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Unlocking Service Provider Excellence:
Expanding the Touchpoints, Context, Qualities (TCQ)
Framework

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Unlocking Service Provider Excellence:

Expanding the TCQ Framework for Enhanced Customer Experience Performance

ABSTRACT

Customer reviews offer scope for better understanding the customer experience (CX), which may be leveraged to improve firms' CX performance. We extend TCQ nomenclature by integrating it with ARC value creation elements and multidimensions of CXs. Our extended TCQ framework comprises nine building blocks to delineate dynamic CX performance trajectories. We test our framework by collecting verbatim text-based reviews, and transforming them into two robust sets (weekly, and monthly), which we examine using a dynamic Hidden Markov Model. We identify three levels of CX performance states and migrations paths between them. We find that the building blocks coherently express mechanisms that are effective at the weekly and monthly levels for helping firms improve and prevent deterioration of CX performance. This research enriches the CX and TCQ literature. In particular, we derive actionable guidance for managers to facilitate the dynamic management of their firm's CX performance.

INTRODUCTION

Companies actively work to perfect customer experience (CX) by continually leveraging new and ever-more advanced marketing technologies. For example, the utilization of tools like social listening and machine learning for analyzing customer reviews is now crucial in discerning the elements that drive customer satisfaction. The strategic importance of CX itself is highlighted by Edelman and Abraham (2022), who posit that CX significantly influences firm performance. This perspective is further bolstered by Becker and Jaakkola (2020), who emphasize that firms with standout CX garner a competitive advantage, especially given customers' increasing value-consciousness. Therefore, CX is emerging as an integral factor for financial performance, fueling customer satisfaction, loyalty, and repurchase intentions.

The dynamic relationship between customers and firms, and the resulting evaluations of those interactions (e.g., Vargo and Lusch 2008) are central to the delivery of quality service. Customers base their CX perceptions on their individual evaluations of service quality (e.g., Dagger, Sweeney, and Johnson 2007; Wang 2011), which in turn influences satisfaction (e.g., Sureshchandar, Rajendran, and Anantharaman 2002). In response, businesses have established a number of concepts and terms that encapsulate this understanding. They include the term *CX Performan*ce (Gartner 2019), which differentiates a customer's personal experience from a firm's assessment of their own performance, or in other words their evaluation of the execution of activities in producing that experience. While the term CX typically captures the customer's perspective, the roots of CX *performance* are in a firm's strategic vision and goals. The term CX performance thus provides a bridge between consumers' subjective experiences and traditional concepts of service delivery, service quality (e.g., Parasuraman, Zeithaml, and Berry 1985), and

overall satisfaction (e.g., Rust and Oliver 2000).

One way in which firms have tried to measure CX performance is through customer ratings of service (e.g., Ho, Wu, and Tan 2017; Simonson 2005). However, simply measuring customer service ratings at a single time point ignores the dynamic nature of CX (Marketing Science Institute 2020). For example, consider a situation where the average customer ratings for Hotel A and Hotel B are both 7 out of 10. The meaning of this single score is different depending on the *trajectory* taken to get there. In practical terms, if within the same month Hotel A's rating increases from 5 to 7 and Hotel B's rating decreases from 9 to 7, the migration paths along the varying CX performance states are clearly divergent. This highlights the pertinence of a *CX Performance Trajectory* perspective, spotlighting the importance of monitoring varying performance over time (e.g., from low to high performance) rather than at a single time point.

Wolter et al.'s (2019) work serves as a foundation for our trajectory perspective, particularly their insights into the dynamism of satisfaction trajectories and the significant impact of employee trajectories on customer satisfaction. Their work points out how positive employee trajectories, characterized by job satisfaction, organizational commitment, and low turnover, enhance service quality. In this study we draw from Wolter et al. (2019) and adopt similar approaches in our exploration of CX performance trajectories. Employee contentment, they emphasize, experiences evolving trends, which parallels our assertion that CX performance similarly evolves. Diverging from their approach however, we define CX performance trajectories more holistically as: (1) a firm's consolidation of customer feedback, (2) the collective responses from customer interactions, and (3) the trajectory that delineates how a firm's CX performance – the quality of execution of its CX activities – varies over periods, reflecting the changing tides of customer perceptions.

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        The foundation of any meaningful discussion on CX performance trajectory lies in a

robust theoretical framework. Our framework is rooted in the foundational principles of the

Touchpoints, Contexts, Qualities (TCQ) nomenclature (De Keyser et al. 2020), which we

integrate with the Activities, Resource, Context (ARC) value creation components (Ordenes et

al. 2014) and the multifaceted nuances of CX (Lemon and Verhoef 2016). Our synthesis of these

theoretical frameworks develops the identification of nine building blocks of the CX

performance trajectory. Notably, these elements are not siloed, but are in fact intricately

connected, with their interactions sculpting the dynamics of the CX performance trajectory.

        We explore CX performance trajectories through a textual analysis of customer feedback,

using a Hidden Markov Model (HMM). In doing so we are one of the few studies to take a firm-

level perspective on such data (see Web Appendix A. Table A). By employing HMMs, our

research provides service providers with a clear map of their CX performance states. We identify

three main outcomes of CX performance states and the pathways to reach them. Additionally, we

pinpoint effective strategies that can enhance or prevent deterioration of their performances,

offering managers practical guidance for improving their services. Our model thus supplies firms

with the strategic insights needed for real-time CX enhancements (Fader and Hardie 2010;

Homburg, Steiner, and Totzek 2009; Netzer, Lattin, and Srinivasan 2008; Rust and Verhoef

2005; Zhang et al. 2016).

        This study addresses a critical research question: What drives service firms' CX

performance trajectories? Our contribution to answering this question stands on three pillars.

First, our extended TCQ framework, comprising nine elements and their potential interactions,

enriches De Keyser et al.'s original TCQ nomenclature, adding depth to the service-centric CX

discourse. Second, employing an HMM empirical model, we spotlight the determinants that

modulate CX performance states, allowing for a temporal mapping of such shifts. Third, our

empirical findings provide actionable managerial implications by delineating three core

outcomes of CX performance and their causes. This includes pathways to attain these outcomes

and tactical recommendations to either amplify or safeguard their performance, equipping

managers with actionable insights to enhance service delivery.

THEORETICAL BACKGROUND

In this section, we first define the concept of CX performance and its trajectory. We then

expand upon the TCQ framework, integrating the TCQ nomenclature with the ARC value

creation elements and the multiple dimensions of CX as defined by Lemon and Verhoef (2016).

We conclude by presenting the CX performance trajectory. This encompasses various levels of

CX performance states (e.g., from low to high state), the transition pathways between these

distinct performance states, and our extended TCQ framework, which incorporates its nine

building blocks/elements. By identifying the building blocks, we intend to identify effective

strategies that can enhance or prevent deterioration of CX performances, offering managers

practical guidance for improving their services.

CX Performance and its Trajectory

Understanding customer experience (CX) is paramount in today's business environment.

Lemke, Clark, and Wilson (2011) defined CX as the customer's "subjective response to the

holistic direct and indirect encounter with the firm." Importantly, customers evaluate CX based

on their entire experience with a firm, and this evaluation plays a significant role in shaping

customer relationship outcomes (Lemke, Clark, and Wilson 2011).

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While a significant portion of CX research has been customer-centric, there is an emerging pivot toward the service provider's perspective. This shift explicitly recognizes that services naturally involve *interactions* between customers and firms, resulting in subsequent evaluations (Fisk, Brown, and Bitner 1993; Ordenes et al. 2014). However, these two perspectives are often quite different in terms of the perception of CX. The firm-centric evaluation is what we term *CX performance*. Customer perception of CX is formed through the evaluation of service quality, which firms often find challenging to quantify. CX performance by contrast is a firm's holistic assessment of its service delivery and the impact it has on customers. As such, the value of the CX performance concept to firms is that it quantifies consumers' experiences and evaluations, supplying a foundation to assess and refine service quality.

As mentioned earlier, static assessment of CX or CX performance allows only a partial picture of their true nature. Indeed, studies on dynamic relationship management (e.g., Fader and Hardie 2010; Homburg, Steiner, and Totzek 2009; Netzer, Lattin, and Srinivasan 2008; Rust and Verhoef 2005; Zhang et al. 2016) provide foundational insights into how a service providers' CX performance evolves. Building on this, Netzer, Lattin, and Srinivasan (2008) and Zhang et al. (2016) emphasize the temporal shifts in customer evaluations and their subsequent impact on firm performance. Wolter et al.'s (2019) research underscores the significance of trajectories within firms. They explore the influence of employee trajectories on customer experience quality, asserting that these trajectories can both enhance and diminish customer experience. Further, they highlight the correlation between employee satisfaction trajectories and customer satisfaction, emphasizing the evolutionary and dynamic nature of satisfaction for both employees and customers.

CX, with its inherent dynamism and trajectory, shapes customer perceptions, evaluations,

and the evolution of firm performance over time . It is against this backdrop that we introduce

the *CX performance trajectory*. This term describes the evolutionary patterns of a firm's CX

performance over time. Drawing from the dynamic relationship and trajectory-related literature,

we illuminate the evolving nature of a firm's CX performance. This trajectory delineates: (1) The

firm's interpretation over time of its aggregated customer evaluations as a reflection of the

execution of its CX activities; (2) The accumulation over time of customer evaluations across

continuous interactions with service providers, and (3) The reflection of consumers' perceived

service quality and overall satisfaction, shaped by the dynamics they recognize. As such, this

approach takes in the perspectives of both consumers and firms.

We underscore here the importance of understanding a firm's CX performance trajectory.

This trajectory captures the multifaceted nature of CX performance, detailing the different stages

firms navigate through and the transitions between these performance levels. Equally important

are the mechanisms that firms utilize to manage these transitions to enhance or prevent

deterioration of CX performances, discussed below.

The Extended TCQ Framework

We delve into five critical ideas in this subsection. First, we begin by presenting the

foundational TCQ nomenclature as proposed by De Keyser et al. (2020). Second, to enrich the

touchpoint components within the TCQ framework, we integrate the ARC value creation

elements. Third, to further enhance the framework, we incorporate CX dimensions, resulting in a

more comprehensive understanding of the framework. Fourth, we emphasize the elevated status

of quality elements, differentiating between two distinct quality types: functional and

experiential. Five, we conclude by presenting the elements of our expanded TCQ framework,

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elaborating on the interaction effects between quality elements and other elements.

The Touchpoints, Contexts, and Qualities (TCQ) Nomenclature

The TCQ perspective is the keystone of the CX performance trajectory. A touchpoint can

be a person, a physical entity, or a combination thereof, and it can occur at any stage of the

customer journey (Bolton et al. 2014; De Keyser et al. 2020; McColl-Kennedy et al. 2015;

Verhoef et al. 2009). Touchpoints may be controlled by third parties, such as customers or

influencers (Lemon and Verhoef 2016). However, we focus here on firm-controlled touchpoints

(Verhoef et al. 2009) since these are where managers can have the most impact.

Contexts (situational states in which customers interact with the service provider)

markedly affect touchpoint experiences (Bettencourt 2014; Chandler and Vargo 2011;

Thompson, Locander, and Pollio 1989). Drawing on De Keyser et al. (2020), we categorize

context as internal or external. External context elements include social, market, and

environmental factors, while internal context elements include cognitive, emotional, sensory,

social, and physical factors (Bolton et al. 2014; Gentile, Spiller, and Noci 2007; Lemke, Clark,

and Wilson 2011; Verhoef et al. 2009). An internal context reflects the transient personal state of

the focal customer at the touchpoint (De Keyser et al. 2020, pp. 440-1; Sandström et al. 2008),

and can therefore be multidimensional.

Qualities capture attributes reflecting customers' responses to interactions with service

providers (De Keyser, Schepers, and Konuş 2015; De Keyser et al. 2020; Keiningham et al.

2020). De Keyser et al. (2020) conceptualize CX qualities as participation level (high/low

involvement), time flow (duration and dynamic), valence (negative, positive, indifferent), and

ordinariness (ordinary, extraordinary). We specifically focus on the valence of CXs in

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developing an extended TCQ framework.

In summary, we focus on firm-controlled touchpoints, where the internal context components relate to customers' perceptions of CX, external context includes environments (e.g., time or place), and qualities capture customers' responses and reactions to touchpoints and contexts. We next introduce the ARC value creation elements, to enrich the conceptualization of firm-controlled touchpoints in the TCQ nomenclature.

Integrating the TCQ Nomenclature with ARC Value Creation Elements

Ordenes et al.'s (2014) ARC framework process-oriented perspective illustrates how a customer's holistic perception of their service provider's activities and resources is embedded in the interaction context. This includes personal elements that the service provider cannot always control. Consequently, it is important to holistically examine the CX context (Lemke, Clark, and Wilson 2011). The ARC value creation elements offer a practical architecture for service companies to manage their CX performance.

By integrating the ARC elements with the TCQ nomenclature, we respond to Becker and Jaakkola's (2020) call for an atomistic understanding of CX. This approach increases the actionability of CX management (CXM) as it delineates what services firms should monitor. Because TCQ touchpoints reflect an array of individual contacts between firms and customers that are critical to CX formation, they can be combined with the ARC perspective's activities and resources. Hence, a customer will assess (by referencing a set of qualities) the service provider's activities and resources in the touchpoint interaction.

Note that the ARC and TCQ frameworks both refer to context. ARC defines the main contextual elements affecting the CX as situational and personal factors; TCQ considers

contextual factors to be related to individual, social, market, and environmental influences. Our

integration of the ARC and TCQ perspectives gains parsimony advantages by recategorizing the

specific ARC contextual elements as elements of the TCQ's internal or external contexts. The

internal context refers to the personal/individual state of the focal customer at various

touchpoints along the CX performance trajectory. The external context refers to situational,

social, or environmental conditions that are composed of broader externalities and include all the

factors specific to a certain time and/or place throughout the CX performance journey. Internal

context is, we suggest, also important to the multidimensionality of CX, which we discuss next.

Integrating the Multiple Dimensions of CX

To enrich the theoretical insights of the internal context in our extended TCQ framework,

we integrate Lemon and Verhoef's (2016) multidimensional conceptualization of CX. The

constituents of experience are much debated in the CX literature (see Brakus, Schmitt, and

Zarantonello 2009; De Keyser, Schepers, and Konuş 2015; Schmitt 1999; Verhoef et al. 2009)

but there is some consensus on the inclusion of customer's cognitive, emotional, sensory, social,

and physical responses to interactions with a service firm (e.g., Lemon and Verhoef 2016). In the

current research, we draw on previous contributions to specify the dimensions of CX from the

focal customer's point of view. We assert that individually subjective responses to service

encounters, categorized as multiple dimensions of perceived CX, can be seen as the internal

contextual components for each focal customer.

We thus propose that four dimensions of CX should be holistically considered when

measuring these internal context components. These are: (1) Emotional CX, including valence

and emotional arousal responses (Marinova, Singh, and Singh 2018; Yin, Bond, and Zhang

2017) in line with De Keyser et al. (2020)'s psychological factor, suggesting that mood can deeply affect experience; (2) Cognitive CX, including thinking and intellectual responses, aligning with what De Keyser et al. (2020) say about forming opinions; (3) Social CX, including affiliation and relational responses, reflecting what De Keyser et al. observe about the influence of culture and groups; and (4) Physical CX, including sensory and behavioral responses, in line with De Keyser's mention of the physical factor.

Repositioning the Quality Elements

Our most significant addition to the TCQ framework focuses on the quality element, highlighting customer responses as output-based attributes, including valence (whether positive or negative) and extraordinariness (as exemplified by customer feedback descriptors like *incredibly perfect* or *amazingly awesome*). Essentially, our extended TCQ framework views *quality elements* through the lens of consumer evaluations. Consumers form these assessments based on their perceived activities, available resources, experienced CXs, and interpretations of external contexts. Within our study, we categorize these into two categories: functional qualities (related to activities, resources, and the external context) and experiential qualities (associated with four dimensions of CX). We particularly spotlight attributes of valence and novelty within these quality categories. To clarify, we consider both the valence and extraordinariness attributes of functional quality elements as well as those attributes of experiential quality elements. Finally, to underscore their significance, we have given Qualities a heightened position relative to the Touchpoints and Context elements. This repositioning is meant to accentuate the interaction effects between quality attributes and the other components, discussed next.

