behavioural) and, as such, a holistic understanding of the fundamental building blocks of CE, namely CE qualities (e.g., constituent experiential elements, valence, and temporal characteristics) (De Keyser et al., 2020; Wieseke et al., 2012). A holistic understanding is required since the gestaltic nature of CE elements are not only influenced by the firm’s touchpoint interaction with the customer but also the external stimuli outside the control of the firm (Lemon & Verhoef, 2016; Walden, 2017). These external stimuli might prove challenging to manage, but ultimately provide firms with more insights that can help in improving service design and management to account for such factors (Becker & Jaakkola, 2020).

As has been mentioned in this thesis, a holistic understanding at this level needs to account for the phenomenological nature of CE as a human phenomenon, which in addition to objective measurements (e.g., heatmaps and eye tracking), requires customers to exchange their perception of their experiences with firms via introspection (Fisk et al., 2020; Holbrook & Hirschman, 1982). In the process of introspection, customers would be required to recall their perceived experiences from memory flavoured by their current attitude to these experiences (Palmer, 2010). How these introspective experiences are exchanged occurs via storytelling narratives, surveys, and interviews, which are geared towards capturing experiential elements and the temporal contexts (i.e., series of events) in which these experiences occur within (Connelly & Clandinin, 1990; Helkkula et al., 2012). The mechanics of how this could be achieved will be discussed in later sections of this thesis.

In summary, firms should aim to achieve a more holistic overview of their CEs to develop transformative value along with their customers (Anderson & Ostrom, 2015). To achieve this, companies need to observe CE beyond the customer journey and focus on the human experiences of their customers (Fisk et al., 2020). This does not by any means neglecting service touchpoints throughout the customer journey but instead adopting a more human-centric phenomenon-based approach to understanding their CEs. As a result, storytelling and narratives become crucial to allow this understanding to propagate from customers to the firm in supplementation of more objective measures.

1.2 Research gaps

Building off the previous review section, the main gap this thesis highlights and addresses is that CE has mainly been studied via its antecedents (e.g., touchpoints, servicescape) and outcomes (e.g., satisfaction and loyalty) (Kawaf & Tagg, 2017) rather than via a focus on the underlying subjective phenomenon. This has led the experiential human phenomenon to be generally treated as a black box and has streamlined the representation and measurement of CE in academia and practice based on factors surrounding the phenomenon instead.

As a result, much scholarly activity has been inferring CE instead of directly attempting to decipher it. This has led to an approach where CE antecedents and outcomes are manipulated and measured to fine-tune the experience rather than understanding what occurs during the experience to manage its outcomes (e.g., customer loyalty and satisfaction) (Kawaf & Tagg, 2017). This does not dismiss the relevance of constructs such as customer loyalty and satisfaction in the evaluation of CE, nor does it discount the customer journey and servicescape as constructs that could impact it (Bitner, 1992; Lemon & Verhoef, 2016). However, to progress and validate the CE body of knowledge, a data-driven approach needs to be developed. While a great deal of recent research has aided in the better conceptualization of CE (e.g., Becker & Jaakkola, 2020; De Keyser et al., 2020; McColl-Kennedy et al., 2019), a unified empirical approach to studying the CE phenomenon is yet to be established.

First, there is a discrepancy in what constitutes CE elements. For instance, many scholars claim the elements of CE to be *cognitive*, *emotional*, *social*, *behavioural*, and *sensorial* (e.g., De Keyser et al., 2020; Lemon & Verhoef, 2016; Schmitt, 1999b), while others include elements such as *economic* (Verleye, 2015) or forgo these elements altogether in favour of contextualized versions such as *leisure*, *joy*, *distinctive* and *mood* in retail experience (Bagdare & Jain, 2013). Such contrasting conceptualizations hinder the progress of an empirical understanding of the CE phenomenon since it becomes challenging to develop a concise and verified set of data-driven methods to measure them. To address this gap, a framework that can accommodate these different interpretations while maintaining data-driven compatibility is a necessary step. However, this is not trivial since there are multiple approaches and lenses to viewing CE, which will be discussed in more detail in the upcoming sections of this introduction. It is, however, essential to point out that from a phenomenological perspective, different approaches to measuring the CE phenomenon exist, such as introspection and neuroscience measurement (Holbrook & Hirschman, 1982; Lim, 2018). For instance, introspective approaches rely on developing an experiential exchange with the customer to understand how they recall their perceived experience and has been suggested by some authors as a recommended way of measuring the phenomenon (Holbrook, 2006; Holbrook & Hirschman, 1982; Schmitt, 1999a). Another approach is to use methods from neuroscience such as electroencephalography (EEG), functional magnetic resonance imaging (fMRI), eye tracking, and biochemical tools (Verhulst et al., 2019).

As such, the first research gap is established:

G1: A data-driven framework for CE is lacking that can aid academics and managers by providing them with a means to empirically measure the constituent experiential CE elements using various approaches depending on the context and industry.

Second, while AI data-driven approaches make use of, for example, unstructured experiential data such as text, images, and video that attempt to analyse experiential expressions from customers (e.g., Mahr et al., 2019), such methods still need to be validated in conjunction to such a data-driven framework. The challenge in addressing this gap has been the multidimensionality and subjectivity of CE and the many service and customer-centric factors affecting it (Lemon & Verhoef, 2016; McColl-Kennedy et al., 2019). More specifically, making sense of multiple customer extrinsic elements (e.g., servicescape, touchpoints) in addition to a slew of intrinsic ones (e.g., customer's state of mind, activities, sensations) that are specifically challenging to measure, exacerbates the problem of uncovering the phenomenological aspects of

CE when considering these elements together in a data-driven framework. As such, the second research gap is established:

G2: Developing and verifying methods that extract experiential data from CE elements, accounting for the activities, contexts, and resources surrounding the customer's journey are needed and missing in extant literature; this can lead to more standardization, accessibility, and benchmarking of data-driven CE measurement in academia and industry.

Third, the complexity in approaching CE is not only challenging due to the plethora of ways it could be measured, its multidimensionality, as well as its customer-centric intrinsic and extrinsic variables but also due to its changing subjectivity. This has been described as the *attitude* towards the experience which could change over time (Kranzbühler et al., 2018; Palmer, 2010). As a result, introspective CE measurements become volatile, making CE challenging to measure in the first place and a moving target adding to the challenge in uncovering the phenomenon. Attitude change is believed to be influenced by motivations, and thus, CE measurements need to be holistic and account for variables beyond the customer journey context (Lerner, 2004). Thus, while examining the CE phenomenon using customer-facing technology such as chatbots could be advantageous in extracting experiential data, it also creates a new CE resulting from this interaction between the customer and technology. As a result, the design of these technologies and methods needs to account not only for volatility as a result of *attitude* for example, but also for the current experience of the customer with the technology. For instance, a customer recalling a previous experience to a customer service chatbot could influence the experience with the chatbot itself. As such, the third research gap is established:

G3: Understanding of the CE phenomenon dynamics occurring within data-driven technology interactions is limited; a better understanding would not only aid in designing better *customer-facing methods to examine CE, but also result in developing solutions capable of exhibiting the "human touch" and taking into consideration the customer's state of mind and well-being (Anderson et al., 2013; Fisk et al., 2020)*

1.3 Research programme

This section of the introduction provides the reader with the research objectives, paradigm and design adopted, as well as an overview of the research programme under which this thesis was conducted.

1.3.1 Research objectives

As has been established so far in the research gap section of this introduction, a promising way of progressing the understanding of the CE concept seems to be via a data-driven approach to its underlying phenomenon. However, CE itself is a subjective and multidimensional construct consisting of multiple constituent elements (e.g., thoughts and feelings) (De Keyser et al., 2020). As such, breaking down this complex phenomenon into its consistent gestaltic elements and establishing ways to empirically measure and analyse them, is the overarching research objective of this thesis. Due to the complexity of these elements, it is suggested that using a data-driven approach to collect and analyse experiential data using multidisciplinary methods (e.g., AI and neuroscience) could empirically shed light on each of the elements, and in turn, on the CE phenomenon as a whole. Taking the aforementioned research gaps into consideration, the objectives of this thesis are threefold.

The first objective (O1) is to establish a data-driven framework capable of providing CE insights from experiential data relating to each of its constituent elements (e.g., thoughts, feelings) addressing G1 (Study 1). This framework would address inconsistencies in the conceptualization of the CE elements. For example, some researchers refer to the elements as dimensions (e.g., De Keyser et al., 2020; Verhoef et al., 2009), components (e.g., Gentile et al., 2007), or elements (e.g., De Keyser et al., 2015; Keiningham et al., 2017). Another aspect relates to the elements themselves. For instance, some authors iterate five elements (cognitive, affective, physical, social, and sensorial) (e.g., De Keyser et al., 2020), others include pragmatic and economic elements (e.g., Verleye, 2015). As such a data-driven framework would address such conceptual inconsistencies. Additionally, data-driven methods require more accurate representations of the data to be extracted and analysed. Thus, methods leveraging natural language processing, for example, would require more consistent semantic language to be able to better identify and distinguish CE element insights from experiential data. As a result, a data-driven CE framework would need to account for such semantic differences. An example of such semantic inconsistencies can be observed with the 'thought' element that is also referred to as 'cognitive' (e.g., De Keyser et al., 2020; Lemon & Verhoef, 2016). These two terms are semantically different since cognition, from a psychological perspective could include affect (Holbrook & Hirschman, 1982).

Additionally, to resolving and clarifying the above inconsistencies in conceptualisation and semantics, a data-driven framework would also need to be specific enough for the methods to correctly identify the element insights within experiential data. Thus, breaking down the CE concept further into experiential sub-elements might provide a way forward.

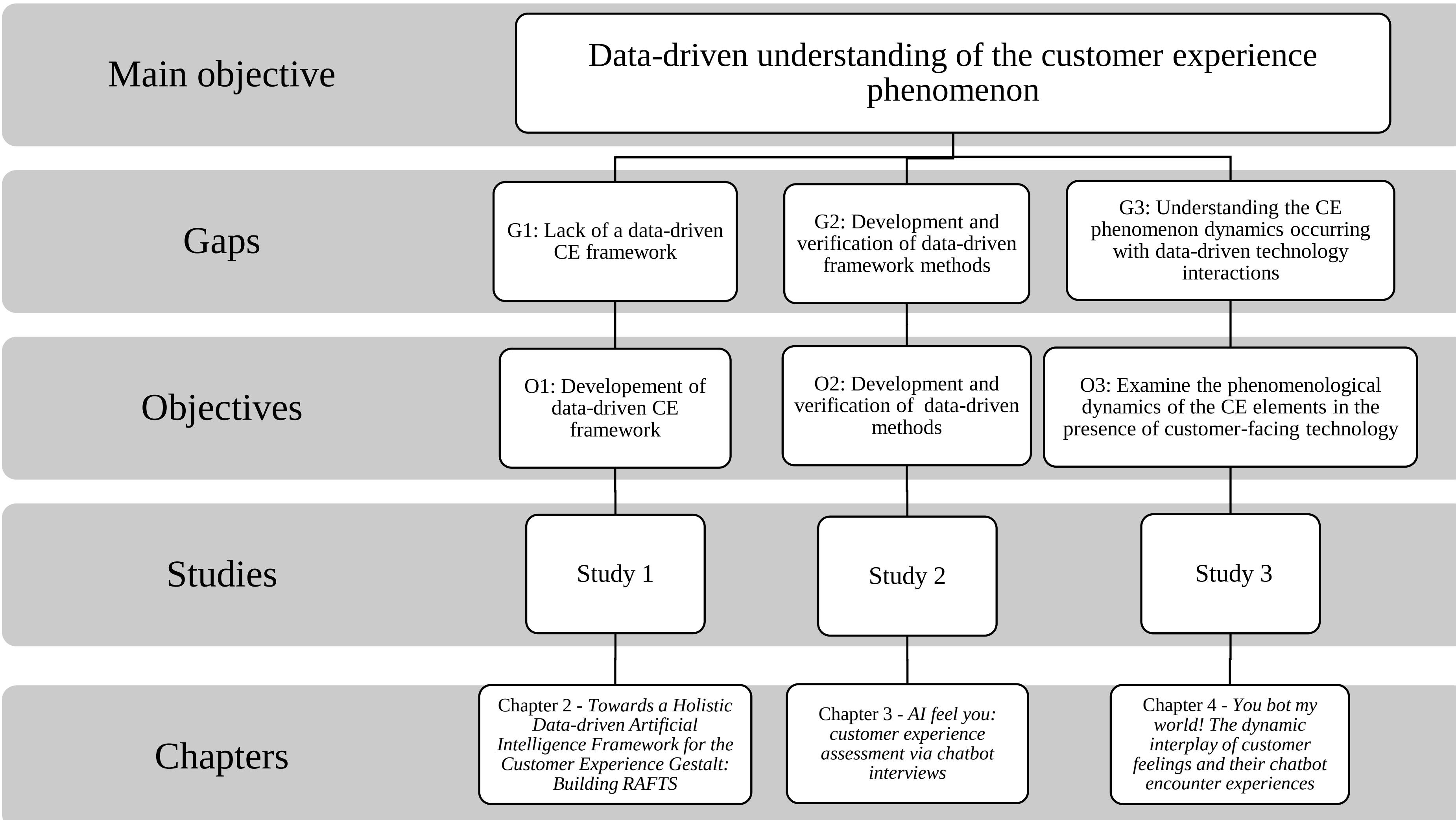
The second objective (O2) of this thesis is to build on this framework and demonstrate how methods can be developed and validated for such a framework, demonstrating its potential value addressing G2 (Study 2) (Sidaoui et al., 2020). The challenge in achieving this objective lies in the subjectivity and introspective nature of the elements of CE (Holbrook & Hirschman, 1982). As a result, in addition to capturing the activities, context, and resources of an experiential encounter, the complexity increases with the temporal changes to the perceived experience (Ordenes et al., 2014). For instance, CE feelings can change over time via attitude or even be influenced by other CE feeling sub-elements (i.e., the pre-encounter mood could influence the emotions of a customer during an encounter with a firm's resource) (Palmer, 2010; Sidaoui et al., 2020). This highlights not only the importance of a method that is context-aware, but one that captures as many CE (sub)elements as possible and accounts for the temporality of the experience. As such, the objective extends into devising a method that would address these matters while remaining data-driven compatible.

The third objective (O3) concerning the sequence of the research gaps portrayed at the beginning of this chapter covers the phenomenological dynamics of the experiential elements with customer-facing touchpoints such as technology addressing G3 (Study 3). This objective is designed to expand on the interplay between the experiential (sub)elements stated in the previous objective. As has been established, not only is CE a volatile construct in that it changes over time but can also be influenced by factors outside the scope of the service experience offering (e.g., customer-facing technology) (Kranzbühler et al., 2018). Thus, the design of data-driven methods needs to account for such volatility (e.g., the attitude of customers over time) (Palmer, 2010). One area to explore is the interplay of the method itself and the sub-elements of the experience. For instance, how does interfacing with a CE interviewing conversational agent influence the experience? Conversely, how does a recollection of a CE influence the experience with that conversational agent? From these questions, it can be noticed that in some cases, a negative experience may arise that is completely not the fault of the experience provider. As such, the objective of understanding the interplay of the (sub)elements of a CE with interfacing data-driven methods such as chatbots, could yield insights to better design them. This results in not only a better understanding of the experiential dynamics at play, but also delivers a way to improve future CEs.

Together these research objectives address the main gap of furthering the empirical understanding of the CE phenomenon by (O1) developing a data-driven CE framework to act as a foundation for this empirical measurement, (O2) portray and demonstrate the development and validation of methods for this framework, and (O3) examine the phenomenological dynamics of the CE elements in the presence of customer-facing technology. These research objectives are rather ambitious and constitute an extensive future research agenda aiming to address all the (sub)elements of CE. Figure 5 depicts how the previously mentioned gaps and objectives are addressed by each of the studies and respective chapters in this thesis, aiming to fulfil the main objective of a data-driven understanding of the customer experience phenomenon.

In this thesis, a semantically clear data-driven framework consisting of CE sub-elements is established along with the development of a novel method to extract CE feelings using storytelling and chatbots. Furthermore, this thesis explores the CE feelings dynamics introduced by such a method (i.e., chatbots). As such, this thesis also creates a research stream to develop and validate new methods to explore the rest of the remaining four elements (e.g., using biofeedback to measure the sensation of the customer during an experience and/or developing a heatmap of customer movements in conjunction to these sensations).

Figure 5. Research gaps, objectives, and related studies



1.3.2 Research paradigm and design

The previous section discussed the concept of breaking down CE into its constituent elements. This section discusses the research paradigms selected to accommodate this breakdown and overall research objectives.

A research paradigm directs the thoughts and actions of researchers by providing them with a lens, constituted by philosophical assumptions, to view the world through (Milliken, 2001). As such, "the way we think the world is (ontology) influences: what we think can be known about it (epistemology); how we think it can be investigated (methodology and research techniques); the kinds of theories we think can be constructed about it; and the political and policy stances we are prepared to take" (Fleetwood, 2005, p. 197). To this extent, a relationship exists between an ontology and a selected methodology, which dictates the methods used in the underlying research (Sayer, 1992). Furthermore, the epistemological position of the researcher is vital since it drives the theoretical perspectives, methodology, and thus methods adopted to conduct the research (Crotty, 1998).

Two broad and opposing epistemological stances that have historically caused many heated debates, now under "rhetorical cease-fire," are positivism and interpretivism, which are associated with quantitative and qualitative research methodologies, respectively (Milliken, 2001, p. 72). The positivists view reality as objective and observed externally (with respect to the researcher) via quantitative methods such as experiments and statistics that aim to generalize the produced knowledge as a result (Crotty, 1998). The interpretivists on the other hand claim that the search for truth stems internally, and is both subjective and complex relying on qualitative methods such as interviews to acquire knowledge (Milliken, 2001).

Adopting either stance exclusively is problematic, especially with the increasing demand for interdisciplinary research (Danermark, 2002). This is especially problematic in this thesis due to the leveraging of software as a methodology which can be developed from both a positivist or interpretivist perspectives (McCarthy, 1981). To avoid this "either/or" pitfall, critical realism offers a solution allowing "methodological pluralism" (Danermark, 2002, pp. 60, 63). Thus, the stance of critical realism is adopted in this thesis, as will be elaborated further in the following section.

Adoption of critical realism

Critical realism is a relevant and widely used research paradigm in marketing (Healy & Perry, 2000). The advantage of adopting critical realism is that it allows researchers to study the "transfactual processes" beyond the facts themselves (Price & Martin, 2018, p. 90). As a result, it allows us "to see science as a social activity, and as structured and discriminating in its thought" switching from events to mechanisms ontologically, but also more broadly switching from epistemology to ontology (Bhaskar, 2015, p. xxx; Danermark, 2002). In other words, critical realism suggests that knowledge is a social output set out in a real-world independent from us with no absolute truth, majorly rejecting positivism (Bhaskar, 2015). Three ontological domains exist within critical realism, 1) the empirical domain housing our direct and indirect experience, 2) the actual domain containing observed or unobserved events, and 3) the mechanisms domain explaining the causations of the events.

The domains described above portray how the CE phenomenon examination was approached. First, the conceptualization of the CE social construct, which is experience at its core, exists in the empirical domain. Identifying how the CE elements impact this experience can be interpreted as the events and can be observed as the actual domain. Understanding how these elements operate and how they are interlinked forms the mechanisms domain which is the overarching question this thesis explores. Traversing these domains within the studies of this thesis are further explained in the next section.

Research design and process

> *"… a scientist never doubts for a moment that there are reasons for the behaviour he has identified and described. It is in the search for such reasons, at a deeper level of reality, at present known to him only through its effects, that the essence of scientific discovery lies"*
>
> *(Bhaskar, 2015, p. 173).*

This section provides the methodology and process attempted to traverse the domains described by the critical realism ontology in search of a better understanding of the CE construct.

CE is a complex construct, attributed to the notion of "life itself" (Csikszentmihalyi, 1991, p. 192). A common approach to tackle complicated problems is the divide-and-conquer paradigm, which attempts to recursively build up solutions from simplified broken-down complex structures (Cormen, 2009). This paradigm is often used with big data and parallel computing to make sense of massive datasets and was adapted in this thesis to explore the CE gestalt (Dean & Ghemawat, 2008).

Thus, an empirically informed understanding of CE could now be achieved by breaking it down into its simpler components. This was the starting point of this research and matches the empirical domain acknowledging the experience in the contexts of a firm and customer in the critical realism ontology. The events domain consists of the CE (sub)elements unified through the systematic literature review conducted in Study 1. This resulted in refining this domain and, as a result, allowing interdisciplinary methods to provide us with better and more varied experiential data which, when brought together via the divide-and-conquer paradigm, could provide insights into the underlying mechanisms (domain). The way to achieve this was by developing the RAFTS framework in Study 1, which breaks down CE into a two-level hierarchical element framework that is unified with respect to the literature and semantically clear for automated methods. The unification and semantic clarity of RAFTS means that an empirical approach consisting of both introspective and objectively measured datasets could be combined into a single framework.

Study 2, proposes a novel verified method which leverages chatbots and storytelling to break down a recalled experience and extract its feeling sub-elements (Sidaoui et al., 2020). This method brings to light one of the ways to traverse the empirical domain to the events domain, whereby the analysis of such resulting data would provide more understanding of the underlying mechanism. The possibility of automating this process using chatbots, is the main contribution of this study, allowing firms and services to expand their event domain-level knowledge which would aid in informing the mechanisms of CE.

Taking a more in-depth view, study 3 traverses the critical realism ontology into the mechanics domain by studying the recalled CE feeling effects on the CE undergoing the automated method in study 2. In other words, what sheds light on the mechanisms in play when applying a method of extracting the events domain (CE elements) on the experience itself (empirical domain). At this stage, to achieve a deeper understanding of the mechanisms, more studies need to be conducted to both validate and analyse the results of methods mapping experiential data to the RAFTS framework.

As such, this thesis aims to provide an empirical means to enable researchers to traverse the critical realism ontology of CE using a data-driven framework. The framework, coupled with data-driven interdisciplinary methods, would aid in not only uncovering more empirical insights into the conceptualization of CE, but also aid in the design of data-driven methods that account for human experience (Fisk et al., 2020).

1.3.3 Research programme overview

This section provides an overview of the studies undertaken by the doctoral candidate. It details the format, structure, planned timelines, and studies within this research project.

Thesis study overview

The three intersecting papers of this thesis are listed below and covered in more details in the following subsections:

- **Chapter 2 – Study 1:** Sidaoui, K., Burton, J., Jaakkola, M., & Gustafsson A., *Towards a Holistic Data-driven Artificial Intelligence Framework for the Customer Experience Gestalt: Building RAFTS* (Submitted to the Journal of Service Research and pending reviewer comments – 06-04-2021)
- **Chapter 3 – Study 2:** Sidaoui, K., Jaakkola, M., & Burton, J. (2020). *AI feel you: customer experience assessment via chatbot interviews*. Journal of Service Management, Vol. 31, No.4, pp.745-766, DOI:10.1108/JOSM-11-2019-0341
- **Chapter 4 – Study 3:** Sidaoui, K., Jaakkola, M., & Burton, J., *You bot my world! The dynamic interplay of customer feelings and their chatbot encounter experiences* (Targeted at the Journal of Business Research by end of 2021)

The three studies contained in this thesis will be formatted in manuscript form, including the journal accepted manuscript form proof of Study 2. The rest of the chapters of this thesis consist of the introduction (this chapter), followed by the study chapters mentioned above, and lastly chapter 5, which will conclude this thesis and discuss the contributions and future work related to the findings in this project.

Study 1

<u>Title:</u> Towards a Holistic Data-driven Artificial Intelligence Framework for the Customer Experience Gestalt: Building RAFTS

<u>Abstract:</u>

Customer experience has become a focal construct within service and customer-oriented research paradigms, and an important topic in the experience economy debate for academics and practitioners alike. However, research into customer experience remains semantically fragmented as its gestaltic elements lack solid empirical grounding. Consequently, customer experience is often measured by its antecedents or outcomes, while treating the phenomenon as a black box. Emergent artificial intelligence (AI) technologies offer an opportunity to gain a more holistic and data-driven understanding of the customer experience phenomenon. This opportunity, however, can only be realized with high semantic clarity and conceptual compartmentalization of the customer experience elements. In an effort to achieve such clarity, we report a systematic literature review of conceptual and empirical studies of the experiential (e.g., emotional and cognitive) elements of customer experience. Drawing on this review, we then develop a semantically coherent and data-driven AI customer experience framework RAFTS, that enables the measurement of customer experience phenomenon as a holistic lived experience. We extend this experiential framework by incorporating it in the customer journey to pave the way for insights into understanding and improving customer experiences. Moreover, our theoretical and managerial discussion highlights the impact of the RAFTS framework for both researchers and managers. Future research avenues include customer experience prediction and improvement in customer experience management methods using multidisciplinary realtime data collection methods that leverage AI.

Keywords – Customer Experience, Artificial Intelligence, Systematic Literature Review, Customer centricity, RAFTS framework

Authorship:

* Karim Sidaoui, *Jamie Burton, *Matti Jaakkola, ** Anders Gustafsson

* Alliance Manchester Business School / ** BI Norwegian Business School

Candidate contribution:

This study started off as a systematic literature review of the CE elements based on exploratory guidance from the supervisors. Eventually, the candidate took an interest in the psychological roots of CE, and from his computer science background, proposed the development of a conceptual paper based on this review. The paper has been in development since late 2017 and has gone through multiple refinements, revisions, and submissions. An extended abstract of an earlier version was accepted at the 22nd Academy of Marketing Science World Marketing Congress 2019 held in Edinburgh. As a result, the short abstract was published in a book chapter of "Enlightened Marketing in Challenging Times" (Sidaoui et al., 2019). Realising the potential of an empirical CE framework, and in conjunction with supervisory agreement, the candidate sought to add another collaborator (Prof. Anders Gustafsson) to the project to further aid in shaping it for top-tier publication in early 2019. Together, the authorship team guided the candidate to submit at the Journal of Service Research resulting in a reject and resubmit verdict in November 2019. The candidate has majorly rewritten and repositioned the paper in light of recent publications on the topic.

Publication strategy:

The newly rewritten paper is currently in revision at the Journal of Service Research (Submitted on 06-04-2021)

Study 2

<u>Title:</u> AI Feel You: Customer Experience Assessment via Chatbot Interviews. Sidaoui, K., Jaakkola, M. and Burton, J. (2020), Journal of Service Management, Vol. 31 No. 4, pp. 745-766. https://doi.org/10.1108/JOSM-11-2019-0341

<u>Structured abstract:</u> (As it appears in the Journal of Service Management)

Purpose – While customer experience (CE) is recognized as a critical determinant of business success, both academics and managers are yet to find a means to gain a comprehensive understanding of CE cost-effectively. We argue that the application of relevant artificial intelligence (AI) technology could help address this challenge. Employing interactively prompted narrative storytelling, we investigate the effectiveness of sentiment analysis (SA) on extracting valuable CE insights from primary qualitative data generated via chatbot interviews.

