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The role of customer experience dimensions in expanding customer–firm relationships: A customer expansion journey approach

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ABSTRACT

Expansion of customer–firm relationships has become crucial for firms to ensure survival and growth. However, siloed management of multiple expansion behaviors represents the dominant approach in academic research and business practice. This study advocates an expansion as a journey approach, where the customer expansion process is modeled through a customer expansion journey comprising a number of states that can be inferred from customer expansion behavioral manifestations and that represent varying intensities in the interdependencies and ties between the customer and the firm. In addition, we adopt a multidimensional view of the customer experience and investigate the roles of the various experience dimensions (i.e., recency, peak, trend, and fluctuation) in determining consumers' upward and downward movements along the expansion journey at different rates. Using a uniquely rich dataset in the Spanish telecom market for a representative sample of 12,496 customers over four years, and applying advanced hidden Markov modeling techniques, we provide an empirical illustration of the proposed framework. We derive novel theoretical and practical insights into the multifaceted and dynamic customer expansion process, its underlying states, and the role of customer experience dimensions in the transitions across states.

1. Introduction

Expanding relationships with current customers has always been a major focus for business organizations (Scarpi et al., 2022; Shamsollahi et al., 2021). With the current economic environment and the evolving competitive landscape, customer expansion has gained momentum, becoming a top priority for ensuring firm survival and fueling growth (Du et al., 2021; Marketing Science Institute, 2024; Scarpi et al., 2022). In a recent survey conducted by Deloitte (2023), 73 % of executives said that expanding the relationship with customers is one of the top driving forces for organizations. Companies in industries as diverse as retail, banking, entertainment, telecommunications, and e-commerce invest vast amount of resources in developing strategies for promoting various expansion behaviors, including cross-buy, purchase of additional products or services (e.g., through the use of recommendation systems), increase in usage of existing products or services (e.g., by providing personalized training resources), or trial and adoption of new products and

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services (e.g., through limited-time promotions and early access offers).

Despite the widespread focus on relationship expansion, companies usually adopt a siloed management approach to expansion behaviors, developing actions that try to promote each behavior separately. For example, a consumer in the telecom market can receive multiple offers from the current operator to buy additional products or services (e.g., a TV package), upgrade to a superior offering (e.g., unlimited calls and high-speed broadband), or try new products and services (e.g., 5G connectivity). Rather than producing a positive outcome, the indiscriminate and uncoordinated use of these actions can result in just the opposite, with negative consequences for the expansion of the customer–firm relationship such as unprofitable cross-buying (Shah et al., 2012), product returns (Reimer & Becker, 2015), and negative word of mouth (Mende et al., 2013). In-depth knowledge of consumers' predisposition to expand the relationship with the firm is needed before companies can implement a successful customer expansion strategy.

In parallel with the focus in practice on separate management of expansion behaviors, the marketing literature has provided only a fragmented and partial understanding of customer relationship expansion, studying specific behaviors separately, including cross-buying (Kamakura et al., 2003; Li et al., 2011), upgrading (Bolton et al., 2008), new product adoption (Prins & Verhoef, 2007), and service usage (Lemon & Wangenheim, 2009). Despite the value of these studies in providing in-depth knowledge of various expansion behaviors, we still lack a comprehensive understanding of the process that consumers go through in their expansion decisions.

To address this gap, our study builds on previous work on the development of customer–firm relationships (Dwyer et al., 1987; Jap & Ganesan, 2000) where customer expansion is conceptualized as a state of mind of the customer that reflects a willingness to strengthen existing ties with the company via different behavioral manifestations to increase interdependence and ensure a continual increase in benefits (Jap & Ganesan, 2000). This predisposition to expand the relationship with the firm can manifest itself in multiple behaviors, including cross-buying, increasing usage of products and services, adoption of new products or services, and product upgrading (Verhoef & Lemon, 2013). Our work aims to provide an integrative understanding of the customer expansion process by introducing the notion of the *customer expansion journey*: the dynamic process that consumers go through in their expansion decisions with a firm. The journey is unobservable, but its latent states can be captured based on the behavioral manifestations of the customer expansion. Hence, we aim to move from the current dominant view of customer expansion as a single behavioral manifestation toward a view of expansion as a journey comprised of distinct phases that require managerial attention.

In addition to uncovering the customer expansion journey, firms need an understanding of the strategic levers they can use to move customers along that journey. Nowadays, companies are turning to customer experience to improve and expand relationships with existing customers. As highlighted by McKinsey & Company (2023), improving the customer experience of existing customers can increase cross-sell rates (from 15 % to 25 %), strengthen service usage (from 5 % to 10 %), and deliver breakthrough growth (30 %) higher than that of competitors. In contrast, companies delivering a poor customer experience have seen a negative impact on their bottom line (e.g., a 60 % decrease in customer retention and a 57 % loss of revenue). Similarly, according to Forrester (2020), 62 % of business leaders surveyed agreed that more customers than ever before are making decisions (e.g., repeat service usage, what to buy) based on customer experience.

In academia, earlier research has approached customer experience through the lenses of psychology (e.g., Egan Brad et al., 2016; Fredrickson, 2000) and behavioral decision-making (e.g., Ariely, 1998; Ariely & Carmon, 2000; Ariely & Zauberman, 2003). Building on these foundations, more recent studies (e.g., De Keyser et al., 2020; Schouten et al., 2007; Verhoef et al., 2004) have shifted from viewing customer experience as a unidimensional construct—often represented by its (average) level—to recognizing its inherently multidimensional nature. This shift aligns with the memory-based framework (Montgomery & Unnava, 2009), which posits that customer behavior is influenced not by isolated experiences, but by the cumulative effect of remembered interactions over time. Accordingly, not only the most recent interaction (recency), but also the most intense (positive or negative) experiences (peak), the trajectory of past encounters (trend), and the consistency or variability of experiences (fluctuation) can play a critical role in influencing a consumer's decision to expand their relationship with the firm at any given point in time.

Building on this theoretical foundation, our study investigates how customer experience dimensions influence the transitions along the expansion journey, both in terms of direction (upward vs. downward) and rate (fast vs. slow) of movement. Specifically, we focus on four key dimensions: (1) the recency effect—the most recently encountered experience with the firm (Verhoef et al., 2004); (2) the peak effect—the most intense value (minimum or maximum) of the customer experience (Ariely & Zauberman, 2000; Schouten et al., 2007; Verhoef et al., 2004); (3) the trend effect—the upward or downward development of the customer experience over time (Palmatier et al., 2013); and (4) the fluctuation effect—the perceived dispersion (i.e., standard deviation) in the level of customer experiences (Menguc et al., 2020; Voorhees et al., 2021).