The Extended TCQ Framework

Our extended TCQ framework integrates nine building blocks of TCQ nomenclature combined with the ARC value creation elements and the multidimensional CX perspective. By locating the two elements of qualities (functional /experiential qualities) on a different plane to touchpoints and contexts, we show how qualities interact with elements of the others to drive a low CX performance state to a high one. The seven other elements (activities, resources, external contexts, and the four dimensions of CXs) potentially generate 21 three-way interactions with the elements of qualities. However, we limit our focus to seven critical interactions: functional qualities*activities, functional qualities*resources, experiential qualities*emotional CX, experiential qualities*social CX, experiential qualities*cognitive CX, experiential qualities*physical CX, and functional qualities*external context. We justify this choice in the following section.

Figure 1 illustrates the CX performance trajectory. This encompasses various levels of CX performance states, the transition pathways between these distinct performance states, and our extended TCQ framework, which incorporates nine building blocks/elements. The diagram also highlights the interaction effects among these elements, serving as mechanisms that influence the transitions between performance states. This extended TCQ framework can provide service providers with a clear map of their CX performance states. Next, by applying HMM, we identify main outcomes of CX performance states and the pathways to reach them. Additionally, we pinpoint effective strategies that can enhance or prevent deterioration of the CX performances, offering managers practical guidance for improving their services.

【Insert Figure 1 about Here 】

METHODOLOGY

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Modeling the Service Firms' CX Performance Trajectory

The Hidden Markov Model (HMM) empirically captures the dynamic migration patterns of latent states (Netzer, Lattin, and Srinivasan 2008). Researchers have used this approach to examine marketing effects on client product awareness (Montoya, Netzer, and Jedidi 2010) and explore how pricing influences B2C (Zhang, Netzer, and Ansari 2014) and B2B relationship states (Zhang et al. 2016). This implies the HMM can effectively represent service firms' CX performance states.

We used the building blocks from our TCQ framework to explain firms' migrations between CX performance states. Consequently, we determined the relative influences of all elements for each migration path and identified the most effective component combination for a given path. We could thus identify the particular *mixture* of components that improved or prevented deterioration of CX performance. We examined the CX performance dynamics of hotels through a non-homogeneous HMM where overall customer rating scores defined the particular states. This approach simultaneously captured the rating dynamic and the effects of the positive or negative mechanisms migrating firms' CX performance. In the HMM, CX trajectory elements had regime-shifting effects on the rating score and hence on CX performance states, thereby capturing their strategic effectiveness. The HMM states, not known a priori, represented varying levels of CX performance in customers' rating scores. Firms stochastically transition between these states through a first-order Markov process as a function of the TCQ elements. Please reference Web Appendix B.1 for the detailed mathematical foundation and the components of the Hidden Markov Model (HMM) that underpin our analysis, including the initial state distribution, transition probabilities, state-dependent distribution, and the likelihood

functions.

Moreover, our control function approach (Petrin and Train 2010; Villas-Boas and Winer 1999) reduced potential endogeneity in the CX trajectory elements. We ran a first-stage linear regression of the TCQ elements on three instrumental variables relating to the hotel: its star rating, inclusion in a chain, and average room rate (one night, two adults). These variables were both relevant and exogenous in that they were outside the unit of analysis (individual customer's level) (Kennedy 2008). Next, we incorporated the residuals from the first-stage regression as additional control variables.

Data Description

We used two longitudinal datasets of customers' verbatim textual reviews to develop the HMM (Web Appendix B.2-B.3 justifies use of textual data). We scraped consumers' online reviews and rating scores at two time periods from a hotel reservation site (Booking.com) for hotels in New York city (U.S.A.).

The first data collection period, from June to December 2019 (preceding the outbreak of the COVID-19 pandemic), resulted in 408,553 comments. The second period, from January 2020 to September 2022, covers the pandemic (2020 and 2021) and post-pandemic (from 2022 onward) periods and resulted in 451,151 comments from 616 hotels. We used pre-pandemic textual data to develop the custom dictionaries and then tested their validity using both pandemic and post-pandemic data.

Our analysis started by converting unstructured textual data (UD) into numeric values (Marinova, Singh, and Singh 2018; Singh, Marinova, and Singh 2020). We integrated them with Berger et al.'s (2020) guidelines which led us through dictionary-based analysis via text

extraction, dictionary development, the examination of the internal and external validity of the

developed dictionary, and the production of text analysis metrics.

Text Mining and Dictionary-Based Analysis

We started with text mining, the process of extracting meaningful patterns and trends

from large amounts of text (Feldman and Sanger 2006, p. 1). Dictionary-based analysis in text

mining involves analyzing texts using a predefined set of words or phrases with the aim of

identifying and measuring the presence of these terms to extract insights. Since data sets are

discrete, this requires custom-built, rather than standard, dictionaries (Humphreys and Wang

2017). To analyze our extended TCQ framework, we employed both a custom (for five elements:

activities, resources, external contexts, functional qualities, and experiential qualities) and a

standard (for four elements: emotional CX, social CX, cognitive CX, and physical CX)

dictionary. By referencing Singh, Marinova, and Singh (2020), Marinova, Singh, and Singh

(2018), Balducci and Marinova (2018), Humphreys and Wang (2017), Rocklage, Rucker, and

Nordgren (2018) and Perreault and Leigh (1989), we created a four-step process for custom

dictionary development and validation (Table 1).

【Insert Table 1 about here】

Our first step was to formulate a coding schema congruent with our extended TCQ

framework. We gave two coders (A and B) a random sample of 300 reviews from our dataset.

Both coders were given a set of general coding instructions directing them to independently

identify words or phrases resonating with hotels' activities, resources, external contexts, and

functional quality attributes (activities, resources, and external environments). We also asked

coders to identify quality attributes related to dimensions of customer experiences, such as

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emotional, social, cognitive, or physical CX, which did not align directly with quality attributes. The coding instructions also applied part-of-speech tagging. For instance, verbs were tagged to activities, nouns to resources, adjectives to qualities, and prepositions (as well as temporal or locative words) to external contexts. (Web Appendix B.4 gives more detail about the coding instructions).

To prepare the coders (A and B), we asked them to analyze 50 of the 300 sample reviews as training sessions based on the coding instructions we provided. We iterated through phases of categorizing, review, and further category building until the coders were clear on the principles for assigning data. Then, coders A and B went on to code the remaining 250 sample reviews. During the main data coding, meetings between coders A and B were scheduled to resolve discrepancies. Finally, we conducted inter-reliability checks and, after three iterations, arrived at a .88 Kappa coefficient, comfortably exceeding the recommended threshold of .7 (Bowers and Courtright 1984; Cohen 1960; Fleiss 1981). This intensive process yielded a coherent coding schema spanning the five pivotal elements in our augmented TCQ framework: (1) hotels' activities, (2) resources provided by hotels, (3) the external contexts of hotels, (4) functional qualities related to hotels' activities, resources, or external contexts, and (5) experiential qualities related to CXs.

In our second step, we drew a list of words and phrases from customers' verbatim texts (408,553 comments from June to December 2019) and used WordStat 9 natural language processing (NLP) software (WordStat 9) to mine our textual data set. The list contained 1,690 words and phrases for utilization in the next step of developing a custom dictionary encompassing the five TCQ elements.

Our third step was to develop a custom dictionary anchored in the coding schema from

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Step 1. To this end, we enlisted two new coders (C and D) and gave them training in how to classify various words and phrases. Coders C and D then sorted our dataset (1,690 words/phrases extracted in Step 2) into the five categories based on the coding schema (developed in Step 1). Whenever Coders C and D encountered discrepancies in their categorizations, a collaborative discourse ensued – involving one of the authors when necessary – to ensure alignment in their interpretations and classifications. After multiple iterations, we arrived at a 93% agreement rate representing strong category reliability (Bowers and Courtright 1984; Fleiss 1981; Landis and Koch 1977). This endeavor culminated in our custom dictionary See the Web Appendix B.5, Table B.1 for the coding schema (in blue) and the resultant dictionary (in yellow). Table B.2 details our custom dictionary.

The fourth step evaluated the validity of our custom dictionary. We invited two industry experts (Coders E and F) to review the words and phrases under each of the dictionary's five categories, leveraging their practical experience. The average agreement rates between Coders E and F were as follows: 96% for activities, 98% for resources, 96% for external contexts, 92% for experiential qualities, and 94% for functional qualities. Since these percentages surpass the recommended level (.90) (Rust and Cooil 1994), they support the face validity of our dictionary. We made changes based on Coders E and F's disagreements before moving to the next validation task, in which we leveraged Weber's (2005) saturation approach to ensure constructs in our dictionary were valid. We implemented the saturation method by sampling 20% of words/phrases from each category. Coder G then independently assigned these to the appropriate categories. After calculating each category's accuracy rate, any rate below 100% led to discussions with Coder G about potential reassignments. This process was iterated a minimum of five times, ensuring that all words/phrases in the dictionary were correctly categorized by Coder

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G, achieving our 100% accuracy benchmark.

Since our data collection spanned the disruptive period caused by COVID-19 pandemic, we examined the temporal consistency of the customer dictionary (Berger et al. 2020; Netzer et al. 2012). Our approach, confirmatory factor analysis, assessed the temporal consistency of our custom dictionary during the following periods: pre-pandemic (Jun – Dec 2019), pandemic (Jan 2020 – Dec 2021), and post-pandemic (Jan – Sep 2022) periods. We transformed textual data in these three sub-datasets into numerical form using LIWC software. This yielded a dataset suitable for confirmatory factor analysis, comprising five elements. Each element had three measurements: one from the pre-pandemic period, one from the pandemic period, and one from the post-pandemic phase. The factor loadings of the three measurements suggest that five elements remained consistent throughout different periods (see Web Appendix C.1), supporting the construct validity of the custom dictionary.

Guided by the recommendations of Humphreys and Wang (2017), we further explored the external validity of our dictionary. To do this, we employed a separate dataset comprising 202,546 comments from Trip Advisor, which pertained to 616 NYC hotels collected from January to July 2023. Our analysis, detailed in Web Appendix Table H.2, revealed patterns consistent with those observed in our Booking.com dataset presented in Table 3, supporting the external validity of our custom dictionary.

In our research, the first four steps focused on creating and validating a custom dictionary, targeting consumers' perceptions tied to firms' activities, resources, external settings, and both functional and experiential qualities. It is essential to understand that while these steps were geared toward our custom dictionary for categories not present in standardized ones, Step 5 diverged. It leaned on an established dictionary, LIWC 2022 (Boyd et al. 2022; Pennebaker et al.

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2015), to measure internal context elements, drawing from the four CX dimensions in our enhanced TCQ framework: emotional, social, physical, and cognitive CXs. Warriner, Kuperman, and Brysbaert (2013) deepened the emotional aspect by providing an expanded emotional lexicon. To guarantee precision, LIWC assessed: cognitive CX, centering on insights; social CX, emphasizing behaviors and referents like communication and familial ties; physical CX, focused on visual or auditory perceptions; and emotional CX, gauging both positive and negative sentiments in text tone. To enrich our emotional vocabulary, we integrated 289 unique affective words from Warriner's study. One key distinction in our work lies between experiential quality and internal context elements, especially concerning emotional CX. We used our custom dictionary for the former and LIWC for the latter. To maintain clarity, shared words between the dictionaries, such as "amazing" and "happy," were categorized under 'experiential qualities related to CX' and excluded from LIWC's software. This meticulous approach refined our textual analysis and elucidated the intricate aspects of our extended TCQ framework.

In Step 6, we transformed large amounts of unstructured text data into structured, numeric formats using the LIWC 2022 software, known for its precision in text analysis. LIWC matches each word or phrase in the input with its dictionary, assigning a category score based on the percentage of matched words. For instance, a Positive Emotions score of 4.20 in a blog means 4.20% of its words convey positive sentiments. Using both standard and custom dictionaries, we converted review comments into ten main output variables for each review: (1) Activities, (2) Resources, (3) External Contexts, (4) Functional Qualities, (5) Emotional CX, (6) Cognitive CX, (7) Social CX, (8) Physical CX, (9) Experiential Qualities, and (10) the associated consumer rating.

Our resulting dataset comprising 727,266 data points from June 2019 to September 2022,

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underwent cleaning to weed out missing values. We then aggregated the data, first to a weekly

and subsequently to a monthly level. The culmination of this effort yielded two datasets: a

weekly set with a commendable 92,569 data points, and a more consolidated monthly dataset

with 22,616 data points. Both were chronologically organized, providing a comprehensive view

of the hotel reviews over the said period.

Our approach to data aggregation was shaped by a twofold rationale. First, the granularity

of our aggregation served a dual purpose in that we could zoom into micro-trends while also

efficiently working with an expansive and manageable dataset (Lemon and Verhoef 2016;

Schweidel et al. 2022). Second, our aggregation increased accuracy and representativeness. The

aggregation at weekly and monthly intervals painted a holistic view of the CX landscape from a

firm's point. This method showcased the intricate interplay of hotel activities, resources, and

external contexts in shaping CX outcomes (Meyer and Schwager 2007).

We performed an intraclass correlation (ICC) to test the potential for data aggregation.

The ICC(1) estimates the proportion of total variance in the data attributable to between-group

differences. Higher values indicate the within group similarity of individual observations, and so

support data aggregation. The ICC(2) measures the reliability of the groups' mean scores whilst

accounting for both the between-group and within-group differences. Higher values indicate the

reliability of the aggregated data thereby supporting aggregating individual data points (McGraw

and Wong 1996). For the weekly dataset, the ICC(1) and ICC(2) for 168 weeks ranged from .63

to .85, and from .69 and .92, respectively. For the monthly dataset, the ICC(1) and ICC(2) for 40

months ranged from .38 to .62, and from .53 and .95, respectively. The average ICC(1) index for

the weekly and monthly datasets were .74 and .42, respectively. Since both exceed .25, our data

was suitable for data aggregation (LeBreton and Senter 2008). Furthermore, since the ICC(2) for

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the weekly dataset was .81 and for the monthly dataset was 0.78, both values exceed the .70

threshold for data aggregation (LeBreton and Senter 2008).

Finally, we considered the discriminant validity and predictive capability of all focal

elements. An analysis of the correlation matrices for the nine variables (Table D.1 of Web

Appendix D) showed that our constructs possess discriminant validity (Berger et al. 2020). Next,

we used regression analysis to consider predictive performance. We examined the extent to

which our nine text-based categories (nine elements) anticipated a key performance metric: the

rating scores (see Web Appendix D, Table D.2). Our findings effectively supported an

association between our text-based categories and the rating scores, providing a robust validation

of the predictive performance of our approach.

RESULTS

Firms' CX Performance Trajectories: Identifying the Number of CX Performance States

With no a priori knowledge about the number of service firms' CX performance states,

we estimated two- to five-state models with the full set of migration strategies, and selected the

one that offered the best fit by reference to AIC, BIC (Bartolucci, Farcomeni, and Pennoni 2014)

and CAIC (Netzer, Lattin, and Srinivasan 2008). Both the AIC and SAIC suggested an HMM

with three hidden states for the weekly dataset. To assess the extent of dynamics and

heterogeneity, we performed model comparisons and robustness checks (see Appendix E, Table

E). If the CX performance states are dynamic, then we would expect a better fit from HMMs

than from static latent class segmentation. The fact that the AIC, BIC, CAIC, and SAIC values of

the latent class model were a worse fit than those of the HMM model supports this assertion. To

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determine whether the path migrations were random or were influenced by the nine elements in

the CX performance trajectory, we conducted the model fit test. Our test showed a worse fit for a

set of HMMs without a variable specification in the transition matrix. Therefore, we concluded

that our set of nine TCQ elements explains the migrations of CX performance states. For

completeness, we tested HMM and latent class models under differing states. While the models

produced a better fit with an increasing number of states, the final decision on model

specification depended on the interpretability of the dynamics of the CX performance states and

their sizes. We also considered alternative model specifications (a regression model and an

ordinal logit model) and the fit was worse than the three-state HMM model. Finally, we repeated

the model comparison processes for the monthly dataset. We concluded that the three-state

HMM model also fitted that data better than alternative specifications. This battery of model

comparisons and robustness checks gave us confidence that our model parsimoniously captures

the dynamics of the CX performance trajectory, identifies the number of CX performance states,

and properly specifies the migrations among performance states.