Design/methodology/approach – Drawing on a granular and semantically clear framework we developed for studying CE feelings, an AI-augmented chatbot was designed. The chatbot interviewed a crowdsourced sample of consumers about their recalled service experience feelings. By combining free-text and closed-ended questions, we were able to compare extracted sentiment polarities against established measurement scales and empirically validate our novel approach.

Findings – We demonstrate that SA can effectively extract CE feelings from primary chatbot data. Our findings also suggest that further enhancement in accuracy can be achieved via improvements in the interplay between the chatbot interviewer and SA extraction algorithms.

Research limitations/implications – The proposed customer-centric approach can help service companies to study and better understand CE feelings in a cost-effective and scalable manner. The AI-augmented chatbots can also help companies foster immersive and engaging

relationships with customers. Our study focuses on *feelings*, warranting further research on AI's value in studying other CE elements.

Originality/value – The unique inquisitive role of AI-infused chatbots in conducting interviews and analyzing data in realtime, offers considerable potential for studying CE and other subjective constructs.

Keywords – Customer Experience, Customer Feelings, Sentiment Analysis, Chatbot, Artificial Intelligence, Storytelling.

Authorship:

* Karim Sidaoui, *Matti Jaakkola, and *Jamie Burton

* Alliance Manchester Business School

Candidate contribution:

This study is continuation of the first paper and is the first in this thesis to propose a new empirical method leveraging chatbots in extracting CE feelings. The ideation, data collection, method implementation, analysis, and full writeup of this paper was driven by the doctoral candidate and guided by his supervisors solely. The candidate also worked on this paper during his three month research visit to Fordham University in New York at the end of 2019. An initial draft of this paper was presented during the QUIS 16 (Quality in Service) conference held on June 10-13 of 2019 in Karlstad, Sweden. The conference was the Service Research Center, Karlstad University in conjunction with both the Center for Services Leadership, Arizona State University, USA and Cornell Institute for Healthy Futures, Cornell University, USA. As a result, the paper was nominated for submission in a special issue at the Journal of Service Management.

Publication strategy: The paper was published in the Journal of Service Management, Vol. 31 No. 4, pp. 745-766. 10.1108/JOSM-11-2019-0341

Study 3

<u>Title:</u> You bot my world! The dynamic interplay of customer feelings and their chatbot encounter experiences

<u>Abstract:</u>

Due to recent advances in artificial intelligence-infused technologies, such as conversational agents and chatbots, many service organizations have adopted such technologies to assist them during service encounters. The global COVID-19 global pandemic has further accelerated the adoption rate of chatbots as they serve as a cost-effective interface between a firm and its customers. This study takes an experiential approach to examining the dynamic interplay between customer experience (CE) feelings and chatbot encounter experience, which has implications on, for example, customer satisfaction, brand perception and loyalty.

Specifically, the purpose of this study is to empirically demonstrate whether and how a customer's mood influences their recalled feelings, feelings towards conversational technology, and mood. Crowdsourced participants were interviewed by a chatbot on positive and negative service experiences they had previously encountered. The findings suggest that customer's mood prior to the encounter, as well as feelings from recalled experiences, have a positive effect on feelings towards the chatbot that in turn influence the customer's mood at the end of the encounter. Furthermore, a positive or negative recalled experience could further influence how recalled experience feelings influence the feelings towards the chatbot.

The study contributes to CE theory by adopting an experiential perspective, demonstrating how customer feelings propagate and influence not only how customer feel at the end of the encounter, but also the feelings towards customer-facing technology. Furthermore, the study highlights the importance of studying and developing customer facing technologies, such

as chatbots, that strive to evaluate and manage the customer's mood and feelings to aid in improving CE and related customer-centric service management aspects (e.g., loyalty and satisfaction).

Keywords – Chatbots, artificial intelligence (AI), customer experience, mood congruency, customer feelings, customer moods

Authorship:

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* Alliance Manchester Business School / ** Nijmegen School of Management

Candidate contribution:

This is the third and final research paper in this thesis. It was conceived and developed by the doctoral candidate and utilised unpublished data from the second study. The candidate took the lead and drafted a first version which was later refined and shaped with supervision guidance. The candidate aimed, after the publication of the second feelings-based study, to portray the importance of understanding human feelings and the way they interacted with front-facing technology. The development of this paper started in late 2019 with steady progress being made. The candidate faced some challenges with developing a model which effectively portrayed what the data was suggesting. After many attempts, and with some supervisory guidance, the candidate managed to find a model that fully explained the discrepancies in the data and aligned with the focus of the thesis.

Publication strategy: This publication is currently at the final stage of write-up and targeted for submission at the Journal of Business Research by the end of 2021.

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Chapter 2 - Towards a Holistic Data-driven Artificial Intelligence Framework for the Customer Experience Gestalt: Building RAFTS

ABSTRACT

Customer experience has become a focal construct within service and customer-oriented research paradigms, and an important topic in the experience economy debate for academics and practitioners alike. However, research into customer experience remains semantically fragmented as its gestaltic elements lack solid empirical grounding. Consequently, customer experience is often measured by its antecedents or outcomes, while treating the phenomenon as a blackbox. Emergent artificial intelligence (AI) technologies offer an opportunity to gain a more holistic and data-driven understanding of the customer experience phenomenon. This opportunity, however, can only be realized with high semantic clarity and conceptual compartmentalization of the customer experience elements. In an effort to achieve such clarity, we report a systematic literature review of conceptual and empirical studies of the experiential (e.g., emotional and cognitive) elements of customer experience. Drawing on this review, we then develop a semantically coherent and data-driven AI customer experience framework RAFTS, that enables the measurement of customer experience phenomenon as a holistic *lived* experience. We extend this experiential framework by incorporating it in the customer journey to pave the way for insights into understanding and improving customer experiences. Moreover, our theoretical and managerial discussion highlights the impact of the RAFTS framework for both researchers and managers. Future research avenues include customer experience prediction and improvement in customer experience management methods using multidisciplinary realtime data collection methods that leverage AI.

A growing body of research (e.g. Homburg, Jozić, and Kuehnl 2017; McColl-Kennedy et al. 2019) suggests that creating and managing superior customer experience (CE) is a key objective of many contemporary firms. The importance of CE appears to be increasing in today's "digital, physical, and social realms" (Bolton et al. 2018, 777) with evidence suggesting that superior CE is linked to enhanced customer satisfaction and revenue (Rawson, Duncan, and Jones 2013). Further still, Gartner's recent report (McIntyre and Virzi 2018) suggests that chief marketing officers allocate as much as 18% of their budgets to CE initiatives. However, only 15% of business leaders rate their organization's ability to deliver a relevant and reliable CE as very good, even though 73% of the same leaders consider CE effectiveness to be critical to business performance (Harvard Business Review 2017). This discrepancy suggests that the CE *gap* remains wide open.

While the recent identification of CE as an MSI research priority (Marketing Science Institute 2018) signals the potential value attached to closing the *gap*, it is first important to try to understand why such a gap exists in the first place. Specifically, we attribute this to CE being a complex concept that comprises *cognitive*, *emotional*, *behavioral*, *sensorial*, and *social* elements (Lemon and Verhoef 2016, 70) that are unavoidably triggered (Berry, Carbone, and Haeckel 2002) during a customer interaction with market actors, so that the multi-faceted, internally perceived *lived* experience is externally influenced (Tax, McCutcheon, and Wilkinson 2013). Moreover, since perceived CE is holistic in nature and a lived experience that is internal to the customer (Heinonen et al. 2010) it is also highly subjective (Meyer and Schwager 2007; Padgett and Allen 1997; Lemke, Clark, and Wilson 2011; Otto and Ritchie 1996) and unavoidably influenced by customers' emotional experiential elements.

Recent studies have made notable efforts in further building a better understanding of CE as a concept, but still pose research avenues that can be addressed via an empirical data-driven understanding of the CE phenomenon such as CE element interactions with touchpoints throughout the customer journey (e.g., De Keyser et al. 2020, 443; Lemon and Verhoef 2016, 87). We expand on such questions further in this study and evidence that a data-driven approach to understanding CE, as a phenomenon, could complement these studies and provide a way forward for a more holistic understanding, and practical application, of this concept (Jain, Aagja, and Bagdare 2017). This also resonates with the research questions raised in the studies mentioned above, including what is the relative importance of individual CE elements in a particular context (De Keyser et al. 2020) and how the holistic, inherently multi-dimensional concept of CE should be measured (Lemon and Verhoef, 2016).

We posit that building up the meaning of CE in a data-driven manner through its elements (e.g., thoughts, feelings) is key for reaching this objective. Identified via our systematic literature review, 53 empirical studies enabled us to identify 90 unique expressions of these elements. Such a lack of consensus in the literature has resulted in contributing to the fragmentation of CE as a concept, and critically, prevented the effective application of CE management in an empirical manner (Palmer 2010). This has led to less uniform empirical study results, oftentimes focusing individual elements of CE, or opting for measurements that describe its outcomes such as customer satisfaction and Net Promoter Score (Reichheld 2003). These further contribute to the widening CE gap and ultimately also impact business performance.

To address this, we believe that a data-driven framework composed of all the CE elements could help portray the concept as a phenomenon which in turn would develop the concept abductively. Such a foundational framework could be leveraged using current technologies, such as artificial intelligence (AI) – “the science and engineering of making intelligent machines, especially intelligent computer programs” (McCarthy 2007, 2) – to extract, analyze, and manage vast amounts of CE element data to build up this meaning. AI-driven technologies such as text-mining are valuable for building rich intersubjective portraits of service CEs (e.g. McColl-Kennedy et al. 2019; Ordenes et al. 2014; and Zolkiewski et al. 2017) since they enable the mapping of enormous and unstructured experiential data to specific CE elements (Brynjolfsson and Mcafee 2017). Such technologies would help overcome scalability and technological limitations of more established, but labor and time intensive, approaches such as interviews (Brynjolfsson, Rock, and Syverson 2017). We posit that building a data-driven CE framework would not only result in less fragmented interpretations of CE, but incorporated within the customer journey, allows for novel and accelerated means to study this principal concept in the digital age in both academia and practice (Lemon and Verhoef 2016).

Our study makes an important contribution to CE theory by adopting a data-driven approach, setting out a framework for empirical means to develop dynamic frameworks to assess, interpret and understand CE as a *lived* phenomenon, rather than measuring it as the sum of its antecedents or consequences (Kawaf and Tagg 2017). Drawing on a systematic literature review of the CE elements, we develop a two-level hierarchy of the CE elements which make up the basis of our data-driven CE (RAFTS) framework and develop a semantically unified conceptualization of the parent elements containing 13 distinct sub-elements. Building on the RAFTS framework, our paper offers three attendant contributions. It (i) addresses research avenues from extant literature to provide a better empirical understanding of CE, (ii) provides a unified and granular structure that can be deployed by multidisciplinary data-driven methods to measure and analyze CE more accurately, and (iii) sets the stage for theoretical advancements in CE prediction and means to improve CE and CE management.

The remainder of this study consists of five sections. The first provides an overview of CE as phenomenon and describes the manner of which its elements make up its *lived* meaning. The second outlines how AI and data can contribute to an improved understanding of CE given a framework. The third describes the two methods that were used, along with the different phases of this study; the results are analyzed in the fourth section. Lastly, in the fifth, the theoretical and managerial contributions, limitations, and opportunities for future research are outlined.

BACKGROUND

CE as a phenomenon

While the notion of the *experience economy* envelopes the CE concept around service logic and value co-creation emphasizing the interaction between customer and firm, CE emerged from the subjective interpretation of consumption (Pine and Gilmore 1998; Holbrook and Hirschman 1982). Thus, CE as a phenomenon, must be differentiated from the service offering or the service outcome such as loyalty and satisfaction (Becker and Jaakkola 2020). As a result, a particular CE needs to be reconstructed as a phenomenon constituting it elements (e.g., sensations, feelings). This is particularly difficult since the customer's attitude towards experiences changes over time and is highly contextual (Palmer 2010; Kranzbühler et al. 2018). More importantly, CE in its barebone form and non-business context is human experience, an unavoidable, ongoing result of living (Berry, Carbone, and Haeckel 2002; Csikszentmihalyi 1991).

Adding to the complexity are the number of attributes which need to be identified within an experience including: touchpoints, resources, activities, contexts, and qualities (De Keyser et al. 2020; Ordenes et al. 2014). As a result, achieving a holistic empirical understanding of CE becomes a daunting task without a paradigm or framework to address this complexity. Fortunately, the nature of this problem is not foreign to mathematicians and computer scientists. The divide-and-conquer[1] paradigm uses recursion to break down complex problems into their simpler forms and then attempts to construct the answer from the result of solving single subproblems (Cormen 2009). In addition to being a great contender for solving complex problems, it is also characterized by being compatible with parallel computing and big data (e.g., The MapReduce programming model) (Dean and Ghemawat 2008).

Thus, the divide-and-conquer paradigm provides strong candidacy in addressing the complex problem of putting together the many pieces of the CE gestalt. This can be achieved by breaking down CE into its most basic elements, followed by measuring and analyzing these elements to finally build up a more holistic CE overview. For example, CE feelings are made up multiple sub-elements (mood, emotion, and hedonic value), and so by finding measures to these sub-elements a better and more holistic understanding of CE feelings is established (Sidaoui, Jaakkola, and Burton 2020; Kranzbühler et al. 2018). If we follow this same logic for the other elements of CE (e.g., thoughts, sensations), we could potentially develop a much more granular and holistic picture of what CE is in a specific context. More importantly, because these elements are interlinked within the experience, an empirical understanding of all the elements together would help isolating problems and highlighting potential avenues of improving the experience in the future (Brakus, Schmitt, and Zarantonello 2009).

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[1] Decrease-and-conquer was used prior to the divide-and-conquer term and dates back to at least 200 BC (Knuth 2011)

A data-driven AI framework for CE

In order to apply the divide-and-conquer paradigm in achieving a more holistic understanding of the CE phenomenon, a framework capable of breaking down CE into its elements is needed. This however is not enough; the framework needs to be able to provide enough semantic clarity in describing CE to enable efficient empirical measurement. There is not yet agreement on robust measurement approaches to evaluate the various aspects of CE across the customer journey, with practice not moving beyond assessing satisfaction (Lemon and Verhoef 2016). Various established approaches such as SERVQUAL (Parasuraman, Zeithaml, and Berry 1988), customer satisfaction and NPS (Reichheld 2003) perform relatively well in offering predictions of firm performance, but these capture simple externalized proxies for measures related to experience and tend to focus on organization-centric criteria. Specifically, we would also like to leverage the data-driven characteristics of the divide-and-conquer paradigm, utilizing AI and data mining to facilitate capture and measurement of a much more complex, internalized, CE.

AI, one of the recent advances in what some term the fourth-industrial revolution (Syam and Sharma 2018), is a key technology to focus on. AI fosters novel technologies that enable the extraction and analysis of enormous customer-related datasets (Brynjolfsson and Mcafee 2017; Brynjolfsson, Rock, and Syverson 2017) and advancements within, for example, service encounters (Larivière et al. 2017), and service experiences (Van Doorn et al. 2017) that have already been determined by these technologically-driven changes.

Paired with data mining methods, AI could be for example used by employing text mining to extract CE assessments based on activities, resources, and contexts to better understand outcomes from a customer's perspective (McColl-Kennedy et al. 2019; Ordenes et al.

2014; Zolkiewski et al. 2017). Likewise, companies could use Internet of Things (IoT) (Ray 2018) technologies and neurophysiological tools (e.g. eye tracking and thermal imaging), to transmit, measure, and better understand people's emotions and sensations (Verhulst et al. 2019). Tailored CEs could then be delivered by technology-enabled devices, such as service robots (Bolton et al. 2018; Wirtz et al. 2018), virtual digital assistant chatbots like Apple's Siri (Kaplan and Haenlein 2019). Even certain smartphone applications can tap into CEs and feelings based on customer usage, for example, Spotify uses advanced machine learning to generate predictions models using their customer's moods and emotional personality profile (Anderson et al. 2020).

While these technologies are already being used to improve CE, they are yet to be used in understanding the CE phenomenon. To exploit their potential value, a divide-and-conquer framework capable of breaking down CE into its simpler elements and provide a means for such data-driven technologies to map experiential data to it is what this study attempts to develop. We posit that such a framework would push the conceptual boundaries of CE and provide a means for researchers and managers alike to empirically validate and explore CE as a phenomenon.

METHODS

To study the multifaceted CE construct and establish a common empirically founded footing on which to base our data-driven framework, we conducted a systematic literature review to gain insights on how CE elements are portrayed in empirical studies. After collating the experiential elements identified in the literature, we cluster these elements using an inductive mapping method (Lofman 1991). An overview of our research procedure, detailed below, is illustrated in Figure 1.

[Insert Figure 1]

The Systematic Literature Review Method

Following Tranfield, Denyer, & Smart (2003) and Boland, Cherry, & Dickson (2017), a systematic literature review was conducted using the Preferred Reporting Items for Systematic Reviews and Meta-analyses (PRISMA) (Shamseer et al. 2015) evidence documentation protocol (Figure 2). Additionally, cross-referencing and/or snowballing (Jalali and Wohlin 2012; Wohlin 2014) was used to complement our literature review and diminish the potential pitfalls of semantic meaning that can limit literature populations (Papaioannou et al. 2009).

We sourced 1,825 articles from two repositories, which are limited to published journal articles in the English language: (i) Scopus by Elsevier and (ii) EBSCO's Business Source Elite to achieve a robust and comprehensive set of results constituting a wider range of domains while still maintaining business-oriented inclusiveness. The search terms constituted the titles, keywords, and abstracts for *customer experience* and the following associated phrases: *consumer experience*, *service experience* (Kranzbühler et al. 2018), and *customer engagement* along with the experiential element equivalents phrases: *element*, *dimension, sens**[2]*, relat*, social, cogniti*, think, rational, physical, emotion*, hedonic* (Lemon and Verhoef 2016)*, activity, sentiment, resources*, and *context* (Ordenes et al. 2014). We included customer engagement in the list of CE equivalents since the concept is a direct co-creator of CEs and possesses similar experiential elements (Brodie et al. 2011; Lemon and Verhoef 2016).

The screening and filtering process aligns with previous systematic literature reviews on CE (Kranzbühler et al. 2018) and abides by the appropriate standards (Boland, Cherry, and Dickson 2017; Shamseer et al. 2015; Tranfield, Denyer, and Smart 2003). Extracting the

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[2] The use of the stem form e.g. “sens*” for instance allows the search engine to accommodate all words starting with “sens” for example, “sensation”, “senses”, and “sense”.

experiential elements from the gathered 53 empirical studies facilitates their bottom-up mapping and resulted in our framework. In addition, we identified 41 cross references and 43 conceptual and supporting studies.

[Insert Figure 2]

The Inductive Experiential Mapping Method

The Mapping Approach and Semantic Significance

In order to establish a CE element-based framework for AI, high levels of granularity and specificity are required. So far, there have been few attempts to collate the CE elements and map them semantically into groups. An exception is a coding scheme developed by Lofman (1991) that summarizes the literature representation of seven coded CE elements, including a seventh catch-all category. Lofman's (1991) study is based on the Thought-Emotion-Activity-Value (TEAV) model developed by Hirschman & Holbrook (1986), and uses an inductive and iterative process to code the experiential elements using a coding scheme built around an input-output process. This scheme includes a *setting* code that signifies the input and *sensation*, *thought*, *feeling*, and *activity* that result in the evaluation code, thereby signifying the output (Lofman 1991). While this coding scheme includes two levels of sub-codes that further detail the specifics of each broader element, our scheme focuses solely on a single set of sub-codes gathered from the collated experiential elements.

The advantages of "speaking the same language" not only aid in reducing contextual misunderstanding but are paramount in supporting the design of AI related frameworks and tools that require semantic consistency to function effectively. Hence, it becomes important to set forth a semantic target since not all authors use the same terms. Examples of this variation in terminology can be seen at the highest coding level in the use of descriptors like: *elements*

(Keiningham et al. 2017, 150; De Keyser et al. 2015, 1), *components* (Gentile, Spiller, and Noci 2007, 398), and *dimensions* (Grundey 2008, 138; Gilboa, Vilnai-Yavetz, and Chebat 2016, 52; Verhoef et al. 2009, 34; Otto and Ritchie 1996; 1995) when describing experiential elements. While both *components* and *elements* do reflect constituents, the *dimensions* describe an aspect or feature (Cambridge online dictionary n.d.; n.d.; n.d.). We adopted the term *elements*, as it reflects the semantic meaning of a standalone constituent. It is relatively straightforward to manually identify the semantic meanings of the terms used to represent concepts by reading "between the lines"; however, this process becomes challenging when attempting to group synonymy and polysemy (i.e., different interpretations for the same word) terms in the literature search, thus creating hurdles for AI models, future research, and concept consolidation (Ravin and Leacock 2000).

Phase 1 - Stemming

The inductive mapping method is set across three phases (see Figure 1). The first phase constitutes normalizing 249 of the identified experiential elements using the process of linguistic stemming (Lovins 1968). For example, an instance of the element *emotional* would be stemmed to *emotion*.

Phase 2 - Semantic Mapping

Phase 2 encompasses semantically grouping similar *descriptive* experiential element codes (Miles, Huberman, and Saldana 2013). For instance, the elements *think* and *cognitive*, *feel* and *emotion*, and *activity* and *behavior* would be grouped respectively under a common term. What follows is assigning the remaining elements to sub-elements, enabling the classification of lower level and more granular descriptions within broader *interpretively* coded (Miles, Huberman, and Saldana 2013) elements. For instance, the elements signifying utilitarian value are involved in cognition and could arguably be placed under a *thought* element as opposed to *hedonic value*, which is then processed as an *emotional* and *felt* event. We argue that using sub-levels similar to the Lofman (1991) scheme would be beneficial by reducing semantic mislabeling in the main elements and adding granularity, which is crucial for an AI-ready framework. A notable instance would be the *economic* element (Verleye 2015) which signifies the utilitarian value of an experience and can be attributed to either a *cognitive* or a *relational* function. On the one hand, utilitarian value is associated with a cognitive process (Hilken et al. 2017); on the other hand, one could also argue that the term represents the relationship it represents to the person and thus, should potentially be labelled a *relational* element. Because utilitarian value is evaluated using a thought process (Hilken et al. 2017) in relation to *hedonic value* which resides as a *feeling,* our scheme considers utilitarian value to be a *thought* rather than a *relational* element.

Phase 3 – Contextual Grouping

To finalize the mapping process, we contextually analyzed the remaining elements as portrayed by their authors and assigning them to parent elements. A notable example of such mapping is the term *novelty*, which refers to customers being “attentive and attracted to something that is new and different” (Poulsson and Kale 2004, 272). Since the uniqueness of that experience is solely dependent on the previous experiences that a customer encountered, one could argue that *novelty* can be coded under *relation* in terms of pertaining to how the customer temporally relates to that particular experience. Another example would be the educational realm (Pine and Gilmore 1998) that includes intellectual elements, and thus can be grouped as a *thought* element.

ANALYSIS AND FINDINGS

As discussed earlier, the screening and filtering process adopted for our analysis mirrors the standards of previous research. We supplement similar approaches which utilize a systematic literature review to develop a conceptual framework (Kranzbühler et al. 2018; Becker and Jaakkola 2020) with the addition of an inductive mapping method that involves a greater range of associated CE elements to better serve our objectives (Lofman 1991).

Experiential Element Mapping

In Phase 1, we analyzed the empirical and conceptual studies gathered relating to CE elements. A stemming normalization process (Lovins 1968) on the experiential elements collated in this study was conducted with the aim of unifying similarly stemmed elements. For instance, *affective* was normalized to be *affect*, *hedonism* was normalized to be *hedonic*, and *sociability* was normalized to *social* resulting in 90 unique elements. Table 1 highlights the frequencies and percentage distribution for the top 15 elements. The highest frequencies align with the five experiential elements commonly expressed by recent literature, namely, *sense*, *cognition*, *social*, *emotion*, and *behavior* with 8.4%, 8.0%, 7.6%, 6.0%, and 5.6% respectively (Verhoef et al. 2009; De Keyser et al. 2020). The relatively low percentages of the five highest frequencies (comprising just over a third (35.6%) in sum) further highlights the inconsistency and lack of agreement in the terms used to describe the CE elements (Verhoef et al. 2009; Brun et al. 2017).

[Insert Table 1]

Semantic Mapping

In Phase 2, we proceeded to semantically group the 90 unique normalized elements identified by our search[3]. We succeeded in mapping and clustering 70.2% of the elements semantically together (i.e., using their descriptive meaning), leaving us with 29.8% of the elements lacking a direct semantic equivalent (including, for example, *adventure*, *surprise*, and *motivation*).

Contextual Grouping

Finally in Phase 3, the final coding structure used for contextual grouping is adapted from Lofman (1991), however it differs in its objective: which is in creating a CE phenomenon framework with enough granularity (via sub-element identification) and semantic clarity (via the inductive experiential mapping) to support data-driven methods to accurately extract and analyze experiential data. We argue that our assembly of the experiential (sub-)elements is exhaustive, accommodating both conceptual and empirical codes from our systematic literature search. Another difference is the restructuring of the coding scheme in relation to the contextually analyzed and identified sub-elements. The latter is also a reason for adopting the terms *relation*, *activity*, *feeling*, *thought*, and *sensation* to distinguish them from the less granular and semantically clear terms such as *affect*, *behavior*, and *cognition*[4].

Thus, as a result of the semantic mapping and our semantic adoption, Table 2 highlights the resulting 62 normalized experiential elements extracted from the accumulated empirical

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[3] This extensive chronological list is found in the appendix in Table A I, and provides further tabular depiction of the semantic disparity in the representation and measurement of CE elements.
[4] For example, cognition, historically portrayed in ABC models (Affect, Behavior, Cognition), can carry elements of thought, relation, and forms of emotion (Holbrook and Hirschman 1982, 133). As a result, we adopt the semantics of authors (e.g., Schmitt 1999) who use semantics that can be less ambiguous for data-driven methods.

literature, and their mapping to five parent elements. The table reveals that there is indeed a variation in not only the semantic meaning, but also in the perspectives different authors adopt to approach the elements of CE, thereby contributing to the fragmentation of CE elements.

[Insert Table 2]

Another difference in our coding structure is the classification of the physiological elements that have been grouped as a *feeling* in the coding scheme, and as a *sense* in our mapping. From our analysis, we noted that senses could be stimulated either externally or internally. For example, intense lights in a shop stimulate a person's senses externally; however, the sensation of tingling or hunger is internally physical.

Lastly, we include the personal and temporal sub-elements to the *relation* element as a result of the mapping in the cases of *personal* (Poulsson and Kale 2004; Verleye 2015; Klaus and Maklan 2011) and the *novelty* (Chauhan and Manhas 2014; Rageh, Melewar, and Woodside 2013; Tynan and McKechnie 2009; Poulsson and Kale 2004; Otto and Ritchie 1996; 1995) related elements.