Against this background, our study has two main goals. First, we aim to provide a comprehensive and integrative understanding of the expansion of customer–firm relationships through the customer expansion journey lens. To accomplish this goal, we discuss the theoretical underpinnings of the customer expansion process and its behavioral manifestations, and we propose a conceptual model of the multifaceted and dynamic nature of the customer expansion journey. On this basis, we develop an empirical illustration of the customer expansion journey that enables us to uncover the latent customer expansion states. Second, we investigate the role of the customer experience and its multiple dimensions (i.e., recency, peak, trend, and fluctuation) in transitioning customers along the expansion journey both in terms of the direction (upward vs. downward) and rate (fast vs. slow) at which the movements occur. To address these goals, we use a uniquely rich dataset from the Spanish telecom industry that comprises attitudinal and behavioral information for a sample of more than 12,000 customers over a four-year period (2013–2016), and we apply advanced hidden Markov model techniques using a hierarchical Bayesian approach to capture unobserved heterogeneity across customers. This approach enables us to provide a practical illustration of the customer expansion journey that identifies and characterizes latent customer expansion states, as well as clarifying the multiple and varied effects of the customer expansion dimensions in the transitions that customers make along the journey over time.

Our study contributes to the customer expansion literature in at least three important ways. First, we offer a comprehensive view of the customer expansion process through the lens of the customer expansion journey. We expand the dominant (both in theory and practice) siloed and fragmented approach, which focuses on specific manifestations separately, into an *expansion as a journey* approach that can capture the dynamic and multifaceted nature of the customer expansion process holistically and comprehensively. Second, we shed light on the role of the customer experience in the transition of customers across the various stages of the expansion journey. Importantly, we consider the customer experience as a multidimensional construct, and we investigate the varied effects that different dimensions (i.e., recency, peak, trend, and fluctuation) have on the direction (upwards vs. backwards) and rate (fast vs. slow) of the transitions that customers make along the expansion journey. Third, we provide an empirical illustration of our framework to demonstrate how firms can use the information available on the various manifestations of expansion (i.e., cross-buying, service usage, new product adoption, and product upgrading) to uncover the expansion journey and the latent expansion states. What they uncover forms a basis for identifying where consumers are in their expansion journeys and for understanding how the various dimensions of the customer experience influence each customer's transitions in terms of direction and rate. This knowledge is instrumental for the development of tailored and coordinated expansion strategies that strengthen customer–firm relationships.

2. Theoretical background

In this section, we review the theoretical underpinnings of the expansion of customer–firm relationships and their behavioral manifestations to lay the foundation for the development of the customer expansion journey. Table 1 offers an overview of key studies on customer relationship expansion across various contexts.

The evolution of customer–firm relationships has received significant attention within the marketing literature (Shamsollahi et al., 2021; Zhang et al., 2016). To understand the development of the relationship between customers and firms over time, researchers have proposed various stages or phases of the relationship life cycle (Jap & Ganesan, 2000; Kusari et al., 2013). Each stage represents significant transitions in how exchange partners perceive and interact with each other, broadly symbolizing the beginning, development, reinforcement, and dissolution of the relationship. Although customer expansion is the stage that can bring the most intensive business growth (Dwyer et al., 1987), we know relatively little about how customer–firm relationships are expanded (Bolton & Tarasi, 2017).

Customer expansion involves the recognition of the continual increase in benefits to exchange partners (Jap & Ganesan, 2000). The initial interactions with a firm help customers to reduce uncertainty and assess the potential benefits of further interactions (Mullins et al., 2014). If customers feel a high level of perceived trustworthiness of the company, they are more likely to participate in future interactions and take more risks with the exchange partner. These behavioral expectations may help customers to develop confidence and encourage relational continuity (Jap & Ganesan, 2000; Reichheld & Sasser, 1990). Consequently, both the range and the depth of mutual dependence increase and promote customer–firm relationship governance at a more advanced relationship state, encouraging customers to deepen or strengthen their relational bonds with the firm (Zhang et al., 2016). Accordingly, and in line with prior research (Bolton et al., 2004; Dwyer et al., 1987; Jap & Ganesan, 2000; Verhoef & Lemon, 2013), we take customer expansion as a willingness to strengthen existing ties with a firm to ensure a continuing increase in benefits obtained by the exchange partners, leading to an increased interdependence between them (Dwyer et al., 1987; Jap & Ganesan, 2000).

The predisposition to expand the relationship conveys customers' evolving preferences toward relationship continuity with the firm (Bolton et al., 2004; Hyun & Perdue, 2017; Reinartz et al., 2008, 2004; Verhoef et al., 2007; Zhang & Chang, 2021; Zhang et al., 2016) and manifests in a number of key *expansion behaviors* including (1) cross-buying, (2) increasing usage of products and services, (3) adoption of new products or services, and (4) product upgrading (Verhoef & Lemon, 2013). *Cross-buying*, which has been a common focus in previous customer relationship expansion research (Liu & Wu, 2008; Kumar et al., 2008; Verhoef, 2003; Soureli et al., 2008; Nitzan & Ein-Gar, 2019), refers to the acquisition of additional products and services from the existing provider in conjunction with the products/services currently possessed (Ngobo, 2004). Cross-buying is often considered a strategic asset that companies obtain from broadening customer relationships (Bolton et al., 2004), with specific applications to the retailing setting (Kumar et al., 2008) and a large variety of service contexts (Kamakura et al., 2003; Li et al., 2011, 2005; Verhoef et al., 2001). *Service usage* reflects the depth of the relationship and the intensity at which customers use a specific service from the provider (Bolton et al., 2004). When customers exhibit high usage frequency of a product or service, it implies a strong level of satisfaction (Bolton et al., 2000) and greater dependence on the firm (Aurier & N'Goala, 2010), thus serving as an important reflection of the state of customer expansion. *New product adoption* indicates the degree to which a customer adopts products/services newly introduced by the firm (Im et al., 2007; Prins & Verhoef, 2007). Although both cross-buying and new product adoption are related to relationship expansion through buying more products and services, there are fundamental differences between them. As highlighted by Prins and Verhoef (2007), new product adoption involves more uncertainty in the relationship expansion than does cross-buying, since the products or services are new. In contrast, cross-buying pertains to services that are already mature and known to the customer. *Product upgrading* refers to the situation where the customer opts to acquire an enhanced offering with a higher price, improved service levels, and/or additional features (Bolton et al., 2008). This upgrade decision can take various forms, including transitioning from a non-contractual to a contractual relationship (Polo & Sese, 2013), renewing at a higher level of service membership (Marinova & Singh, 2014), or progressing from free to premium options (Datta et al., 2015).