Table 2 presents the results for the HMM for three levels of performance state at the

weekly level. Note that the customers' rating scores are associated with substantial differences in

the three states. For ease of discussion, we refer to the three CX performance states as low,

medium, and high (L, M, H), which correspond to CX performance scores of 3.42 (L state), 6.18

(M state), and 9.52 (H state) respectively. We used latent class analysis to describe the main

characteristic of each state with reference to the building blocks of the CX performance

trajectory. From Section A of Table 2, we see that the most prominent negative influencers for

the L state appear to be the experiential qualities and social CX elements. Conversely, the M

state prominently features positive influences from resources, emotional and social CX elements,

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and experiential qualities. Lastly, the H state is predominantly characterized by the experiential

qualities, functional qualities, and both the emotional and social CX elements.

【Insert Table 2 about here】

Table 2, Section B, shows the initial probabilities of a hotel being in a specific CX

performance state. Section C shows the probabilities of the performance migrating to a different

state (state stickiness). The probability of stickiness for the L state is 44% and the probability of

migration from this state is 56%. The stickiness probability of M state is 78.10%, and the

probabilities of upward and downward migrations from this state to high state and low state are

11.16% and 10.75% respectively. Finally, the stickiness probability of H state is 67.34%, and the

probability of migration from this state is 32.66%. Therefore, even if a service firm achieves an

H state, it can relatively easily migrate downwards. The L state is somewhat transitory, meaning

that firms can readily migrate to a higher state as long as they know the mechanisms that will

achieve this. This is what we discuss next.

The Influence of Nine TCQ Elements on CX Performance Dynamics

Table 3 shows how the TCQ elements cause firms to switch among performance states

(See Web Appendix F for details).

【Insert Table 3 about here】

It is essential, however, to consider interaction effects among the basic components when

evaluating firms' CX performance. We therefore controlled the 9 basic elements in Model 2 with

the goal of examining the interaction effects for (1) functional qualities*activities, (2) functional

qualities*resources, (3) functional qualities*activities*resources, and (4) functional

qualities*external contexts. We chose these interactions because they help determine if better

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resources/activities/external context improve CX performance, with implications for firms'

strategic resource allocation. We also examined (1) experiential qualities*emotional CX, (2)

experiential qualities*social CX, (3) experiential qualities*cognitive CX, and (4) experiential

qualities*physical CX because these interactions shed light on how different aspects of CX

influence firms' CX performance dynamics. Finally, we examined the interactions between

elements that firms can directly control (resources and activities) and consumers' internal

contexts (four dimensions of CX). That is, (1) activities*resources*emotional CX, (2)

activities*resources*cognitive CX, (3) activities*resources*social CX, and (4)

activities*resources*physical CX. Understanding these interactions can guide hotel resource

allocation, CX improvements, and ultimately CX performance **(**see Web Appendix G for results

of this analysis).

As an additional robustness check, we examined a monthly-level dataset (22,616

aggregated data points) with reference to our other customer dataset (727,266 unique and non-

aggregated data points). Results show that individual-level and aggregated monthly-level

datasets express similar patterns to those of the weekly-level dataset (see Table H.1 in Web

Appendix H.1).

Additionally, we applied both our customized and standardized dictionaries to a new

dataset comprising 201,546 textual reviews from 616 hotels in NYC. These reviews, sourced

from TripAdvisor, span from January to July 2023. After converting text to numerical values, we

aggregated the data at the weekly level, resulting in 18,480 aggregated data points. The findings

(see Web Appendix H.2, Table H.2) from this sample align closely with the results presented in

Table 3 for the weekly data points on Booking.com.

We identified two interesting patterns from our findings. First, the interactions among

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activities, resources, and qualities can be used as prevention mechanisms to decrease firms'

downward migrations. Specifically, functional qualities*activities*resources (a three-way

interaction) exerts larger effects than functional qualities*activities and functional

qualities*resources (two-way interactions). Second, the three-way interactions between activities

and resources and the four internal contexts (dimensions of CX) effectively act as a promotion

mechanism, which can increase firms' upward migrations. Specifically, to migrate from an L to

an M state, activities*resources*social CX exerts a greater effect than the other combinations.

We suggest both activities*resources*emotional CX and activities*resources*social CX to

migrate from M to H state. We recommend using activities*resources*emotional CX and

activities*resources*physical CX to migrate from an M to an H state.

Hypothetical Scenarios Analysis

【**Insert Table 4 about here**】

Next, we examined the performance of the promotion and prevention mechanisms in

more detail. We started by running a series of hypothetical scenarios featuring a one-standard

deviation increase in the elements contributing to each migration path. For the prevention

mechanisms, we tested the likelihood of the three strategies identified in Table 3: (1) functional

qualities*activities, (2) functional qualities*resources, and (3) functional

qualities*activities*resources, decreasing the downward migration paths (from M to L, H to M,

and H to L states). To explore the promotion mechanisms, we tested the likelihood of the four

strategies from Table 3: (1) activities*resources*emotional CX, (2) activities*resources*social

CX, (3) activities*resources*cognitive CX, (4) activities*resources*physical CX, increasing the

upward migration paths (from L to M, M to H, and L to H states). As Table 4 shows, increasing

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various combinations of the components boosts the likelihood of firms moving to a higher

performance state (to a greater or lesser degree) and decreases the likelihood of them dropping to

a lower state (again, to a greater or lesser degree). The effect on downward migration (from an M

to an L, and from an H to an M state) is most pronounced under small increases of functional

qualities*activities*resources. The effect on upward migration (from M to H and from L to H) is

particularly apparent under small upward increments in activities*resources*emotional CX and

activities*resources*social CX. Figure 2 summarizes the results from Tables 2-4.

【Insert Figure 2 about here】

GENERAL DISCUSSION

In this work, we extend the TCQ nomenclature (De Keyser et al. 2020) by integrating the

ARC model (McColl-Kennedy et al. 2019; Ordenes et al. 2014) with a multidimensional CX

perspective (e.g., Lemon and Verhoef 2016), and incorporating a dynamic perspective to model a

CX performance trajectory (e.g., Wolter et al. 2019; Zhang et al. 2016). We model our

framework with a novel naturalistic data set collected through web crawling, which we mine for

meaning using standard and customized dictionaries. We capture service firms' CX performance

trajectories using 727,266 verbatim comments made by guests about New York hotels on the

reservation website Booking.com, focusing on three CX performance states: low (L), medium

(M), and high (H), represented by rating scores of 3.42, 6.18, and 9.52, respectively. We identify

six fundamental migration paths between three performance states (L, M, and H), and the

promotion and prevention mechanisms that are significantly effective across these six migration

paths.

Our findings demonstrate four promotion mechanisms: activities*resources*emotional

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CX, social CX, cognitive CX, and physical CX. We also surface three key prevention

mechanisms: functional qualities*activities, functional qualities*resources, and functional

qualities*activities*resources. Additionally, we identify elements that operate on specific

migration paths. Our study has both theoretical and managerial implications, discussed next.

Theoretical Contributions

Drawing on Wolter et al.'s (2019) nuanced appreciation that trajectories over time are of

greater import than static snapshots, our extended TCQ framework expands the understanding of

how elements of trajectories dynamically influence the overall CX trajectory in an industry. Our

engagement with the work of Wolter et al. (2019) accentuates the trajectory-centric paradigm.

Their exploration of employee satisfaction trajectories and resulting customer satisfaction sheds

light on the importance of adopting a dynamic methodology. Our research augments these

insights by surfacing how determinants, especially within the hotel industry, dynamically sculpt

overall CX trajectories. Moreover, we amplify the narrative initiated by scholars like Zhang et al.

(2016) through our nuanced identification and analysis of promotion and prevention

mechanisms.

Our study also engages with the perspective proposed by Harmeling et al. (2015).

However, while they sketch a broad outline of the customer-firm relationship trajectory, we flesh

out specific details. Our focus is on discerning how distinct CX building blocks and their

multifaceted interactions shape trajectories. While Harmeling et al. (2015) perceive trajectories

as separate instances of customer-firm interactions, be they positive or negative, our study

encapsulates both dimensions, providing a more comprehensive perspective.

Furthermore, our effort to interweave our findings with those of Ye et al. (2022) and

McColl-Kennedy et al. (2019) showcases the depth and breadth of our research. McColl-Kennedy et al. (2019) presented a blueprint featuring seven value-creation elements, spanning resources, activities, context, interactions, and customer roles, alongside cognitive responses and discrete emotions across the customer journey. Their value-creation elements and our nine building blocks for the CX performance trajectory support each other, painting a vivid picture of both the customer and the firm's CX performance journeys. Ye et al. (2022) propose an analytical structure enabling service managers to sift through online reviews for competitor identification, leveraging vast customer feedback from platforms like Ctrip.com. This fusion of online reviews and competitor identification in service sectors, coupled with our methodological approach of textual review analysis through the HMM model, offers fertile ground for CX researchers and service firms. These insights enable the virtually real-time gleaning of knowledge from customer feedback, spotlighting customers' pivotal concerns, tracking firms' performance, safeguarding firms' service quality, and crafting strategies. Together, these contributions substantially elevate the discourse on CX and service performance management.

Additionally, the promotion and prevention mechanisms identified in our research touch on a novel domain. That is, these findings extend foundational psychological theories like Herzberg's two-factor theory (Herzberg 1968) and the regulatory focus theory (Higgins 1997) from the individual to the organizational realm. Traditionally, these theories have been confined predominantly to understanding individual psychological states, motivations, and behaviors. We have, however, employed these principles to elucidate the strategic underpinnings that drive firm decisions, especially in the context of CX analytics. Herzberg's two-factor theory traditionally posits that individual satisfaction is determined by two sets of factors: hygiene factors (which, when absent, cause dissatisfaction) and motivators (which, when present, drive satisfaction).

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Drawing a parallel to our findings, firms' CX performance trajectories can be seen through a similar lens. The prevention mechanisms that we identified act as organizational *hygiene* factors. When firms invest strategically in these elements, they prevent performance deterioration, mirroring the role of hygiene factors at the individual level. On the other hand, the promotion mechanisms function as organizational *motivators*, enhancing the firm's CX performance when adequately harnessed. The regulatory focus theory traditionally speaks to the psychological orientations of individuals: promotion focus (aspiring and achieving) and prevention focus (maintaining and avoiding losses). Our research translates these individual orientations into an organizational context. We propose that firms, like individuals, exhibit a promotion or prevention focus in their strategic thinking. Firms emphasizing prevention mechanisms, such as those we have identified, showcase an organizational prevention focus. They prioritize averting pitfalls, especially when migrating from higher-performance states. On the contrary, those focusing on promotion mechanisms exhibit an organizational promotion focus, aspiring to elevate their CX performance.

Finally, within the expansive domain of service research, our study heralds a unique blend of the Hidden Markov Model (HMM) with the TCQ components that frame the CX performance trajectory. While the HMM (a prominent state-sequence modeling technique) has found application across domains, pairing it with our refined TCQ framework is a novel endeavor in the services research field. This combination provides a nuanced lens to explore customer experiences over time, adding depth to current understanding. Specifically, the HMM aids in differentiating underlying states in CX performance trajectories, capturing temporal shifts and intricate dependencies. Further, our extended TCQ framework provides a structured way to navigate these trajectories, effectively translating extensive textual data into meaningful insights.

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While our methodology is influenced by the growing trend of text mining in both marketing and service research, it is vital to highlight our unique position in this landscape. Previous contributors like Chung et al. (2022) have utilized text-mining techniques in specific areas, such as understanding Airbnb host motivations. Similarly, Jedidi et al. (2021) have adopted text-mining to devise a marketing terms dictionary, primarily centering on topic extraction. Our approach dives into the intricate dynamics of customer experiences over time and through various states. Our methodology captures evolving patterns within customer feedback. Employing HMM and the TCQ framework offers more than a snapshot of customer feedback. This hybrid presents a dynamic view, tracing the undulating landscape of customer sentiments and perceptions. This focus on evolution, temporality, and trajectories distinguishes our research from the broader realm of text-mining studies in the literature.

Managerial Implications

Our findings provide practitioners with valuable and immediately actionable insights to accelerate improvements in their firms' CX performance. By breaking down the CX performance trajectory into three distinct performance states, small actionable building blocks, and migration paths among the performance states, we establish a practical foundation for CX design and management of a firm's CX performance. First, our findings equip managers with a useful tool for auditing their CX performance that can support both internal assessment and competitive benchmarking. Second, our empirical findings emphasize the importance of auditing for marketing strategies. A rigorous audit is essential for developing effective marketing strategies, as it answers the question, "Where are we now in terms of CX performance?" Such understanding readily translates into the design of CX improvement strategies tailored to a firm's

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specific circumstances.

Third, our research provides a roadmap for CX performance improvement. Our research insights not only help managers comprehend their current CX performance but also offer a roadmap for future growth. By analyzing transition probabilities and identifying the most desirable upward migrations, and the downward migrations to avoid, managers can determine the direction in which to pursue CX performance. Our approach therefore enables managers to approach CX performance improvement more effectively by focusing on state-specific migration strategies.

Fourth, our findings offer step-by-step guidance for achieving strategic CX goals. To answer the question, "How can we get there?" we propose a practical architecture that enables firms to design and facilitate their CX performance trajectories. Firms can follow our approach, leveraging our results from Tables 2, 3 and B2 in the Web Appendix to manage their CX performance trajectory for each migration path. The five-step approach is given next.

Step 1: Identify the current CX performance state by determining the firm's current CX performance state as low, medium, or high. This current state of understanding represents a baseline from which firms can identify areas for improvement. Step 2: Analyze transition probabilities of the firm moving between performance states whilst accounting for upward migrations (promotions) and downward migrations (preventions). Understanding these probabilities enables firms to prioritize which transitions to pursue and which to avoid. Step 3: Leverage strategic combinations by selecting the most suitable strategic combinations for promoting upward migrations or preventing downward migrations in the firm's CX performance trajectory. These combinations, given in Table 3, include qualities, activities, resources, and various types of customer experiences. By choosing appropriate strategies, firms can effectively

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target their efforts to improve CX performance. Step 4: Consult the dictionary of actionable

insights. This involves using the dictionary in Table B2 in the Web Appendix to find specific

words, phrases, and concepts associated with the strategic combinations chosen in Step 3. This

dictionary offers actionable insights for firms to enhance CX performance by identifying the

focal concepts, activities, qualities, and resources that contribute to a positive customer

experience. Step 5: Apply and monitor the chosen strategies. This involves implementing the

selected strategies and continuously monitoring their impact on the firm's CX performance

trajectory. It is important to regularly assess the effectiveness of these strategies and adjust them

as needed to ensure ongoing improvement and to adapt to changing market conditions.

Lastly, managers need to avoid making assumptions of a monotonic model of CX

performance. Instead, they should consider the possibility of different migration patterns of CX

performance. By using our model, managers can identify their CX performance transition across

different states over time and develop state-specific migration strategies (the promotion and

prevention mechanisms found in this current study). With our five-step approach and the

practical architecture we propose, firms have a clear roadmap to optimize their CX performance

trajectories.

【insert Table 5 about here】

Limitations and Future Research Avenues

Our research, while contributing valuable insights, has limitations that pave the way for

future investigation. First, our single-industry findings may not be fully generalizable. Future

research could delve into consumer reviews from various service sectors, employing our text

mining approach and HMM model to gain a more comprehensive understanding of CX

performance trajectories. Second, firms may differ in their state transitions, behaviors, and the number of states they encompass. Examining HMMs with varying state numbers, and factoring in both exogenous and endogenous elements would shed deeper light on CX dynamics. Third, another point of contention is our reliance on dictionary development for measuring CX. While dictionary methods are very useful for measuring specific constructs like concreteness, arousal, and problem-solving, we recognize that the CX construct is more nuanced. As such, the generalizability and adaptability of dictionary-based methods, when applied to CX, might be constrained. We call for future research to explore the potential of integrating machine learning (ML) techniques with our current dictionary method. The objective of this hybrid methodology is to combine the precision of dictionary approaches with the flexibility and scalability of ML. This merger promises to offer a dynamic and evolving means to probe complex constructs, such as CX. Lastly, we advocate for scholars to leverage data fusion, amalgamating various information sources like transaction data, CRM databases, and customer feedback, to paint a more holistic picture of customer service experiences and CX performance trajectories.