Achieving realtime data-driven insights using the RAFTS Framework

In order to build a bottom-up approach of CE from experiential element data, we conducted the inductive experiential mapping to unify and gain a more granular perspective to the CE elements covered by the literature. This exercise enables us to standardize the gestaltic (parent) elements of CE along with their sub-elements, which in turn, provides the basic building blocks to create a sufficiently granular CE framework mappable to experiential data. In other words, the granularity of the identified sub-element semantic grouping provides data-driven technologies (e.g., data mining) a clear experiential extraction approach that will generate more accurate data.

The results of Phase 3 (contextual grouping), were developed into the Customer RAFTS framework (we will refer to this as RAFTS for brevity from this point on) which can be found as a component in Figure 3, incorporating the parent elements *Relation, Activity, Feeling, Thought,* and *Sensation*. This framework inherits the granularity (i.e., hierarchy) and elemental semantic grouping (i.e., a clear and unified understanding of the experiential element) from our mapping method to enable the experiential data to be merged into the framework. From this, and leveraging the divide-and-conquer paradigm, the framework provides a means to build a holistic CE profile from experiential data collected by appropriate methods for each CE sub-element.

While RAFTS presents a means to construct an understanding of the CE phenomenon using experiential sub-elements to provide the necessary granularity for data-driven methods to collect, how this is incorporated into the customer journey to provide both customer and service-centric insights is portrayed in Figure 3. The premise of this framework leverages how CE is represented in the customer journey (Lemon and Verhoef 2016) isolating the CE phenomenon or what occurs internally within the customer (i.e., data represented by RAFTS) and the external context the customer is surrounded by. The external context can consist of data that relates to a factor under the firm's control (e.g., lighting levels in a showroom), or data on factors which are not (e.g., temperature/humidity or data on a customer's belonging, such as a device specific attribute like 5G compatibility).

With these distinctions made, a realtime data collection spans multiple current CEs (i.e, multiple: pre, mid, and post purchasing stages) occurring within the customer journey. Ideally data collection would be continuous (e.g., a heatmap of customer activities as they interact with different touchpoints), which would contribute toward amassing a big dataset that can help generate causal insights or even predictive CE models. The realtime data collection would, importantly, measure not only RAFTS (sub-)elements but it would also be temporally synchronized with data from external context since this would help pinpoint environmental triggers or stimuli influencing CE (Becker and Jaakkola 2020). From the data collected, inferences could then be made on the effects of the external context on CE; these would enable improvements to service design, servicescape, and CE management. Furthermore, the analyzed data could yield instrumental insights into the understanding of CE as a phenomenon, thus leveraging data-driven methods and AI models to create CE prediction models at both individual and aggregate levels.

[Insert Figure 3]

Further reflection on the theoretical contributions and managerial implications of this framework are discussed next.

DISCUSSION AND IMPLICATIONS

Despite numerous conceptualization efforts, an empirically driven understanding of CE throughout the customer journey is essential in progressing this concept both theoretically and managerially. The developed RAFTS framework and its incorporation into the customer journey (Figure 3) expands the CE research *greenfield* by providing (Lemon and Verhoef 2016, 89) an empirical means to better understand CE as a *lived* phenomenon beyond its antecedents or consequences as well as CE triggers from contexts external to the customer (e.g., servicescape stimuli) (Kawaf and Tagg 2017; Becker and Jaakkola 2020). Generally, these outcomes are observed via externalized proxies (e.g., loyalty and satisfaction) for internally realized experience or externally observed measures of phenomena, which tend to focus on organization-centric criteria. However, also understanding the *lived* internal phenomenon is key to understanding CE.

Due to the holistic and multidimensional nature of CE, this *lived* understanding is difficult to evaluate without analyzing large amounts of touchpoint data across the customer journey (McColl-Kennedy et al. 2019). It is also necessary to generate AI and machine learning models to "identify opportunities for intervention and influence" (Lemon and Verhoef 2016, 87). Thus, the development of RAFTS framework and its incorporation in the customer journey (Figure 3) offers many benefits to both theory and practice as will be discussed below.

Theoretical Contributions

The key contribution of this study stems from the RAFTS framework and how it enables the empirical evaluation of the CE phenomenon as a holistic *lived* experience throughout the customer journey. More specifically, this study (i) paves the way for a better empirical understanding of the CE concept, and provides a foundation to address pending research questions, (ii) provides a semantically unified and granular means for data-driven methods to more accurately extract and analyze experiential and contextual data which carves a path for transdisciplinary methods (e.g., neuroscience, big data analytics, IoT) to accelerate and aid in developing CE (realtime) measurement methods, and (iii) offers an avenue to progress CE and CE management (e.g., service design and recovery) as well as set the stage for theoretical progress towards models that could build and possibly predict CE.

First, by utilizing RAFTS within the customer journey to produce data-driven CE insights, the framework has potential to address several proposed research questions from extant literature. For instance, "How can we measure the CX construct across multiple touch points and journey stages?" and "What are the effects of different touch points on customer experience, conversion, and loyalty?" (Lemon and Verhoef 2016, 87). The framework in Figure 3 not only provides a means to measure the CE phenomenon empirically across multiple touchpoints of the customer journey, but since it measure multiple current customer experiences ($t_1 - t_n$) including the external context, it allows researchers to evaluate the effects of these touchpoints throughout the different segments of the customer journey.

Other questions relating to the CE elements (RAFTS) and firm controlled touchpoint effects such as “How do the various dimensions work in combination?” or “How does CX with noncontrolled touchpoints affect CX with firm-controlled touchpoints?” can also be answered (De Keyser et al. 2020, 443). The former can leverage the granular nature of RAFTS and analyze the interactions of not only the parent elements (e.g., thoughts and feelings) but also their sub-elements (e.g., effects of mood on utilitarian value perception). The latter question can be addressed via comparing the effects of firm-controlled and noncontrolled touchpoints in the external context on RAFTS (Figure 3). These are merely a few examples where our framework can aid progressing our understanding of the CE concept empirically.

Second, our review and inductive mapping of the CE elements contributes in addressing the fragmentation of the CE concept which has been “widely used and abused” (Palmer 2010, 196). We identified 90 unique elements (prior to contextual grouping) that contribute to not only the fragmentation of CE knowledge but also – more importantly – to a challenge in empirically studying this concept. Moreover, because the RAFTS framework depends on experiential data (ideally in realtime) a range of data collection methods spanning multidisciplinary boundaries could be used for data collection and analysis. Methods could vary from active data collection that involves direct interaction with the customer (e.g. chatbots or sensors attached to the customer), to passive data collection (e.g. social media data mining and heatmap analysis). Additionally, introspective and extrospective data collection methods can also be used. Introspective methods, while portraying a clearer view of the perceived experience are also subject to attitude changes over time (Palmer 2010; Kranzbühler et al. 2018), whereas extrospective measured data provides a more objective data stream resulting from sensors or realtime text analysis. Furthermore, AI can be leveraged as a tool to collect and model experiential data such as customer feelings for example (Zaki, McColl-Kennedy, and Neely 2021). Identifying and validating further (realtime) methods for each RAFTS (sub-)element and touchpoint in the customer journey will contribute to further developing this empirical understanding.

Third, the RAFTS framework can aid in developing CE and CE management. To illustrate some of the potential uses of this framework, consider a text mining algorithm that attempts to extract CE elements from a text corpus. It would need to know precisely what these elements are in order to extract them. Would the SEMs model (*think*, *sense*, *feel*, *act*, and *relate*) (Schmitt 1999) be more appropriate or generalizable than the co-creation experience dimensions (*hedonic*, *cognitive*, *social*, *personal*, *pragmatic*, and *economic*) (Verleye 2015)? Would a more contextual model such as the retail CE dimensions (*joy*, *mood*, *leisure*, and *distinctive*) (Bagdare and Jain 2013) provide more a holistic understanding of CE in a retail setting? By what means could we accommodate new or differently termed concepts such as the Japanese *kansei*, for instance, which represents "*feeling*, *taste*, *emotion*, etc." (Nagasawa 2008, 313)? Thus, RAFTS addresses these inconsistencies that could hinder the development of the concept in different contexts.

Even more so, because this framework approaches CE as a phenomenon it could help identify the psychological phenomena attributed to the experience in relevant service research areas such as COVID-19 companion robots (Odekerken-Schröder et al. 2020) or even frontline AI encounters (Robinson et al. 2019). Another example avenue where RAFTS can used in conjunction to the customer journey is service recovery. Because RAFTS leverages realtime experiential data, it can enable swifter service-recovery measures that can even take place at the current stage of the current customer experience. This aids in expanding the theoretical frameworks to account for data-driven insights on factors such as 'recovery time' and 'follow-up' (Van Vaerenbergh et al. 2019, 107). Lastly, the vast amounts of (realtime/big) experiential data can aid in progressing and contributing to developing theoretical CE prediction models by leveraging AI and machine learning (Lemon and Verhoef 2016; McColl-Kennedy et al. 2019).

Managerial Implications

For managers, this study provides manners in which CE, as a phenomenon, could be measured *in conjunction with* typical outcomes such as satisfaction, loyalty, and net promoter score (Kawaf and Tagg 2017). Traditionally, there has been a lack of guidance for measuring CE at scale and the task has proven very resource-intensive and complex. With the AI market forecasts rising to USD 190.61 billion by 2025 ("MarketsandMarkets Research" 2019) and AI systems becoming cheaper and more accessible, companies are becoming better equipped to handle big data and the AI analysis of this data. Thus, the RAFTS framework could provide firms with guidance on how to measure, more holistically, their CEs. Specifically, RAFTS could provide CE managers with more granularity (per CE sub-element) to more accurately identify aspects of the service design that are influencing the CE most and to also build a better understanding of how specific aspects of experiences are changing via different touchpoints and over time. Since RAFTS enables the measurement of the CE phenomenon over time, different touchpoints, activities, contexts, and resources could be evaluated to provide more accuracy as to what aspect of the service design is influencing the CE most (Kranzbühler et al. 2018; Ordenes et al. 2014). For example, the feelings element comprising (moods, emotions, and hedonic value) could explore how, and at what point, are the customer's feelings affected, thus enabling rectification at a specific touchpoint (Sidaoui, Jaakkola, and Burton 2020). Additionally, the phenomenon-focused measurement provides companies with the *lived human* experiences of their customers (Csikszentmihalyi 1991; Fisk et al. 2020). This consequently enables firms to not only leverage the scalability of the *big (experiential) data* provided by RAFTS, but also witness their CEs through a more individual human lens. As a result, firms can build empathetic relationships with their individual customers on a large and resource-efficient scale which leads to better customer relationships and thus better experiences. At the same time, they can also develop improved understanding of the phenomena at the aggregate level across different times, touchpoints, activities, contexts, and resources (Ordenes et al. 2014), thus improving their ability to best manage the aspects that drive CEs.

The facilitation of realtime active data collection, analysis and response has useful implications for immediacy of service recovery approaches, for example. Use of RAFTS could facilitate monitoring a customer's emotional changes over the course of their CE and evaluating customer responses to triggers or stimuli from the external context. These stimuli could be automated by using predictive AI approaches and hence manipulated by service management with an aim to manage the emotional volatility of the customer and improve their experience. Based on an ever-growing database of customer experiences and responses, thanks to immediate AI-driven interactive responses to service failure, firms would become increasingly effective at dealing appropriately with reported service failures. Demonstrating suitable levels of empathy, for example, and rectifying the issue quickly would likely boost CE and customer loyalty (Bove 2019).

Limitations and future research

A systematic literature review method in the social sciences is not without its limitations. Specifically, articles do not always reflect their intended purpose in their titles, abstracts and keywords (Papaioannou et al. 2009). Thus, the search terms used will not always yield the intended results. In some cases, there could even be a semantic alternative similar to the discussed *dimension*, *element*, or *component* scenarios. The researcher needs to anticipate and incorporate these alternatives in their search terms. In other cases, the content sought could still be a focus of another study, but not highlighted in the actual title, abstract, or keywords. These limitations are not specific to the current research, and apply to social science research in general (Papaioannou et al. 2009). In an attempt to mitigate this limitation, we expanded our search terms with synonyms and alternative keywords and also included cross-referencing and snowballing as a supplementary referencing methods (Jalali and Wohlin 2012; Wohlin 2014).

A second limitation derives from the subjectivity relating to the constituent elemental mapping procedure. Although we have taken the utmost care to ensure that the contextual meaning of the originating element terms are preserved, the bias could occur in the descriptive nature of the constituent CE element terms in the studies themselves. Due to our normalization, semantic grouping, and contextual mapping process, the experiential (sub-)elements derive their final descriptive meanings from a shared understanding between the different authors, thus reducing subjectivity when deciphering the terms. We acknowledge that certain experiential elements, such as relation, are more challenging to map than others are due to, for example, the internal (un)awareness and introspection abilities of the customer to such elements. We see this issue, too, as a potential avenue for future research.

Future work could focus on further exploring the RAFTS (sub-)elements to explore and determine their individual qualities (De Keyser et al. 2020). Ultimately, because experience is a holistic evaluation that requires holistic measurement, we encourage merging insights from multiple comparable methods together. For example, neuroscience methods could be utilized alongside interactive data collection: if biofeedback sensors (e.g., heartrate) are utilized to measure physiological emotional responses, then a conversational agent (e.g. chatbot) could also be used in conjunction, to provide more data on thoughts and feelings and thus a more holistic perspective. As more methods become verified, future work could investigate different ways to merge these results using AI algorithms. Such algorithms could be leveraged to perform classification and prediction tasks, thus further expanding the research horizons of CE. Using RAFTS as the frame of reference, such work could ultimately make assessing CE less intrusive to the individual.

In terms of the practicality of data collection and measurement *in real time*, we recognize limitations to the volume of data that can be collected via interactive methods in particular. For example, there is a limit to how many times one can ask follow-up questions on the same topic without that influencing customer journey and CE, which can be alleviated by AI (Zaki, McColl-Kennedy, and Neely 2021). However, it is important to note that the RAFTS framework is designed to facilitate and encourage parallel use of multiple data collection methods. Such methods may include more traditional observatory approaches, but future research should also focus on developing contemporary methods (whether realtime or post-event, active or passive) enabled by emerging technologies. Firms could utilize these in parallel to explore and understand CE via RAFTS (sub-)elements and measures used to assess external context. In sum, addressing these avenues by adopting a data-driven approach to CE contributes to bridging the CE gap.

Tables and Figures

Figure 1. Overview of the research procedure

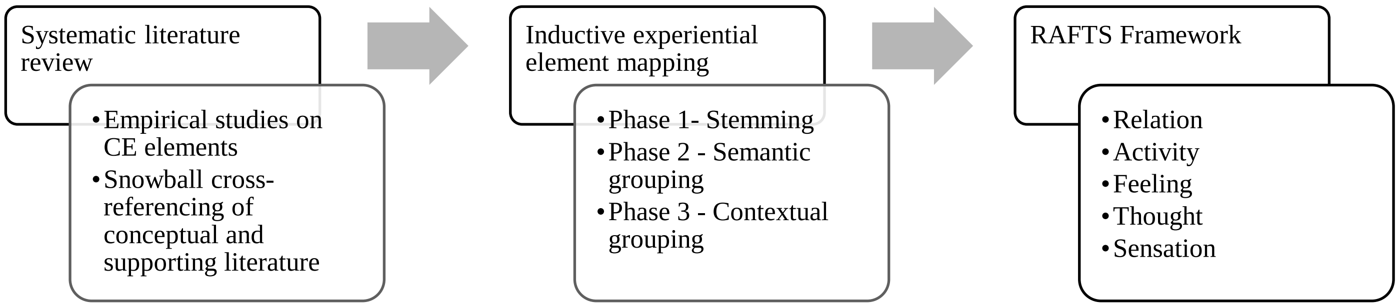

Figure 2. PRIMSA Diagram based on Shamseer et al. (2015)

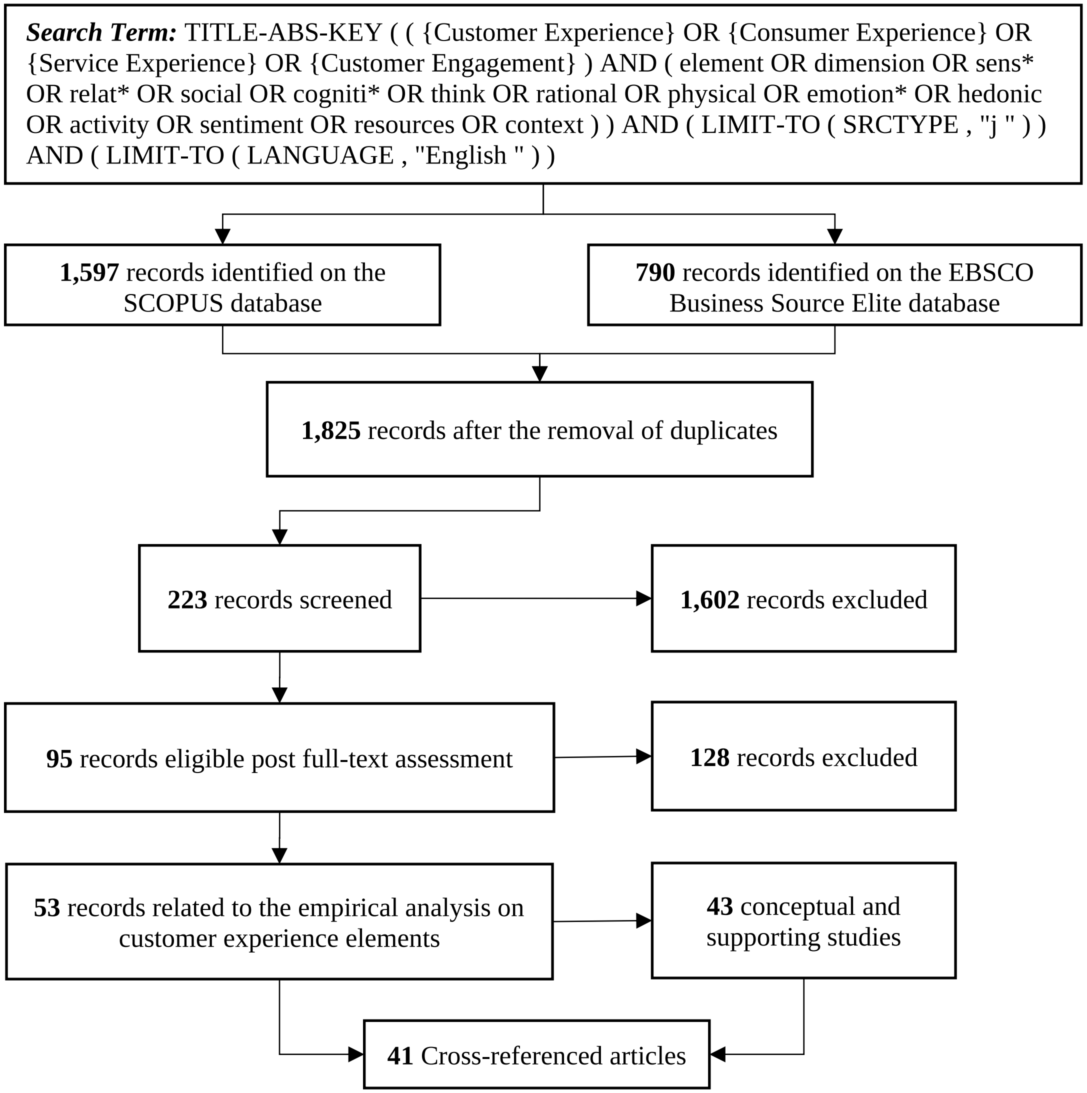

Figure 3. Data-driven customer experience measurement using RAFTS throughout the customer journey

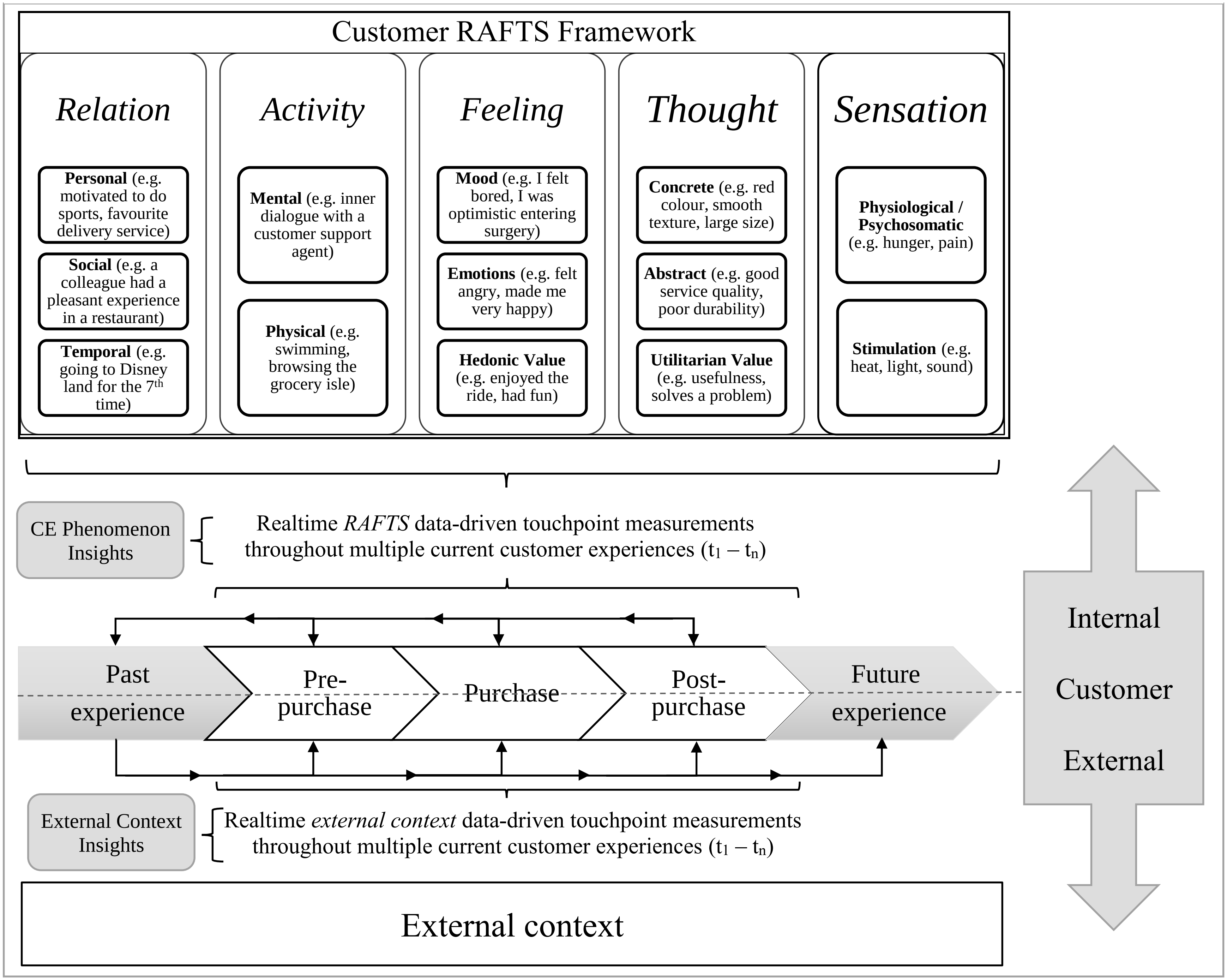

Table 1. Normalized elements

Normalized Elements (top 15)	Count	% Distribution
Sense	21	8.4
Cognition	20	8.0
Social	19	7.6
Emotion	15	6.0
Affect	14	5.6
Behavior	13	5.2
Relate	13	5.2
Feel	9	3.6
Hedonic	9	3.6
Act	8	3.2
Physical	8	3.2
Think	8	3.2
Novelty	5	2.0
Educational	4	1.6
Pragmatic	4	1.6

Table 2. Experiential Semantic Element Mapping

Mapped element	Normalized elements	Frequency	Mapped element	Normalized elements	Frequency
Activity	Act	8		Interaction	2
	Behavioral	12		Internal Dialogue	1
	Decision	1		Lifestyle	1
	Physical	6		Location	1
	Pragmatic	4		Memory	1
	Recognition	2		Novelty	3
Feeling	Affect	12		Personal	2
	Emotional	11		Personal Progression	1
	Entertainment	2		Relational	6
	Feel	8		Social	14
	Hedonic	8		Spontaneity	1
	Joy	1		Symbolic	1
	Leisure	1		Transportation	1
	Mood	1		Volition	1
	Safety	3	Sense	Aesthetic	1
Relation	Absorption	1		Beauty	1
	Adventure	1		Comfort	3
	Altered Experience	1		Environment	1
	Attention	1		Esthetic	2
	Awareness	1		Seductive	2
	Civic Orientation	1		Sensorial	4
	Community	1	Thought	Access	1
	Distinctive	1		Benefit	1
	Employees	1		Cognitive	17
	Escapist	2		Discovery	1
	Ethical	1		Economic	1
	Identity	1		Educational	3
	Imagery	1		Efficiency	2
				Functional	2
				Intellectual	3
				Stimulation	1
				Think	7
				Usability	1
				Utilitarian	2

Appendix

Table A I. Customer Experience Conceptually and Empirically Studied Elements

Authors	Type	Context	Conceptual Area	**Elements**
Jamshidi, Keshavarz, Kazemi, and Mohammadian (2018)	QT	Banking	Flow	**Utilitarian, Hedonic**
Kilian, Steinmann, and Hammes (2018)	QL	Nonspecific	Customer Engagement	**Emotional, Cognitive, Behavioral**
Rajaobelina (2018)	QT	Travel and Tourism	Customer Experience	**Think, Feel, Act, Sense, Relate**
Altschwager, Conduit, Bouzdine-Chameeva, and Goodman (2017)	QT	Food and Beverage	Customer Experience	**Cognitive, Emotional, Sensorial, Pragmatic, Relational**
Bäckström and Johansson (2017)	QL	In-store	Customer Experience	**Unlabeled Elements**
Brun et al. (2017)	QT	Multiple	Customer Experience	**Cognitive, Affective, Sensory, Behavioral, Social**
Bustamante and Rubio (2017)	MX	Retail	Customer Experience	**Cognitive, Affective, Physical, Social**
Heinonen (2018)	QL	Online Communities	Customer Engagement	**Emotional, Cognitive, Behavioral**
Hilken, De Ruyter, Chylinski, Mahr, and Keeling (2017)	QT	Nonspecific	Customer Value	**Utilitarian, Hedonic**
Kawaf and Tagg (2017)	QL	Online Shopping	Flow	**Emotion, Cognition**
Osei-Frimpong and Owusu-Frimpong (2017)	QL	Healthcare	Customer Experience	**Emotional, Cognitive, Behavioral, Social**
Varshneya and Das (2017)	MX	Retail	Customer Experience	**Cognitive, Hedonic, Social, Ethical**
Wu (2017)	QT	Museums	Customer Experience	**Think, Feel, Act, Sense, Relate**
Yoon and Lee (2017)	QT	Hospitality	Customer Experience	**Think, Feel, Act, Sense**
Alan, Kabadayi, and Yilmaz (2016)	QT	Food and Beverage	Customer Experience	**Cognitive, Emotional**
Ali, Hussain, and Omar (2016)	QT	Hospitality	Customer Experience	**Educational, Entertainment, Esthetic, Escapist**
Bagdare and Roy (2016)	QT	Retail	Servicescape	**Affective, Behavioral**
Calder, Isaac, and Malthouse (2016)	QT	Events	Customer Engagement	**Interaction, Transportation, Discovery, Identity, Civic Orientation**
Cetin and Walls (2016)	QL	Hospitality	Customer Experience	**Social, Physical**
Ebrahim, Ghoneim, Irani, and Fan (2016)	MX	Electronics	Brand Experience	**Sensorial, Emotional, Intellectual, Behavioral**
Gilboa, Vilnai-Yavetz, and Chebat (2016)	QT	Retail	Customer Experience	**Seductive, Functional, Social Recreation, Social Scene**