These behavioral manifestations show the complex nature of the customer expansion decision process. Cross-buying, service usage, new product adoption, and product upgrading individually represent different and unique facets of a relationship's richness and jointly capture the *multifaceted* nature of relationship expansion (Zhang et al., 2016). However, the existing body of research (e.g., Aurier &

Table 1
Customer expansion literature review.

Customer Expansion Behaviors	Authors	Context	Dataset			Methodology	Drivers	Conclusions
			T	*P*	*L*			
Cross-buying	Kumar et al. (2008)	Retailing	✓		✓	Seemingly unrelated regression (SUR) model	Exchange characteristics, firm's marketing efforts, customer characteristics, product characteristics	This study investigates the drivers and consequences of cross-buying. The results show that average interpurchase time has an inverted U-shaped with cross-buy, while the ratio of product returns exhibits an inverted U-shaped relationship with cross-buy. This study provides strong support for the effect of marketing efforts of the firm on customers' cross-buying behaviors and indicates that cross-buying can positively impact firm performance.
	Li et al. (2011)	Financial sector	✓		✓	Multinomial probit hidden Markov (HMM)	Financial state, promotional effect of solicitations, advertising effect of solicitations, account transactions, household characteristics	The focus of this research is to understand the role of solicitation in a cross-selling campaign, how it interacts with customer purchase decisions, and how cross-selling can be improved. The authors show that households have different preferences and responsiveness to cross-selling solicitations. In addition to generating immediate sales, cross-selling solicitations also help households build up goodwill and move faster along the financial continuum (educational role).
	Li et al. (2005)	Banking services	✓	✓		Multivariate probit model	Latent financial maturity, relationship with competitor, satisfaction, switching costs	This study investigates how customer demand for cross-buying evolves over time and its implications for the sequential acquisition patterns of naturally ordered products. The results show that women and older customers prioritize overall satisfaction with a bank when considering cross-buying, more so than men and younger customers. Households led by more educated or male heads progress faster along the financial maturity continuum than those with less education or female heads.
	Mende et al. (2013)	Financial services	✓	✓		Ordinary least squares (OLS); multinomial logistic regression	Customer attachment anxiety, customer attachment avoidance, anxiety, preference for closeness	The objective of this research is to decode how attachment styles help create and expand the relationship with customers. Attachment styles are found to be more accurate predictors of customers' inclination for

(continued on next page)

Table 1 (*continued*)

Customer Expansion Behaviors	Authors	Context	Dataset T	Dataset P	Dataset L	Methodology	Drivers	Conclusions
								closeness compared to well-established marketing factors. Additionally, both attachment styles and preferences for closeness play a role in influencing loyalty intentions and behavior, even when established factors such as relationship quality are accounted for. The authors also demonstrate that the preference for closeness serves as a partial mediator in the influence of attachment styles on cross-buying behavior.
	Schweidel et al. (2011)	Telecom industry	✓		✓	Multinomial logit hidden Markov (HMM)	Promotional offering, portfolio inertia, service stickiness	Distinguishing between portfolio inertia and service stickiness, this research explores how customer service portfolios evolve over the course of relationships. The authors show that customers who have discarded a particular service may have an increased risk of canceling all services in the near future but also may be more likely to acquire more services.
Service usage, cross-buying	Bolton et al. (2004)	—				Conceptual	Marketing instruments, customer perceptions (satisfaction, commitment, price equity)	This article proposes an integrated framework that enables service organizations (1) to make a comprehensive assessment of the value of customer relationship length, depth (e.g., service usage), and breadth (e.g., cross-buying) and (2) to understand the influence of marketing instruments on them.
	Lemon and Wangenheim (2009)	Airline service	✓	✓	✓	Generalized method of moments	Core service usage, duration, satisfaction	This study delves into how customer experiences with a company's main service impact both cross-buying from associated loyalty program partners and continued use of the core service. The findings indicate that customer satisfaction and utilization of the core service drive cross-buying behavior. This strengthens the customer's connection with the core service, leading to increased future purchases. The authors also note that the type of cross-buying service (partner) plays a role in shaping these reinforcing effects.
New product adoption	Prins and Verhoef (2007)	Mobile e-service	✓		✓	Hazard model	Direct marketing communication, mass marketing communication,	This study investigates the effects of direct marketing communications and mass

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Table 1 (*continued*)

Customer Expansion Behaviors	Authors	Context	Dataset *T*	Dataset *P*	Dataset *L*	Methodology	Drivers	Conclusions
							competitive mass marketing communication, relationship characteristics, customer characteristics	marketing communications on the adoption timing of a new e-service among existing customers. The results show that service advertising shortens the time to adoption, even when it is initiated by competitors. Furthermore, certain mass marketing efforts have a greater effect on loyal customers.
	Prins et al. (2009)	Telecom service	✓		✓	Linear regression, random effects Tobit specification	Adoption timing, relationship age, category usage	The authors examine the effects of adoption timing on post-adoption usage and disadoption. The results reveal that the earliest adopters have lower initial usage levels than do later adopters. However, early adopters show increasing usage after adoption, whereas late adopters tend to decrease their usage over time. Disadoption rates are higher among later adopters.
	Risselada et al. (2014)	Smartphones	✓		✓	Fractional polynomial hazard model	Social influence, direct marketing stock, relational characteristic (usage)	In this study, the authors examine how social influence and direct marketing impact the adoption of a new high-technology product over time. They demonstrate that the influence of cumulative adoptions within a customer's network diminishes after the product's introduction, whereas the impact of recent adoptions remains consistent. The positive effect of direct marketing gradually wanes after the product's introduction.
Product upgrading	Bolton et al. (2008)	B2B; Computing system support services	✓	✓	✓	Binary logit model	Satisfaction, criticality, service quality, price	The authors propose that the firm's decision to upgrade is influenced by the decision maker's perceptions of the supplier (i.e., at the relationship or account level), contract-level service experiences with the supplier, and interactions between supplier- and contract-level variables. The results indicate that modest improvements in service quality for a focal contract can have a relatively large, positive effect on the likelihood that the firm will upgrade. In addition, the results suggest specific windows of opportunity for suppliers when firms may be more likely to upgrade to

(*continued on next page*)

Table 1 (*continued*)

Customer Expansion Behaviors	Authors	Context	Dataset T	Dataset P	Dataset L	Methodology	Drivers	Conclusions
								higher-level service contracts.
	Ngobo (2005)	A theater company	✓			Nested logit model	Service quality, customer satisfaction, relationship-specific variables, socio-demographic variables	This paper examines why some customers migrate downward while others migrate upward. The results show that the service experience (i.e., service quality, satisfaction) primarily influences the consumer repeat purchase decision. It does not prevent customers from migrating downward. The influence of service experience on upward migration is subject to moderating individual-specific factors such as age of the consumer.