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TABLES

Table 1. Developing and Validating Our Custom Dictionaries

Steps	Actions	Outputs or Results

Step 1: Formulation of coding schema for the five elements that require a custom dictionary:
(1) Activities
(2) Resources
(3) External Contexts
(4) Functional Qualities
(5) Experiential Qualities
	Research Team:
	· Drew a random sample of 300 reviews.
	· Employed two coders: Coder A and Coder B.
	· Provided coding instructions and training session.
	
	Coders A and B conducted the manual annotation:
	· Identified words/phrases from the 300 sample reviews related to the five elements.
	· Involved in coder training sessions.
	· Held periodic meetings for clarification and consensus-building during the coding process.
	· Had iterative rounds of inter-rater reliability evaluations:
	  Targeted Cohen's kappa coefficient threshold of 0.70.
	  Achieved inter-rater reliability of .88.
		From 300 sample comments, we achieved a coding schema with five categories.
		· Activities (32 indicative words/phrases)
		· Resources (50 indicative words/phrases)
		· External Contexts (23 indicative words/phrases)
		· Functional Qualities related to activities, resources, and external contexts (27 indicative words/phrases)
		· Experiential Qualities related to consumer-perceived overall experiences (23 indicative words/phrases)

Step 2: Extraction of words/phrases from the pre-pandemic (June-December, 2019) textual dataset	We used WordStat 9 software for entity extraction to extract and identify the most frequently occurring words and phrases in our dataset (408,533 comments).	Generated an initial 1,690 words/phrases and cleaned the data by removing stop words and spell-checking.
Step 3: Development of a custom dictionary based on the established coding schema in Step 2, using the pre-pandemic dataset (June-December, 2019)	**Research Team:** · Enlisted two fresh coders: Coders C and D. · Provided coders' training. **Coders C and D conducted the categorization task:** · Categorized lists of words/phrases from the pre-pandemic dataset extracted in Step 1 into the five categories based on the coding schema developed in Step 2. · Conducted iterative checks for consistency throughout the classification. If discrepancies arose, engaged in discussions to achieve alignment in categorization. · Achieved a notable 93% agreement rate. · The remaining inconsistencies were addressed by direct intervention of the research team.	We arrived at a final custom dictionary, including five categories/elements: · Activities (172 words/phrases) · Resources (338 words/phrases) · External Context (181 words/phrases) · Functional Qualities related to the above three elements (273 words/phrases) · Experiential Qualities related to consumers' perceived experiences (97 words/phrases)
Step 4: Validity of the custom dictionary using separate datasets: pre-pandemic (June-December, 2019), pandemic (January 2020 - December 2021), and post-pandemic (January - September 2022), as well as a new dataset, collected from another platform (TripAdvisor's comments toward NYC hotels from January-July, 2023)	**Face Validity:** · Engaged two industry experts: Corders E and F. · Reviewed the five dictionary categories for congruence with real-world service lexicons. · Overall agreement: 0.93 average across categories. **Construct Validity-Saturation Approach (Weber, 2005):** · Executed by: Coder G. · Assessed 20% sample from each category. · Reassigned words/phrases to their fitting categories. · Went through the iterative process; halts once a 90% accuracy rate is achieved for a category. **Construct Validity-Temporal Applicability:** · Used Factor Analysis: To validate the temporal stability and consistency of the dictionary's categories over distinct periods. · Assessed dictionary's consistency across three phases: Pre-pandemic, Pandemic, Post-pandemic **External Validity- Humphreys and Wang (2017):** · Tested dictionary's validity across varied datasets · Introduced a new dataset: Trip Advisor reviews on NYC hotels (January-July 2023). · Confirmed dictionary's robust external validity.	We achieved face validity, construct validity, and external validity for the five categories in the custom dictionary.

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Table 2. HMM Results: Identified CX Performance States and Transition Probabilities

A. Service Firms' CX Performance States

Categories of States			Low (L)	Medium (M)	High (H)
Size of the States			24.04%	41.64%	34.32%
Indicator of CX Performance	**Rating Scores**		3.42	6.18	9.52
Nine Building Blocks of the CX Performance State	**(1)**	Activities	0.002	-0.006	-0.001
	(2)	Resources	0.004	0.005	-0.002
	(3)	External Context	0.002	-0.001	-0.007
	(4)	Functional Qualities	-0.017	0.002	0.011
	(5)	Emotional CX	-0.004	0.003	0.009
	(6)	Social CX	-0.029	0.008	0.021
	(7)	Cognitive CX	0.007	-0.015	-0.002
	(8)	Physical CX	-0.007	0.002	0.004
	(9)	Experiential Qualities	-0.010	0.008	0.017

B. Initial State Probabilities of Each CX Performance State

	Low (L)	Medium (M)	High (H)
	10.34%	48.54%	41.12%

C. Transitional Probabilities between States

		To Next State	
Move from the Previous State	Low (L)	Medium (M)	High (H)
Low (L) State	44.00%	30.66%	25.34%
Medium (M) State	10.75%	78.10%	11.16%
High (H) State	11.80%	20.86%	67.34%

Table 3. HMM Results: Effects among TCQ Elements on Distinct Migration Paths

Model 1 focused on and examined the effects of the nine basic components on firms' migration paths.	Upward Migration Paths			Downward Migration Paths		
	L→M	**M→H**	**L→H**	**M→L**	**H→M**	**H→L**
	Positive coefficients expected			Negative coefficients expected		
1 Activities	0.24	**2.13*****	**0.67****	-0.02	-0.01	-0.02'
	(0.18)	(0.58)	(0.23)	(0.05)	(0.01)	(0.01)
2 Resources	0.03	**0.26****	0.01	-0.02	**-0.06****	-0.01
	(0.02)	(0.01)	(0.01)	(0.05)	(0.02)	(0.01)
3 External Contexts	0.04	**2.47*****	0.09	-0.07	**-0.12*****	**-2.81*****
	(0.03)	(0.39)	(0.05)	(0.03)	(0.02)	(0.03)
4 Functional Qualities Related to Activities, Resources, or External Contexts	**0.28****	0.02	0.01	**-0.88*****	-0.04	-0.02
	(0.02)	(0.03)	(0.02)	(0.19)	(0.02)	(0.02)
5 Emotional CX	**0.11****	**0.31*****	0.02	**-0.06***	-0.01	-0.01
	(0.01)	(0.06)	(0.01)	(0.03)	(0.01)	(0.01)
6 Social CX	**0.15*****	**0.18*****	**0.12*****	**-0.07***	**-0.09****	**-0.10*****
	(0.03)	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)
7 Cognitive CX	0.01	0.02	0.02	-0.01	-0.02	-0.02
	(0.02)	(0.05)	(0.02)	(0.02)	(0.01)	(0.01)
8 Physical CX	0.03	0.02	0.03	-0.05	-0.05	-0.01
	(0.03)	(0.02)	(0.030	(0.04)	(0.03)	(0.01)
9 Experiential Qualities Related to CXs	**0.26****	**1.44****	0.08	-0.30	-0.13	**-0.05***
	(0.06)	(0.48)	(0.07)	(0.25)	(0.07)	(0.02)
Model 2: controlled the basic components in model 1, focusing on the examination of interactions among focal variables	Upward Migration Paths			Downward Migration Paths		
	L→M	**M→H**	**L→H**	**M→L**	**H→M**	**H→L**
	Positive coefficients expected			Negative coefficients expected		
1 Functional Qualities * Activities	0.10	**1.94****	0.01	**-5.10*****	**-5.19*****	**-0.51*****
	(0.06)	(0.71)	(0.05)	(2.07)	(2.50)	(0.15)
2 Functional Qualities * Resources	0.10	0.97	0.01	**-6.03*****	**-5.59*****	**-0.63*****
	(0.08)	(0.09)	(0.08)	(1.97)	(2.18)	(0.10)
3 Functional Qualities * Activities * Resources	0.15	1.15	0.03	**-7.10*****	**-11.17*****	**-0.83****
	(0.13)	(1.27)	(0.12)	(2.01)	(3.01)	(0.16)
4 Functional Qualities * External Contexts	0.13	0.12	0.23	-0.05	-0.05	-0.01
	(0.03)	(0.02)	(0.13)	(0.04)	(0.03)	(0.01)
5 Experiential Qualities * Emotional CX	0.02	0.03	0.03	**-5.03*****	**-6.58*****	-0.01
	(0.01)	(0.02)	(0.01)	(0.07)	(1.01)	(0.01)
6 Experiential Qualities * Social CX	0.05	**0.11****	0.05	-0.01	**-0.08***	**-0.10*****
	(0.03)	**(0.02)**	(0.02)	(0.01)	(0.03)	(0.03)
7 Experiential Qualities * Cognitive CX	0.05	0.02	0.05	-0.07	-0.05	**-0.09*****
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
8 Experiential Qualities * Physical CX	0.01	**0.13*****	0.03	-0.05	-0.05	-0.01
	(0.01)	(0.02)	(0.03)	(0.04)	(0.03)	(0.01)
9 Activities * Resources * Emotional CX	**0.10****	**0.21****	**0.79*****	-0.19	-0.05	-0.01
	(0.02)	(0.04)	(0.13)	(0.13)	(0.03)	(0.01)
10 Activities * Resources * Social CX	**0.50*****	**0.19*****	**0.54****	-0.07	-0.10	-0.05
	(0.06)	(0.02)	(0.14)	(0.04)	(0.05)	(0.02)
11 Activities * Resources * Cognitive CX	**0.08***	**0.10***	**0.11***	-0.06	-0.05	-0.02
	(0.04)	(0.04)	(0.05)	(0.03)	(0.02)	(0.01)
12 Activities * Resources * Physical CX	**0.12****	**0.09****	**0.16*****	-0.05	-0.04	-0.07
	(0.03)	(0.03)	(0.02)	(0.01)	(0.02)	(0.03)

Note:*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Coefficients that are boldfaced and gray-shaded are significantly effective; Values in the parentheses are the standard errors (s.e.) of the coefficients.

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Table 4. Results of Promotion/Prevention Strategies to Change Upward/Downward Migration Probabilities

A. The Effectiveness of Three Prevention Mechanisms to Decrease Downward Probabilities

Original Migration Probability	From M to L	From H to M	From H to L
	10.75%	20.86%	11.80%
1. Functional Qualities*Activities (the changed migration probabilities)	7.77% (Decrease by 2.98%)	18.92% (Decrease by 2.06%)	9.47% (Decrease by 2.33%)
2. Functional Qualities*Resources[1] (the changed migration probabilities)	8.52% (Decrease by 2.23%)	18.75% (Decrease by 2.11%)	10.55% (Decrease by 1.25%)
3. Functional Qualities * Activities * Resources[1] (the changed migration probabilities)	7.51% (Decrease by 3.24%)	17.85% (Decrease by 3.01%)	11.59% (Decrease by 0.21%)

B. The Effectiveness of Four Promotion Mechanisms to Increase Upward Probabilities

Original Migration Probability	From L to M	From M to H	From L to H
	30.66%	11.16%	25.34%
1.Activities*Resources*Emotional CX[1] (the changed migration probabilities)	33.90% (Increase by 3.24%)	17.17% (Increase by 6.01%)	37.38% (Increase by 12.04%)
2.Activities*Resources*Social CX[1] (the changed migration probabilities)	40.78% (Increase by 10.12%)	19.68% (Increase by 8.52%)	34.37% (Increase by 9.03%)
3.Activities*Resources*Cognitive CX[1] (the changed migration probabilities)	32.89% (Increase by 2.23%)	13.42% (Increase by 2.26%)	27.67% (Increase by 2.33%)
4.Activities*Resources*Physical CX[1] (the changed migration probabilities)	35.73% (Increase by 5.07%)	13.17% (Increase by 2.01%)	30.86% (Increase by 5.52%)

Note: One standard deviation increases of all elements that contribute to each migration path

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Table 5. Summary of Major Findings, Contributions, and Implications

Key Findings	Relation to the Literature	Contributions to Theory Development	Practical Applications
1**. Our proposition of the extended TCQ framework** is to constitute the firms' CX performance trajectory using nine elements and the interactions among the elements. Our proposed extended TCQ framework articulates firms' CX performance trajectory through a nuanced constitution: · CX Performance States · Transitional Paths · Migration Mechanisms	The extended TCQ framework builds on · TCQ Nomenclature by De Keyser et al. (2020) · ARC-related models by McColl-Kennedy et al. (2019) and Ordenes et al. (2014) · The multidimensions of CXs (Lemon and Verhoef 2016) · Trajectory dynamics (Wolter et al. 2019; 2020).	· **Wolter et al. (2019) Influence**: Inspired by Wolter et al. (2019), we transition from static views to dynamic trajectories, highlighting how hotel industry nuances shape the customer experience, further building on Zhang et al. (2016). · **Comparison with Harmeling et al. (2015)**: Diving deeper than Harmeling et al. (2015), we emphasize key CX components, capturing the full range of both positive and negative customer interactions. · **Integration with Ye et al. (2022) & McColl-Kennedy et al. (2019)**: Merging insights from McColl-Kennedy et al. and Ye et al., we enhance the discourse with our nine CX elements and a refined HMM textual analysis approach.	Through the dictionary development process, we identify nine building blocks for the extended TCQ framework. Firms can leverage our extended TCQ framework as a basis for CX design. Firms should be aware of the elements that are highly determinative of their CX performances.
2. **We identify two promotion mechanisms** that can be used to trigger improvements across all upward migration paths among CX performance states. 3. **We identify three overall prevention mechanisms** that can be used to prevent service deterioration across all downward migrations among CX performance states.	Our findings echo Zhang et al.'s (2016) findings of specific migration mechanisms for specific migration paths.	· **Expansion to Organizational Context**: The research innovatively extends individual-centric theories into the realm of organizational strategy and decision making, particularly within CX analytics. · **Reinterpretation of Herzberg's Theory**: At the organizational level, prevention mechanisms mirror hygiene factors, while promotion mechanisms act as motivators. · **Translating Regulatory Focus Theory**: Our findings suggest that firms, much like individuals, manifest promotion or prevention strategic focuses.	The two overall promotion mechanisms are combined with firms' controllable elements and consumers' internal context, which means firms should leverage their resources and abilities to correspond to consumers' inner emotional and social states. (1) activities*resources*emotional CX (2) activities*resources*social CX The three overall prevention mechanisms focus on hotels' directly controlled elements and their qualities (1) Functional qualities*activities (2) Functional qualities*resources (3) Functional qualities*activities*resources
4. **Our study heralds a unique blend of the Hidden Markov Model (HMM) with the TCQ elements that frame the CX performance trajectory**.	Our methodological framework in light of previous contributions by Singh et al. (2020); Marinova et al. (2018), Balducci and Marinova (2018), and Berger et al. (2020)	· **Methodological Breakthrough:** By blending the Hidden Markov Model with TCQ, we revolutionize the CX trajectory in service research, offering an evolution-focused perspective. · **Distinctive Research Approach:** Despite the text-mining surge in service research, our methodology uniquely hones in on the dynamics of CX/CX performance and CX management, setting us apart from conventional text-mining studies.	· **Strategic CX Goal Guidance**: We provide a structured five-step approach that empowers firms to design and navigate their CX performance trajectories. Companies are equipped with a robust blueprint to enhance and maintain their CX performance trajectories. · **Dynamic Model Emphasis**: Managers are cautioned against a linear understanding of CX performance.