Authors	Type	Context	Conceptual Area	**Elements**
Liu, Sparks, and Coghlan (2016)	QT	Events	Customer Experience	**Sensory, Emotional**
Lucia-Palacios, Pérez-López, and Polo-Redondo (2016)	QL	Retail	Customer Experience	**Cognitive, Affective, Behavioral**
Majra, Saxena, Jha, and Jagannathan (2016)	QT	Self Service Technology	Customer Experience	**Think, Feel, Act, Sense, Relate**
Ren, Qiu, Wang, and Lin (2016)	MX	Hospitality	Customer Experience	**Sensorial, Relational, Aesthetic, Location**
Chahal and Dutta (2015)	MX	Banking	Customer Experience	**Cognitive, Affective, Behavioral, Relational, Sensory**
Chang and Lin (2015)	QT	Creative Life Enterprises	Customer Experience	**Educational, Entertainment, Esthetic, Escapist**
Beltagui, Darler, and Candi (2015)	MX	Food and Beverage	Service Experience	**Absorption, Adventure, Community, Employees, Environment, Spontaneity**
De Keyser et al. (2015)	CN	Nonspecific	Customer Experience	**Cognitive, Physical, Sensorial, Social, Emotional**
Song (2015)	QT	Online Shopping	Customer Experience	**Sensory, Affective, Intellectual, Behavioral, Relational, Decision, Access, Benefit**
Verleye (2015)	QT	Nonspecific	Service Experience	**Hedonic, Cognitive, Social, Personal, Pragmatic, Economic**
Abubakar and Mavondo (2014)	QT	Travel and Tourism	Servicescape	**Physical, Emotional, Social**
Ahn and Picard (2014)	QT	Food and Beverage	Customer Experience	**Affective, Behavioral, Cognitive**
Cetin and Dincer (2014)	QT	Hospitality	Customer Experience	**Physical, Social**
Chauhan and Manhas (2014)	MX	Airlines	Customer Experience	**Hedonism, Novelty, Safety, Recognition, Comfort**
Knobloch, Robertson, and Aitken (2014)	QL	Travel and Tourism	Customer Experience	**Cognitive, Emotional**
Bagdare and Jain (2013)	QT	Retail	Retail Customer Experience	**Joy, Mood, Leisure, Distinctive**
Gilboa and Vilnai-Yavetz (2013)	QL	Mall Experience	Mall Customer Experience	**Seductive, Functional, Social Arena, Interactive Museum**
Hart, Stachow, and Cadogan (2013)	QT	Retail	Customer Experience	**Cognitive, Affective, Sensory, Behavioral, Social**
Rageh, Melewar, and Woodside (2013)	QL	Hospitality	Customer Experience	**Comfort, Educational, Hedonic, Novelty, Recognition, Relational, Safety, Beauty**
Salehi, Salimi, and Haque (2013)	QT	Nonspecific	Customer Experience	**Pragmatic, Hedonic, Sociability, Usability**
Walls (2013)	QT	Hospitality	Consumer Experience	**Physical, Interaction**
Nasermoadeli, Ling, and Severi (2012)	QT	Nonspecific	Customer Experience	**Sensory, Emotional, Social**
Klaus and Maklan (2011)	QL	Sports Tourism	Customer Experience	**Personal Progression, Efficiency, Surreal Feeling, Social, Hedonic Enjoyment**

Authors	Type	Context	Conceptual Area	**Elements**
Dirsehan (2010)	QL	Zoo	Customer Experience	**Think, Feel, Act, Sense**
Stachow and Hart (2010)	QL	Shopping	Customer Experience	**Cognitive, Sensory, Affective, Social, Physical, Symbolic**
Brakus, Schmitt, and Zarantonello (2009)	MX	Multiple	Brand Experience	**Sensory, Affective, Behavioral, Intellectual**
Lywood, Stone, and Ekinci (2009)	QT	Call Centers	Customer Experience	**Unlabeled Elements**
Tynan and McKechnie (2009)	CN	Nonspecific	Customer Experience	**Informational, Functional, Sensory, Relational, Social, Emotional, Novelty, Utopian**
Verhoef et al. (2009)	CN	Nonspecific	Customer Experience	**Cognitive, Physical, Affective, Social, Emotional**
Nagasawa (2008)	QL	Car Manufacturing	Customer Experience	**Think, Feel, Act, Sense, Relate**
Gentile et al. (2007)	MX	Nonspecific	Customer Experience	**Cognitive, Pragmatic, Sensorial, Relational, Emotional, Lifestyle**
Ho, Li, and Su (2006)	QL	Healthcare	Customer Experience	**Think, Feel, Act, Sense, Relate**
Poulsson and Kale (2004)	CN	Nonspecific	Commercial Experience	**Personal, Relevance, Novelty, Surprise, Learning, Engagement**
Shaw and Ivens (2002)	CN	Nonspecific	Customer Experiences	**Physical, Emotional**
Gupta and Vajic (2000)	CN	Nonspecific	Service Experience	**Environment, Social Interaction, Participation**
Schmitt (1999)	CN	Nonspecific	Customer Experience	**Think, Feel, Act, Sense, Relate**
Pine and Gilmore (1998)	CN	Nonspecific	Customer Experience	**Educational, Aesthetics, Entertainment, Escapism**
Otto and Ritchie (1996; 1995)	QT	Hospitality	Service Experience	**Hedonic, Interactive, Novelty, Comfort, Safety, Stimulation**
Marks, Higgins, and Kamins (1988)	QT	Nonspecific	Product Evaluation	**Internal dialogue, Awareness, Imagery, Volition, Affect, Altered Experience, Attention, Memory**
Csikszentmihalyi and Larson (1987)	QT	Nonspecific	Common Experience	**Cognitive Efficiency, Motivation, Activation/Potency, Affect**
Holbrook and Hirschman (1982)	CN	Nonspecific	Consumption Experience	**Cognitive, Behavior, Affect**

(Type: QT = Quantitative, QL = Qualitative, MX = Mixed methods, CN= Conceptual)

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Chapter 3 - AI feel you: customer experience assessment via chatbot interviews

Abstract

Purpose – While customer experience (CE) is recognized as a critical determinant of business success, both academics and managers are yet to find a means to gain a comprehensive understanding of CE cost-effectively. We argue that the application of relevant artificial intelligence (AI) technology could help address this challenge. Employing interactively prompted narrative storytelling, we investigate the effectiveness of sentiment analysis (SA) on extracting valuable CE insights from primary qualitative data generated via chatbot interviews.

Design/methodology/approach – Drawing on a granular and semantically clear framework we developed for studying CE feelings, an AI-augmented chatbot was designed. The chatbot interviewed a crowdsourced sample of consumers about their recalled service experience feelings. By combining free-text and closed-ended questions, we were able to compare extracted sentiment polarities against established measurement scales and empirically validate our novel approach.

Findings – We demonstrate that SA can effectively extract CE feelings from primary chatbot data. Our findings also suggest that further enhancement in accuracy can be achieved via improvements in the interplay between the chatbot interviewer and SA extraction algorithms.
Research limitations/implications – The proposed customer-centric approach can help service companies to study and better understand CE feelings in a cost-effective and scalable manner. The AI-augmented chatbots can also help companies foster immersive and engaging relationships with customers. Our study focuses on *feelings*, warranting further research on AI's value in studying other CE elements.
Originality/value – The unique inquisitive role of AI-infused chatbots in conducting interviews and analyzing data in realtime, offers considerable potential for studying CE and other subjective constructs.

Keywords Customer Experience, Customer Feelings, Sentiment Analysis, Chatbot, Artificial Intelligence, Storytelling.

Article Classification – Research paper

1. Introduction

Understanding customer experience (CE), comprised of experiential elements (e.g., cognitive, emotional), is paramount for service organizations aiming to successfully co-create value with their customers (McColl-Kennedy et al., 2015). As a result, CE has remained an area of interest for both managers (McIntyre and Virzi, 2018) and researchers (Marketing Science Institute, 2018) for more than 50 years (Lemon and Verhoef, 2016).

Despite the growth of CE research, the body of literature remains fragmented and overlapping (Kranzbühler et al., 2018), mainly focusing on the antecedents and outcomes of CE rather than defining and understanding it as a holistic, complex, and subjective phenomenon (Kawaf and Tagg, 2017). Additionally, attempts to assess CE using survey approaches tend to possess an organizational bias. Such approaches focus on aspects deemed to be important by researchers or managers and not the elements of a context-specific experience, perceived significant by the customer (Ordenes et al., 2014). Specifically, they fail to recognize that CE is perceived, and thus should also be measured within the domain of an individual's overall human experience (Fisk et al., 2020). To address this, more appropriate approaches to study holistic CE, spanning the "digital, physical, and social realms" of today's digital age, are required (Bolton et al., 2018, p. 777; Holmlund et al., 2020).

Arguably, phenomenological and introspective approaches – involving a process of narrative inquiry via data collection mechanisms such as storytelling and interviews (Connelly and Clandinin, 1990) – are better suited for capturing comprehensive understanding of experiential constructs such as CE (Carù and Cova, 2003; Holbrook and Hirschman, 1982). This is because, in storytelling, key experiential elements like thoughts, feelings, and behaviors are exchanged in the form of encompassing narratives, which are useful for studying critical events (Webster, 2007) and understanding CE in context.

While attempts have already been made to understand CE via storytelling in service research (e.g., Gentile et al., 2007), these methods largely remain within the confines of interviews conducted by researchers. Such qualitative approaches constitute a minority of service research as they are more resource, time, and cost-intensive compared to more efficient but potentially less informative quantitative methods (Benoit et al., 2017). Finding an approach that is both highly informative and efficient has until now seemed unattainable. However, contemporary services firms could now attain the "best of both worlds".

This could be achieved by employing chatbots and exploiting their ability to engage customers via storytelling. With growing recognition of their potential in service research (Kumar et al., 2016), chatbots equipped with artificial intelligence (AI) could automatically extract CE from narrative conversations with customers – using a sentiment analysis (SA) algorithm – and hence contribute to CE theory. This could provide a useful starting point for a cost-effective service excellence strategy for service organizations (Ordenes and Zhang, 2019; Robinson et al., 2019; Wirtz and Zeithaml, 2018).

The use of AI methods generally, and SA in particular, call for high semantic clarity (i.e., precise mapping to linguistic meanings). As a result, a bottom-up abductive approach was adopted to develop a granular and semantically clear model for feelings, one of the five elements of CE: thought, feeling, sensation, activity, and relation (De Keyser et al., 2020; Schmitt, 1999). There are several reasons why focusing on these elements individually, and on feelings in particular, could yield advantageous results. Firstly, there is an academic need to address the challenges in measuring feelings in CE (Richins, 1997) as well as understanding them better using empirically validated multi-methods (McColl-Kennedy et al., 2015). Feelings relating to outcomes of service encounters are holistically connected with a person's overall assessment of their human experience. Thus, an improved understanding of this CE element would aid managers to co-create service encounters with their customers to better satisfy their needs (Fisk et al., 2020). Secondly, focusing on the CE feeling element addresses managerially-driven research priorities of (i) establishing robust emotional connections between customers and brands (Marketing Science Institute, 2016) and (ii) improving emotional experiences (Temkin, 2018). Tackling the entirety of the CE elements simultaneously would require multiple methods tailored to each element and is beyond the scope of this paper.

The objective of this study is to develop and validate a novel and cost-effective approach, employing the recognized potential of AI in the service context to gain an improved holistic understanding of CE. Specifically, the study contributes to CE literature in three key ways, via: (i) the development of a granular and semantically clear CE feeling model (CEFM) that is employable using AI techniques; (ii) proposing a unique approach utilizing chatbots and SA to extract CE (feelings) from primary interview data; and (iii) empirically validating the effectiveness of this approach in extracting CE feelings. A detailed research agenda geared towards exploiting the potential of the proposed approach to inform and manage CE is outlined.

The following sections present an overview of relevant CE and AI literature, details of the AI approach used, key findings, and discussion of contributions and implications, concluding with limitations and a research agenda for future work.

2. Literature Review

2.1 The feeling component of Customer Experience

There is rapid growth in recognizing that "experience is everything", acknowledging the importance of CE, and that companies who focus their strategy on improving it could gain a competitive edge by bridging the experience gap (Clarke and Kinghorn, 2018). This relatively recent growth in the significance of CE in services has been evolved from the identification of related concepts including consumption experience (Holbrook and Hirschman, 1982) and the experience economy (Pine and Gilmore, 1998). Understanding and measuring experience effectively has been an ultimate goal for philosophers and researchers for some time, but it has proven difficult in practice.

CE is often defined as a dynamic and holistic, direct or indirect, interaction between a customer and a firm, involving elements of thoughts, feelings, activities, relations, and sensations[5] (Lemon and Verhoef, 2016; Schmitt, 1999). The holistic nature of CE[6] renders this phenomenon challenging to observe and gauge accurately. Consequently, many practitioners tend to fall back on the use of dated tools such as Net Promoter Score (Reichheld, 2003) and CSAT (Anderson and Narus, 1984) as proxies (Maklan et al., 2017). To address these shortcomings, tools such as the EXQ multiple-item scale, which leverages product experience, outcome focus, moments-of-truth, and peace-of-mind (Klaus and Maklan, 2012), in addition to emerging text mining approaches (e.g., McColl-Kennedy et al., 2019) have been developed to evaluate CE.

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[5] While other elements, such as the economic and lifestyle elements (Gentile et al., 2007; Verleye, 2015) have also been proposed, the above five elements are the most widely adopted (De Keyser et al., 2020).
[6] Experience has been conceptualized as being "life itself" (Csikszentmihalyi, 1991, p. 192)

Nevertheless, as the importance and impact of (customer) experiences in our daily lives (Fisk et al., 2020) keep increasing, further study of this subjective and holistic concept is warranted.

This study focuses on CE *feelings* specifically and responds to the surge of interest in examining this particular element of experience both in academia and management (Marketing Science Institute, 2016; McColl-Kennedy et al., 2019). Drawing on a comprehensive review of CE literature, the experiential element of feelings has been referred to as affect (e.g., Holbrook and Hirschman, 1982), feelings (e.g., Schmitt, 1999), emotions (e.g., Shaw and Ivens, 2002), hedonic value (e.g., Klaus and Maklan, 2011), or mood (Bagdare and Jain, 2013). Table 1 summarizes the semantic interpretations associated with the CE feeling element.

*Table 1. Consolidated hierarchical interpretations of CE feelings**

Conceptual level	CE feeling term used	Key studies
1	Affect	Brakus, Schmitt, & Zarantonello (2009), Csikszentmihalyi & Larson (1987)
	Feeling	Rajaobelina (2018), Klaus & Maklan (2011), Schmitt (1999)
2	Emotion	Heinonen (2018), Verhoef et al. (2009), Gentile et al. (2007)
	Hedonic Value	De Ruyter, Chylinski, Mahr, & Keeling (2017), Verleye (2015), Klaus & Maklan (2011), Otto & Ritchie (1996)
	Mood	Bagdare & Jain (2013)

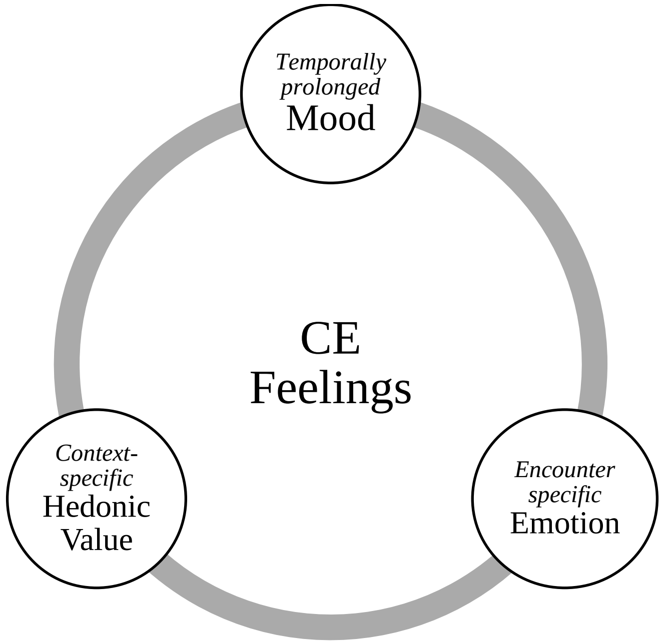
**Key studies (comprehensive review available from authors on request).*

Accommodating the interpretations from Table 1 into a semantically precise model requires understanding how these terms differ in meaning and how they are represented within the fields of psychology concerned with studying subjective experience. Dividing these terms into two hierarchical levels (as shown in Table 1) allows for a natural grouping and increased semantic clarity. Provided that the hierarchical levels can be distinguished based on their temporal characteristics (Fox, 2018), it is argued here that feelings and affect act as higher-level umbrella terms (level 1) to the feeling element. Terms such as mood, emotion, and hedonic value (level 2), on the other hand, represent a more experience-specific embodiment of feelings or affect (Babin et al., 1994; Beedie et al., 2005; Fox, 2018).

From the CE literature, it is also possible to find terms, such as entertainment (Ali et al., 2016), leisure (Bagdare and Jain, 2013), safety (Otto and Ritchie, 1996), and joy (Bagdare and Jain, 2013), which all operate hierarchically below level 2. However, these level 3 concepts represent specific hedonic values attained within an experience and vary depending on the context under study (Babin et al., 1994; Holbrook, 2006). Thus, to maintain robust model generalizability, a CE feeling model (CEFM) that focuses on levels 1 and 2 is proposed.

The CEFM (Figure 1) represents the three sub-elements (at level 2; mood, emotion, and hedonic value) reflecting their context and temporality characteristics (temporally prolonged, encounter specific, and context-specific) (Babin et al., 1994; Fox, 2018). Capturing all three sub-elements simultaneously is vital for a holistic understanding of experiential feelings (Kranzbühler et al., 2018). For instance, CE might be influenced by a customer engaging with a service in a negative mood. Similarly, emotions detail (one or more) encounter-specific feelings (i.e., towards firm resources and activities during the encounter) (Larivière et al., 2017; Ordenes et al., 2014), whereas hedonic value symbolizes how customers feel after having experienced the service. Combined, these sub-elements enable CEFM to compartmentalize different experiential feelings throughout the customer journey (pre, mid, and post) (Lemon and Verhoef, 2016).

Figure 1. Conceptual framework: CE feeling model (CEFM)



2.2 Enabling CE feeling extraction with AI

The purpose of the CEFM is to provide a consolidated, holistic, and sufficiently granular framework for CE feelings to allow technologies such as AI to map experiential data onto it. AI is a prominent technological milestone that some claim ushered in the fourth industrial revolution (Maynard, 2015). AI technology, along with increasing levels of global (big) data production, generates new opportunities to advance and improve a myriad of research areas (Boyd and Crawford, 2012; Marr, 2018). Among these are service and technology (Mende et al., 2019; Wirtz et al., 2018), customer engagement (Kunz et al., 2017), service encounters (Larivière et al., 2017), sales (Syam and Sharma, 2018), customer relationship management (Berry and Linoff, 2004), and CE (Kabadayi et al., 2019; Ordenes et al., 2014; Zolkiewski et al., 2017).

Companies must however understand the benefits and deficiencies of alternative approaches when they attempt to find the most appropriate AI technology. Each technology stack consists of various techniques, which utilize different AI methods to achieve a specific objective.

For instance, supervised and unsupervised machine (deep) learning methods are useful for predicting results from either structured (e.g., tabular and transactional) or unstructured (e.g., captured images, audio, video, or text) datasets (Brynjolfsson and Mcafee, 2017). AI technologies involving data mining (e.g., text analysis), for example, add to the body of big data, which then feeds into machine learning algorithms and ultimately leads to improved prediction accuracy (Boyd and Crawford, 2012; Ng and Wakenshaw, 2017). In a storytelling environment based on experiential exchange via narrative, as in this study, an AI technology capable of extracting insights from unstructured conversations is required. This technology would need to analyze text via natural language processing to decipher not only feeling-related content but also context and temporality (Ordenes and Zhang, 2019).

Tackling this task is challenging, specifically for advanced AI methods that rely on secondary data sources (e.g., social media text) due to the possibility of incomplete data (i.e., data which might not be there) and passive data collection (i.e., there is no reciprocal data exchange). Therefore, primary data collection efforts are deemed necessary.

2.3. Rationale for using chatbot interviewers and sentiment analysis

When companies consider their (primary) data collection techniques, they are faced with several alternative methods. Each method possesses its unique set of strengths and weaknesses. Finding an appropriate balance between data quality and cost-effectiveness is key. On the one hand, traditional (face-to-face) in-depth interviews, represent a more engaging and personal method in which the interviewer can probe interviewees for clarification or more details (laddering). This method also provides critical supplementary data, such as facial gestures and body language (Novick, 2008). Surveys, on the other hand, are generally less costly and can be deployed faster and with more flexibility (not limited to time or location) while reaching a broader audience. When implemented using technology (e.g., online), surveys can provide realtime analysis of the results (Benoit et al., 2017).

Chatbots can reap the benefits of both surveys and interviews. They already interact with customers in various service sectors such as banking and insurance and provide a cost-effective solution targeting a broad customer base independent of time and location (Riikkinen et al., 2018). However, by switching the more traditional chatbot role from acting as an information source (i.e., passively answering questions) to a more inquisitive role (i.e., proactively asking interview questions), the chatbot starts to resemble an interviewer and assimilates many of the advantages of widely used interview and survey methods. Thus, chatbot interviews have the potential to become an efficient and widely used AI approach capable of collecting primary data via conducting storytelling narrative interviews that are well suited to examine subjective constructs like CE.

In addition, chatbot technology can also handle multiformat data (i.e., text, audio/voice), support automation (e.g., automatic transcription and translation), and could be developed to seek required information via laddering and probing questions. It can also become more engaging by adapting its 'personality' to the interviewee (i.e., it can assume a customizable persona based on current or past conversations) featuring; eye, electrodermal activity, and facial gesture, tracking technologies widely considered to be useful for studying emotions (De Keyser et al., 2019; Ng and Wakenshaw, 2017).

A comparison of key CE data collection approaches (traditional interviews, surveys, and chatbot interviews), including their potential advantages, is depicted in Table 2. From this, the potential of chatbot interviews as an effective and efficient data collection approach of CE can be observed.

Table 2. Comparison of key CE data collection approaches

Advantages	Traditional interviews	Surveys	Chatbot interviews
Rich data	X		X
Personal/empathetic	X		X
Engaging	X		X
Laddering and probing questions	X		A
Body language observation	X		A
Low cost		X	X
Broad reach/scalability		X	X
Fast deployment/speed		X	X
Flexible availability		X	X
Realtime analysis		X	X
Multiformat conversation availability			X
Automation			X
Adaptable personality			A

Note: "A" denotes further development potential via augmentation

Extant literature recognizes that data mining – a set of tools and techniques utilizing statistics, artificial intelligence, and machines learning methods in order to discover meaningful patterns and rules in a dataset – has much potential for analyzing the data collected during a chatbot interview (Berry and Linoff, 2004, p. 7; Rygielski et al., 2002). Since chatbots can leverage data mining techniques to extract meaning from text (Feldman and Sanger, 2006; Ordenes and Zhang, 2019), they are thus technically capable of extracting CE feelings from collected text responses. This ability further adds to the value of our proposed approach in utilizing chatbots for data collection purposes.

More specifically, SA, a text mining method used to determine the overall attitudes, opinions, and emotions within text (Humphreys and Wang, 2018), could be used to map experiential interview feeling data to the CEFM. For instance, a question relating to a participant's mood could be analyzed using SA, resulting in a polarity score for that statement (i.e., positive, negative, and neutral). A typical SA algorithm would compare sets of terms from the input text against a sentiment lexicon such as WordNet, then calculate the distance between these terms and provide a polarity score as an output (Feldman, 2013). Thus, SA has the potential to attribute sentiment scores to experiential interview data, enabling companies to gain useful quantitative CE insights from natural language.

3. Method

In an attempt to improve the understanding of CE, this research adopts a bottom-up abductive approach using technologies that collect and evaluate experiential CE element data to build up a general and context-specific notion of the CE feeling concept (Brodie et al., 2017). Developing a one-size-fits-all technological solution to the entirety of CE is not desirable, as studying different elements calls for different methodological strategies (e.g., SA works well for studying feelings but less so for studying sensations, where electrodermal activity measures and others may be more suitable). Focusing on a single CE element is also meaningful due to the fragmented literature on CE and its elements (Kranzbühler et al., 2018; Palmer, 2010); high levels of semantic clarity are thus required for the effective implementation (e.g., extraction of experiential data) of the proposed approach.

Methodologically, this study consists of four inter-connected phases: data collection and preprocessing, scale validation, sentiment analysis, and the comparison between scale and sentiment scores. The phases are elaborated below.

3.1 Phase 1: Data collection and preprocessing

In Phase 1, data was collected via a crowdsourcing platform, followed by data preparation, cleaning, and filtering. Crowdsourcing platforms are satisfactory ways to provide a random pool of participants across which studies related to attitudes and behaviors can be conducted (Hulland and Miller, 2018). The platform employed in this study is Prolific Academic, which draws on a more transparent and diverse population of consumers more naïve to everyday experimental research tasks compared to platforms such as Amazon's MTurk (Palan and Schitter, 2018; Peer et al., 2017).

Using Prolific Academic, 200 participants were recruited to interact with a chatbot named *Marvino*. Marvino was designed to ask interview-like questions about a recent service experience with a firm of the participants' choice. The chatbot interviewer first asked the participants to provide a descriptive, free-text answer to an inquiry, which was immediately followed by closed-end survey-type question(s) in the same (chatbot) conversation so that an understanding of mood, emotion, and hedonic value was gained for comparison purposes. For example, questions on a participant's (recalled) mood would start by asking for a free-form textual response, followed by questions (items) adopted from an established and validated measurement scale (Table A II). Between each question, Marvino utilized conversational acknowledgments (e.g., "Thank you", "I see") to promote a more natural storytelling experience.