Note: T, P, and L represent transactional, perceptual, and longitudinal datasets, respectively.

N'Goala, 2010; Bolton et al., 2008) is characterized by separate study of each of these expansion behaviors (see Table 1), which produces a narrow and fragmented understanding of the customer expansion process (Zhang et al., 2016). In addition to being multifaceted, the process through which customers expand their relationships with a firm is also *dynamic*. Scholars and managers (Lemon et al., 2002; Palmatier et al., 2013; Zhang et al., 2016) agree that relationships between firms and customers evolve over time and are fundamentally dynamic. However, as noted above, customer expansion is generally considered as a discrete stage along the common relationship trajectory (i.e., exploration, expansion, maturity, and decline) (Cambra-Fierro et al., 2018; Jap & Ganesan, 2000), a view that provides a static snapshot of the relationship at a specific point. Indeed, much of the marketing literature has considered customer expansion as temporally static (e.g., Li et al., 2011; Risselada et al., 2014; Verhoef et al., 2002), which obscures its dynamic nature (Zhang & Chang, 2021). Neglecting the temporal dimension limits our understanding of the entire customer expansion process, potentially leading to misconceptions about its nature.

Given the above, we lack a proper understanding of the ways in which customer expansion evolves over time and of how to capture the process empirically to analyze the drivers and consequences in terms of the development of the customer–firm relationship (Luo & Kumar, 2013; Zhang et al., 2016). We also lack a theoretical framework that can suggest strategic levers upon which firms can act to proactively manage the expansion of the relationships with their customers. In the next section, we introduce the notion of the customer expansion journey and develop a conceptual model to understand the role of the customer experience in the transitions of customers along the journey.

3. Conceptual framework: the customer expansion journey and the role of the customer experience dimensions

In this work, we move away from the current dominant approach of studying customer expansion through a separate analysis of each of its various manifestations, and instead to adopt a broader perspective that considers holistically the spectrum of expansion behaviors and its dynamics. We therefore introduce the notion of the *customer expansion journey*, which we define as the dynamic, round-trip process that consumers go through at different rates in their expansion decisions with a firm and that comprises a series of (latent) expansion states of varying behavioral manifestations. From this definition, two core characteristics of the customer expansion journey can be identified: (1) its direction and (2) its rate. The *direction* refers to the round-trip nature of the customer expansion journey, where consumers can move upwards, deepening and strengthening their relationships with the firm (upward trajectory), move downwards, reverting to weaker states of relationship expansion (downward trajectory), or remain stable. The *rate* indicates the speed at which consumers progress or regress along the expansion journey, indicating the magnitude of their expansion with the firm. This is a latent process, because the expansion journey captures an unobservable mental process reflecting consumers' willingness to engage in stronger bonds with the firm; it features different (latent) states that reflect varying intensities of relationship expansion expressed through different behavioral manifestations. Identifying and empirically capturing the customer expansion journey is thus fundamental to a proper understanding of the complex, multifaceted, and dynamic nature of the customer expansion process.

In addition to conceptualizing the customer expansion journey, we also provide a theoretical discussion of the role that the customer experience may play in the development of the journey and the transitions across the stages. Customer experience is an internal, psychological, and subjective response that customers have during their interactions with a company (Meyer & Schwager, 2007; Rose et al., 2011; Verhoef et al., 2009). Practitioners and scholars alike agree that the customer experience is a key element in the development of customer–firm relationships (Homburg et al., 2017; Witell et al., 2020). However, as shown in Table 2, research investigating the role of the customer experience in the customer expansion process is limited. Customer expansion research has

Table 2
Customer experience literature review.

Authors and Year	Recency Effect	Peak Effect	Trend Effect	Fluctuation Effect	Dependent Variables	Method	Field	Objectives	Findings
Ariely (1998)	Yes	Yes	Yes		Overall experience evaluations	Experiment	Behavioral decision making and psychology	To examine how factors like duration, intensity changes, and continuous ratings affect retrospective evaluations of painful experiences, focusing on the role of final intensity, trend, and duration in shaping memories of painful episodes.	Retrospective evaluations of pain are influenced more by the final intensity and the trend of intensity changes rather than the duration. Duration impacts evaluations only when intensity varies over time, not when it remains constant. Continuous on-line ratings during experiences lessen the sensitivity to duration in final evaluations.
Ariely and Carmon (2000)	Yes	Yes	Yes		Overall experience evaluations	Experiment	Behavioral decision making and psychology	To examine how people summarize and evaluate experiences over time, focusing on the role of peak moments, final moments, and changes in intensity (trends) on overall evaluations.	Summary evaluations of experiences are heavily influenced by key moments, such as the peak (most intense point) and the end of an experience, rather than by its duration. Trends in the experience, like improvement over time, also affect retrospective assessments, especially when experiences are perceived as continuous.
Ariely and Zauberman (2000)		Yes	Yes		Overall experience evaluations	Experiment	Behavioral decision making and psychology	To investigate how breaking up or segmenting experiences, as well as the use of continuous on-line ratings, influence the integration rules people use to form overall evaluations of experiences.	Continuous experiences are evaluated more strongly based on their trends, particularly toward the end, while segmented experiences rely more on the average intensity.
Ariely and Zauberman (2003)			Yes	Yes	Overall hedonic evaluations	Experiment	Behavioral decision making and psychology	To examine the way people evaluate experiences that extend overtime	The improving trends are evaluated more positively than deteriorating trends of equal objective level; The relationship between the pattern of the experiences and their overall evaluations is strongly influenced by the extent and location of the partitioning (i.e., high variations).
Baumgartner, Sujan, and Padgett (1997)	Yes	Yes	Yes		Advertising liking, brand liking, brand recall	Experiment	Marketing	To examine how moment-to-moment emotional reactions to advertisements integrate into overall ad evaluations, focusing on the effects of peak experiences, final moments, duration, and trends of emotional change.	Overall judgments of advertisements are primarily influenced by peak emotional moments, the final moments, and the general trend of emotional change. Duration of the advertisement has little direct impact, but longer durations can be beneficial if they build toward a peak or end on a high note.
Caruelle et al. (2024)					Customer behavioral responses (Store visit duration, Customer spending, Unplanned	Experiment; EDA data analysis	Marketing	To assess the fluctuations in customers' arousal levels throughout a service encounter and their impact	It found that peak arousal levels, or the highest emotional intensity experienced, positively impact customer engagement, leading to