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FIGURES

The Constitution of the CX Performance Trajectory
• **Nine TCQ elements**: activities, resources, external context, functional qualities, emotional CX, cognitive CX, social CX, physical CX, and experiential qualities • **The interactions between TCQ elements**: e.g., functional qualities * activities • Different levels of **CX performance states** • **Transition paths** among CX performance states

Goal: Identify the mechanisms from TCQ's nine elements and their interactions that can be used to migrate firms' CX performances from lower levels to higher levels

Higher Levels of CX Performance

Lower Levels of CX Performance

Goal: Identify the mechanisms from TCQ's nine elements and their interactions that can be used to prevent firms' CX performances from dropping from higher levels to lower levels

Figure 1. The Research Framework

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Overall Promotion Mechanisms for Three Paths :
1. **Activities*Resources*Emotional CX**
2. **Activities*Resources*Social CX**

High Performance State
- State Performance Indicator: 9.52
- State Size: 34.32%
- State Performance is Mostly Positively Determined by:
  1) Qualities Related to Activities, Resources, External Contexts
  2) Qualities Related to CX
  3) Emotional CX
  4) Social CX

The largest effect of increasing upward probability is 9.03 %

The largest effect of increasing upward probability is 8.52 %

The largest effect of decreasing downward probability is 3.01%

Medium Performance State
- State Performance Indicator: 6.18
- State Size: 41.64%
- State Performance is Mostly Positively Determined by:
  1) Resource
  2) Social CX
  3) Qualities Related to CX

The largest effect of increasing upward probability is 10.12 %

The largest effect of decreasing downward probability is 3.24%

Low Performance State
- State Performance Indicator: 3.42
- State Size: 24.04%
- State Performance is Mostly Negatively Determined by:
  1) Qualities Related to Activities, Resources, External Contexts
  2) Qualities Related to CX
  3) Social CX

The largest effect of decreasing downward probability is 2.33 %

Overall Prevention Mechanisms for Three Paths :
1. **Qualities*Activities**
2. **Qualities*Resources**
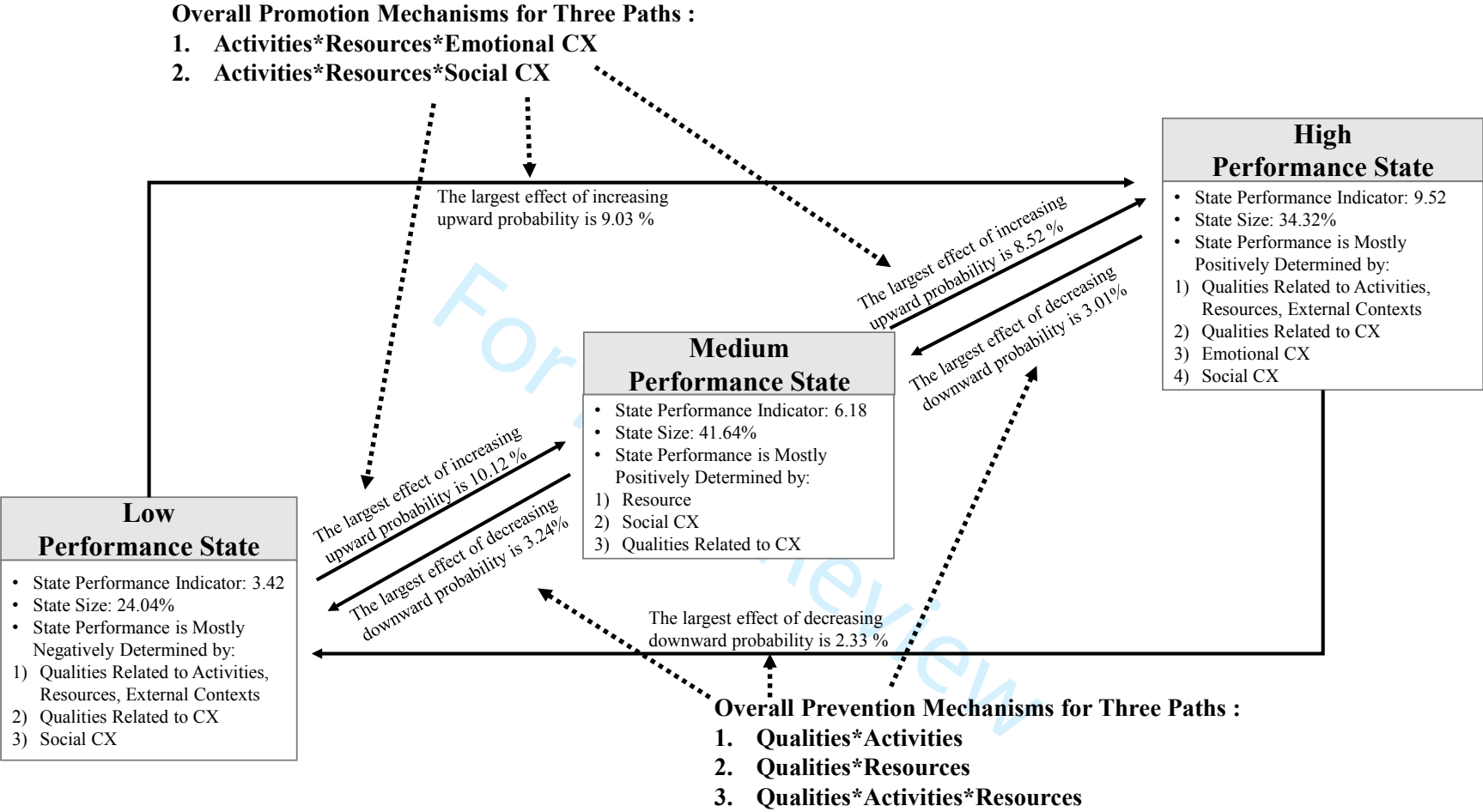3. **Qualities*Activities*Resources**

Figure 2. The Identified Promotion and Prevention Mechanisms

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WEB APPENDICES

Web Appendix A: Literature Review

We sample publications in top-ranked marketing journals (i.e., Journal of Marketing, Journal of Marketing Research, Journal of Consumer Research, Journal of the Academy of Marketing Science, Marketing Science and the Journal of Service Research) for studies (conceptual or empirical) that refer to the use and analysis of textual data. We identify 15 relevant papers and then summarize their focus, approach and contribution (see Table A-1) as the basis for positioning our study.

Table A.1 Studies conceptualizing or using and analyzing textual data published in top-ranked marketing journals between 2019 – 2022

Authors (Year)	Research Focus	Data	Analytical Approach	Research Domain	Contribution/Finding
Berger et al. (2020)	How can marketers best use textual data?		Conceptual paper exploring how text analysis has the potential to serve the entire marketing field with a common set of tools and approaches.	The authors argue that by involving skills and ideas from each of the marketing sub-areas, text analysis has the potential to help unite the field with a common set of tools and approaches.	The authors argue that by involving skills and ideas from each of the marketing sub-areas, text analysis has the potential to help unite the field with a common set of tools and approaches. An overview of automated textual analysis and its application to generate marketing insights.
Büschken and Allenby (2020)	A model allowing for serial dependency of topics in text.	Multiple data sets of customer evaluations of restaurants, camping tents, luxury hotels, and dog food.	Using sentence conjunctions and punctuation to explore how meanings carry over from word to word in a	Restaurants Camping tents Luxury hotels Dog food	Improvements relative to an unconstrained, standard-type latent Dirichlet allocation (LDA) model in

Authors (Year)	Research Focus	Data	Analytical Approach	Research Domain	Contribution/Finding
			document		all cases, Improvement relative to a sentence constrained model (SC-LDA) for longer reviews.
Chakraborty, Kim, and Sudhir (2022)	Exploring how to: (1) convert text into fine-grained numerical sentiment scores on pre-specified attributes by accounting for language structure, and (2) accounting for missing attributes in attribute sentiment scoring.	Yelp restaurant review data	Implementation of a deep learning convolution-LSTM model to address missing attributes by accounting for reviewer rating behavior using an imputation procedure.	Restaurants	Identification of three review-based segments with different motivations: status seeking, altruism/want voice, and need to vent/praise. Attribute mentions in reviews are driven by the need to inform and vent/praise rather than by attribute importance.
Homburg, Theel, and Hohenberg (2020)	Examining: (1) how do managers understand and exercise marketing excellence? and (2) how do investors evaluate marketing excellence?	Letters to shareholders (8,317) in annual reports from diverse industry sectors.	Dictionary development. A machine learning algorithm performing text analysis using a custom dictionary to classify texts.	Cross-Industries	Quantify the manifestation and value of marketing excellence.
Jedidi et al. (2021)	Exploring the topicality of academic marketing articles to marketing practice.	Marketing articles (50,000) in practitioner publications (1982 - 2019).	Dictionary development employing linear discriminant analysis	Marketing academy	Development of the relevance to marketing (R2M) index to compare articles' potential for winning practice-related awards.
Liu, Lee, and Srinivasan (2019)	Relating consumers' use of product reviews to purchase behavior	Quality and price information from 500,000 reviews of 600 diverse product categories on an e-commerce website	An application of deep learning, based on natural language processing, to track individual-level review reading, searching, and purchasing behaviors.	Cross-Product Industries	Aesthetics and price content significantly increase conversion across almost all product categories. Review content

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Authors (Year)	Research Focus	Data	Analytical Approach	Research Domain	Contribution/Finding
					has a greater impact on sales when the average rating is higher. Lower rating variance reflects a competitive or immature market, or brand information is not accessible.
McColl-Kennedy et al. (2019)	Developing a customer CX framework comprising value creation elements, customer discrete emotions, and customer cognitive responses at distinct touchpoints.	The authors collect a longitudinal CX survey dataset from a B2B heavy asset service	Linguistic model combined with predictive models and statistical clustering analysis	B2B heavy asset service offering both physical goods and services	A conceptual CX framework comprising value creation elements (resources, activities, context, interactions, and customer role), cognitive responses, and discrete emotions at touchpoints across the customer journey.
Narang, Yadav, and Rindfleisch (2022)	An investigation of the relationship between content sharing, learners' identity and engagement with learning processes	Posting (12,000) from online learning platforms over an 18-month period. Field experimental data from 2,000 learners enrolled in an online course	LDA topic modeling and Linguistic Inquiry and Word Count [LIWC])	Online learning platforms	A systematic guide to implementing text mining. The effect of learners sharing ideas (vs. their identity) has a stronger effect on their video consumption and assessment completion. The effect is greatest for learners from English-speaking countries and new online learners.
Ryoo, Wang, and Lu (2020)	Exploring the effect of online movie reviews containing spoilers (prematurely resolving	Online reviews from an online movie review site. Box office data from	Correlated topic model.	Movie Industry	Degree of resolution of plot uncertainty has a positive and significant

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Authors (Year)	Research Focus	Data	Analytical Approach	Research Domain	Contribution/Finding
	the plot) on box office revenue and online word-of-mouth	online sources			association with box office revenue. Uncertainty reduction is the behavioral mechanism that drives the positive effect of spoiler intensity.
Singh et al. (2021)	Exploring salespeople's use of influencing tactics to influence buyers' attention during B2B e-negotiations.	Longitudinal data from emails between buyers and salespeople. In-depth interviews, survey, and archival performance data	Dictionary development from email data	B2B sales negotiations from a global B2B industrial manufacturing firm that is one of the top competitors in the custom manufacturing of specialized equipment for heavy industrial plants	The concurrent use of compliance or internalization-based tactics as textual cues bolsters buyers' attention and associates with greater likelihood of contract award.
Stead et al. (2022)	The potential to transform service experiences across the touchpoints of customer journeys with input from diverse disciplines to reduce the fragmented state of research regarding multisensory CX topics,	Papers published in service and marketing journals focusing on multisensory research	Text mining and co-citation analyses.	Journal Articles	Developing a research agenda around employing diverse theories and methods to investigate multisensory stimuli – particularly in the context of the design of multisensory omnichannel service experiences
Timoshenko and Hauser (2019)	Use of user-generated content (UGC) for identifying customer needs.	The UGC (12,000 sentences) relating to current and potential needs for oral care products	Use of a convolutional neural network to filter out non-informative content and to cluster dense sentence embeddings to avoid sampling repetitive content.	Oral care products	The UGC is at least, if not more, valuable than conventional methods for identifying customers' needs during product development. Machine-learning methods improve efficiency of identifying customer needs from UGC.

Authors (Year)	Research Focus	Data	Analytical Approach	Research Domain	Contribution/Finding
van Laer et al. (2019)	Relating the narrative in the content of consumer reviews to consumer behavior.	Verbatim, online consumer reviews (190,461) from TripAdvisor's "things to do" in Las Vegas.	A computerized technique for determining the degree of narrativity in consumer reviews	Hotel industry	Consumer reviews that develop the definitional features of stories well (i.e., narrative content, such as characters and events) while also being shaped to evoke a more emotionally changing genre and a more dramatic event order, are more transporting and persuasive than those not shaped this way.
Zhang, Wang, and Chen (2020)	Exploring in-consumption social listening.	Live comments in response to online movies and other entertainment product	Consumers comments mined from unstructured video, audio, and text data. Analysis through moment-to-moment synchronicity (MTMS) which captures viewers' in-consumption engagement.	Entertainment products: Online movie watching	The MTMS approach significantly predicts viewers' post-consumption appreciation of movies. The approach also facilitated fine grained analysis to surface engaging content.
Zhong and Schweidel (2020)	Capturing the underlying shifts in social media content.	Social media posts from a brand crisis and a new product launch.	An extension of Dirichlet allocation (LDA) by incorporating multiple latent changepoints through a Dirichlet process Hidden Markov Model that allows the prevalence of topics to differ before and after each changepoint, without requiring prior knowledge about the number of changepoints.	Volkswagen's 2015 emissions testing scandal Under Armour's 2018 data breach Burger King's 2016 launch of the Angriest Whopper	A model for marketers to monitor on-going conversations around their brands particularly relating to changes in the conversation arising from a shift in the contributor base and underlying changes in the topics discussed by contributors.

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Table A.1 indicates studies which focus on the following topics:

● Technical explanations for conducting text-based analysis of large data sets (e.g., Büschken and Allenby 2020; Chakraborty, Kim, and Sudhir 2022; Jedidi et al. 2021; Zhong and Schweidel 2020)

● Examining firms' strategic actions and effectiveness (e.g., Homburg, Steiner, and Totzek 2009; Singh et al. 2021)

● Understanding consumers' evaluation or decision processes (e.g., Jedidi et al. 2021; Liu, Lee, and Srinivasan 2019; Ryoo, Wang, and Lu 2020; Timoshenko and Hauser 2019; van Laer et al. 2019; Zhang, Wang, and Chen 2020)

● Conceptual papers provide guidance or a conceptual framework for future research (e.g., Berger et al. 2020)

Based on Table A.1, we argue that there are two gaps to be filled:

● Gap 1: In Table A.1 only McColl-Kennedy et al. (2019) and Ordenes et al. (2014) examine service customers textual responses to their experiences. Given that online textual reviews are increasingly prevalent and result in large datasets that are challenging to analyze, this observation suggests the need for guidance on how to gain insight into customers' service experiences from their verbatim textual data. Our work directly responds to this issue.

● Gap 2: Few studies directly relate to CX, the CX trajectory, or CX performance from the firm's perspective. For exceptions, please see McColl-Kennedy et al. (2019) and Stead et al. (2022).

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Table A.2 Terminology in this research

Terminology	Explanation
CX (Customer Experience)	The subjective response of customers is a holistic response to direct and indirect interactions with the firm.
CX Performance	A firm-centric evaluation that mirrors consumers' perceptions and service quality evaluations, offering a ground for firms to assess and refine their service delivery.
CX Performance Trajectory	Describes the evolutionary patterns of firms' CX performance over time. It captures the progression of a firm's CX performance, detailing the different stages and transitions between performance levels.
TCQ Nomenclature	Framework emphasizing the importance of touchpoints, contexts, and qualities in the CX performance trajectory. – Touchpoints: a point of interaction (person, physical entity, or combination) between customer and firm, mostly focusing on firm-controlled touchpoints. – Contexts: a situational state in which customers interact with a service provider. It is categorized as internal or external. – Qualities: attributes reflecting customers' responses to service interactions. It emphasizes aspects like participation level, time flow, valence, and ordinariness, particularly focusing on valence.
ARC Value Creation Elements	Components related to activities, resources, and contexts that influence customer perception and enrich the TCQ framework. – Activities: interactions that a service company initiates to deliver value. – Resources: assets that a service company uses to deliver value.
Extended TCQ Framework	Integration of the TCQ nomenclature, ARC value creation elements, and the multidimensions of CX, resulting in nine elements/building blocks for the CX performance trajectory.
HMM (Hidden Markov Model)	A statistical model to elucidate the dynamism of phenomena by identifying and modeling transitions between latent states. It captures the dynamics of CX performance trajectories.