In order to enhance the generalizability of the CE findings, each participant was randomly allocated a personal experience to recall, consisting from four options. Positive and negative shopping, and positive and negative vacation experiences (N = 48, N = 53, N = 47 and N = 45, respectively). Next, participants were asked how well they recalled the self-chosen service experience and were filtered out if their answer was less than 5 (i.e., "neutral") on the 9-point scale used. This left 193 participants in the final sample where a wide range of demographics are represented (Table A I).

IBM SPSS Statistics and AMOS 25 (2017) were used to analyze the resultant data. A missing data analysis revealed that only 2.1% of the data was missing. Little's missing completely at random (MCAR) test (Little, 1988) yielded a non-significant result ($\chi^2 = 27.745$, df = 24, p = .271) suggesting that the absent values can be assumed to be missing entirely by chance[7]. The multiple imputation (Rubin, 1987) approach was used, and a fully conditional specification method (m = 10) in SPSS (2017) was employed for estimating the missing values.

3.2 Phase 2: Scale validation

In Phase 2, the reliability and validity of the measurement scales were tested from the data related to mood, emotion, and hedonic value, as recalled by the participants. The procedure consisted of a maximum likelihood confirmatory factor analysis (CFA) conducted in AMOS 25 (2017). The measurement scales, along with the corresponding measurement items and their standardized loadings, relating to each feeling sub-element are shown in Table A II.

3.3 Phase 3: Sentiment analysis and model performance metrics

In Phase 3, the effectiveness of the SA algorithm on the extracted CEFM data was validated. While there are many SA algorithms to consider, the Valence Aware Dictionary for Sentiment Reasoning (VADER) algorithm was adopted for its efficiency and performance at handling short and informal social media text (Hutto and Gilbert, 2014; Ribeiro et al., 2016). Also, because VADER "was created from a generalizable, valence-based, human-curated gold standard sentiment lexicon", it exhibits the flexibility needed to handle human conversation where domain-specificity would be hard to determine (Ribeiro et al., 2016, p. 7).

The performance of this algorithm is evidenced by how well it managed to predict and score each descriptive question of the CEFM. Specifically, the scores outputted by the algorithm were compared to their manually coded labeled counterparts. For finer sentiment granularity

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[7] Upon further analysis, the missing values appear to be a result of connectivity (i.e., network) issues between the chatbot and the participants.

(Ordenes et al., 2017), the compound scores (-1,1) produced by VADER were normalized to match the scale items in Table A II (i.e., sentiment score of -1 refers to the scale score of 1 "extremely negative"; sentiment score of zero refers to 5 "neutral"; and sentiment score of 1 refers to 9 "extremely positive"). The statements then underwent a binary classification where they were split into (i) positive (scores ≥ 5) versus negative (scores < 5) cases, in line with the compound sentiment score provided by the SA algorithm; and (ii) true versus false, depending on whether the algorithm correctly predicted the statement sentiment (elaborated below).

To achieve this, a manual coding procedure involved the coder to first categorize the participant's statement into one of the five categories (i.e., "extremely negative", "average negative", "neutral", "average positive", and "extremely positive") corresponding to the respective scale points of 1, 3, 5, 7, and 9. If the score of the SA algorithm fell within two scale points of the coder's selected statement category (e.g., if the coder scores the statement as "average positive" and the sentiment score is 8, which is only 1 point from 7), then the coder would denote the prediction as true. Otherwise, the prediction was denoted as false. The potential reasons for false predictions were analyzed further to understand whether an inaccuracy was due to the SA algorithm or the participant; this and the inter-coder reliability are discussed in the results section.

Based on the automated (VADER) SA as well as the manual coding, each statement was categorized into a confusion matrix (Sokolova and Lapalme, 2009), splitting the results into true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) depending on their respective polarity (i.e., positive or negative classification by the algorithm and coders). This classification allowed for the calculation of key metrics (Table 4) that give valuable information about the effectiveness of the VADER SA algorithm. For a detailed account on these measures, refer to Sokolova and Lapalme (2009, p. 430).

4. Results

4.1 Phase 2: Scale validation results

The reliability and validity analysis, along with the descriptive statistics, of the key constructs under study are reported in Table 3. The final CFA model fitted the data well (χ^2 = 49.51, df = 25, p = .001, RMSEA = .07, SRMR = .02, GFI = .95, CFI = .99, TLI = .99) (Brown, 2015; Hu and Bentler, 1999; Kline, 2016). In support of convergent validity, all relevant construct reliabilities (CR) were above the recommended level of .70 (Fornell and Larcker, 1981). The discriminant validity of the scales was also satisfactory as the relevant Maximum Shared Variance (MSV) indices were shown to be greater than the corresponding average variance extracted (AVE) indices (Hair et al., 2010), and the square-roots of the AVE appeared to be greater than the inter-construct correlations (Fornell and Larcker, 1981) as shown in Table 3.

Table 3. Descriptive statistics, correlations, and construct reliability and validity

Construct	Mean (S.D.)	CR	AVE	MSV	1	2	3
1. Experience emotion*	5.29 (2.63)	-	-	-	-		
2. Experience mood	5.61 (2.42)	.95	.81	.28	.53	**.90**	
3. Experience hedonic value	6.01 (2.66)	.98	.93	.84	.92	.52	**.97**

Notes: Square-root of AVE on the diagonal in bold; correlations off-diagonal
** This construct consists of one item only; hence, CR, AVE and MSV are not meaningful*

4.2 Phase 3: Sentiment analysis and model performance metrics results

To determine the effectiveness of the VADER algorithm in correctly extracting the sentiments of the CE feelings in the dataset, a confusion matrix for each of the sub-elements was constructed. The inter-coder reliability kappa (Fleiss, 1971) of .95, for 60[8] data-points for three coders across each of the CE feeling sub-elements, refers to an "almost perfect" agreement (Landis and Koch, 1977, p. 165).

The performance of the SA algorithm for each CE feeling sub-element is portrayed in Table 4. The results suggest that VADER is highly effective in extracting the sub-elements and CE feelings overall. Specifically, high accuracy, precision, recall, F_1-score, specificity, and AUC scores are reported (Sokolova and Lapalme, 2009). The lowest relative scores are reported for the extraction of hedonic value, whereas the highest effectiveness is evident for mood.

Table 4. The SA algorithm (VADER) performance on CEFM

	Pos	Neg	Total	Accuracy	Precision	Recall	F_1-Score	Specificity	AUC
Mood									
True	110	60	170						
False	4	2	6						
Total	*114*	*62*	*176*	*.97*	*.97*	*.98*	*.97*	*.94*	*.96*
Emotion									
True	104	58	162						
False	5	1	6						
Total	*109*	*59*	*168*	*.96*	*.95*	*.99*	*.97*	*.92*	*.96*
Hedonic value									
True	103	52	155						
False	10	0	10						
Total	*113*	*52*	*165*	*.94*	*.91*	*1.00*	*.95*	*.84*	*.92*
CEFM									
True	317	170	487						
False	19	3	22						
Total	*336*	*173*	*502*	*.96*	*.94*	*.99*	*.97*	*.89*	*.95*

Notes: The F_1 harmonic mean was used as the F-score measure
CEFM refers to the customer experience feeling model, which consists of mood, emotion, and hedonic value

4.3 Phase 4: Comparison between scale and sentiment scores

[8] A full coding assignment was not deemed necessary, since VADER is already a validated SA algorithm (Hutto and Gilbert, 2014)

While the findings in Phase 3 established that, in principle, the SA algorithm used is effective for studying CE feelings, the final phase (Phase 4) set out to address two important follow-up questions: (i) How closely the extracted sentiment scores from the AI chatbot interview match those of the respective scale scores; and (ii) to what extent the approach's potential inaccuracies are due to the SA algorithm? Addressing these questions provides further understanding regarding the performance and future development potential of this approach.

In addressing the first question, the full sample ($N = 193$) was used to examine the similarities between the sentiment scores and the average measurement scale scores for each of the feeling sub-elements. The findings are promising, as the similarity percentages are 86.88% for mood, 84.66% for emotion, and 84.33% for hedonic value. A series of paired t-tests further revealed that, at the 95% confidence level, the differences between the sentiment and scale scores are statistically insignificant for mood ($p = .18$) and emotion ($p = .07$), but statistically significant for hedonic value ($p = .03$).

To address the second question, post-hoc analyses with two sub-samples of the full dataset were conducted. Cases were included in these sub-samples based on the absolute percentage difference between the sentiment and scale scores, and whether the substantial differences were considered to be due to the participants (i.e., input error) or the SA algorithm. Two explicit thresholds (18.75% and 12.5%[9]) for the absolute differences were chosen; the sub-samples thus consisted of all cases at or above (e.g., difference ≥ 12.5%) each threshold, where errors caused by the SA algorithm were included, but input errors caused by the participants were not.

[9] These, respectively, refer to ±1.5 and ±1 scale point difference on the 9-point scale used

Therefore, the two sub-samples were manually coded to distinguish between input errors (i.e., participant induced errors such as spelling and unclear statements) and errors caused by the SA algorithm (VADER). The coding scheme, along with code descriptions and illustrative examples from our dataset, is presented in Table A III. The inter-coder reliability for two independent coders resulted in a kappa (Fleiss, 1971) of .62 for the 259 data-points across the CE feeling sub-elements, suggesting "substantial agreement" (Landis and Koch, 1977, p. 165).

The distribution of the coded items for both thresholds (i.e., difference ≥ 18.75% and 12.5%) are shown in Table 5. The number of cases identified at the 18.75% threshold varies between 43 and 61, and expectedly increases to range between 82 and 97 at the 12.5% threshold. Evidently, "Statement-Scale Mismatch" (at the 12.5%: 60.98% for mood, 56.10% for emotion, and 43.30% for hedonic value) represents the most prominent reason for the differences in the sentiment and scale scores, followed by the sentiment algorithm accuracy, which at the 12.5% threshold explains between 19.51% (mood) and 31.96% (hedonic value) of the discrepancies.

Table 5. Distribution of the coded items

Sub-elements / Codes	Experience Mood		Experience Emotion		Experience Hedonic Value	
Threshold	*18.75%*	*12.5%*	*18.75%*	*12.5%*	*18.75%*	*12.5%*
Sentiment Algorithm Accuracy	13.95%	19.51%	21.05%	20.73%	22.95%	31.96%
Statement Unclear	2.33%	3.66%	5.26%	6.10%	8.20%	6.19%
Statement Language	6.98%	3.66%	3.51%	2.44%	3.28%	2.06%
Statement Irrelevant	0%	0%	8.77%	8.54%	16.39%	10.31%
Statement-Scale Mismatch	65.12%	60.98%	56.14%	56.10%	44.26%	43.30%
Statement Multiple Context / Time	11.63%	12.20%	5.26%	6.10%	4.92%	6.19%
Total items*	43	82	57	82	61	97

* Denotes how many items out of the full sample (N = 193) were coded at each threshold

A series of paired t-tests, reported in Table 6, concludes the post-hoc analyses. In the two sub-samples, all such cases where participant-induced errors are the underlying cause for the difference in sentiment and scale scores are excluded. The results suggest that isolating the effect of sentiment algorithm accuracy improves the similarity percentages for all feeling sub-elements. Specifically, using the tighter threshold (12.5%), the similarities improve to 92.58% (Mood, N = 127), 89.90% (emotion, N = 128), and 90.27% (hedonic value, N = 127). The mean differences also decrease as the thresholds are applied and, more importantly, the hedonic value's score differences become statistically insignificant (p = .06). In sum, the findings in Table 6 show that the two approaches produce closely similar scores, especially when input errors are accounted for. The potential improvements to the approach proposed in this study are discussed in section 5.3.

Table 6. Similarity percentages and paired difference t-tests for the feeling sub-elements

CE feeling sub-element	Sample[1]	Similarity %[2]	Mean difference (S.D.)	Std. Error	t (df)	Sig. (2-tailed)
Experience Mood	Full Sample	86.88%	.14 (1.43)	.10	1.36 (192)	.18
	Threshold 18.75%	91.25%	.06 (.87)	.07	.87 (155)	.39
	Threshold 12.5%	92.58%	.04 (.76)	.07	.56 (126)	.58
Experience Emotion	Full Sample	84.66%	.21 (1.61)	.12	1.82 (192)	.07
	Threshold 18.75%	89.23%	.06 (1.16)	.10	.63 (147)	.53
	Threshold 12.5%	89.90%	.03 (1.16)	.10	.26 (127)	.80
Experience Hedonic Value	Full Sample	84.33%	.24 (1.56)	.11	2.16 (192)	.03
	Threshold 18.75%	89.51%	.23 (.97)	.08	2.84 (145)	.01
	Threshold 12.5%	90.27%	.16 (.94)	.08	1.88 (126)	.06

Notes: [1] The "Threshold 18.75%" and "Threshold 12.5%" sub-samples include all cases at or above the difference threshold where the differences were caused by the SA algorithm (i.e., excludes all cases with participant's input errors); [2] "Similarity %" refers to the percentage similarity between the sentiment score and the average scale score

5. Discussion

The objective of this study was to develop and validate a novel and cost-effective approach, drawing on the recognized potential of AI in the service context for gaining an improved understanding of CE. The empirical findings support the effectiveness of SA chatbot interviews for eliciting and examining CE feelings, highlighting the promise that the approach holds in the digital age. The key theoretical and methodological contributions, practical implications, research agenda, and limitations are highlighted and discussed below.

5.1 Theoretical and methodological contributions

This study contributes to the service management literature in three main aspects. First, a granular and semantically clear framework (CEFM) for studying CE feelings is developed via a comprehensive literature review. The CEFM informs CE theory by providing a holistic understanding of CE feelings, consisting of three complementary sub-elements: mood (temporally prolonged feelings) (e.g., Beedie et al., 2005), emotion (encounter-specific feelings) (e.g., Fox, 2018), and hedonic value (context-specific feelings) (e.g., Babin et al., 1994). In line with the recent service literature, the framework recognizes that feelings need to be treated as a continuous phenomenon occurring within and outside of the service context, where the experience of service encounters is linked with broader human experience (Fisk et al., 2020; Lemon and Verhoef, 2016). The semantic clarity embedded into CEFM is critical, as this makes it deployable by AI techniques such as text mining (Ordenes et al., 2017). Developing such semantic clarity within the experience domain of service research also responds to the recent call (Fisk et al., 2020) for researchers to develop service language that can be used to facilitate improved wellbeing for everyone. Specifically, the CEFM distinguishes the different feeling sub-elements and facilitates the understanding of CE feelings holistically.

Second, leveraging the CEFM, a novel approach where a chatbot and SA are employed to collect primary data and extract valuable CE (feeling) insights is proposed. The approach offers distinct advantages over alternatives as it addresses notable weaknesses of traditional interviews (e.g., high costs and lack of scalability) and survey approaches (e.g., lack of engagement, limited depth of data, poor response rates). Using a chatbot as an interviewer would enable service companies to collect rich primary data from large samples quickly and cost-effectively. This fundamentally atypical use of chatbots (i.e., proactive rather than reactive) helps alleviate many of the potential downsides of traditional interviews since it inherits the efficiencies typically related to surveys (Benoit et al., 2017). Using an AI-augmented chatbot interviewer to analyze and (immediately) respond to CE (feelings) can also improve the way CE is managed.

An AI-enriched chatbot interview approach possesses two important characteristics: immersion and engagement. Compared to a survey, Marvino adds the crucial element of a reciprocal – even if simple and linear – immersive conversational narrative around experiences. Some participants highlighted that they felt being part of a conversation that helped them express their "experience story" via the "chat experience" (participant 85). Engagement, on the other hand, helps establish personal trust and gratitude: "It makes the exchange more personal and adds a bit of fun/imagination" (participant 193). Naming the chatbot Marvino created an approachable human-like anthropomorphic persona, further signifying the natural human tendency to exchange experience via storytelling: "the conversation was very nice and this study was an interesting experience for me ;-) Goodbye Marvino! Thanks for this conversation ;-)" (participant 172); "it was comfortable to chat with you, Marvino" (participant 133); and more playfully, "you're perfect Marvino don't let no-one tell you different … you should become a therapist" (participant 54). The above comments show how valuable natural storytelling narratives can be; by helping customers relive and surface their experiences through conversational retelling, more profound holistic inputs and outputs can be achieved with the use of AI-augmented chatbot interviewers.

Third, the key findings demonstrate that the SA algorithm used in this study (VADER) was able to extract the sentiments expressed by the participants adequately. It did particularly well with mood and emotion, struggling slightly more with hedonic value; this might be due to the latter indirectly portraying an outcome feeling (i.e., how a participant feels as a result of a service encounter) as opposed to an explicit feeling (i.e., those of mood and emotion). Direct comparisons between the extracted sentiment scores and the measurement scale scores offered further validation for the proposed method; the two approaches produce closely similar scores especially when input errors are accounted for. The post-hoc analyses reveal that it is essential to distinguish between the SA algorithm being at fault (i.e., when the sentiment scores do not match the text description) and participant-induced errors (e.g., typos). In sum, this study makes a convincing case for the promise that the proposed approach holds. Thus, developing AI-enabled frameworks such as CEFM, coupled with an analytical chatbot implementation, appears effective for measuring aspects of CE and consequently complements existing methods such as EXQ and generic text-mining. This is achieved by incorporating further qualitative analysis of the raw output conversations (Kuppelwieser and Klaus, 2020). The findings also point to the need for further refinements to this approach; how this could be done in practice is discussed below.

5.2 Practical implications

"I've never spoken to a chatbot before! I must say, I found it interesting and futuristic! I love it!" (Respondent 18)

Each of the key contributions of the study also points to potential managerial implications. First, adopting and applying the CEFM logic would allow service companies to establish a deeper understanding of individual CE feelings, serving as a useful guide for any adjustments to service experience design. Importantly, managers could not only develop an understanding of how individual service encounters affect customer feelings, but also how their mood or extrinsic influences affect their hedonic perception of the service overall in the context of their wider human experience (Fisk et al., 2020).

Second, the use of conversational agents for narrative inquiry has considerable potential for positive business impact. They serve as cost-effective tools to collect primary data on a large scale. A fundamental advantage of using chatbot interviewers lies in the manner in which they direct the conversation and ask participants explicit questions that help unpack complex phenomena such as CE. Without a chatbot asking for specific sentiments related to the feeling sub-elements, the adoption of an analytical AI approach relying on secondary data only, would need to be more complex, use massive training datasets, and assume that the data it requires is correctly labeled and readily present for analysis. Thus, by using chatbots to collect primary data, there is less guesswork involved, especially as chatbots can simply ask a question again if they fail to understand the answer, much like a human interviewer would. Moreover, the approach facilitates the extraction of feelings that might not be defined in a discrete pre-defined spectrum (e.g., anger, fear, joy, and surprise), thus complementing such approaches (Madhala et al., 2018). Thus, by providing chatbots with a positive persona and demonstrated empathetic reciprocal feelings within the interview experience, these conversational agents become useful tools enabling companies to foster immersive and engaging relationships with customers, resulting in improved CE.

Third, the empirically validated novel AI-ready tool, combining chatbot-enabled data collection and text analysis via SA, offers a cost-effective approach for companies to enhance their understanding of CE. The customer-centric approach helps service companies to bridge the current gap in CE measurement enabling a resource-effective analytical implementation. Moreover, chatbot interviewer technology comes with considerable versatility as it offers companies the potential to collect and analyze diverse (e.g., in terms of demographics) and complementary qualitative and quantitative datasets from multiple channels (e.g., live chat and company database). For example, chatbots could tap into local news outlet services and adapt their personality to the macro context's overall sentiment. This could provide a more genuine storytelling experience (e.g., an airline chatbot could sense an overall negative sentiment due to weather-related cancellations and could portray more empathetic responses as a result), which in turn could add to the insights gained during conversation.

5.3 Future research agenda

Drawing on the above discussion, Table 7 outlines a detailed future research agenda, which consists of research topics as well as managerial and technical concerns for the CEFM, the chatbot interviewer, and the SA algorithm. Further research topics for each of these are outlined within the contexts of CE feelings, CE elements, and service management.

Concerning the CEFM, the framework depicted in this study assumes that the sub-elements are related but static. However, in line with Kranzbühler et al. (2018), it is posited that a more dynamic structure could enable the measurement of CE feelings even more effectively. Development of such a dynamic model could, for example, take into consideration the temporality of feelings (e.g., mood before and after service encounter) and multiple emotions exhibited during multiple encounters, and thus help paint a more detailed and holistic picture of the customer’s feelings. How CE feelings and its sub-elements affect other CE elements (e.g., CE thoughts) and service management more broadly would also need to be investigated further.

A relevant question calling for further examination pertains to reducing problematic participant-induced errors (e.g., unclear statement, statement mixes multiple contexts, statement irrelevant) in the chatbot interviews. A potential avenue to address this in the multiple context scenario could, for example, be the incorporation of realtime target-based SA, which would trigger the chatbot to ask for further clarifications to single out the different contexts (Carvalho et al., 2009). Additionally, future research should examine to what extent and how chatbot interviews might influence the participant’s experience and the data collected. It would also be useful to identify other service management research areas that could benefit from the deployment of a chatbot interviewer, while examining the key managerial and technical challenges involved in incorporating this approach.

Finally, the preprocessing phase of the SA algorithm, which is often portrayed in data-mining frameworks such as CRISP-DM, could be further optimized (Azevedo and Santos, 2008). Although the implementation of this phase differs between solutions, for this particular case, removing a more extensive array of stop words and non-influential parts-of-speech (Ordenes and Zhang, 2019), including spelling and grammar checking could precede the SA task. This would result in potentially improving CE feeling extraction accuracy, as highlighted in the managerial/technical SA portion of Table 7.

Table 7. Research agenda

Context	*Research Topics*	*Managerial/Technical Concerns*
CE Feeling Model (CEFM)		
CE Feelings	• *How does temporality affect each of the feeling sub-elements? (e.g., how mood before and after an encounter influences overall CE feelings)?*	• *How could managers score (attribute weights to) different feeling sub-elements?*
CE Elements	• *How do the feeling sub-elements influence other CE elements?*	• *How do feeling sub-elements influence CE decisions compared to other CE elements?*
Service management	• *How do feeling sub-elements influence different service constructs (e.g., customer engagement, and transformative service research)?*	• *How do feeling sub-elements influence different service management facets (e.g., service design, customer journey)?*
Chatbot interviewer		
CE Feelings	• *What is the influence of a chatbot interviewer on the level of expression of participant CE feelings?*	• *What are possible methods for discerning whether participants expressed valid answers to the chatbot's questions?*
CE Elements	• *How well can a chatbot interviewer address and extract the entire CE element spectrum?*	• *What strategies, incentives, and levels of effort would be required for participants to adequately provide the details of their CEs?*
Service management	• *How can different service management research areas benefit from a chatbot interviewer?*	• *How would employment of chatbot interviewers in service management impact costs and resource utilization?*
Sentiment analysis		
CE Feelings	• *How would different algorithms fair against VADER, and how could SA be improved?*	• *What technical improvements could be made to improve the performance of SA of CE feelings?*
CE Elements	• *To what extent is SA an effective method of extracting the remaining CE elements?*	• *What technical SA algorithm modifications would be necessary when evaluating different CE elements?*
Service management	• *How can SA be used to further service constructs (e.g., service failure)?*	• *What are the limitations of the current application of SA in different service contexts? How could these limitations be overcome?*

5.4 Limitations

Despite the promising empirical results reported in this study, some limitations naturally need to be noted. First, the chatbot utilized here was a non-responsive conversational agent. This forced participants to restart the entire conversation if they wanted to modify a previously inputted answer, and this could have affected the results if several participants chose not to reinitiate the conversation again. Using a more advanced chatbot with the option to conversationally request to track back and change a previous answer (as you can in natural discourse) or to clarify a point (as discussed previously) would address this limitation. Second, the fact that European participants (82.9%) represent an overwhelming majority in the sample, which is also skewed toward the younger participants (69.4% of the sample are below 35 years of age), could also affect the findings and needs to be considered when generalizing the findings to a broader population[10]. Third, the study did not account for technology biases the participants could have exhibited and how these would impact the interaction and recollection with the chatbot. For instance, participants might be biased against human or conversational agents. Researchers could address this by incorporating questions that assess potential technology bias. Fourth, to preserve storytelling/narrative immersion, a simple affect model was utilized to measure emotions to alleviate the technical and lengthy measurement scales of more complex variations – such as Mehrabian and Russell's model (1974) Pleasure, Arousal, Dominance, or Plutchik's (1980) emotional model – even if these might have resulted in a slightly more accurate understanding of the sub-elements of CE. Fifth, as noted, a small number of missing values appeared as a result of connectivity (i.e., network) issues between chatbot and participants, thus

[10] Post-hoc tests revealed that our key findings are statistically indifferent for European (vs. others) and under 35 year olds (vs. others), lending support for wider generalizability.

researchers should consider Internet stability in their implementations of this approach. Lastly, VADER was the only SA algorithm used due to the primary objective of the study, which aims at understanding how well SA fairs against validated measurement scales of each of the feeling sub-elements. Testing how other SA algorithms fair against VADER would be interesting and would shed more light on the effectiveness of the proposed chatbot approach. This, as well as the other limitations, could be addressed in future work.