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Table 2 (*continued*)

Authors and Year	Recency Effect	Peak Effect	Trend Effect	Fluctuation Effect	Dependent Variables	Method	Field	Objectives	Findings
					purchasing, Satisfaction with the encounter, Future intentions)			on customers' response to the service environment.	longer store visits, increased spending, and more unplanned purchases. However, a positively skewed distribution of arousal, where lower arousal moments outnumber higher ones, negatively affects satisfaction and approach behaviors. Interestingly, the study found no significant impact of the arousal level at the end of the encounter or the overall trend (whether arousal increased or decreased). This suggests that creating emotionally engaging moments throughout the encounter, rather than focusing solely on the end, is crucial for enhancing the customer experience
Egan Brad et al. (2016)	Yes	Yes			Overall hedonic evaluations	Experiment	Psychology	To explore the evolutionary origins of the peak-end rule and to investigate whether capuchins, children, and adults structure their experiences to maximize hedonic outcomes.	Capuchin monkeys, like humans, show peak and recency (endpoint) effects in their evaluation of experiences. However, neither capuchins, children, nor adults structure experiences to maximize these effects, preferring immediate rewards over improving sequences.
Fredrickson (2000)	Yes	Yes			Overall experience evaluations	Experiment	Psychology	To examine how people extract meaning from past affective experiences, focusing on the importance of peak moments, endings, and the role of specific emotions in shaping overall evaluations.	Global evaluations of affective experiences are strongly influenced by the most intense (peak) and final moments, while the duration of the experience is largely neglected. The personal meaning of specific emotional moments also plays a role in shaping retrospective assessments.
Montgomery and Unnava (2009)	Yes	Yes	Yes		Purchase intention	Experiment	Consumer behavior	To understand how experience temporal sequences (i.e., trend, peak, and trend) affect purchase intentions.	Improving sequences are preferred over declining ones when evaluations are immediate. However, with a delay, preferences reverse, favoring declining sequences. Memory plays a key role, with recency effects dominating immediate evaluations and primacy effects becoming more influential over time. Distinct experiences (e.g., peak moments) are better remembered, impacting overall evaluations significantly

focused on the role of marketing activities (e.g., service and brand advertising, promotions, and marketing communication instruments) (Bolton et al., 2004; Kumar et al., 2008; Li et al., 2011; Prins & Verhoef, 2007; Risselada et al., 2014; Schweidel et al., 2011); on customers' previous transactions with the focal firm (transaction volumes and exchange characteristics) (Kamakura et al., 2003; Kumar et al., 2008; Lemon & Wangenheim, 2009; Li et al., 2011); and on customers' attitudes (customer satisfaction, service quality, and perceived price equity) (Bolton et al., 2004, 2008; Lemon & Wangenheim, 2009; Li et al., 2005; Ngobo, 2005; Verhoef et al., 2001). Importantly, although the customer experience is a multidimensional construct (Lemon & Verhoef, 2016), we lack a systematic understanding of the way in which distinct dimensions of the customer experience may contribute differently to the expansion of the customer–firm relationship.

To address these important gaps, we draw on the memory-based framework (Montgomery & Unnava, 2009) to provide an understanding of how the customer experience and its multiple dimensions influence the customer expansion journey. Specifically, the transitions in the customer expansion journey are determined by (1) the *direction*, that is, whether consumers advance (upward trajectory), regress (downward trajectory), or remain stable in the journey, and (2) the *rate*, that is, the speed at which consumers' upwards or downwards movements occur along the journey. The core principle of the memory-based framework is that memory recall of experiences is marked by salient features (i.e., gestalt characteristics) characterized by *temporality* and *intensity* (Ariely & Carmon, 2000; Ariely & Zauberman, 2003; Kahneman et al., 1993; Kensinger, 2004; Loewenstein & Prelec, 1993; Montgomery & Unnava, 2009; Shehu et al., 2016). Temporality refers to the temporal sequence of experiences over time (Montgomery & Unnava, 2009). Intensity indicates the strength or vividness of customer experience at these specific moments (Kensinger, 2004). The most memorable customer experiences (those marked by significant temporality and high intensity) tend to be recalled more easily, thereby strongly shaping the direction and rate of transitions within the customer expansion journey.

The memory-based framework (Montgomery & Unnava, 2009; Shehu et al., 2016) and related research on customer experience (e.g., Ariely, 1998; Ariely & Carmon, 2000; Reitsamer & Becker, 2024) suggest that such aspects as recent events, peak moments, trends (improving or declining), and variability are particularly prominent during retrospective evaluations. This is because they are related to salient temporal aspects of the customer experience that enhance the individual ability to recall these moments (Kensinger, 2004; Montgomery & Unnava, 2009). Similarly, Master et al. (1983) have shown that the memorability of an experience is closely linked to its intensity; thus, individuals tend to recall moments that are intensely affective more than those that are moderately affective (Harmeling et al., 2015). Accordingly, we identify four key dimensions of the customer experience: (1) the *recency effect*, which refers to a customer's most recent experience with the firm (Verhoef et al., 2004); (2) the *peak effect*, which represents the moments in which individuals undergo an immense intensity of perception, depth of feeling, or sense of significance (Caruelle et al., 2024; Kahneman et al., 1993; Redelmeier & Kahneman, 1996; Schouten et al., 2007); (3) the *trend effect*, which indicates the direction in which an experience evolves over time (Ariely & Carmon, 2000), either improving or declining (Ariely & Carmon, 2000); and (4) the *fluctuation effect*, which reflects the dispersion (i.e., standard deviation) in the customer experience over time (Menguc et al., 2020; Voorhees et al., 2021). Each dimension represents a salient feature that enhances memory recall in a distinct way (Kensinger, 2004; Montgomery & Unnava, 2009). Specifically, the temporal sequence of customer experiences serves as a compass, guiding the direction of the customer expansion journey, while their intensity acts as a throttle, determining the rate of the customer expansion journey. Next, we provide a discussion of the role of the customer experience dimensions in the transition of customers along the expansion journey in terms of direction and rate.