Web Appendix B: Data and Methodology

Web Appendix B.1: The mathematical foundation and components of the Hidden Markov Model

We assume the probability distribution of Y_{it} depends on the realization of an unobserved (latent) discrete stochastic process S_{it}, with a finite state space $\{1,\ldots, K\}$. Hence, we can observe Y_{it} directly, but only observe S_{it} indirectly through its stochastic outcome or noisy measure Y_{it}. We assume the state membership S_{it} satisfies the Markov property: $P(S_{it+1}|S_{it}, S_{it-1}, \ldots S_{i1}) = P(S_{it+1}|S_{it})$. The CX performance of Hotel$_i$ transitioning among K states over T periods is:

$$P(Y_{i1}, Y_{i2}, \ldots Y_{iT}) = \sum_{s_1 = 1,2,\ldots K} P(S_{i1} = s_1) \prod_{t=2}^{T} P(S_{it} = s_t | S_{it-1} = s_{t-1}) \prod_{t=1}^{T} P(Y_{it}|S_{it} = s_{it})$$

This equation includes four main components of the HMM:

(1) *The initial state distribution.* $P(S_{i1}=s_1), s_1=1,2\ldots K$, represented by a $1 \times K$ row factor π. Let s denote a latent CX performance state (s=1,2,3,4, …, K) and π_{is} denote the probability that Hotel$_i$ is in state s during the first period of our dataset, where $\sum_{s=1}^{K} \pi_{is} = 1$.

(2) *The transition probabilities.* $P(S_{it}=s_{it}| S_{it-1}=s_{it-1})$ for s_{t+1}, $s_t=1,2,\ldots, K$, represented by a $K \times K$ transition matrix Q. The HMM transition matrix $Q_{i,t-1 \to t}$ denotes the probability that Hotel$_i$ migrates from one CX performance state to any other defined states over time, modeled as a Markov process Q_{it}, thus:

		State at t				
State at t-1	1	2	3	...	$S-1$	S
1	$W_{it1,1}$	$W_{it1,2}$	$W_{it1,3}$	...	$W_{it1,S-1}$	$W_{it1,S}$
2	$W_{it2,1}$	$W_{it2,2}$	$W_{it2,3}$	...	$W_{it2,S-1}$	$W_{it2,S}$
3	$W_{it3,1}$	$W_{it3,2}$	$W_{it3,3}$	...	$W_{it3,S-1}$	$W_{it3,S}$
.	.	.	.		.	.
.	.	.	.	...	.	.
.	.	.	.		.	.
$S-1$	$W_{itS-1,1}$	$W_{itS-1,2}$	$W_{itS-1,3}$	...	$W_{itS-1,S-1}$	$W_{itS-1,S}$
S	$W_{itS,1}$	$W_{itS,2}$	$W_{itS,3}$	...	$W_{itS,S-1}$	$W_{itS,S}$

$W_{itss'}=P(S_{it} = s' | S_{it-1} = s)$ is the conditional probability a hotel moves from state S at time t-1 to state S☐ at time t and $\forall s,s'$, $\Sigma_{s'} W_{itss'} = 1$. These transition probabilities might be influenced by CX trajectory components (i.e., TCQ elements) at time t-1. Therefore, we define each transition probability as a function of the migration mechanisms using a logit specification to ensure that $0 \leq W_{itss'} \leq 1$. That is, $W_{itss'} = \frac{e^{Xit-1'\gamma s}}{1 + \Sigma_{s=1}^{s-1} e^{Xit-1'\gamma_s}}$, where X_{it-1} is a vector of the migration mechanisms affecting the transition between CX performance states, and γ_s is a state-specific vector of the response parameter that measures the impact of each migration element on the transition probability $W_{itss'}$. Our transition matrix specifies all CX trajectory elements, enabling us to compare their relative effects for each migration path.

(3)   *The state-dependent distribution.* A given Hotel$_i$'s state S_{it}, results in an average rating score in Hotel$_i$ (Y_{it}); a noisy measure and a probabilistic outcome of the state.

(4)   *The likelihood functions.* This describes the evolutionary process of the HMM by combining the initial state distribution, the transition matrix, and the state-dependent distribution.

Web Appendix B.2: The choice of textual data

This study uses longitudinal, unstructured, textual data from customers' verbatim reviews to generate new insights to understand the trajectories of CX performance for service firms. This form of data helps identify salient concepts in our research framework (Gopalkrishnan et al. 2012). Its qualitative characteristics mean that it effectively represents the complexities and dynamic nature of CX and CX performance (Ordenes et al. 2014) by avoiding scaling predefined constructs of interest. Regarding concerns about endogeneity in the variables, we follow Balducci and Marinova's (2018) argument that textual data is multifaceted. A single unit of highly unstructured text data possesses multiple facets, each offering unique information

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enabling the researcher to select and analyze the facet(s) according to the research goals. Text

data maintains concurrent representation (Balducci and Marinova 2018), and, consequently, a

single data unit's multiple facets can simultaneously represent different phenomena. Consider the

text data documenting an email exchange between a salesperson and a customer. A single unit of

text data contains many unique facets that occur simultaneously. Each facet provides distinct

information that scholars can use to assess different phenomena (e.g., persuasion, or affect). The

contemporaneous inclusion of multiple meanings in text data is a characteristic of the data that

can be exploited and offers advantages over a (predetermined) traditionally structured dataset.

To address the potential for endogeneity in CX trajectory elements, we use a control

function approach (Petrin and Train 2010; Villas-Boas and Winer 1999). This involves running a

first-stage linear regression of the TCQ/ARC elements (the 9 independent variables) on two

instrumental variables: the focal hotel's official star ranking and their categories of price (US$)

range for one night with two adults (e.g. 0 = less than 50, 1 = 51 - 100, 2 = 101 - 150, 3 = 151 -

200, 4 = 201 - 250, 5 = 251 - 300, 6 = 301 - 350, 7 = 350 - 400, 8 = 401 – 450, 9 = 451 – 500

and, 10 =   >500). We then incorporate the residuals from the first-stage regression as two

additional control variables into the proposed HMM model.

Web Appendix B.3: The choice of variable operationalization

Following data collection, the researcher needs to determine an appropriate approach for

operationalizing the focal concepts. Researchers suggest that text mining and big data

technologies offer ways of measuring and managing CX that are more effective than traditional

methods such as surveys or lab data (Keiningham et al. 2017; Lemon and Verhoef 2016;

McColl-Kennedy et al. 2019; Ordenes et al. 2014; Verhoef, Kooge, and Walk 2016).

Specifically, text mining is the analysis of data in natural-language texts, using a process that

generally involves turning text into numbers to extract meaningful numeric indices from unstructured information. The numeric indices make the information accessible to statistical and machine learning algorithms for further analysis (Meyer and Schwager 2007; Sebastiani 2002). Following Humphreys and Wang (2017) and Balducci and Marinova (2018), and using Berger et al.'s (2020) design for a text mining workflow, we describe how we gained important insights from the extensive big data that arise throughout a CX.

Web Appendix B.4: The instructions for coders to develop coding schema

1. **Activities**

   Definition: activities provided by the hotels. These are primarily actions or tasks that the hotel offers to its guests.

   Part of Speech (POS) Form: most will be verbs or verb phrases.

   Examples: "Hosting", "Organizing events", "Offering room service".

2. **Resources**

   Definition: resources provided by the hotels. These refer to tangible or intangible assets that the hotel offers for the benefit or convenience of its guests.

   POS Form: most will be nouns or noun-phrases.

   Examples: "Swimming pool", "Gym facilities", "Concierge service".

3. **External Context**

   Definition: consumers' perceived external context. This relates to the environment, external situations, or events that the consumer experiences while staying at the hotel.

   POS Form: the majority will be prepositional phrases.

   Examples: "Near the airport", "Adjacent to a shopping mall", "Surrounded by restaurants".

4. **Functional Qualities**

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Definition: quality attributes used to describe the hotel's provided activities, resources, and consumers' external contexts. These attributes give insights into the functional aspects of what the hotel offers.

POS Form: most will be adjectives or adjective-phrases.

Examples: "User-friendly", "State-of-the-art", "Clean".

5. **Experiential Qualities**

Definition: quality attributes used to describe the overall consumer experience. These attributes provide insights into how the consumers felt about their overall stay, which may include the emotional experience, cognitive experience, social experience, or physical experience.

POS Form: Most will be adjectives and adjective phrases.

Examples: "Our stay was **enchanting**, from the serene ambiance of our room to the **insightful** historical tour given by the hotel."

"The social dinners organized were **engaging**, leading to **memorable** connections with fellow travelers."

Instructions for Coders

1. **Training:**

    – Training session goal: ensuring coders have a clear and deep understanding of each category.

    – Approach: coding practice to ensure everyone is on the same page.

2. **Initial Coding:**

    – Reading the content: start by thoroughly reading the review to grasp the overall

content.

- Highlighting and labelling: highlight or underline the portions of the text that fit into any of the five categories. Once identified, assign the appropriate label from the categories to these highlighted sections.

- Handling ambiguity: if you find sections of the text that could belong to multiple categories, then prioritize the category that encapsulates the main essence of that section.

3. **Consistency Checks:**

- Review: After independently coding 30 reviews, come together with your coding partner. Compare and discuss your coding choices to ensure consistency and to reduce individual biases.

- Discussion: Regularly discuss any anomalies to ensure that everyone remains aligned.

- Reference the instructions: regularly review the instructions to resolve uncertainties.

- If any differences in coding decisions arise during your joint reviews, this is the time to clarify any misunderstandings, refine your understanding of the categories, and reach a consensus.

- If you are unsure or feel a particular review could be contentious, make a note or annotation. This can be a point of discussion during your consistency checks.

Your collaboration and open communication are key to the success of this project.

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Web Appendix B.5

Table B.1 Summary of the coding schema and the final custom dictionary

Category	Step 2: Develop a coding schema[1] based on a random sample of 300 reviews			Step 3: Conducting formal coding tasks based on the coding schema to develop a custom dictionary		
	Definitions of each category	Words/phrases of each category for the coding schema	The total number of words/phrases of each category in the coding schema	The total number of words/phrases for each category in the final dictionary	The number of overlapping words or phrases with other categories	The number of words/phrases of the specific category in the dictionary divided by the number of words/phrases used in the current dataset
1. Activities	Words/phrases that represent the activities conducted by the hotels (most are verbs).	accommodate, activities, addressed, allocate, assist, booking, cleaning, check-in, check-out, cleaned daily, customer service, housekeeping, maid service, organizing, providing, renovating, reservation, restoring, room service, room upgrade, sanitizing, seating, serving, setting, sharing, situated, starting, stopping, studying, testing, unpacking, updating, washing	32	186	None	17.24%
2. Resources	Words/phrases that represent the resources provided by the hotels (most are nouns).	adapter, air conditioner, air conditioning, amenities, bar, bathroom, bed, bellhop, blanket, breakfast, buffet, building, bus, barbecue facilities, bathrobe, beauty salon, café, car, carpeting, chair, cleaning staff, coffee, complimentary breakfast, continental breakfast, desk, door, doorman,	50	385	None	35.68%

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Category	Step 2: Develop a coding schema[1] based on a random sample of 300 reviews		The total number of words/phrases of each category in the coding schema	Step 3: Conducting formal coding tasks based on the coding schema to develop a custom dictionary		The number of words/phrases of the specific category in the dictionary divided by the number of words/phrases used in the current dataset
	Definitions of each category	Words/phrases of each category for the coding schema		The total number of words/phrases for each category in the final dictionary	The number of overlapping words or phrases with other categories	
		facilities, fitness center, free water, fridge, front desk, gift, gym, hair dryer, heating, ice machine, in-room iron, kitchenette, laundry, luggage storage, maps, microwave, mini fridge, minibar, Nespresso, newspapers, parking garage, pool, refrigerator, restaurant and bar, robes, room, shower, slippers, snacks, soap, spa, staff, storage, tea and coffee, valet parking, view from the room, Wi-Fi, window				
3. External Contexts	Words/phrases that represent the external contexts of the hotel settings	airport, battery park, bridge Broadway, Brooklyn, Brooklyn bridge, central park, Chinatown, city, cinemas, downtown, financial district, Hudson, Hudson yards, landmark, lower Manhattan, Madison square garden, Manhattan, metropolitan, neighborhood, public transportation, Rockefeller center, skyline, SoHo, sightseeing sites, statue of liberty, theater district, times square, tourist attractions	23	190	None	17.61%

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Category	Step 2: Develop a coding schema[1] based on a random sample of 300 reviews			Step 3: Conducting formal coding tasks based on the coding schema to develop a custom dictionary		
	Definitions of each category	Words/phrases of each category for the coding schema	The total number of words/phrases of each category in the coding schema	The total number of words/phrases for each category in the final dictionary	The number of overlapping words or phrases with other categories	The number of words/phrases of the specific category in the dictionary divided by the number of words/phrases used in the current dataset
4. **Functional Qualities**	Words/phrases that represent the qualities of the hotels' activities, Resources or external contexts. (most are adjectives).	big, clean, comfortable, convenient, cozy, efficient, friendly, furnished, generous, good, large, luxurious, neat, professional, quiet, refreshing, resourceful, responsive, safe, secure, simple, soothing, spacious, standard, strong, supportive, warm	**28**	**209**	**7 overlapping words with the category of experiential qualities[2]**	**19.37%**
5. **Experiential Qualities**	Words/phrases that represent the qualities of the consumers' perceived overall experiences, the internal contexts including emotional CX, social CX, cognitive CX and physical CX (most are adjectives).	authentic, breathtaking, brilliant, engaging, fantastic, ideal, incredible, lovely, loving, magical, marvelous, memorable, pleasant, positive, relaxing, satisfactory, spectacular, splendid, stunning, superb, unforgettable, unique, wonderful	**23**	**109**	**7 overlapping words with the category of functional qualities[2]**	**10.10%**

Notes:
1. The results of the coding schema are presented on the left side of this table, and the results of the final custom dictionary are presented on the right side of this table, highlighted by gray color.
2. Seven overlapping words appear in functional qualities and experiential qualities in the custom dictionary: nice, nicely, outstanding, pleasant, superb, unbeatable, and valued. Details of the lists of words/phrases belonging to each category are in the following table.