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Appendices

Table A I. Sample frequencies

Demographic (N = 193)		Frequency	Percent %
Age	18-24	72	37.3
	25-34	62	32.1
	35-44	29	15.0
	45-54	20	10.4
	55+	10	5.2
Gender	Female	87	45.1
	Male	101	52.4
	Undisclosed	5	2.5
Region	Australia	1	.5
	Balkans	9	4.7
	Europe	160	82.9
	Middle East	3	1.6
	North America	12	6.2
	South America	1	.5
	Southeast Asia	1	.5
	Undisclosed	6	3.1
Mobile device	Yes	50	25.9
	No	143	74.1
Student	Yes	65	33.7
	No	123	63.7
	Undisclosed	5	2.6

Table A II. Measurement items and standardized loadings

Source	Constructs	Chatbot questions[1]	Stand. loading
Mood Short Form (MSF) (Peterson and Sauber, 1983)	Experience mood	"You would say your mood in general THAT day was …" (Extremely negative – Extremely positive)	.881
		"THAT day you recall feeling …" (Extremely Dull - Extremely Cheerful)	.847
		"How emotionally comfortable or uncomfortable do you remember feeling THAT day?" (Extremely Uncomfortable - Extremely Comfortable)	.795

Source	Constructs	Chatbot questions[1]	Stand. loading
Hedonic Consumer Attitudes (Batra and Ahtola, 1991)	Experience hedonic value	"As per your recollection, how did you feel THAT day?" (Extremely Tense - Extremely Calm)	.729
		"Overall this experience was …" (Extremely Displeasing - Extremely Nice)	.970
		"In the end you felt the experience was …" (Extremely Unpleasant - Extremely Pleasant)	.944
		"How agreeable or disagreeable would you say the whole service experience was?" (Extremely Disagreeable - Extremely Agreeable)	.896
		"This experience left you feeling …" (Extremely Sad - Extremely Happy)	.917
Watson and Tellegen (1985)	Experience emotion	"How positive/negative was this interaction[2]?" (Extremely Negative - Extremely Positive)	-

Notes: [1]All responses were obtained using 9-point scales; [2] "this interaction" refers to a context built by previous questions inquiring about a memorable service encounter moment, and the service resource (object or person) (Ordenes et al., 2014)

Table A III. Phase 4 coding scheme

Code	Description	Examples
Sentiment Algorithm Accuracy	The algorithm did not pick up sentiments accurately	"Upset as it was a special occasion" (sentiment score 5.1) "I didn't feel happy because of the meal" (sentiment score 7.3)
Statement Unclear	The statement did not convey the intended sentiments correctly and was not clear	"Awkward", "I felt normal", "more secure"
Statement Language	Errors with grammar and spelling affecting sentiment words	"Annoid", "irritability", "10/10"
Statement Irrelevant	The participant did not provide (any) sentiments targeted at the sub-element in question	"[company x] flight staff", "Felt like my problem was important", "She was very nice and understanding"
Statement-Scale Mismatch	A mismatch between the scales answered and the description (e.g., an average sentiment but an extreme scale response)	"very disappointed and angry" (avg. scale score 5.8) "I was very calm" (avg. scale score 9.0)
Statement Multiple Context / Time	Multiple timelines / contexts in the description	"first I was a bit shocked, then sad, afterword I was angry", "I have been in a very good mood but feel a bit down this evening"

Chapter 4 - You bot my world! The dynamic interplay of customer feelings and their chatbot encounter experiences

Abstract

Due to recent advances in artificial intelligence-infused technologies, such as conversational agents and chatbots, many service organizations have adopted such technologies to assist them during service encounters. The global COVID-19 pandemic has further accelerated the adoption rate of chatbots as they serve as a cost-effective and socially distanced interface between a firm and its customers. This study adopts an experiential approach to examining the dynamic interplay between customer mood, customer experience (CE) feelings and chatbot encounter experience, which has implications on a range of key outcomes such as customer satisfaction, and brand perception. Specifically, the purpose of this study is to empirically demonstrate whether and how a customer's mood prior to encounter influences their recalled feelings, feelings towards conversational technology, and outcome mood. Two hundred crowdsourced participants were interviewed by a chatbot on their positive or negative service experiences. The findings suggest that customer's mood prior to the encounter, as well as feelings from recalled experiences, have a positive effect on feelings towards the chatbot that in turn influence the customer's mood at the end of the encounter. Furthermore, whether the positive or negative nature of the recalled experience moderates the relationship between recalled experience feelings and a customer's feelings towards the chatbot. The empirical findings demonstrate how customer feelings propagate and influence not only how customer feel at the end of the encounter, but also the feelings towards customer-facing technology. Furthermore, the study highlights the importance of studying and developing customer facing technologies, such as chatbots, that strive to evaluate and manage the customer's mood and feelings (pre- and post-encounter) to aid in improving CE its outcomes.

Keywords: Chatbots, artificial intelligence (AI), customer experience, mood congruency, customer feelings, customer moods, interview

Introduction

Dubbed by some as the fourth industrial revolution, artificial intelligence (AI) has contributed to the computational augmentation of existing technologies and thus helped revolutionize many industries and areas of study (Maynard, 2015; Syam & Sharma, 2018). The COVID-19 global pandemic has caused considerable disruptions to businesses, paving the way for many of them to adopt AI-infused digital technologies (Donthu & Gustafsson, 2020). Examples of AI-infused technology are conversational agents and chatbots, with the latter estimated to reach an average annual growth of 400% over the next four years to reach $142 billion in consumer retail sales by 2024 (*Juniper Research*, 2020).

Chatbots act as cost-effective interfaces between firm and customer, facilitating round-the-clock access by providing instant responses and assistance. With progression towards mechanical thinking and feeling AI, conversational agents imbued with such technology are becoming more capable of taking part in service interaction, creation, and delivery (Huang & Rust, 2021). These agents are not just found on our smartphones, digital speakers, or websites in the form of virtual assistants, but are also making their way to service frontlines (e.g., hotel receptions and airport information kiosks) (McLeay et al., 2021). Chatbots can also be employed as inquirers and companions, often used for well-being applications and first responder scenarios that require a high need for human interaction (e.g., conversation partners for lonely people) (Sheehan et al., 2020). Such agents possess bidirectional conversational abilities (e.g., can lead the conversation and react to answers) and require some level of understanding of the state of mind of the user, as well as ideally being able to demonstrate a *human* touch to handle such situations (Odekerken-Schröder et al., 2020). It is important to note that the way chatbots are designed not only impacts assessments of service quality and customer satisfaction, but also customer's feelings and their experience (Xiao & Kumar, 2021).

Previous studies in marketing (e.g., Humphreys & Wang, 2018; Ordenes et al., 2017; Sidaoui et al., 2020) have addressed some AI and machine learning technical and linguistic aspects of natural language processing that are used in conversational agent design (e.g., text mining and sentiment analysis), however, chatbots still usually lack the *human* touch elements and escalations are often handed over to their human counterparts (Ask et al., 2016). This is costly, resource intensive, and risks customer dissatisfaction by increasing the steps involved in completing the service encounter. One reason for this ineffectiveness could lie in the inability of chatbots to fully understand what customers experience, including their feelings (De Keyser et al., 2020).

Hence, conversational agents need the capability to identify key aspects of the customer experience (CE) shaping phenomena within storytelling and narratives, which are the core mechanics governing the exchange of experience and knowledge in conversations. These phenomena include: activities (of customer and firm, e.g., check out), firm resources utilized (e.g., ATM machine), and context in which the CE is taking place (e.g., Bank branch on a rainy day) (Dawson & Sykes, 2018; Ordenes et al., 2014). Equipped with such a capability, AI-driven chatbots that empathize and manage human feelings could mitigate negative psychological consequences of the conversational agent encounter on not only CE, but also loyalty and satisfaction (Robinson et al., 2019). Achieving this automated mood or feeling detection and context awareness capability calls for transdisciplinary collaboration (e.g., human-computer interaction, neuroscience) (Gustafsson et al., 2016).

In addition to transdisciplinary collaboration, accounting for the temporality of how these feelings transpire (Becker & Jaakkola, 2020; Kranzbühler et al., 2018) is also required. Customer attitudes change throughout the customer journey as they experience and recall different touchpoints (Palmer, 2010). The study presented considers the dynamic nature of experience as encapsulating "life itself" as it uses temporality to study how mood affects the experience and how they are affected at the boundaries of the customer journey (i.e., before and after the journey starts / ends) (Csikszentmihalyi, 1991, p. 192; Kranzbühler et al., 2018; Lemon & Verhoef, 2016). The impact of the customer's state of mind (e.g., pre-encounter mood) is an important element to factor in when studying customer feeling dynamics (Knowles et al., 1999). The possible effects of mismanaging this span not only risks to the customer's mental health and wellbeing, but also their satisfaction, loyalty, and overall experience towards the firm or brand (Robinson et al., 2019; Xiao & Kumar, 2021).

Because chatbots are poised to deal with customers, they not only contribute to a CE, but also in certain cases, prompt customers to recall previous experiences simultaneously (e.g., customer support or well-being chatbots). Such experiential recollections could cause changes in how customers feel, and as a result influence how they feel about the chatbot. From a psychological standpoint, this is referred to as mood-memory congruency, where people would for instance recall a larger portion of experiences reflecting their current mood and vice-versa (Bower, 1981). With calls for firms to provide customers with more human-centric experience (Fisk et al., 2020), it is critical to understand the underlying psychological dynamics between customer, chatbot, and firm to manage customer well-being (Anderson et al., 2013).

While studies highlight the significance of conversational agents possessing a certain level of *human* touch and understanding of a customer's state of mind and feelings, achieving a more profound empirical understanding of such dynamics could influence not only the design of such agents but also the CE after engaging with them (Odekerken-Schröder et al., 2020; Xiao & Kumar, 2021).

Therefore, this study aims to examine the dynamics of how customer feelings and their state of mind (mood) influences their experience with chatbots. More specifically, by leveraging storytelling inquisitive chatbots as a means for experiential exchange, the study explores how the pre-encounter and recalled experience feelings of the customer influence feelings towards the chatbot and in turn, the customer's post-encounter mood. This study is among the first to empirically examine CE feeling dynamics within a chatbot encounter, and highlights the importance of understanding these dynamics (i.e., mood-memory congruency, previous experience recall) in order to inform CE theory and provide insights into more effective conversational agent encounter design to improve customer-centric service management (e.g., satisfaction, and loyalty) (Dick & Basu, 1994; Knowles et al., 1999).

Conceptual background

Chatbots and storytelling experiential exchange

Chatbots are not a recent technological innovation as they have been in development in various shapes and forms for decades. One of the first chatbots, ELIZA, mimicked the way psychotherapists converse by leveraging a set of hardcoded linguistic conditional rules to form its replies (Weizenbaum, 1966). More recently however, chatbots have started to leverage unique AI (a system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation (Kaplan & Haenlein, 2019, p. 3)) methods (e.g., natural language processing) to augment their abilities and perform optimally at the objective task.

In business practice, chatbots take on two major distinctive roles. They can either act as assistants (e.g., hotel concierge or booking agent) or play a more inquisitive role (e.g., human resource job screeners). In some cases, such as customer support, a chatbot might have to assume both roles, adding to its technical complexity. However, no matter the role and the technical capabilities the chatbot assimilates, its core performance depends on its ability to converse.

While a chatbot's semantic understanding of the conversation it has with a customer is a core function (e.g., understand and react to greetings and questions), neglecting the detection of the context of which this understanding takes place could disrupt the entire narrative and possibly lead to a negative CE (Ordenes et al., 2014). A simple example is the chatbot's ability to distinguish how the customer is feeling now and how they felt during a recalled service encounter. This is further exacerbated by the reliance on text as the prevalent medium of the conversational exchange curtailing the agent's (human or virtual) capabilities from distinguishing other sensorial queues (e.g., body language). As a result, the state-of-mind, including the current mood of the customer is often undetected and uncontrolled for in such circumstances.

Chatbots and the experiential approach to understanding human feelings

Much work has gone into the automated analysis and detection of human feelings using AI. For instance, in marketing, social media and feeds are analyzed for positive or negative valance using sentiment analysis, a text mining method used to determine the overall attitudes, opinions, and emotions within text (e.g., Humphreys & Wang, 2018; Ordenes et al., 2017; Sidaoui et al., 2020). In human-computer interaction studies, affective computing tackles the creation of human emotion-state models and is facilitating the development of technology capable of social-emotional skills (Picard, 1999; Siegert et al., 2012). While more efforts in respective fields on the automated analysis and detection of human feelings are still ongoing, more transdisciplinary breadth could provide a way forward to enhance the level of service value these technologies could provide (Gustafsson et al., 2016).

In addition to transdisciplinary breadth, feelings, studied in marketing or psychology, do not solely exist on their own and form a key constituent of an experience (Schmitt, 1999). Feelings, along with cognition, sensation, relation, and behavior are key constituent elements of an experience (De Keyser et al., 2020). Thus, to achieve a more holistic understanding of emotions, they need to be studied within an experiential context. With feelings comprising an element of CE, a chatbot or any other computer-human interface needs to account for a customer's state-of-mind even when engaging in discussions involving more cognitive functions (De Keyser et al., 2020; Schmitt, 1999). In fact, cognition is not void of emotional interference, and enabling technology to become aware of this with built-in risk mitigation mechanisms within its core design, could yield more empathetic and effective technology (Holbrook & Hirschman, 1982) better equipped to understand the holistic CE.

Moreover, human feelings are dynamic, varying in type by their temporal and contextual attributes (i.e., moods could span hours or days while emotions are experienced in seconds to minutes usually exhibited towards an object or situation) (Fox, 2018). Thus, the automated study of human feelings not only requires transdisciplinary efforts, but also an experiential perspective accounting for temporality and context (Caruelle et al., 2019). To better visualize how different disciplines aid a data-driven experiential build-up of holistic understanding of human feelings, Table 1 presents these disciplines in relation to their conceptualization layers.

Table 1. Data-driven experiential approach to understanding customer feelings

Layer	Disciplines	Selected citations
Applied	Marketing and consumer behavior	(e.g., Kronrod et al., 2017; Ordenes et al., 2014; Sidaoui et al., 2020; Verhulst et al., 2019)
Algorithm	Data science and artificial intelligence	(e.g., Ma & Sun, 2020; Siegert et al., 2012; Sokolova & Lapalme, 2009)
Interface	Human-computer interaction	(e.g., Ahn & Picard, 2014; Lake et al., 2017; Picard, 1999)
Theoretical	Psychology and neuroscience	(e.g., Fox, 2018; Lerner, 2004; Lim, 2018; Sytsma & Machery, 2010)

At the bottom layer, psychology and neuroscience establish the theoretical and empirical foundations to understand and measure human feelings (Lim, 2018). To extract and map these feelings into a format in which AI is able to process, human-computer interaction provides hardware and software acting as an interfacing layer to enable this (Picard, 1999). As a result, experiential data, including feelings, become available for AI algorithms to process and analyze. Thus, machine (deep) learning algorithms and natural language process could be used to not only make sense of this data, but also develop models to aid in predicting it (Siegert et al., 2012). From these insights, researchers could develop new approaches to studying CEs and feelings in an applied manner. For instance, a theoretical model of human feelings has been used in conjunction with a chatbot interface to better understand feelings surrounding chatbot-driven conversations (Fisk et al., 2020; Sidaoui et al., 2020).

What follows is a set of hypotheses and a statistical model, which leverages theories in psychology and uses human-computer interaction and AI to inform marketing and consumer behavior about the dynamics of customer feelings in chatbot-enabled conversations, in accordance to the framework presented in Table 1.

Hypotheses development

A customer's mood plays a pivotal role in the way they experience a service a firm is offering (Puccinelli et al., 2007). Moods are characterized as a mild affective state, taking place over a relatively longer period of time compared to other feelings (e.g., emotions, hedonic value) (Fox, 2018). Moods within an experience are also dynamic, influencing the experience itself (e.g., a customer's mood affecting an employee or front-facing technology such as a chatbot) or being influenced by the experience (e.g., the experience triggering a bad memory) (Kranzbühler et al., 2018). As a result, a customer's mood at the start (i.e., pre-encounter) and at the end (post-encounter) could change as they interact with a firm, influencing how they feel towards its different touchpoints (e.g., interactive chatbots) (Mattila & Enz, 2002).

Mediating effects of recalled experience and chatbot feelings

While a relationship between the pre- and post-encounter mood is expected to exist in a chatbot conversation, the pre-encounter mood of the customer might also influence their feelings towards their recalled experiences and towards the chatbot (Bower, 1981; Knowles et al., 1999). *Memory and feelings pertaining to specific experiences are highly related* (LaTour & Carbone, 2014). *Furthermore, experiences are said to be dynamic and perpetuate between services* (Kranzbühler et al., 2018). *Thus, recalled experience feelings could show congruency effects with the current experience and, as a result, influence customer's feelings towards the chatbot* (Bower, 1981). *For example, a negative recalled experience during a customer support interaction could enlist negative feelings, which could influence the current experience and interactions with a firm resource (e.g., a frontline employee or conversational agent as in this study)* (Puccinelli, 2006) *as well as the post-encounter mood.* Thus, the following hypothesis is proposed:

H1: The impact of pre-encounter mood on post-encounter mood are mediated by recalled experience feelings, and further by feelings towards the chatbot.

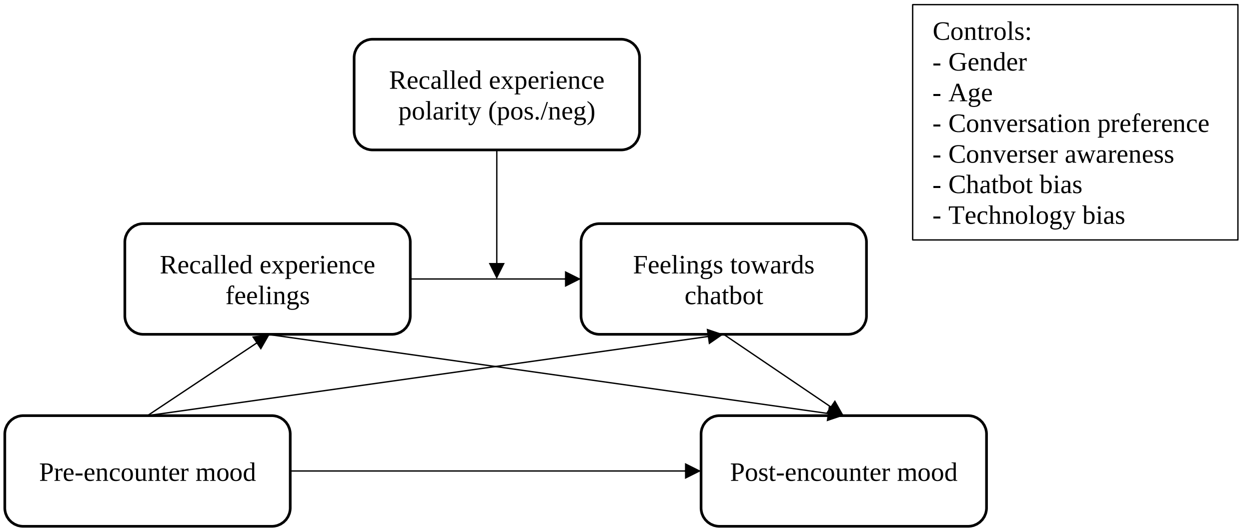
Moderating role of recalled experience polarity

While pre-encounter mood could influence how participants feel towards the chatbot, another dynamic influencing the latter could be the feelings from a recalled experience. One might argue that the effect between recalled experience feelings and feelings towards the chatbot is influenced by the recalled experience feelings; if a customer recalls a happy moment, they might feel more positively towards the chatbot, and vice versa. As a result, the polarity of the experience (i.e., remembering a positive or negative experience) could influence the strength of the relationship between recalled experience feelings and the feelings towards the chatbot due to possible memory-mood congruency *(Bower, 1981)*. This suggests, another congruency effect relating to memory and feelings could be present, allowing for further exploring the feeling dynamics in the chatbot encounter *(Bower, 1981)*. This is presented in the following hypothesis:

H2: The relationship between the recalled experience feelings and the feelings towards the chatbot is moderated by the recalled experience polarity (positive/negative experience).

The full model resulting from these hypotheses is depicted in Figure 1.

Figure 1. Moderated serial mediation model



Method

Data collection and preprocessing

To test the conceptual model, data collection was conducted using Prolific Academic (*Prolific*, 2021), an online crowdsourcing platform was used to recruit 200 participants. Sample frequencies are detailed in Table A I. Overall, 69.4% of the participants consisted of young adults aged between 18 and 34, and the full sample exhibited a balanced gender distribution (45.1% female, 52.4% male with the rest being undisclosed) with the majority of the participants residing in Europe (82.9%). This data collection method has been shown to be an adequate manner in which to study attitudes and behaviors of a random set of participants (Hulland & Miller, 2018). Furthermore, compared to Amazon's MTurk (*MTurk*, 2021), Prolific Academic (*Prolific*, 2021) is capable of providing a more diverse and transparent set of participants unfamiliar with ordinary research experiments (Palan & Schitter, 2018; Peer et al., 2017). This as a result, creates a more genuine interaction with the chatbot which in addition, used conversational stop words (e.g., “thanks”, “I see”) to accentuate participant engagement (Berger et al., 2020).

During the interaction with the chatbot, participants were asked to recall one of four randomly allocated scenarios ((i) positive or (ii) negative holiday experience, or (iii) positive or (iv) negative shopping experience) that they could recollect reliably. While scenario polarity (positive or negative) is collected to test for moderation effects between recalled experience feelings and the feelings towards the chatbot, a further balanced split (within positive and negative scenarios) between ordinary (shopping) and extraordinary (holiday) scenarios ensures such feelings are not tending towards a certain intensity in one scenario polarity over another (e.g., too many ordinary positive experiences as opposed to too many negative extraordinary experiences) (Carù & Cova, 2003; De Keyser et al., 2020). Furthermore, to ensure recall strength was sufficient, participants were asked to answer a 9-point scale question on how well they could remember this experience. Answers from participants with less than a neutral score (i.e., 5) were omitted, resulting in a sample of 193 participants (N = 48, N = 53, N = 47 and N = 45, respectively, for the four scenarios).

Furthermore, the dataset was analyzed using IBM SPSS 25 Statistics (IBM Corp., 2017) revealing only 2.1% of missing values. These values were concluded to be missing by accident as suggested by Little’s missing completely at random analysis and do not introduce non-response bias issues ($\chi^2 = 27.745$, df = 24, p = .271) (Little, 1988). Missing values were then estimated using a fully conditional (m = 10) multiple imputation method in SPSS (Rubin, 1987).

Method design

To test the hypotheses, a serial mediation model was used to test H1 while a moderation analysis was employed to test H2; this was done by using the PROCESS macro models 6 and 1, respectively, in SPSS 25 (Hayes, 2018; IBM Corp., 2017). To further validate the full model (Figure 1), a moderated serial mediation was conducted using the same tools with the PROCESS macro model 91. The main constructs consisted of the independent variable pre-encounter mood; the mediators, recalled experience feelings and feelings towards the chatbot respectively, the scenario polarity (i.e., whether the customer remembers a positive or negative experience) moderating the latter relationship between the mediators, and finally the post-encounter mood as the dependent variable.

In addition, control covariates consisted of gender, age, and questions pertaining to opinions on chatbots and technology. These questions took the form of 9-point items consisting of: (1) how likely the participants felt their answers would differ if they had chatted with a human, (2) how important it was knowing who the participants were chatting to (human or chatbot), (3) preference of chatting with a human or chatbot, and (4) agreeableness with the use of automated technology to replace company employees in conversations with customers. These questions aim to control for (1) answer deviations when conversing with chatbots; (2) ethical considerations of knowing who the participants were speaking to; (3) whether the participants had issues with communicating with chatbots ; and (4) whether the participants were accepting of such technologies (Blut et al., 2016; Parasuraman & Colby, 2015). It is important to note that these questions were designed for brevity to maintain the conversational experience with the chatbot while accounting for potential variance explained by their representative items.

Participants were guided from the crowdsourcing platform via web link to directly chat with the bot. The chatbot, named *Marvino* which was developed for the programme of studies by the first author, used a linear conversation style (i.e., it did not respond to participant questions) which the participants were made aware of by initial instructions from the bot. The chatbot then proceeded to ask the participants about their current mood, recall an experience from one of four service scenarios (positive/negative shopping/holiday), state their recall confidence, ask about how that experience felt, ask how they feel about the bot, and then conclude with an assessment of their current mood. The mood and feelings were captured using the short-form scales described in Table 2. Although newer scales have been developed for the constructs under study, the short-form variants were chosen to preserve the narrative conversational attributes of the chat and avoid making the conversation lengthy enough to disrupt the experience with the chatbot.

Table 2. Constructs and measurement items by source and sequence

Source	Constructs	Chatbot questions[1]
Mood Short Form (MSF) (Peterson & Sauber, 1983)	Pre/post-encounter mood[2]	"You would say your mood is currently …" (Extremely negative – Extremely positive) "As you answer these questions, you feel …" (Extremely Dull - Extremely Cheerful) "How emotionally comfortable or uncomfortable do you feel right now?" (Extremely Uncomfortable - Extremely Comfortable) "Presently you feel …" (Extremely Tense - Extremely Calm)
Hedonic Consumer Attitudes (Batra & Ahtola, 1991)	Experience feelings	"Overall this experience was …" (Extremely Displeasing - Extremely Nice) "In the end you felt the experience was …" (Extremely Unpleasant - Extremely Pleasant) "How agreeable or disagreeable would you say the whole service experience was?" (Extremely Disagreeable - Extremely Agreeable) "This experience left you feeling …" (Extremely Sad - Extremely Happy)
	Feelings towards the chatbot	"Overall this experience was …" (Extremely Displeasing - Extremely Nice) "You feel our chat was …" (Extremely Unpleasant - Extremely Pleasant) "How agreeable or disagreeable would you say our whole chatting experience was?" (Extremely Disagreeable - Extremely Agreeable) "Chatting with me left you feeling …" (Extremely Sad - Extremely Happy)

Notes: [1] 9-point scales were used to obtain responses; [2] end mood was captured at the end of the interaction yet used the same items as starting mood for consistency; [3] "this interaction" refers to a *context built by previous questions inquiring about a memorable service encounter moment, and the service resource (object or person)* (Ordenes et al., 2014)

The reliability and validity analysis, along with the descriptive statistics, of the key constructs under study are reported in Table 3. The final CFA model fitted the data well (χ^2 = 204.42, df = 98, p = .000, RMSEA = .08, SRMR = .04, GFI = .88, CFI = .97, TLI = .96) (Brown, 2015; Hu & Bentler, 1999; Kline, 2016). The well-fitted CFA model also suggests a minimized common method bias as suggested by Podsakoff, MacKenzie, and Podsakoff (2012). In support of convergent validity, all relevant construct reliabilities (CR) were above the recommended level of .70 (Fornell & Larcker, 1981). The discriminant validity of the scales was also satisfactory as the relevant Maximum Shared Variance (MSV) indices were shown to be greater than the corresponding average variance extracted (AVE) indices (Hair et al., 2010), and the square-roots of the AVE appeared to be greater than the inter-construct correlations (Fornell and Larcker, 1981) as shown in Table 3.

Table 3. Construct loadings, reliability, and validity

Construct	Mean (SD)	CR	AVE	MSV	1	2	3	4
1. Pre-encounter mood	6.42 (1.26)	.87	.63	.62	**.79**			
2. Recalled experience feelings	6.01 (2.60)	.98	.93	.06	.20	**.97**		
3. Feelings towards the chatbot	6.73 (1.28)	.94	.79	.56	.47	.24	**.89**	
4. Post-encounter mood	6.58 (1.32)	.92	.75	.62	.79	.20	.75	**.86**

Notes: Square-root of AVE on the diagonal in bold; correlations off-diagonal

Results

Testing the mediating effects of recalled experience and chatbot feelings

The regression results conducted using PROCESS model 6 (Hayes, 2018) to test Hypothesis 1 are described in Table 4. The results support a direct positive relationship between pre- and post-encounter moods confirming that starting moods could influence the mood towards the end of the encounter (β=0.52, t=10.87, p=0.00). The pre-encounter mood also exhibits a positive relationship with recalled experience feelings to support mood-memory congruency (β=0.39, t=2.43, p=0.02). A positive significant relationship also exists between the recalled experience feelings and the feelings towards the chatbot (β=0.07, t=2.30, p=0.02) signaling that recalled experiences play a role in the way chatbots are perceived. The results also show a positive and significant relationship between the feelings towards the chatbot and the post-encounter mood (β=0.48, t=9.23, p=0.00). This highlights the significance of how chatbots could influence the state-of-mind of the customer and, as a result, their attitude towards brands and firms (Elen et al., 2013). Furthermore, the goodness of fit indices (R^2=0.71, F(9,178)=48.86, p < 0.00) suggest good overall model fit.