Recency effect refers to a customer's most recent experience with the firm (Verhoef et al., 2004). The memory-based framework (Montgomery & Unnava, 2009) and customer experience literature (Garnefeld & Steinhoff, 2013; Kranzbühler et al., 2018; Verhoef et al., 2004) suggest that the most recent parts of an experience (i.e., the recency effect) are more likely to be retrieved and recalled accurately. Prior research (e.g., Baumgartner et al., 1997; Montgomery & Unnava, 2009; Shehu et al., 2016) has shown that the recency effect of customer experience is one of the best predictors of purchase intention and of brand and advertising liking. Consequently, recent customer experience is very likely to carry substantial weight in determining the direction of the customer expansion journey. A more positive recent interaction can significantly enhance customers' satisfaction and confidence in the firm's ability to meet their needs, thereby fostering an upward trajectory (or preventing a downward trajectory) in the customer expansion journey. However, when it comes to the rate of the customer expansion journey, the influence of the recency effect is more limited. This is because the recency effect is primarily tied to the temporal closeness of an experience rather than its experiential intensity. As such, it does not typically drive rapid acceleration in customer behavior. Instead, it functions as a stabilizing force, anchoring recent interactions in the customer's memory and enhancing immediate recall. This anchoring effect helps maintain steady, gradual progress, reinforcing continuity in the customer's relationship with the firm, rather than triggering sudden growth or shifts.

Peak effect represents the extraordinary moments in which individuals undergo an immense intensity of perception, depth of feeling, or sense of significance (Caruelle et al., 2024; Duerden et al., 2018; Kahneman et al., 1993; Kirillova et al., 2017; Redelmeier & Kahneman, 1996; Schouten et al., 2007). According to the memory-based framework, such peak experiences, whether positive or negative, play a critical role in shaping retrospective judgments due to their vividness and emotional impact (Montgomery & Unnava, 2009). These moments can drive profound changes in customer-firm relationships, influencing the direction and rate of the customer expansion journey (Hargreaves & Stych, 2013; Harmeling et al., 2015; Kranzbühler et al., 2018; Verhoef et al., 2004). Positive peaks can strengthen customer bonds, promoting upward expansion, while negative peaks may trigger disengagement and contraction (i.e., downward expansion journey). The enduring impression of these experiences can lead to lasting shifts in in beliefs and attitudes, and even subjective self-transformation (Schouten et al., 2007), thereby dramatically increasing the customer expansion journey rate. Depending on whether the peak experience is positive or negative, the customer expansion journey may accelerate in either an upward or downward direction.

Trend effect reflects the direction in which an experience evolves over time (Ariely & Carmon, 2000), either improving or declining

(Ariely & Carmon, 2000). Unlike peak experiences, which can trigger rapid, profound changes, trend effects develop gradually over time through repeated interactions rather than singular, intense events (Kahneman, 2000). Individuals often infer trends from temporal sequences, integrating them into their existing beliefs, which in turn shape future evaluations to align with prior perspectives (Ariely, 1998; Johnson et al., 2005). Drawing from the memory-based framework, an improving trend is typically perceived as a series of gains, fostering favorable evaluations and encouraging an upward customer expansion journey. In contrast, a declining trend is seen as a series of losses, which can either slow down or reverse expansion, promoting a downward trajectory. Although trend effects lack the dramatic intensity of peak moments, they play a significant role in gradually slowing the rate of customer expansion journey (Ariely, 1998; Johnson et al., 2005).

Fluctuation effect captures the variability or dispersion in customer experience over time, typically measured by the standard deviation of those experiences (Menguc et al., 2020; Voorhees et al., 2021). Fluctuations often arise from anomalies such as positive surprises, crises, or conflicts, which tend to be more memorable and significantly influence relationship-related decisions (Shamsollahi et al., 2021). Research on interpersonal relationships shows that such temporal instability is associated with doubts and a higher likelihood of dissolution (Arriaga, 2001; Arriaga et al., 2006; Knopp et al., 2014). Similarly, in customer-firm relationships, high variability across experiences can erode confidence, leading customers to perceive greater risk and uncertainty in continuing or expanding the relationship (Palmatier et al., 2013; Sriram et al., 2015; Verhoef et al., 2004). These variations contribute to a sense of instability in the relationship trajectory, which can slow or reverse the customer expansion journey. Ultimately, pronounced fluctuations can heighten customers' perceptions of volatility, intensifying concerns about stability and consistency (Arriaga 2001; Arriaga et al., 2006), thus increasing the rate of the customer expansion journey (in a downward direction).

Together, these effects should play a significant role in the development of the customer expansion journey affecting the rate and the direction at which consumers transit along the various stages of the journey. In the next section we develop an empirical application that helps demonstrate how firms can capture the customer expansion journey and identify the role of the customer experience dimensions in the journey.

4. Empirical application

4.1. Data description and measurement of variables

A leading marketing consultancy provided the data for this study. The dataset consists of a panel that covers 12,496 customers from the telecommunications industry in Spain, with longitudinal customer-level information for a time window of 48 months from January 2013 to December 2016. All the key telecom product categories (mobile, broadband, landline, and television) and all the firms in the industry are captured by the panel, and we ensured that the mobile service provider was known for each customer in the data sample. The dataset contains monthly individual customer-level transactional and perceptual information, alongside firm-level and market-level information.

To capture customer relationship expansion, the panel tracked a wide variety of transactions between customers and firms over the 48 months. The four key behavioral manifestations of customer expansion are cross-buying, service usage, new product adoption, and product upgrading. Cross-buying is a category variable for the number of product categories acquired by customer i from the focal firm at time t. Service usage is measured in five categories according to the amount of mobile credit consumed monthly by customer i at time t. Both new product adoption and product upgrading are dummy variables. New product adoption reflects whether customer i adopts the innovative product category offered by the focal firm at time t, and product upgrading indicates whether customer i acquires the upgraded offering of the main product category from the focal firm at time t.