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Table B.2 The details of custom dictionary results

Categories	Words/Phrases Belonging to the Category
Activities	able, accommodate, accommodated, achieve, activities, add, addressed, addressing, agree, allocated, allocating, allow, answer, apologized, appointed, approved, arrange, assist, assistant, assume, assured, attached, book, booking, bring, brought, buy, called, calling, care, caring, catch, catching, caused, causing, change, changed, check, checked, checking, check-in, check-out, choose, cleaned daily, cleaning, cleaning service, communicate, compared, compensate, complete, completed, confirm, confirmed, consider, contact, control, customer service, delivered, describe, design, designed, directly, dry, ease, eat, enter, extend, filled, finding, fit, fixed, flew, flush, flushing, furnished, gave, giving, grabbed, greeted, handed, handling, held, helped, house keeping, housekeeping, inquired, interacting, job, jobs, keeping, kicking, letting, loading, maid service, maintaining, making, maximizing, meeting, moving, offer, offering, opting, ordering, organizing, performing, picking, planning, playing, preparing, printing, providing, queries, rated, receiving, recommendations, remaining, removing, renovating, repairing, replacement, replacing, replenishing, requesting, requiring, reservation, reservations, reserving, restored, restoring, returning, room service, room upgrade, sanitize, sanitizing, seating, selecting, selling, serve, served, serving, setting, sharing, sitting, situated, spending, starting, stepping, stopping, storing, studying, talking, tasting, topped, touching, treating, turning, unpack, unwind, updating, upgrade, washing, watching, working, testing, unpacking
Resources	ac, access, accessibility, accommodation, adapter, air conditioner, air conditioning, amenities, apartment, bar, bar and restaurant, bar restaurant, bath, bathroom, bathtub, bed, bed and pillows, bedroom, beds, beds and pillows, beer, bellboy, bellhop, biscuits, blanket, block, Bluetooth, bobby, booth, bottle, bottled water, bottles, boutique, breakfast, breakfast area, breakfast at the hotel, breakfast buffet, breakfast included, breakfast options, breakfast was included, brick, bridge, brownstone, brush, buffet, buffet breakfast, building, buildings, bunk, bus, barbecue facilities, bathrobe, beauty salon, cab, café, cake, candy, cans, car, card, cards, carpeting, cereal, chair, champagne, charger, check in staff, chicken, children, chocolate, choice, choices, cigarette, clean staff, cleaning staff, club, clubs, coffee, coffee and tea, coffee and water, coffee maker, complimentary breakfast, complimentary coffee, complimentary water, continental breakfast, cookies, corner room, crew, cups, curtains, deck, deco, décor, decoration, design of the room, desk, detail, diner, diners, dining, dinner, door, doorman, doors, double room, drink, drinks, dryer, dryers, facilities, facility, factor, fan, feature, features, fee, feet, filter, fitness, fitness center, fixtures, floor, floors, flower, flowers, food, food options, foods, free water, freezer, fridge, fridge and microwave, front, front desk, front desk staff, front-desk, fruit, fruits, game, games, garage, gentleman, gift, glasses, ground floor, gym, hair dryer, hairdryer, hall, hallway, hangers, heater, heating, hospitality, hostel, hostess, hot water, hotel, hotel staff, hotels, housekeeping staff, ice, ice machine, inclusion, information, in-house, inn, inquiries, in-room, interior design, iPad, iron, ironing,

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Categories	Words/Phrases Belonging to the Category
	issue, issues, jazz, kettle, key, king suite, kiosk, kitchen, kitchenette, lamps, laundry, layout, library, light, lighting, lights, linens, lines, liquid, living room, lobby, lobby area, lounge, lounge area, lounges, luggage storage, machine, machines, management, manager, managers, maps, mask, masks, materials, mattress, microwave, microwave and fridge, mini bar, mini fridge, minibar, mirrors, mugs, music, musical, necessities, Nespresso, Netflix, newspapers, oatmeal, package, paintings, pans, parking garage, pool, queen bed, radio, rarity, receipt, reception, reception area, reception staff, receptionist, refreshments, refrigerator, registration, reimbursement, resort, resources, restaurant and bar, restaurants and bars, restroom, restrooms, reviews, robes, roof, roof top, rooftop bar, rooftop view, room, room and bathroom, room design, room size, room view, room with a view, rooms, safety, salad, sandwiches, sanitizer, sheets, shelf, shoes, shop, shower, shower head, shower pressure, showers, signs, sink, sinks, size, size of room, sizes, slippers, small fridge, snack, snacks, soap, sockets, sofa, sofas, spa, speakers, staff, staff at the front desk, staff member, standards, star, stars, storage, tea and coffee, tea coffee, USB, valet, valet parking, vehicle, vendors, view from my room, view from our room, view from the room, voucher, vouchers, waffle, waffles, wallpaper, walls, washroom, water, water pressure, website, wheelchair, wi fi, Wi-Fi, window, windows, wine, yard, yards, yoga, yogurts
External Contexts	airport, battery park, bridge, Broadway, Brooklyn, Brooklyn bridge, central park, Chinatown, city, cinemas, downtown, financial district, Hudson, Hudson yards, landmark, lower Manhattan, Madison square garden, Manhattan, metropolitan, neighborhood, public transportation, Rockefeller center, skyline, SoHo, sightseeing sites, statue of liberty, theater district, times square, tourist attractions, airtrain, Amsterdam, avenue, Broadway show, Broadway shows, Bryant Park, bus, bus station, bus terminal, centrally located, church, cinema, city center, city view, city views, close to Broadway, coffee shop, college, Columbus, corona, covid19, Covid-19, district, downtown Manhattan, east, empire state, galleries, gallery, garden, gardens, gateway, golden, grand central station, great views, Greenwich, ground, Harrison, heart of Manhattan, herald, highline, hill, historic, history, holiday, Holland, hotel location, Lincoln, Lincoln center, local, location and view, location in Manhattan, location in the heart, location of the hotel, location of the property, lots of restaurants, Macy's, Maddison, Madison, main attractions, marathon, Marie, maritime, mark, market, McDonald, metro station, metro stations, mid-town, middle of Manhattan, Moore, Moynihan, museum, museums, nearby, neighbors, nice views, nomad, North, NY, NYC, October, outdoor, outdoors, outlets, pandemic, panorama, parade, park, Penn, Penn station, people, pharmacy, place, places, policy, port, porter, porters, position, proximity, public transport, rain, restaurants and shopping, restaurants in the area, river, riverside, road, routes, shopping, shops, shops and restaurants, sightseeing, site, sites, sitting, situation, skyscraper, snow, southern, square park, store, stores, street, streets, subway, subway lines, subway station, subway stations, subway stops, subways, theater, time square, train station, train stations, UK, uptown, urban, view, view of the city, views,

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Categories	Words/Phrases Belonging to the Category
	village, Wall Street, weather, world trade, world trade center
Functional Qualities	acceptable, accessible, accommodating and friendly, adequate, affordable, alternative, ample, appointed, assisted, automatic, available, big, bigger, biggest, bright, calm, cheap, clean, cold, comfort, comfortable, common, complimentary, convenient, cool, cooperative, courteous, cozy, daily, dated, decent, delicious, drinkable, dry, easier, efficient, elegant, environmentally, exceeded my expectations, excellent value for money, exceptional, exquisite, extended, extremely, fair, fair price, fake, famous, fancy, fast, firm, fitted, flat, flawless, flexible, fresh, friendliness, friendly, functional, furnished, furnishing, gentle, good, great, great job, great price, great value for money, handicapped, handy, heated, high, high quality, high-quality, highly, huge, immaculate, immediately, important, incredibly friendly, incredibly helpful, independent, individual, informative, interesting, inviting, kind, large, leading, leisurely, light, lively, long, luxurious, medium, minimal, minimalistic, modern, multiple, natural, neat, new, **nice**, **nicely** decorated, noticeable, optimal, organized, original, **outstanding**, perfect, **pleasant** and helpful, polite and helpful, practical, pretty, pretty good, pretty nice, pretty quiet, prime, priceless, private, professional, prompt, properly, public, pure, purified, quaint, quality, quiet, quick, quick and easy, rare, reasonable, reasonable price, refreshing, refurbished, regular, relaxed, reliable, renovated, resourceful, restful, respectful, restorative, responsive, safe, secure, sensitive, serene, shining, silence, silent, simple, sleek, small, smart, smooth, softly, soothing, spacious, spotless, standard, straight, strong, straightforward, stylish, super comfortable, super comfy, super convenient, super easy, super friendly and helpful, super helpful, super nice, superb, supportive, ultra, **unbeatable**, understanding, updated, upper, usual, **valued**, varied, warm, welcoming, worth, worth the price
Experiential Qualities	absolutely, absolutely amazing, absolutely perfect, aesthetic, amazing, anniversary, appreciate, appreciated, appreciation, attractive, beautiful, birthday, breathtaking, brilliant, celebrate, celebrated, celebration, charming, classic, classy, comfortable stay, connected, discover, divine, engaging, enjoy, enjoyable, enjoyed my stay, enjoyed our stay, enriching, expect, explore, fabulous, fantastic, favorite, favorites, glad, good experience, good stay, gorgeous, great experience, great stay, great time, happy, happy hour, heartfelt, hearty, heavenly, ideal, impressive, incredible, love, love this hotel, loved our stay, loved the hotel, lovely, loving, lucky, magical, marvelous, memorable, missing, nicer, **nice**, **nice** stay, **nicely**, **outstanding**, partner, party, peaceful, **pleasant**, pleasant stay, pleasantly, pleasantly surprised, pleased, pleasing, positive, purposeful, remembered, relaxing, returning, rip-roaring, rocking, satisfactory, satisfying, satisfied, serene, smooth, special, specious, spectacular, splendid, stunning, superb, super cute, surprisingly, **unbeatable**, unbelievable, unforgettable, unique, unexpected, **valued**, wonderful, wonderful stay

Note: overlapping words appearing in functional and experiential qualities categories: nice, nicely, outstanding, pleasant, superb, unbeatable, valued.

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Web Appendix C: Dictionary Validity

Web Appendix C.1: Results of confirmatory factor analysis among three sub-datasets

These categories—activities, resources, external context, functional qualities and

experiential qualities—were applied to three distinct datasets, each corresponding to a different

time period: pre-pandemic, during the pandemic, and post-pandemic. We converted the text data

into numerical form using LIWC software, resulting in three numeric datasets. Each dataset

provided measurements for all five categories.

The three datasets corresponded to the following periods:

- Pre-pandemic: June-Dec 2019

- Pandemic: Jan 2020 - Dec 2021

- Post-pandemic: Jan - Sep 2022

We conducted a confirmatory factor analysis for each of the five categories using

measurements obtained from these three datasets. This approach allowed us to investigate

whether the underlying structure/measures of each category remained stable over time.

Factor Analysis Dataset Composition:

- Activities: three measurements corresponding to each time period.

- Resources: three measurements corresponding to each time period.

- External context: three measurements corresponding to each time period.

- Functional qualities: three measurements corresponding to each time period.

- Experiential qualities: three measurements corresponding to each time period.

Below, we provide the factor loadings for each category:

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Activities:

– First measurement from the pre-pandemic dataset: .81

– Second measurement from the pandemic dataset: .79

– Third measurement from the post-pandemic dataset: .78

Resources:

– First measurement from the pre-pandemic dataset: .85

– Second measurement from the pandemic dataset: .71

– Third measurement from the post-pandemic dataset: .80

External Context:

– First measurement from the pre-pandemic dataset: .85

– Second measurement from the pandemic dataset: .64

– Third measurement from the post-pandemic dataset: .82

Experiential Qualities:

– First measurement from the pre-pandemic dataset: .82

– Second measurement from the pandemic dataset: .60

– Third measurement from the post-pandemic dataset: .79

Functional Qualities:

– First measurement from the pre-pandemic dataset: .84

– Second measurement from the pandemic dataset: .72

– Third measurement from the post-pandemic dataset: .80

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Web Appendix C.2: The instructions for coders to check face validity of the dictionary

Why Your Role Matters:

As we deepen our exploration of customers' hotel experiences through dictionaries, the

accuracy and resonance of our findings hinge upon the precision of these tools. We seek the

insight of industry veterans like you to ensure that our dictionaries are not only theoretically

accurate but also resonate with real-world industry nuances.

Understanding Face Validity:

Face validity is akin to the "first glance" or the "gut feeling" one gets when looking at our

dictionary. Does it feel right? Does it seem to capture the essence of the industry's language?

With your industry background, you have the eyes to gauge this. Consider yourself the guardian

of our dictionary's first impression.

Key Areas for Checking:

1. Activities

–   Definition: activities provided by the hotels. These are primarily actions or tasks

that the hotel offers to its guests.

–   Part of Speech (POS) Form: most will be verbs or verb phrases.

2. Resources

–   Definition: resources provided by the hotels. These refer to tangible or intangible

assets that the hotel offers for the benefit or convenience of its guests.

–   POS Form: most will be nouns or noun-phrases.

3. External Context

–   Definition: consumers' perceived external context. This relates to the

environment, external situations, or events that the consumer experiences while

staying at the hotel.

– POS Form: the majority will be prepositional phrases.

4. Functional Qualities

– Definition: quality attributes used to describe the hotel's provided activities, resources, and consumers' external contexts. These attributes give insights into the functional aspects of what the hotel offers.

– POS Form: most will be adjectives or adjective-phrases.

5. Experiential Qualities

– Definition: quality attributes used to describe the overall consumer experience. These attributes provide insights into how the consumers felt about their overall stay, which might include the emotional experience, cognitive experience, social experience, or physical experience.

– POS Form: Most will be adjectives and adjective phrases.

Checking Instructions (for Coders E and F)

1. Check the words/phrases under each category.

2. Pinpoint the words/phrases you think are inappropriate and give your opinion about dropoff or reassigning to another category.

3. Avoid categorizing words into multiple categories. In cases where a word or phrase might fit into more than one category, use your industry knowledge to determine the best fit.

Your collaboration and open communication are vital to the success of this project.

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Web Appendix D: The Descriptive Statistics and Predictive Performance of Focal Variables

Table D.1 Descriptive statistics and correlation coefficient matrix of the focal variables

	1	2	3	4	5	6	7	8	9
1. Activities	1.00								
2. Resources	.063**	1.00							
3. External Context	.013**	.049**	1.00						
4. Functional Qualities	.053**	.342**	.071**	1.00					
5. Emotional CX	.070**	.368**	.083**	.365**	1.00				
6. Social CX	.063**	.153**	.031**	.152**	.268**	1.00			
7. Cognitive CX	.046**	.060**	.021**	.095**	.119**	.408**	1.00		
8. Physical CX	.031**	.249**	.283**	.125**	.151**	.065**	.033**	1.00	
9. Experiential Qualities	.035**	.199**	.060**	.092**	.361**	.052**	.070**	.066**	1.00
Mean	0.308	3.747	1.329	4.106	5.022	2.089	2.306	2.206	0.710
S.D.	2.220	9.159	5.241	10.852	10.866	7.310	9.243	7.753	3.774

Note: ** significant at 1%

Table D.2 The regression results of the nine TCQ elements on consumers' rating scores

DV=Rating Scores	Non-standardized β	S.E	Standardized β	T	Significance
Constant	7.86	0.01		787.19	0.00
1. Activities	0.01	0.01	0.01	2.39	0.02
2. Resources	0.00	0.00	0.01	2.79	0.01
3. External Context	0.01	0.00	0.02	3.35	0.00
4. Functional Qualities	0.01	0.00	0.06	9.38	0.00
5. Experiential Qualities	0.02	0.00	0.03	6.14	0.00
6. Cognitive CX	0.01	0.00	0.03	2.52	0.01
7. Social CX	0.06	0.00	0.20	33.96	0.00
8. Emotional CX	0.04	0.00	0.18	31.39	0.00
9. Physical CX	0.01	0.00	0.03	5.81	0.00

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Web Appendix E: Model fit examinations

Table E Model Fit Comparison at the Weekly Level			
	Two-State HMM (Dynamic Model)	**Three-State HMM (Dynamic Model)**	**Four-State HMM (Dynamic Model)**	**Ordinal Logit Model**
Log-likelihood	-180,519.96	-107,008.88	-119,818.49	-204,095.61
Log-posterior	-180,525.85	-117,616.99	-127,267.42	-204,096.55
BIC	361,191.98	214,467.29	220,078.12	408,204.45
AIC	361,085.93	214,153.76	219,712.99	408,195.23
AIC3	361,108.93	214,221.76	219,750.99	408,197.23
CAIC	361,214.98	214,535.29	220,116.12	408,206.45
	Two-Class (Static Model)	**Three-Class (Static Model)**	**Four- Class (Static Model)**	**Regression Model**
Log-likelihood	-182,865.754	-109,569.18	-127,008.88	-185,202.83
Log-posterior	-182,871.18	-120,178.67	-127,616.99	-185,205.28
BIC	365,894.03	219,440.19	214,621.28	370,637.03
AIC	365,759.50	219,190.37	214,256.14	370,475.66
AIC3	365,773.50	219,216.36	214,294.14	370,510.66
CAIC	365,908.03	219,466.19	214,559.28	370,672.03

Web Appendix F – Description of the migration paths relating to the selected 9 components

(1)   **Activities.** The activities element effectively migrates CX performance from an M to an H state (2.13, $p = .001$) and from an L to an H state (.67, $p < 0.01$).