Notably however, the indirect effects on post-encounter mood (Table 4) reveal significant results for paths solely through feelings towards chatbot (Bootstrap [5,000]; β indirect = 0.13, SE = 0.03, 95% CI [0.07,0.20]) and through recalled experience feelings and feelings towards chatbot (in support of H1) (Bootstrap [5,000]; β indirect = 0.01, SE = 0.01, 95% CI [0.00,0.03]). The indirect effects on post-encounter mood through recalled experience feelings alone did not prove significant (Bootstrap [5,000]; β indirect = 0.00, SE = 0.01, 95% CI [-0.02,0.02]), highlighting the important role that is played by how customers feel toward the chatbot.

Table 4. Testing the mediating roles of recalled experience feelings and feelings towards the chatbot on post-encounter mood

Predictors	*β*	*SE*	*t*	*p*
Outcome: Recalled experience feelings (R^2 = 0.06)				
Pre-encounter mood	**0.39**	0.16	2.43	0.02
Conversation preference	0.07	0.09	0.74	0.46
Converser awareness	0.12	0.14	0.86	0.39
Chatbot bias	-0.16	0.11	-1.49	0.14
Technology bias	-0.11	0.10	-1.05	0.30
Gender	-0.23	0.40	-0.58	0.56
Age	0.03	0.02	1.39	0.17
Outcome: Feelings towards chatbot (R^2 = 0.38)				
Pre-encounter mood	**0.29**	0.07	4.37	0.00

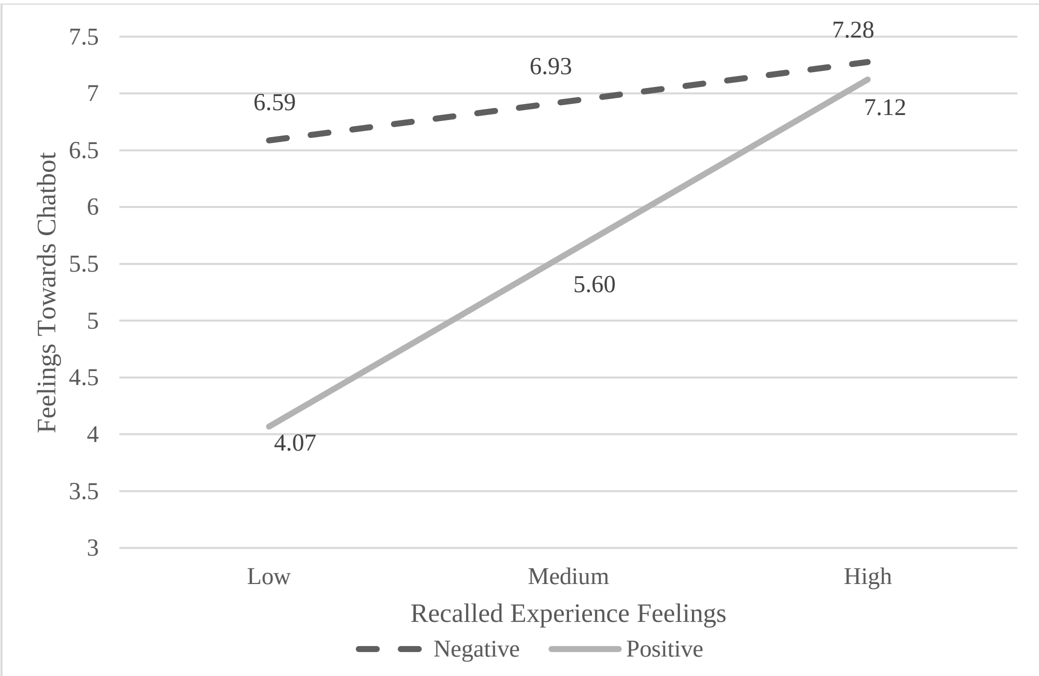
Predictors	*β*	*SE*	*t*	*p*
Recalled experience feelings	**0.07**	0.03	2.30	0.02
Conversation preference	-0.07	0.04	-1.76	0.08
Converser awareness	**0.15**	0.06	2.69	0.01
Chatbot bias	**-0.18**	0.04	-4.14	0.00
Technology bias	**0.17**	0.04	4.30	0.00
Gender	0.25	0.16	1.53	0.13
Age	0.00	0.01	-0.05	0.96
Outcome: Post-encounter mood ($R^2 = 0.71$)				
Pre-encounter mood	**0.52**	0.05	10.87	0.00
Recalled experience feelings	0.00	0.02	-0.10	0.92
Feelings towards chatbot	**0.48**	0.05	9.23	0.00
Conversation preference	0.05	0.03	1.89	0.06
Converser awareness	0.00	0.04	-0.01	0.99
Chatbot bias	-0.01	0.03	-0.35	0.73
Technology bias	**0.07**	0.03	2.22	0.03
Gender	-0.04	0.11	-0.35	0.73
Age	0.00	0.01	0.14	0.89
Indirect effects on post-encounter mood	*β*	*SE*	*95% CI*	
Pre-encounter mood through recalled experience feelings	0.00	0.01	[-0.02,0.02]	
Pre-encounter mood through feelings towards chatbot	**0.13**	0.03	[0.07,0.20]	
Pre-encounter mood through recalled experience feelings and feelings towards chatbot	**0.01**	0.01	[0.00,0.03]	

Note. N = 188. CI = confidence interval. Bootstrap sample = 5,000. Significant ($p < .05$) coefficients in bold.

Testing the moderating role of recalled experience polarity

To test the moderating effects of the recalled experience polarity on the relationship between recalled experience feelings and the feelings towards the chatbot (H2), the PROCESS macro (model 1) was employed (Hayes, 2018). In line with the previous results, the relationship between recalled experience feelings and feelings towards the chatbot is positive (β=0.13, t=2.86, p=0.01). Additionally, a positive significant interaction effect is observed (β=0.45, t=3.04, p=0.00). Furthermore, the overall model fit is good (R^2=0.36, F(9,178)=11.39, p < 0.00). From these results, it can be noted that in the negative scenarios, feelings towards the chatbot change less (from 6.59 to 7.28, when moving from M-1SD to M+1SD on recalled experience feelings) than in the positive scenarios (from 4.07 to 7.12), supporting H2 and exhibiting a stronger effect for positive scenarios on the feelings towards the chatbot. Figure 2 offers further insight into the moderating effect tested in H2.

Figure 2. Moderation effects of recalled experience polarity



Testing the full mediated moderation model

In addition to the separate serial mediation and moderation tests, a full serial moderation model (Figure 1) was tested using the PROCESS regression macro 91 (Hayes, 2018). This post-hoc analysis not only helps further validate the mediation and moderation results presented separately, but also in conjunction.

The results pertaining to this model are portrayed in Table 5 and align with the results of the previous models discussed to test H1 and H2. Specifically, and confirming the mediation analysis of Table 4, Table 5 shows similar significant indirect mediation effects from both recalled experience feelings and feelings towards the chatbots on pre- and post-encounter moods (H1). This can be seen via following path *a* (X→M1; β indirect = 0.39, 95% CI [0.07,0.71], p =

0.02), *b* (M1→M2; β indirect = 0.11, 95% CI [0.02,0.20], p = 0.01), and *c* (M2→Y; β indirect = 0.48, 95% CI [0.38,0.59], p = 0.00). Furthermore, the moderated mediation effect is positive (β = 0.07, 95% CI [0.00,0.18]) with recalled experience polarity as moderator. Lastly, the overall fit of the full regression model is good, as evidenced by the goodness of fit indices (R^2=0.71, F(9,178)=48.86, p < 0.01).

Table 5. Moderated mediation effects

Model	Path a	Path b	Path c	Index of moderated mediation
Parameters	(X → M1)	(M1 → M2)	(M2 → Y)	(recalled experience polarity as moderator)
β	0.39	0.11	0.48	0.07
95% CI	[0.07,0.71]	[0.02,0.20]	[0.38,0.59]	[0.00,0.18]
p value	0.02	0.01	0.00	-

X=pre-encounter mood, M1=recalled experience feelings, M2=feelings towards chatbot, Y=post-encounter mood

The results presented in Table 4 and Table 5 show support for H1 and H2, and indicate a moderated partial serial mediation due to the statistically insignificant indirect effects on post-encounter mood and pre-encounter mood through recalled experience feelings (CI [-0.02,0.02]). While the latter portrays that post-encounter mood is not influenced via recalled experience feelings, the model supports the evidence of the pre-encounter mood and recalled experience feelings influencing the feelings towards the chatbot which in-turn, influence post-encounter mood. These results will be discussed further in the next section.

Discussion

The purpose of this study is to highlight the importance of better understanding customer feelings dynamics during a human customer to machine (AI chatbot) interaction. Specifically, this study aims to bring forth empirical insights relating to how customer moods impact and are impacted by CE recall and feelings towards a chatbot. It leverages storytelling as a core mechanism for experiential exchange which, when utilized with chatbots, enables such technology to interface with customers about their experiences. Exploring the feeling dynamics that occur between a customer and a chatbot about their previous CEs aid in: (i) exploring feeling propagation throughout a chatbot encounter, (ii) examining the influence of recalled experience feelings and their polarity on the current encounter experience, (iii) highlighting the critical role a chatbot has in not only identifying but also managing the state of mind of the customer to provide a better experience. This is important, since mood influences many customer-centric tendencies towards the service such as purchasing behavior, satisfaction, and loyalty (Dick & Basu, 1994; Knowles et al., 1999).

Theoretical contribution

This study makes four main theoretical contributions. Firstly, this study draws from feeling and memory congruency theory (Bower, 1981) and highlights at a phenomenological level, how feelings and memory influence one another (LaTour & Carbone, 2014). The results show a congruency between pre-encounter mood and both recalled experience feelings and the feelings towards the chatbot (Table 4). This suggests that feelings originating outside the customer journey and beyond the firm's control, prime the customer, and thus can have a big impact on their experiences during an encounter even with an optimal service design (Lemon & Verhoef, 2016). While the pre-encounter mood is a variable that lies outside the firm's realm of control, an experiential approach to service design based on human experience can aid in both identifying and managing risks to the customer journey and manage CE more holistically and therefore more accurately (Fisk et al., 2020; Lemon & Verhoef, 2016).

Second, while mood-memory congruency has been studied in various facets of psychology, the pre-encounter mood has been shown to potentially affect the feelings surfaced by recalled experiences (i.e., mood perpetuation) (Bower, 1981). What this study adds to the body of service literature is that, in addition to mood being an influencer of service evaluation and behavioral intentions, mood can influence the feelings of customers when they recall an experience (e.g., such as in a customer support setting) (Knowles et al., 1999). Furthermore, these recalled feelings can propagate through different touchpoints (e.g., frontline employees) and as this study shows, customer-facing technology such as chatbots (Puccinelli et al., 2007). This study has also shown that a positive or negative recalled experience can strengthen/weaken the relationship between recalled experience feelings and feelings towards chatbots (H2). This was expected as a positive memory could yield positive present feelings (Bower, 1981). With regards to negative experience feeling recall, the moderating effects were not as strong, suggesting participants did not let their negative feelings influence the chatbot. The reason for this could lie in the way participants perceive chatbots empathizing with them about negative experiences and could provide an interesting avenue for future research. Overall, the results suggest that feelings towards customer-facing technology, similar to frontline employees, can be influenced by customer moods and recalled experiences (Knowles et al., 1999; Puccinelli, 2006).

Third, the results of this study highlight the effects of customer feelings towards customer-facing technology (AI chatbot) on the post-encounter mood; which can influence firm performance. For example, studies have shown that mood plays an important role in attitude-behavior enhancing the learning of brand names when positive, and affecting customer behavior when negative (Elen et al., 2013; Knowles et al., 1999; Lee & Sternthal, 1999). While the analysis shows that recalled experience feelings do not seem to influence the post-encounter mood (Table 4), they do influence the feelings towards the chatbot. Thus, not only does the study reinforce existing theoretical work and extend it to chatbot and conversational agent contexts, but it also portrays the importance of the feelings exhibited from the customer to the chatbot.

Fourth, theories that consider customer interactions with technology (e.g., technology acceptance models) take into account factors such as perceived effort, ease of use, and even hedonic enjoyment that influence the attitudinal and behavioral intentions towards customer-facing agents such as service robots and chatbots (Blut et al., 2016; Davis, 1989). While such studies have shown that factors such as anthropomorphism and humanlike features influence service outcomes and quality (e.g., Jörling et al., 2019; McLeay et al., 2021; Moriuchi, 2019), they do not take into account the customer's state of mind through this journey. This is important since as this study has shown, even the pre-encounter mood can influence how customers feel about such front-facing technology.

Managerial implications

At the time of writing of this article, the COVID-19 virus has disrupted many businesses and lead them to transition to and embrace digital technology (Donthu & Gustafsson, 2020). As a result, getting the digital CE right has never been more important and is considered a strategic investment with many services transitioning to online-only offerings (Sheth, 2020). Chatbots play a key role in this strategy for many organizations, and business executives could benefit from the results of this study as follows.

First, CE enabled by the service provision is dynamic and changes even when the service is executed consistently as designed (Palmer, 2010). With more firms competing in the digital space, excelling at providing a great CE will require the design of services that go beyond the market standards and consider CE as a more holistic, lived construct, encapsulating influencing experiences over extended periods, beyond the live touchpoint interaction within the defined customer journey. Moreover, as firms increasingly rush towards adopting customer-facing technology during the COVID-19 pandemic, customers associating their negative "lived experiences" (i.e., their moods and state of mind) could also influence how they feel towards front-facing technology, and as a result, the firm itself (Sheth, 2020). Thus, the need for customer-facing technologies to constantly measure and react to customer feelings and their state of mind is imperative to building and managing more empathetic technologies that can lead to better CE (Sidaoui et al., 2020; Zaki et al., 2021). As such, managers need to design services and technology that incorporates customer feeling management to improve the CE (Lemon & Verhoef, 2016). In the case of chatbots, feeling-aware agents could be adopted to provide a more empathetic experience, creating not only a more authentic CE, but also provide a competitive edge in the market (Odekerken-Schröder et al., 2020). Another extension to this is the use of chatbots and conversational agents to collect data and "interview" customers about their experiences. As a result, these agents could provide researchers and managers with a less biased means of collecting qualitative data while able to conduct difficult/uncomfortable conversations that a customer might feel embarrassed to discuss, for example.

Second, this study reaffirms the complexity of human feelings, how they influence the designed experience and outcome, and how they change and influence touchpoints within a service encounter (Kranzbühler et al., 2018). Managers need to consider technology that attempts to become aware of customer feelings over the course of the service encounter, ideally in real-time (Zaki et al., 2021). Furthermore, this monitoring needs to occur on multiple temporal feeling elements such as longer-termed moods or shorter more context-driven feelings such as emotions (Sidaoui et al., 2020). Moods for instance can influence the recall of memories and experience with the firm, and thus monitoring for this state-of-mind can help develop mitigating strategies to circumvent this during customer service and support encounters that utilize customer-facing technologies, for example. A customer could be in a certain state of mind and then recall a previous negative experience which could result in a service failure if the customer's feelings are not constantly monitored and managed by the interfacing technology (De Keyser et al., 2019). Another example where customer is well-being services that offer companion conversational agents to combat loneliness; here, too, a constant evaluation of customer feelings appears imperative (Odekerken-Schröder et al., 2020). Furthermore, as this study shows, negative recalled experiences don't moderate the relationship of recalled experience feelings on the feelings towards the chatbot as strongly as positive experiences, suggesting managers should be critical about the use of empathetic chatbots depending on the context the customer recalls.

Third, in line with our findings, firms would benefit from making use of chatbot technology in both inquisitive and informative roles simultaneously, where possible. Since feelings are dynamic, ideally chatbots possess the ability to not only monitor customer feelings in realtime, but also to react to them (Zaki et al., 2021). These reactions also need to move beyond scripted demonstrations (e.g., asking about a customer's day if the customer has an urgent matter) to more dynamic reactions taking the current context into consideration (Ordenes et al., 2014). Furthermore, this means that these reactions should not be binary (e.g., use of apologetic vs non-apologetic language) but varying depending on the customer's feeling intensity (e.g., use of *more* apologetic vs. *less* apologetic language) (Sheehan et al., 2020). As such, conversational agents need to account for context and temporality (e.g., are feelings exhibited by the customer towards this encounter or another one), in addition to responding accordingly based on customer feeling intensity. To achieve this, these conversational technologies need to provide information and assistance as well as attempt to inquire about the customer's state of mind (if the situation calls for it) to avoid negative CE and service failure.

Limitations and future research

This study is not without limitations which could be addressed in future related work. First, and as highlighted in this paper, feelings are dynamic and a person's attitude changes over time (Palmer, 2010). This means that CE feeling recall will represent the current attitudes of the participant which might be skewed from how they originally felt at the time of the encounter. The effects of this in the context of current study have not been assessed, and thus call for future work to address whether and how the time elapsed from the encounter affects the results. For instance, does a fresh experience carry more intense emotions, which could skew the outcomes? Would a repeated experience with an agent imply different consequences in chatbot design?

Second, while the method used in this study uses to bootstrapping to mitigate issues relating to smaller sample sizes, a larger sample would have been more optimal to derive more generalizations (Hayes, 2018). Additionally, the nature of the chatbot being text-based might influence how participants felt about it. Previous studies have shown that anthropomorphic features could for example impact how customers feel and enjoy interacting with a conversational agent (e.g., Blut et al., 2016; McLeay et al., 2021). Being outside the study's focus, future studies evaluate the effects of incorporating anthropomorphic features on customer feelings.

Third, the chatbot's design and implementation can influence the customer's mood in a similar manner an employee could, leading to behavioral and attitude changes (Furnham & Milner, 2013). Furthermore, technology acceptance and readiness could influence how customers feel about interacting with technology and, as a result, influence their mood (Davis, 1989) (e.g., some technology-conservative customers may be upset that they have shifted from interacting with human employees to their artificial counterparts in certain portions of a service encounter). The study adopts a portion of these controls in order to not sacrifice the storytelling elements of this conversational interaction. Thus, future work could attempt to design a study focused on understanding the effect of different chatbot implementations, such as anthropomorphic features previously mentioned, while controlling for technology acceptance and readiness (Blut et al., 2016).

Fourth, because CE is a multidimensional and holistic phenomenon, a chatbot would need to be able to break it down to its basic fundamental elements (e.g., feelings, thoughts) while making sense of its touchpoints, contexts, and qualities (De Keyser et al., 2020; Schmitt, 1999). Thus, there is great potential in using chatbots to evaluate different CE elements such as thoughts or relations, in order to develop a holistic understanding of the perceived phenomenon (e.g., Sidaoui et al., 2020). As such, a deeper and complementary theory-driven layer of experiential analysis ("Psychology and neuroscience" in Table 1) would move beyond addressing customer feeling interactions with technology as an outcome (e.g., Beaudry & Pinsonneault, 2010; Blut et al., 2016), and move towards a more dynamic conceptualisation in which the technology constantly, and in realtime, evaluates and manages customer feelings and their state of mind (Zaki et al., 2021).

With customer feelings being dynamic, and with the increased adoption of customer-facing technologies it becomes apparent that technology needs to both measure and manage customer feelings (De Keyser et al., 2019; Kranzbühler et al., 2018). Neglecting this area of research could lead to impediments to achieving better CEs when using chatbots or other customer-facing technologies. More transdisciplinary research and service innovation efforts that consider the human experience approach in service design would be helpful for better understanding and automating service processes effectively. Crucially, this would help companies provide their customers with better CEs when they use chatbots or other human-machine interfaces (Fisk et al., 2020; Gustafsson et al., 2016) and ultimately provide a route to improving the consistency and quality of CE beyond what is possible in person-to-person interactions

Appendix

Table A I. Sample frequencies

Demographic (N = 193)		Frequency	Percent %
Age	18-24	72	37.3
	25-34	62	32.1
	35-44	29	15.0
	45-54	20	10.4
	55+	10	5.2
Gender	Female	87	45.1
	Male	101	52.4
	Undisclosed	5	2.5
Region	Australia	1	.5
	Balkans	9	4.7
	Europe	160	82.9
	Middle East	3	1.6
	North America	12	6.2
	South America	1	.5
	Southeast Asia	1	.5
	Undisclosed	6	3.1

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Chapter 5 - Discussion and Conclusion

This concluding chapter covers the contributions, limitations and future directions of this thesis.

5.1 Contributions

The main contribution of this thesis is to provide a foundation towards the path of advancing the understanding of CE using data-driven methods. Since the CE phenomenon is experiential and "lived", this thesis adopts a bottom-up multi-layered and multidisciplinary framework combining knowledge from different disciplines to enable this data-driven approach (Csikszentmihalyi, 1991; Holbrook & Hirschman, 1982). As such, the studies included within this thesis attempt to bridge these layers and provide a foundational contribution towards a data-driven understanding of the CE phenomenon. The layers, related disciplines, and bridging thesis studies are portrayed in Table 1 which will aid in systematically structuring the contributions for this thesis.

Table 1. Data-driven experiential approach to an understanding of the CE phenomenon

Layer	Related disciplines	Objective	Studies
Applied	Marketing and consumer behaviour		
		Objective 1: Develop a CE data-driven framework	Study 1
Algorithm	Data science and artificial intelligence		
		Objective 2: Portray how a method for this framework might be developed and validated by using chatbots to measure feelings	Study 2 (Sidaoui et al., 2020)
Interface	Human-computer interaction		
		Objective 3: Examine the dynamics of CE elements in the presence of such a human-computer interaction method	Study 3
Theoretical	Psychology and neuroscience		

First, and following the chronological order of the studies conducted within this thesis, the first two layers (the “applied” and “algorithm”) describe how the data-driven algorithms and methods provide disciplines such as marketing and consumer behaviour with CE insights and understanding. As such, the first gap of this thesis is addressed by Study 1, which lays out the fundamental theoretical foundations from a comprehensive literature review to better understand the current state of CE in marketing. From this review, a data-driven CE framework is developed (RAFTS), and a way forward is provided portraying different potential sources for collecting this CE data using its consistent experiential elements (Objective 1).

Second, the “algorithm” and “interface” layers describe how experiential data is collected (e.g., using human-computer interaction) and by what data-driven algorithms and methods it is analysed. Study 2 provides insights into how this can be done using storytelling and chatbot interviewers using natural language processing and the sentiment analysis of CE feelings (Sidaoui et al., 2020) (Objective 2).

The last two layers, “interface” and “theoretical”, describe how CE developed interfaces not only collect experiential data, but also interact with customers. Bridging these layers requires a theoretically rooted understanding of the underlying phenomenological and physiological interactions with customer-interfacing methods. As such, Study 3 aims to provide insights into such interactions by observing the dynamics of how current and recalled CE feelings influence feelings towards chatbots and customer mood (Objective 3).

This bottom-up approach thus provides a means to establish a data-driven conceptualisation rooted in theory, while keeping in mind the design and implementation of the methods that interface and analyse experiential data from customers. It then allows this data to provide more holistic and empirical insights into the CE phenomena. The next section will describe the theoretical, methodological, and managerial and social contributions related to each of the studies described within this bottom-up framework.

5.1.1 Theoretical contributions

While many studies have contributed to the conceptualisation of CE in service research (e.g., Becker & Jaakkola, 2020; Bolton et al., 2018; De Keyser et al., 2020; Lemon & Verhoef, 2016; McColl-Kennedy et al., 2019), a manner of furthering this conceptualisation empirically remains largely a challenging concern. This thesis thus attempts to address this shortcoming by providing a way forward for data-driven CE insights and understanding.

First, the systematic literature review conducted in Study 1 enables the identification and unification of the fragmented experiential elements. Not only is this an important step towards conceiving the data-driven framework (RAFTS) (Objective 1), but it also enables more consistent empirical studies to be conducted in the future. Furthermore, a more refined CE definition is identified and developed as a result of the systematic literature review, emphasizing the intrinsic/extrinsic service touchpoint interactions and that services are not only experienced in real-time but also experienced via recall:

A customer's multifaceted subjective, dynamic, and holistic mental state journey resulting from direct or indirect service-intrinsic/extrinsic touchpoint interactions stimulating a customer's thoughts, feelings, senses, activities, and relations, thereby co-creating value from their current or temporal recollections of service encounter experiences.

Second, the RAFTS data-driven framework developed in Study 1 allows a consistent mapping of the experiential (sub)elements of the CE phenomena which could enable both traditional (e.g., surveys and human-led interviews) and contemporary methods (e.g., eye-tracking and chatbots) to measure these elements. Furthermore, the framework is abstract enough to accommodate multiple methods measuring the same (sub)element (e.g., emotions using sentiment analysis and scales), which when aggregated with others, provide a holistic overview of the CE phenomenon. The framework, thus, provides researchers with a consistent manner in which to empirically measure CE phenomena and advance the conceptualisation of CE abductively (Brodie et al., 2017). This not only aligns with Objective 1 and 2, but also to the general objective of paving the way to a data-driven CE understanding.

Third, Study 3 portrays the effects of a customer's state of mind and recalled CE feelings on the chatbots and the customer's concluding mood. This study goes beyond addressing the shortcomings of customer interfacing technologies (i.e., their acceptance or readiness) and provides novel insights into the dynamics of CE feelings and such technologies. As a result, to better manage and understand the CE, the state of mind of the customer must be taken into consideration as well as the dynamics of how customer feelings propagate and change during the encounter. Thus, it is not only important to study the features (e.g., anthroporphism) or the user acceptance or readiness of technology (Davis, 1989), but also the state of mind of the customer themselves. Establishing a baseline understanding of these dynamics would aid in mitigating risks related to improper and non-empathic responses and avoid design of customer-facing technology which could impact the CE negatively and as a result, influence business performance (Bove, 2019; Lywood et al., 2009) (Objective 3).

5.1.2 Methodological contributions

Two key methodological contributions are presented in this thesis and enabled by theoretical development of the data-driven CE framework in Study 1. The first contribution is related to the approach of empirically validating CE data-driven algorithms (Objective 2). Specifically, Study 2 examines CE feelings and compares the sentiment analysis algorithm results to verified marketing scales of each of the sub-elements of CE feelings (moods, emotions, and hedonic value) (Sidaoui et al., 2020). As such, this verification process can be adapted to other scales and related algorithms and used to expand the repertoire of algorithms data-driven methods can be used for not only CE feelings and but the rest of the CE elements.