Another central variable in our study is the customer experience and its dimensions. We captured this using the likelihood-to-recommend (LTR) question (Boulding et al., 1993; Parasuraman et al., 1988), "How likely is it that you recommend (company X) to a friend or colleague?," measured on a scale of 0 to 10 and widely recognized in marketing (Baehre et al., 2022; De Haan et al., 2015). LTR is considered to be an adequate measurement of customer experience from both the theoretical and practical perspectives. Drawing on prior research (Frow & Payne, 2007; Lemon & Verhoef, 2016), LTR sums up customers' experiential feelings about a firm (Grewal et al., 2009). A higher LTR score indicates a more delightful customer experience, such that the customer is happier to recommend the firm to their friends (Keiningham et al., 2007; Mackintosh, 2015). Given its theoretical underpinnings, LTR has been widely applied in practice across a broad variety of sectors and companies (Cuvillier et al., 2021; De Haan et al., 2015). In the telecom industry, LTR has been used as a measure of customer experience for many years.

We measured LTR through four consecutive annual surveys conducted each December from 2013 to 2016. To represent the selected market accurately, the surveys were administered to customers across all existing firms in the mobile service category. The longitudinal information available for the customer experience over time enabled us to capture its various dimensions (i.e., the recency, peak, trend, and fluctuation effects). Prior research indicates that it is appropriate to measure customer experience annually (Lemon & Verhoef, 2016), as the affective and emotional processing of experience leads to persistent associations in the memory (Rose et al., 2011). Rather (2020) concluded that a delightful customer experience endures in the customer's mind, and Roy (2018) demonstrated empirically the stable nature of the customer experience. Annual LTR surveys have also frequently been applied in empirical studies and business practice (De Haan et al., 2015; Rawson et al., 2013).

The recency effect was measured using the most recent LTR score, reflecting the latest perceived experience by customer i at time t. Following prior research (De Haan et al., 2015; Reichheld, 2003; Sivakumar et al., 2014), the peak effect was measured using dummy variables, where a high peak takes the value 1 for customer i at time t if the LTR score is higher than 8, and 0 otherwise; a low peak takes the value 1 for customer i at time t if the LTR score is lower than 7, and 0 otherwise. Based on the study of Gijsenberg et al. (2015), the trend effect was calculated as the difference between consecutive LTR scores. Two variables were generated to present the direction of the trend. In a positive trend, positive values indicate an increasing trend, while 0 signifies other conditions; in a negative trend, negative values signify a decreasing trend, with 0 representing other scenarios. The fluctuation effect was captured through cumulative variability in LTR scores over time, grounded on the approach of Voorhees et al. (2021). Specifically, we calculated the coefficient of variation for each customer i as the ratio of the standard deviation to the mean of all accumulated LTR scores up to each respective year. This dynamic measure provided an ongoing assessment of fluctuations, reflecting changes in customer experience.

The response rates of LTR for the years 2013 to 2016 were 16.94 %, 53.22 %, 65.85 %, and 40.15 %, respectively. We calculated these rates by considering the number of customers (from the total of 12,496) who responded to the survey at the end of each year. Following Kamakura and Wedel (2000), we used the mean imputation method, an effective and commonly applied method for dealing with missing data (Bill et al., 2020; Kamakura & Wedel, 2000; Verhoef et al., 2002).[1] Of the three standard procedures for dealing with missing data (mean imputation, pairwise deletion, and listwise deletion), mean imputation has been found to perform best, even when up to 60 % of the data are missing (Kamakura & Wedel, 2000). Accordingly, we replaced missing values by the average value for affective customer experience across customers from the same firm in the corresponding service category for that year, and we created a dummy variable to indicate whether each customer had participated in the survey. This method allowed our model to capture potential deviations in behavior by customers who did not respond to the survey.[2]

The dataset was completed by a set of control variables from multiple sources: customer demographic characteristics (gender, age, number of household members, working status, and social class), as provided by the marketing consultancy; data relating to firm characteristics (investment in advertising, product innovation, conflict resolution, and market shares), obtained from the official annual report of the telecommunication sector in the corresponding market; and information on contextual characteristics (acquisitions, new entrants, iPhone release dates, and social media mentions), acquired from news websites and Google Trends. Inclusion of these control variables enabled us to test the proposed conceptual model rigorously. Table 3 summarizes the variables included in our modeling framework and the corresponding descriptive statistics.

4.2. Hidden Markov model development

To test the proposed model, we applied the multivariate hidden Markov model (HMM), which has been employed in prior research (e.g., Ascarza & Hardie, 2013; Ascarza et al., 2018; Kumar et al., 2011; Luo & Kumar, 2013; Schweidel & Knox, 2013; Schweidel et al., 2014; Zhang et al., 2016), to capture the development of customer–firm relationships. An HMM describes the transition process among a finite set of latent states (here, customer expansion states) that are invisible but can be inferred from a set of observable behaviors (Netzer et al., 2008; Zhang et al., 2022). Furthermore, the HMM approach makes it possible to uncover the migration patterns across these states and identify the drivers responsible for them (Ascarza & Hardie, 2013; Ascarza et al., 2018; Schweidel & Knox, 2013; Schweidel et al., 2014; Luo & Kumar, 2013). Applying HMM is therefore appropriate for identifying customer relationship expansion states through a set of behavioral manifestations and, importantly, for assessing how customer experience dimensions influence both the direction and rate of the customer expansion journey, while controlling for customer-, firm-, and context-related variables.

The HMM model that we propose consists of three components: (1) the initial state distribution, which indicates the probability that a customer belongs to a particular state in the first period of our dataset; (2) the state transitions, which denote the probability of a customer migrating from one customer expansion state to another over a period, and the effects of different dimensions of the customer experience on the direction and rate of migration alongside the customer expansion journey; and (3) the state-dependent choices, which control for the influence of firm, market, and customer characteristics.

4.2.1. Initial state distribution

In Eq. (1), s denotes a latent expansion state and π_{is} the probability that customer i is in state s in the first period of the dataset, where the sum of π_{is} is equal to 1 (MacDonald & Zucchini, 1997).

$$\Pr(S_{it} = s_{it}) = \pi_{is,}\, \text{where} s_{it} \epsilon \{1, 2, \ldots K\} \tag{1}$$

4.2.2. State transitions matrix

To extract the customer relationship expansion states, we used four key variables: cross-buying, service usage, new product adoption, and product upgrading (i.e., the behavioral manifestations of the customer expansion). The choice of these four variables was based on the CRM literature (Bolton et al., 2004, 2008); as Table 1 shows, all four variables have frequently been used to study customer relationship expansion, albeit previous studies have investigated them separately. Bolton et al. (2004), in a conceptually oriented study, emphasized that the customer–firm relationship is reflected not in a single type of purchase behavior but rather in different types. This insight entails that various purchase behaviors should be considered to ascertain how the relationship between

[1] In addition to mean imputation, we developed a very conservative robustness check: where customer experience values were missing, we estimated the model without observations. This estimation captured consistent patterns, which provides evidence for the robustness of the proposed model.