(2)   **Resources.** The resource element effectively increases upward migrations (UM) from an M to an H state (.26, $p = .01$) and from an H to an M state (-.06, $p = .01$).

(3)   **External Context.** External context increases firms' UM from an M to an H state (2.47, $p = .001$). External context also reduces the probability of a downward migration (DM) from an H to an M state (-0.12, $p = 0.001$) and from an H to an L state (-2.81, $p = 0.00$).

(4)   **Functional Qualities related to the activities, resources, or external contexts.** This element of quality effectively increases UM from an L to an M state (.28, $p = .01$) and also effectively reduces DM from an M to an L state (-0.88, $p = .001$)

(5)   **Emotional CX.** Emotional CX causes firms' UM from an L to an M state (.11, $p = .01$) and from an M to an H state (.31, $p = .001$). Additionally, emotional CX reduces DM from an M to an L state (-.006, $p = .05$)

(6)   **Social CX.** Social CX causes firms' UM from an L to an M state (.15, $p < 0.001$). For the weekly dataset, this element also causes UM from an M to an H state (.18, $p < 0.001$), and from an L to an H state (.12, $p < 0.001$). Moreover, this component effectively reduces DM from an M to an L state (-.07, $p < .05$), from an H to an M state (-.009, $p < .01$) and from an H to an L state (-.10, $p < .001$).

(7)   **Cognitive CX.** Cognitive CX does not cause significant effects on UM or DM.

(8)   **Physical CX.** Physical CX does not exert significant effects on UM or DM.

(9)   **Experiential Qualities related to CXs.** Qualities effectively increase UM from

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an L to an M state (.26. p =.01) and an M to an H state (1.44, $p < 0.01$). Moreover,

this component effectively reduces DM from an H to an L state (-.05, $p < .05$).

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Web Appendix G – Discussion of the migration results exerted by 12 interactions among

components

(1) **functional qualities*activities**: increases the probability of an upward migration

(UM) from an M to an H state (1.94, $p < .01$). This interaction decreases the

probability of a downward migration (DM) from an M to an L state (-5.10, p

$< .001$), from an H to an M state (-5.19, $p < .001$), and from an H to an L state

(-.51, $p < .001$).

(2) **functional qualities*resources**: reduces the probability of a DM from an M to an

L state (-6.03, $p < .001$), from an H to an M state (-5.59, $p < .001$), and from an H

to an L state (-0.63, $p < .001$).

(3) **functional qualities*external context**: this interaction effect does not have any

significant effect on either UM or DM.

(4) **functional qualities*activities*resources:** reduces probability of a DM from an

M to an L state (-7.10, $p < .001$), from an H to an M state (-11.17, $p < .001$) and

from an H to an L state (-0.83, $p < .01$).

(5) **experiential qualities*emotional CX:** reduces the probability of a DM from an

M to an L state (-5.03, $p < .001$) and from an H to an M state (-6.58, $p < .001$).

(6) **experiential qualities*social CX**: increases the probability of an UM from an M

to an H state (.11, $p < .01$). This interaction effect also reduces the probability of a

DM from an H to an M state (-.08, $p < .05$) and from an H to an L state (-.10, p

$< .001$).

(7) **experiential qualities*cognitive CX**: reduces the probability of a DM from an H

to an L state (-.09, $p < .001$).

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(8)   **experiential qualities*physical CX**: increases the probability of an UM from an

M to an H state (.13, $p < .001$).

(9)   **activities*resources*emotional CX**: increases the probability of an UM from an

L to an M state (.10, $p < .05$), from an M to an H state (.21, $p < .01$) and from an

L to an H state (.79, $p < .001$).

(10)   **activities*resources*social CX**: increases UM from an L to an M state (.50, p

$< .001$), from an M to an H state (.19, $p < .01$) and from an L to an H state (.54, p

$< .01$).

(11)   **activities*resources*cognitive CX**: increases UM from an L to an M state (.08, p

$< .01$), from an M to an H state (.10, $p < .01$) and from an L to an H state (.11, p

$< .01$).

(12)   **activities*resources*physical CX:** increases the probability of an UM from an L

to an M state (.12, $p < .05$), from an M to an H state (.09, $p < .01$) and from an L

to an H state (.16, $p < .01$).

Web Appendix H –Robustness of empirical results
Web Appendix H.1 –Robustness check of different levels of data aggregation from booking.com

Table H.1 Model robustness checks for weekly-, monthly-, and individual-level datasets

Model 2: We controlled the basic components, focusing on the examination of interactions among focal variables at weekly, monthly and individual levels		Upward Migration Paths			Downward Migration Paths		
		L→M	M→H	L→H	M→L	H→M	H→L
		Positive coefficients are expected.			Negative coefficients are expected.		
1 functional qualities *activities	Weekly	0.10	**1.94****	0.01	**-5.10****	**-5.19****	**-0.51****
	Monthly	0.01	**1.31****	0.01	**-7.75****	**-0.51****	**-3.62****
	Individual	**0.07****	**0.05****	0.01	**-0.03***	**-0.05****	**-0.03****
2 functional qualities *resources	Weekly	0.10	0.97	0.01	**-6.03****	**-5.59****	**-0.63****
	Monthly	**0.47***	0.80	0.24	**-0.62****	**-0.46***	**-3.43****
	Individual	0.06	**0.05****	0.01	**-0.03***	**-0.05****	**-0.04****
3 functional qualities *activities* resources	Weekly	0.15	1.15	0.03	**-7.10****	**-11.17****	**-0.83****
	Monthly	0.20	0.16	0.16	**-7.62****	**-1.61***	**-3.48****
	Individual	0.02	0.03	0.01	**-0.03***	**-0.09****	**-0.05****
4 functional qualities *external contexts	Weekly	0.13	0.12	0.23	-0.05	-0.05	-0.01
	Monthly	0.16	**1.63***	0.11	-0.10	-0.15	**-3.62****
	Individual	0.01	0.01	0.02	-0.01	-0.01	-0.01
5 experiential qualities *emotional CX	Weekly	0.02	0.03	0.03	**-5.03****	**-6.58****	-0.01
	Monthly	0.04	**0.62***	0.04	**-7.92****	-0.06	-0.03
	Individual	**0.02***	0.02	0.01	**-0.03***	**-2.24****	0.01
6 experiential qualities *social CX	Weekly	0.05	**0.11****	0.05	-0.01	**-0.08***	**-0.10****
	Monthly	0.04	**0.14****	0.01	**-0.2****	**-0.14****	**-0.12****
	Individual	0.01	**0.03****	**0.04****	-0.01	**-0.04****	**-0.08****
7 experiential qualities *cognitive CX	Weekly	0.05	0.02	0.05	-0.07	-0.05	**-0.09****
	Monthly	**0.09***	0.01	**0.12****	**-0.27****	**-0.14***	**-0.11****
	Individual	0.01	**0.02****	0.04	-0.02	-0.02	-0.01
8 experiential qualities *physical CX	Weekly	0.01	**0.13****	0.03	-0.05	-0.05	-0.01
	Monthly	**0.22****	0.09	0.12	-0.06	-0.04	-0.02
	Individual	0.01	0.01	**0.51****	-0.02	**-0.21****	-0.01
9 activities* resources* emotional CX	Weekly	**0.10****	**0.19****	**0.79****	-0.19	-0.05	-0.01
	Monthly	**0.12****	**1.21****	**1.15****	-0.20	-0.02	-0.01
	Individual	**0.04***	**0.06****	**0.44****	-0.02	-0.03	-0.01
10 activities * resources * social CX	Weekly	**0.50****	**0.21****	**0.16****	-0.07	-0.10	-0.05
	Monthly	**1.01****	**0.35****	**1.21****	-0.09	-0.05	-0.09
	Individual	**0.05****	**0.04***	**0.06****	-0.01	-0.01	-0.01
11 activities* resources* cognitive CX	Weekly	**0.08****	**0.10****	**0.11****	-0.06	-0.05	-0.02
	Monthly	**0.09****	0.05	**0.19****	-0.09	-0.06	-0.03
	Individual	**0.03***	0.01	**0.04***	-0.01	-0.02	-0.01
12 activities* resources* physical CX	Weekly	**0.12***	**0.09****	**0.16****	-0.05	-0.04	-0.07
	Monthly	**0.18****	**0.06***	**0.21****	-0.04	-0.05	-0.05
	Individual	0.02	**0.03***	0.02	-0.02	-0.01	-0.01

Notes: *** = $p < .001$, ** = $p < .01$, * = $p < .05$; Coefficients in boldface are significant at the corresponding level; Coefficients that are both boldfaced and gray-shaded are significant across all three levels (aggregated weekly level, aggregated monthly

level, and non-aggregated individual level)

Web Appendix H.2: Model robustness checks for data from another platform-TripAdvisor
Table H.2 Effects among nine TCQ elements on distinct migration paths (weekly dataset)

Model 1 focused on and examined the effects of the nine basic elements on firms' migration paths.	Upward Migration Paths			Downward Migration Paths		
	L→M	M→H	L→H	M→L	H→M	H→L
	Positive coefficients expected			Negative coefficients expected		
1 Activities	**0.08*****	**0.02***	**0.07*****	**-0.08*****	**-0.02***	**-0.07*****
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
2 Resources	**0.03****	0.01	**0.05*****	**-0.02***	**-0.02***	**-0.03****
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
3 External Contexts	**0.10*****	**0.02***	**0.11*****	**-0.08*****	**-0.03****	**-0.09*****
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
4 Functional Qualities Related to Activities, Resources, or External Contexts	**0.04****	**0.02***	**0.05*****	**-0.04****	**-0.02***	**-0.04*****
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
5 Emotional CX	**0.09*****	**0.02*****	**0.11*****	**-0.10*****	**-0.02*****	**-0.11*****
	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)
6 Social CX	0.01	**0.04*****	**0.04*****	**-0.02***	**-0.04*****	**-0.03*****
	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
7 Cognitive CX	**0.04****	**0.02*****	**0.02***	**-0.03****	**-0.01*****	**-0.01*****
	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)
8 Physical CX	**0.01*****	**0.01*****	**0.02*****	**-0.01*****	**-0.01****	**-0.01*****
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
9 Experiential Qualities Related to CXs	**0.05*****	**0.02*****	**0.07*****	**-0.07*****	**-0.02***	**-0.04****
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)

Model 2: controlled the basic elements in model 1, focusing on the examination of interactions among focal elements	**Upward Migration Paths**			**Downward Migration Paths**		
	L→M	**M→H**	**L→H**	**M→L**	**H→M**	**H→L**
	Positive coefficients expected			Negative coefficients expected		
1 Functional Qualities * Activities	0.02	**0.08*****	**0.08*****	**-0.04***	**-0.07*****	**-0.08*****
	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)
2 Functional Qualities * Resources	0.03	**0.08*****	**0.10*****	**-0.02***	**-0.08*****	**-0.12*****
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
3 Functional Qualities * Activities * Resources	**0.08***	**0.16*****	0.04	**-0.03****	**-0.15*****	**-0.25*****
	(0.04)	(0.01)	(0.04)	(0.01)	(0.02)	(0.04)
4 Functional Qualities * External Contexts	**0.10*****	**0.01****	**0.11*****	**-0.08*****	**-0.02***	**-0.09*****
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
5 Experiential Qualities * Emotional CX	**0.08*****	0.04	0.02	**-0.11*****	**-0.02***	-0.01
	(0.01)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)
6 Experiential Qualities * Social CX	0.01	**0.04*****	**0.04*****	-0.02	**-0.04****	**-0.03****
	(0.01)	(0.00)	(0.00)	(0.02)	(0.01)	(0.01)
7 Experiential Qualities * Cognitive CX	**0.04****	**0.02***	0.02	-0.03	**-0.02***	-0.01
	(0.01)	(0.01)	(0.02)	(0.03)	(0.01)	(0.01)
8 Experiential Qualities * Physical CX	**0.01*****	**0.01*****	**0.02*****	**-0.02*****	-0.01	**-0.01*****
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
9 Activities * Resources * Emotional CX	**005*****	**0.02*****	**0.06*****	**-0.10*****	**-0.02*****	**-0.06*****
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
10. Activities * Resources * Social CX	**0.01*****	**0.03****	**0.03****	-0.04	**-0.02*****	-0.01
	(0.00)	(0.01)	(0.01)	(0.03)	(0.00)	(0.01)
11. Activities * Resources * Physical CX	**0.02*****	**0.02*****	**0.06*****	**-0.01*****	-0.03	**-0.04****
	(0.00)	(0.00)	(0.01)	(0.00)	(0.02)	(0.01)
12. Activities * Resources * Cognitive CX	**0.03****	0.01	0.01	-0.05	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.03)	(0.01)	(0.01)

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Note:*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Coefficients that are boldfaced are significantly effective; Values in the parentheses are the standard errors (s.e.) of the coefficients

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Executive Summary

Unlocking Service Provider Excellence:
Expanding the Touchpoints, Context, Qualities (TCQ) Framework

A recent study has introduced a comprehensive framework that aims to enhance businesses' comprehension and enhancement of their Customer Experience (CX) performance. This framework provides valuable insights to leaders operating in the dynamic and ever-changing business environment. The research presented in this study introduces a novel methodology for effectively interpreting customer feedback, thereby providing firms with the opportunity to refine their customer experience (CX) strategies.

Key Takeaways for Managers

1. The CX Performance Audit Tool:
This research provides firms with a robust tool for conducting an audit of their CX performance. Not only does this tool facilitate internal assessment, but it also confers a competitive advantage in benchmarking. Gaining a comprehensive understanding of a firm's position in terms of its CX performance is crucial for the development of effective marketing and management strategies.

2. Dynamic Management of CX:
By classifying CX performance into three states - namely, low, medium, or high - managers can obtain a more comprehensive understanding of their present position. This nuanced understanding serves as a foundational framework, identifying areas that require attention and facilitating focused enhancements.

3. Roadmap for Improvement:
This study presents a comprehensive roadmap for managers in service settings to enhance their understanding of current CX performance and efficiently plan for future improvements. Through a detailed examination of transition probabilities, it equips managers to identify and pursue upward trajectories while avoiding downward declines. This strategic framework empowers managers to assess their CX performance comprehensively, allocate resources wisely, and strategically plan for CX enhancements.

4. Step-by-Step Guidance:
This study presents a pragmatic five-step methodology for attaining strategic CX goals.
   - Step 1: Determine the firm's current CX performance state.

- Step 2: Analyze transition probabilities between performance states.
- Step 3: Select the most effective strategic combinations for desired transitions, using a detailed matrix provided in the study.
- Step 4: Harness actionable insights from a dictionary of CX-enhancing terms and concepts.
- Step 5: Implement chosen strategies, monitor their impact, and adapt as necessary.

5. A Word of Caution:

The study cautions managers against making the assumption that a single model of CX performance will be universally effective. Instead, individuals are encouraged to acknowledge potential variations in migration patterns and adapt their strategies accordingly. By implementing the proposed model, managers have the ability to monitor the progression of their CX transitions over a period of time. This allows them to customize their strategies for either promoting or preventing certain outcomes, thereby ensuring the achievement of optimal performance.

In conclusion, this groundbreaking research provides managers with a practical framework and roadmap for effectively managing and enhancing their CX performance trajectories. By incorporating customer feedback alongside strategic insights, businesses can adeptly navigate the intricacies of the contemporary market, thereby guaranteeing not only their survival but also their sustained growth. Interested parties are encouraged to thoroughly examine the complete study for further information regarding this research and the actionable strategies it proposes.

Unpacking Excellence:
The TCQ Guide to Elevate Customer Experience (CX)

Overall Promotion Mechanisms for Three Paths :
(Goal: Increasing the Likelihoods of Performance Improvement)
1. Firms' Activities* Firms' Resources* Emotional CX
2. Firms' Activities* Firms' Resources* Social CX

High Level of CX Performance State

Medium Level of CX Performance State

Low Level of CX Performance State

Overall Prevention Mechanisms for Three Paths
(Goal: Decreasing the Likelihoods of Performance Deterioration)
1. Qualities* Firms' Activities
2. Qualities* Firms' Resources
3. Qualities* Firms' Activities * Firms' Resources