The second methodological contribution of this thesis is provided through fusing storytelling and narratives with conversational AI technology. Specifically, Study 2 proposes a novel method of using a chatbot to interview customers about their recalled experience feelings was developed and used (Objective 2). This method used sentiment analysis from the chatbot conversations and mapped them against the CE feelings element of the RAFTS framework. Thus, building off the first methodological contribution related to the verification of the sentiment analysis used, the narrative storytelling environment and design of the chatbot experience is the second contribution. In addition, Study 3 insights show the benefits of this method in offering a superior manner of collecting secondary experiential data (e.g., web scraping customer feelings), since it actively pursues collecting all sub-elements within a major constituent element that can have an effect of on another (i.e., it directly questions the participant rather than using inferences from data) (Objective 3).

5.1.3 Managerial and societal contributions

From a practical standpoint, managers and executives have much to gain from the insights of this thesis and bridge the CE gap. First, the RAFTS framework provides a unified overview of the elements involved in measuring the CE phenomena; it also supports effective, theoretically grounded, and organizational AI adoption (Ransbotham et al., 2017) (Objective 1). The RAFTS framework provides a bridge between the theoretical conceptualisations of CE and data, enabling companies to develop technologies, such as chatbots and service robots which will increasingly be incorporated into customer journeys. The sub-elemental data granularity that the RAFTS framework provides could link perceptions directly with company resources and activities (Ordenes et al., 2014). As a result, managers would be able not only to access and respond rapidly to individual experiences regarding a particular resource or activity, but also gather enough data to establish an overall holistic and intersubjective view of what customers are collectively experiencing with which touchpoints, enabling them to rectify and even predict what customers might want to experience in the future. This enables a more holistic understanding of CE and could help explain the CE service-centric metrics such as loyalty and satisfaction. The RAFTS framework thus provides managers with a starting point of assessing, designing, and managing CE more holistically. For example, depending on the firm priorities, specific methods and tools such as chatbots with sentiment analysis capabilities could be incorporated to measure and manage a specific CE element which needs improvement.

Second, and leveraging the RAFTS framework data-driven characteristics mentioned above, the framework provides the potential to automate the mapping and extraction of firm CE data. As such, traditional, as well as, new and novel methods such as the use of chatbot interviewers (Study 2) could be developed and used as a resource effective and scalable means to automate a holistic evaluation of CE (Sidaoui et al., 2020) (Objective 2). As a result, more cost and time efficient CE insights which could be used to improve firm performance, could be achieved. This scalability also means the potential for companies to use such methods to analyse CE in realtime, thus managing and adapting the experience during the customer journey. Furthermore, Study 3 provides key insights into the dynamics of CE feelings during such interactions with customer-facing technologies as chatbots. These insights help firms design data-driven methods efficient at not only measuring and understanding CE, but also at managing the dynamics of the customer's state-of-mind and feelings during such an encounter (Objective 3).

From a societal standpoint, the COVID-19 pandemic is driving more customers online, forcing companies to revaluate how they design their services to provide more empathy and customer support making chatbots timely instruments to collect and manage CE (Diebner et al., 2020). Moreover, this could result in customer dissatisfaction as they shift from face-to-face interactions to more virtual ones where customer-facing conversational technology could influence their experiences as Study 3 observes. As such, a more human-centric approach towards CE is needed more than ever before in services, especially with the automation and big data capabilities of current technology that can potentially ignore the human experience altogether (Fisk et al., 2020). This thesis aims to progress the understanding of CE by placing a focus on the human phenomena occurring during a customer's experience with a service, and thus emphasizing the "human touch" when designing data-driven CE methods. As a result, firms which understand and empathize with their customers would be better suited to impact their lives and well-being positively (Rosenbaum, 2015). In addition, a better understanding of the CE phenomena aids the progress of societal companion conversational agents that have become more essential due to increased loneliness shaped by the pandemic (Odekerken-Schröder et al., 2020).

In addition, the *introspective* sub-elements of the RAFTS framework would enable the progress and development of empathetic AI in services (Huang & Rust, 2018) by attempting to better understand CE and thus gain valuable insights on how AI-enabled technologies should be built and designed. A resulting outcome would be an increased empathy toward customers, as mentioned above, and could improve CEs and co-create value and cost-efficiencies in customer service centres (Lywood et al., 2009). Such empathy-oriented solutions could then seep into organizational cultures, via technologies such as chatbots, and impact employee behaviour through providing AI-enabled customer insights by generating a better shared intersubjective CE perception between the key triad of customers, employees, and AI systems. Thus, application of the RAFTS framework could result in a better focus on empathy design within company strategies and culture, thereby impacting how CE is managed to optimize organizational performance and reduce or close the CE gap.

5.2 Limitations

Despite the impactful contributions of this thesis, it is not without its limitations. First, the RAFTS framework was devised from a systematic literature review of the marketing discipline. However, as has been highlighted in this thesis, the CE phenomena is experiential in nature and draws from multiple disciplines such as psychology and neuroscience. Although the candidate did consider and cite countless multidisciplinary sources, more inputs from domain experts (e.g., human-computer interaction and neuroscience) could enhance and expand this framework further as a detailed examination of broad disciplines would be outside the scope of the Study 1 and this thesis.

Taking the above into consideration, the RAFTS framework needs to be fully validated. Study 2 has taken a step towards doing this by validating the measurement of CE feelings using sentiment analysis and chatbots. However, a noteworthy limitation when it comes to Study 2 is the cultural and language influences. This mainly presents itself in the limitations of the algorithms used and natural language processing. Specifically, the user-generated errors due to the language and cultural background of the participants including slang, sarcasm, spelling, and comprehension among others require more sophisticated algorithms to take the latter into account. As such, more studies need to be conducted with a wider and more culturally varied set of participants along with more developed language-based algorithms.

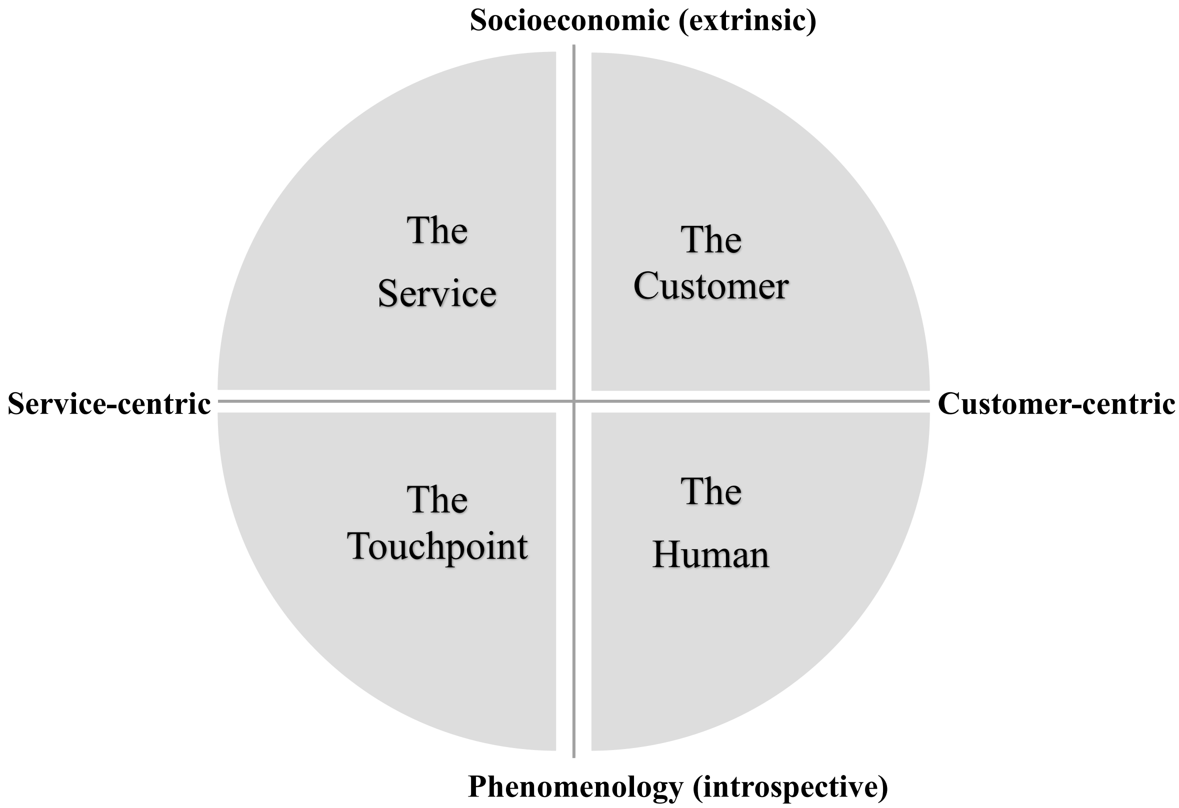
Notable limitations of Study 3 relate to the temporality and attitude of CE feelings. Since the study attempts to provide insights relating to the current state-of-mind of the customer as well as their recalled CE feelings; attitude and temporality are factors that could influence how customers perceive these surfaced feelings (Kranzbühler et al., 2018; Palmer, 2010). As such, the previously described volatility of the CE can come to play and influence the experiential data and resulting dynamics. Thus, future studies need to account for such volatility by developing more robust and isolating study designs that attempt to aid participants in surfacing and reflecting on the desired experiential elements while not priming them unintentionally (Lerner, 2004).

While the full validation task of RAFTS goes beyond the scope of this thesis and is a key future research contribution. Approaching this validation task requires not only technical validation, but also contextual framing. To provide a way forward, the next section proposes the CE archetype map along with a future work agenda.

5.3 The CE archetype map and future work agenda

By using the CE theoretical approaches portrayed in the introduction chapter and the layered approach to a data-driven CE phenomena understanding, the CE archetype map (Figure 1) is presented. It aims to provide a way forward by differentiating 4 quadrants (service, customer, touchpoint, and human) where the RAFTS framework and its experiential elements could be explored. These quadrants are separated by two axes that take into account the theoretical underpinning phenomenology highlighting the "human" perspective of CE as well as the applied socioeconomic perspective.

Figure 1. Holistic CE archetype map



Specific future research questions and key managerial concerns relating to each quadrant are explored below and outlined in a research agenda (see Table 1).

5.3.1 The service quadrant

Starting with the socio-economic lens, the service-centric *service* quadrant includes such aspects as service design, service-centric CEM, and metrics that are designed to measure and improve the overall value proposition. In terms of CE design, this quadrant would aim to bridge the gap between intended and perceived experiences (Ponsignon et al., 2017; Voss et al., 2008). While service design may focus on RAFTS elements shaping *activities,* associated *sensations* and opportunities for *relations* (designed to create real-time experiences), metrics will tend to focus on gauging *thoughts* and *feelings* in response to interacting with organizational resources that relate to service provision (perceived and recalled experiences).

As such, advances in digital and data analytic technologies offer a rich vein for studying the importance of understanding the experiential elements of CE further and make data-driven AI deployment within organizations more effective (e.g., Bolton et al., 2018; Brynjolfsson et al., 2017; Larivière et al., 2017; Lemon & Verhoef, 2016; Ordenes et al., 2014; Ransbotham et al., 2017; Van Doorn et al., 2017; Wirtz et al., 2018).

Thus, two major research fronts are of interest when considering future work in this quadrant. The first relates to studying the means that companies can undertake to optimize their technological readiness and be better positioned to implement data-driven AI solutions geared toward studying and improving CE. The second deals with the impact of organizational change on leadership, structures, processes, culture and strategy when potentially shifting to adopt more customer-centric frameworks and metrics that include less objective constructs like empathy.

5.3.2 The customer quadrant

Within the customer-centric *customer* quadrant, research considers (i) different customer perceptions and behaviours, such as customer expectations, loyalty, and satisfaction that are linked with value creation related to the RAFTS elements and (ii) perceived customer outcomes (Lemon & Verhoef, 2016). These two perspectives are attuned with value (co-)creation (Grönroos, 2008, 2011; Heinonen et al., 2010; Heinonen & Strandvik, 2015; Vargo & Lusch, 2008), especially since CE is viewed as a "vital nutritional element driving" customer value (De Keyser et al., 2015, p. 5). Furthermore, this quadrant may also encompass the customer relationship management elements of CEM (Palmer, 2010), including customer relations and profiling.

There has been considerable dependency placed on service-centric metrics like customer loyalty, satisfaction, and CE quality (EXQ) (Maklan & Klaus, 2011). This is not to say that these metrics are not useful, but rather that they attempt to measure a service-sided output of CE similar to well-established customer satisfaction performance indicators. Thus, it is possible that a more holistic measurement, the intrinsic 'human' experiences within a customer also need to be part of these metrics to improve CE management. As a result, companies could build new customer profile models and metrics that incorporate customer-centric measures, accounting for temporality and service environment. This approach would require not only developing new theoretically driven models and metrics, but also managers to rethink how such models would be implemented and how their organizational performance would be measured.

5.3.3 The touchpoint quadrant

The phenomenological portion of the archetype map can also be viewed through either a service or customer-centric lens by studying explicit customer behaviours introspectively as customers interact with service touchpoints and directly experience the service. Using a service lens, the online or offline *touchpoint* in a customer journey involves interactions (activity) that trigger a direct stand-alone CE (Lemon & Verhoef, 2016). Additionally, assessment of resources in the physical environment dimensions and perceived *servicescape* stimulate and engage the customer thus forming their perceived CE (Bitner, 1992; Bustamante & Rubio, 2017; Pareigis et al., 2012).

The data collected from the RAFTS framework could be partially collected from touchpoints that constitute the interactions between customers and firms. Thus, a set of activities, and resources gathered from both customer and company-centric perspectives may act on the CE (McColl-Kennedy et al., 2019; Ordenes et al., 2014; Zolkiewski et al., 2017). Further research could be conducted into the manner in which activities and resources influence the elements of CE in the RAFTS framework via customer engagement. This could then help companies to better measure customer responses to their experiences with that company. For example, which element is most influenced by customer support? How would predisposed sensations such as a customer with a headache influence the sensation elements of the CE? How could organizations achieve a more empathetic human touch (Bolton et al., 2014) in their offerings, thereby positively influencing the *feelings* of their CEs? Even more so, how could the latter be achieved with less time and greater scalability. Such CE data could be acquired via interfaces or platforms that act as direct or indirect touchpoints, which engage customers. Advances in these platforms, such as the semantic web in Web 3.0 (Hendler, 2009) would allow better identification and design of online assets and better capture of the experiential elements in the RAFTS framework. Chatbots and service robots designed for empathetic interactions (Huang & Rust, 2018) with customers could be specifically tuned to extract experiential elements, such as feelings as shown in Study 2 and 3 (Sidaoui et al., 2020). Furthermore, unobtrusive monitoring, such as eye-tracking (Otterbring et al., 2016), could provide still further insights on whether and how in-store stimuli influences specific experiential elements. When extracting data from interfaces and platforms, different data types could also be impactful targets for further research. For example, in scenarios that incorporate big data, how would *apophenia* (i.e., establishing connections between unrelated matters) (Boyd & Crawford, 2012, p. 668) be avoided when attempting to extract experiential elements? Another example would be the technical data forms and channels required to use IoT to measure emotions (Kim et al., 2018).

5.3.4 The human quadrant

Finally, the customer-centric phenomenological *human* quadrant takes into consideration the experiential, as well as the physiological, the psychological, and in the furthest extreme, the philosophical and existential aspects that influence the perception of the RAFTS elements. An example is temporal studies' affecting CE, and how time, context, and the ability to recall play a significant role in not only what immediate CE constitutes, but also what the customer might perceive they have experienced in the past (Kranzbühler et al., 2018; Palmer, 2010; Zolkiewski et al., 2017). The experiential context is a crucial component to giving CE meanings (Thompson et al., 1989); however, even those experiences occurring outside of the service context should be considered as influencers of the overall CE. For instance, a customer arriving at a retail store while engaged in an argument with their significant other could have an effect on their overall CE.

As highlighted in this study, this quadrant seems to be underrepresented in service-centric driven organizational strategies and adopting a customer-centric strategy could yield a more holistic understanding of CE. However, future work in this quadrant seems to be challenging yet rewarding. Constructs under study in this quadrant not only tend to be more subjective, but also interdisciplinary, involving knowledge that pertains to wider domains such as psychology, and neuroscience.

With this information in mind, the research opportunities pertaining to the RAFTS framework developed in Study 1 will be thus discussed. Most notably, RAFTS represents a context-free framework that promotes context-specificity for a particular implementation scenario. Thus, a way forward would be to approach the framework from two perspectives. The first relates to identifying most appropriate technologies to measure differing CE elements in different situations and how this goal can be accomplished. For example, when would text-mining techniques to extract emotions (Sykora et al., 2013) be more effective than alternative solution? Would a chatbot solution such as the one developed in Study 2 be more effective than a data-mining one? The second perspective relates to which particular CE elements would be more prominent in which domain. For instance, how do CE *feelings* compare to *thoughts* in terms of impact on overall retail CE? What are the dynamics of CE *thoughts* as opposed to CE *feelings* in terms when interfacing with a data-driven method such as chatbots as shown in Study 3?

Table 2. Research Agenda & Managerial Concerns

Research Topics	*Managerial Concerns*
The Service Quadrant	
a) How does an organizational culture influence its ability to focus on a more empathetic customer-centric strategy? *b) Does organizational technology readiness impact its ability to study and implement customer-centric CE?* *c) How ready are organizations to adopt theoretical frameworks like RAFTS?* *d) How would the adoption of a theoretical framework such as RAFTS, impact existing CE measurement and management practices within organizations?*	*a) What are the technological adoption barriers that prevent companies from making use of theoretical frameworks like RAFTS?* *b) How does a company's information management influence the adoption of data-driven AI technologies to extract holistic CEs?* *c) How does company size and financial ability influence the adoption of data-driven AI technologies to extract holistic CE? (What is the difference between start-up, and large corporation strategies?)*
The Touchpoint Quadrant	
a) What experiential elements are most impacted by organizational resources? *b) What are the differences between a direct and indirect touchpoint engagement relative to the experiential elements?* *c) How are the experiential elements, activities, resources, and contexts, viewed differently for customers and services?* ➢ *What means better gauge these intersubjective views?* ➢ *How do these characteristics impact touchpoint and servicescape design?*	*a) Which company resources and activities deployed at touchpoints have a major impact on experiential elements?* *b) What role do frontline employees have on each experiential element, and how can they influence customers with predisposed sensations? (Such as a customer in a bad mood due to personal context).* *c) What methods can be used to determine holistic CEs at single touchpoints?*
The Customer Quadrant	
a) How do different approaches (socioeconomic / phenomenology) impact CEM in terms analytics and reporting? *b) What are the organizational metrics, mapped to the RAFTS framework that can be developed to measure CE relative to service-centric measurements (such as customer loyalty, and satisfaction)?*	*a) How could adoption of theoretical frameworks, such as RAFTS, impact effectiveness of CE measurement and management practices within organizations?* *b) How would existing customer profile models need to be modified to reflect the implementation of customer-centric frameworks such as RAFTS?*

Research Topics	*Managerial Concerns*
c) How could the results of the RAFTS framework be used to predict the CE of current and future customers?	*c) How would organizational performance metrics be impacted as a result of using customer-centric strategies to CE?*
The Human Quadrant	
a) Can we identify efficient data-driven AI methods to measure each of the CE elements within the RAFTS Framework? What are they? ➢ *Can these be generalizable across different domains?* *b) What is an appropriate scoring method for each individually perceived experiential element and does an aggregation of these scores provide clear objective and subjective representation of an intersubjective holistic CE?*	*a) How does theoretical understanding of the different experiential elements compare to the organizational understanding of these same elements?* *b) What data sources / types are best suited for each experiential element? (For instance, is CRM data more accurate than data from social media for 'emotions' extraction?)*

Table 2 thus offers a range of potential research paths from leveraging the RAFTS framework and the different studies conducted in this thesis. These potential paths extend into theory and practice and show the promising value of a data-driven CE understanding to further the conceptualisation and more effective management of CE.

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Reflections on the PhD journey

In this section, the researcher reflects on his PhD journey in the first person.
I started my PhD journey at the Alliance Manchester Business School on the 14th of October 2017. My expectations were as follows: Progressing through the 3-year program in a highly focused and efficient manner, with the goal of securing an academic job towards the end of it. I was also mentally prepared that this goal would require substantial work effort and rigid personal discipline to achieve. Despite this preparation, I can personally attest to the cliché statement that it is not about the goal, but the journey towards it. This statement is one which an individual needs to experience, to fully comprehend. I am writing this section on 31/12/2020 which signifies not only the end of an extremely challenging year for the world, but also as a personal reflection point concluding this journey and starting a new one. Below are some of my accounts and reflections on my progression and learnings from the doctoral program.

Supervision team

To begin with, I have learned that PhD supervisors can have a significant influence on the outcomes of a PhD. Not only do supervisors impact the direction of the research project, but more importantly, they significantly influence the doctoral candidate with respect to their work output and mental state of mind. During our induction week, we were told about how important it was to build a balanced relationship with our supervisors. I could not agree with that more. It is imperative that candidates and supervisors strive to achieve this, since it could sway the project's outcome greatly and have severe consequences on the candidate's mental state during this challenging journey and their career future towards the end of it. Personally, I consider myself lucky to have such supportive and understanding supervisors. They not only helped me navigate through my research shortcomings, but also provided me enough independence to grow and develop my research and academic profile beyond the program's offerings. Without their support, I would have not been able to:

- Co-author an ABS 3 publication alongside many well-known service researchers by my second year (Fombelle et al., 2020) and a high impact ABS 2 PhD-related publication (Sidaoui et al., 2020) by my third
- Secure the Research and Development Management Association (RADMA) doctoral studies award grant totalling £10,000
- Attend, fund, and present in 7 national and international conferences (prior to the COVID-19 pandemic)
- Guest lecture and visit two international universities in both Texas (Texas State University - 2 weeks) and New York (Fordham University - 3 months)
- Be awarded the distinguished achievement award for post-graduate student of the year 2021 in the faculty of humanities in the University of Manchester

These achievements in addition to many others that were a result of personal effort and supervisor support eventually led me to secure an academic post as an Assistant Professor at the Nijmegen School of Management at Radboud University in the Netherlands prior to completing my PhD. Thus, in combination with a candidate's efforts, a healthy and supportive relationship with supervisors can really "make or break" the success and achievements of the doctoral researcher's PhD journey.

Networking

Another crucial realisation is the understated importance of networking and relationship-building. Before I began my doctoral journey, I was involved in business development and management roles during my 8 years of industry experience. A crucial skill in those roles was the element forging and maintaining relationships. In academia, this is a critical area which in my opinion is generally under emphasized. The world of academia is not much different. It loosely built upon one's reputation for research, teaching, and service. In addition, the more specialized the area of research, the smaller the community. As a result, a doctoral candidate should plan and build a strategy around networking within their research program. From my experience, conferences, workshops, and volunteering in academic service greatly helps build new and connections. For example, participating in the Let's Talk About Service conferences (2018/2019) has resulted in teaming up with other service researchers to work on high impact publications (With outputs from the 2018 conference in second round of revisions at the Journal of Service Research). The 2nd CMLG Academic-Practitioner Workshop, one the first workshops I was invited to with supervisory support landed me not only a publication (Fombelle et al., 2020) at the Journal of Business Research (ABS 3), but also allowed me to connect and learn from highly acclaimed researchers in the field. Furthermore, becoming a member of the board of the American Marketing Association service research interest group (ServSig) was the result of volunteering to help with a cyberattack on their website ("AMBS News," 2019). All these efforts and opportunities have had a snowball effect where the relationships built, have continued to other projects, opportunities, and further network expansion.

Research direction, motivation, and inspiration

Finding a research direction at the beginning of the research program can be a daunting task. Although it is customary to hear that research questions and the overall direction of the research will change and evolve along as the program progresses, the starting point and how these changes are directed are challenging aspects that could dramatically influence the research outcomes. From my experience in the doctoral program as well as supervising Master student theses in my current role, the challenge is finding a topic that is both interesting to the research candidate and that can be translated into a research gap within the academic literature. The challenge stems from the candidate's initial lack of knowledge of which area of research would fit this criterion. One way to approach this is to isolate the candidate's initial research motivations and drive them to read as much literature as possible until they stumble across an interesting research gap to address. While this method cannot be faulted, the aspect it lacks is a deepened connection with the individual curiosity of the researcher. As a result, this disconnect makes it harder for the candidate to find motivation to persevere through the research process when encountering challenging obstacles: therefore, not only increasing stress and supervisory dependency, but also increasing the changes for candidates to drop out and not contribute enough in relation to their potential.

My reflections stemming from my experience have been to, at least initially, encourage candidates to explore. This is another point highlighting the importance of supervision at this stage. Before joining the PhD program, I started a Life Coaching business solely out of curiosity to better understand human life experiences. When I began my doctoral program, it never occurred to me that I could tie-in my personal curiosity to a business area. In fact, I was not even aware that such areas of research existed. Thus, highlighting the disconnect challenge I was referring to in the previous paragraph. I recall mentioning this to my supervisor who pointed me to a growing service research topic: customer experience. After reading through the literature, bridging my psychology-related research interests and my industry experience in software development and artificial intelligence, the direction of the research became immediately apparent. This has greatly helped me in not only planning my paper-based thesis, but also aided in drawing more contributions and insights from interdisciplinary areas based on my personal interests.

Candidate's state-of-mind and self-care

Finally, a candidate's performance and outputs are mitigated by how they are able to manage their mental state. During the program, we were offered many workshops and tutorials on how to manage this. However, the challenge here is that these are highly subjective and differ from one individual to the next. Furthermore, the challenges pertaining to the COVID-19 global pandemic have added extra pressures to the already lonely journey of the PhD. Prior to joining the PhD program, I had established self-care routines which helped aid me during stressful times in industry work. This meant, following a proper and healthy diet, regular exercise, and being overall grateful for the opportunities presented to me. For the most part, I could confidently say that I would have not changed anything if I had to go back and traverse this journey once again. One area I could have done better however, which might have impacted my research output negatively, is being too strict and disciplined. My focus from the first day of the program was to be able to reach my goal of securing a job position after my scholarship funding would have ended. This not only made my journey more challenging, but also led me to focus more on the achievement of my goals rather the enjoyment of the process. Adding to the challenge is my acceptance of a full-time assistant professor role and relocation to another country while still attempting to finish my doctoral research during an extended time of world-wide lockdown due to the COVID-19 pandemic. Thus, while I highly attribute my success of achieving an academic position by the end of the program to strict discipline and hard work, I cannot state the importance of striking a balance between optimizing research performance and individual physical and mental well-being.

In closure, I borrow this statement from my colleague, friend, and recent doctor: *"Becoming a Dr has been one of the most difficult things I've done, it destroyed me in almost all of the ways I could possibly be destroyed, but just to be built again. I built every piece back to keep fighting and keep going to make it to this day"*

My overarching conclusion to the PhD journey is that for the most part, and beyond my academic output, the impact of this process has resulted in a significantly better understanding of myself as a researcher and as an individual. From my perspective, this a result of the sheer amount of experiences I encountered which shaped the way I think, reflect, and perceive the world around me. In other words, the more a candidate puts into the program, the more they get in return both academically and personally. In conclusion, if the academic purpose of the doctoral journey is to forge an independent researcher, then by consequence, it is to forge an independent thinker and individual.