[2] We also estimated the model using only data where customer experience responses were available. The results were consistent with the patterns captured using the mean imputation method of Kamakura and Wedel (2000), which provides evidence for the robustness of the proposed research model.

Table 3
Descriptive statistics (N=621,408).

Variable		Description		Time Unit	Mean	SD
Customer expansion behaviors		Cross-buying	Monthly measurement of the number of product categories purchased by customer i from the focal firm at time t, namely mobile service category, broadband service category, landline service category, and TV service category.	Monthly	2.092	1.120
		Service usage	Level of usage is measured monthly via the amount of mobile credit consumed by customer i at time t. It has five categories: (1) less than €2.50 into 0, (2) less than or equal to €8.00 into 1; (3) less than or equal to €25.50 into 3, (4) less than or equal to €55.50 into 4, and (5) less than or equal to €125.50 into 5.	Monthly	.884	1.040
		New product adoption	Monthly measurement of dummy variable: customer i acquires the innovative product category from the focal firm at time t; 0 = otherwise.	Monthly	.247	.431
		Product upgrading	Monthly measurement of the dummy variable: 1 = customer i acquires the upgraded offering of the main product category from the focal firm at time t; 0 = otherwise.	Monthly	.025	.157
Dimensions of customer experience		Recency effect	The recent customer experience perceived by customer i firm the focal firm m in the mobile service category is measured using the likelihood-to-recommend (LTR) question, collected annually through a survey conducted each December (0 = very unlikely, 10 = very likely).	Yearly	7.678	1.922
		Peak effect	The high peak in customer experience is measured by a dummy variable that indicates whether customer *i*'s LTR score for the mobile service category at time *t* is greater than 8 (1 = LTR > 8, 0 = otherwise).	Yearly	.065	.246
			The low peak in customer experience is measured by a dummy variable indicating whether customer *i*'s LTR score for the mobile service category at time *t* is less than 7 (1 = LTR < 7, 0 = otherwise).	Yearly	.545	.498
		Trend effect	The tendency of increasing customer experience is measured by calculating the difference between the current LTR score at time t and the previous LTR score at time t−1. A positive value indicates an increasing trend, while a value of 0 is assigned otherwise.	Yearly	.014	.220
			The tendency of decreasing customer experience is obtained by calculating the difference between the current LTR score at time t and the previous LTR score at time t−1; A negative value indicates a decreasing trend, while a value of 0 is assigned otherwise.	Yearly	-.006	.129
		Fluctuation effect	The fluctuation effect in customer experience is measured using the coefficient of variation, calculated as the ratio of the standard deviation to the mean LTR score, incorporating all available historical data up to the current year t.	Yearly	.008	.051
Control variables	**Customer characteristics**	Gender	Dummy variable: 1 = female; 0 = male.	Yearly	.644	.479
		Age	Age (in years) of customer i at time t.	Yearly	45.651	16.541
		Social class (high)	Whether the customer belongs to a high level of social class (yes 1; no 0).	Yearly	.192	.394
		Social class (low)	Whether the customer belongs to a low level of social class (yes 1; no 0).	Yearly	.207	.405
		Household size	Number of family members of customer i at time t.	Yearly	3.046	1.198
	Firm characteristics	Adver commu (Log)	Investment in advertising communications from firm m at time t and transformed into a logarithm.	Quarterly	4.988	1.891
		Product innovation (Log)	Investment in product innovation from firm m at time t and transformed into a logarithm.	Quarterly	7.758	2.985
		Conflict frequency	Frequency of complaints in mobile services of main operators.	Quarterly	.875	.656
		Conflict length	Average time taken to resolve problems in mobile services of main operators.	Quarterly	11.543	13.373
		Market share	Percentage of total revenues that firm m accounts for over the whole market at time t.	Quarterly	.143	.137
		Social media mention	Frequency with which firm m is mentioned through associated keywords in social media channels at time t.	Monthly	48.551	17.966
	Context characteristics	Acquisition	Dummy variable: 1 = a firm in the telecoms market has been acquired by another firm; 0 = otherwise.	Monthly	.043	.202
		iPhone release	Dummy variable: 1 = a new iPhone is released in the telecoms market at time *t*; 0 = otherwise.	Monthly	.104	.305
		New entrants	Dummy variable: 1 = there are new firms entering the telecoms market at time *t*; 0 = otherwise.	Monthly	.042	.201

customers and firms expands.

The transition matrix between customer expansion states was modeled as a Markov process. Eq. (2) shows the HMM transition matrix Q, which denotes the probability of a customer migrating from one state to another over a period, where $q_{itss'} = P(S_{it} = s' | S_{it-1} = s)$ is the probability of customer i moving from state s at time t−1 to state s' at time t, and where $0 \leq q_{itss'} \leq 1 \; \forall \; s, s'$, and $\Sigma_{s'} q_{itss'} = 1$. As we have highlighted conceptually, the customer expansion journey is dynamic, with customers moving both upwards (i.e., on a positive trajectory, from lower to higher levels of relationship expansion) and downwards (i.e., on a negative trajectory, from higher to lower levels of relationship expansion) at varying rates (slow versus fast). This research investigates how customer experience dimensions (recency, peak, trend, and fluctuation) influence both the direction and rate of customer transitions throughout the expansion journey. To examine this empirically, we allowed customers to transit to any relationship state s = 1, 2, …, KS, where KS denotes the number of states. Each of the matrix elements in Eq. (2) represents a probability of transition.

$$
\begin{array}{cc|cccccc}
 & & & & Stateatt & & & \\
Stateatt-1 & & 1 & 2 & 3 & \ldots & S-1 & KS \\
 & 1 & q_{it11} & q_{it12} & q_{it13} & \cdots & q_{it1S-1} & q_{it1S} \\
\Omega_{i,t-1tot} = & 2 & q_{it21} & q_{it22} & q_{it23} & \cdots & q_{it2S-1} & q_{it2S} \\
 & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\
 & KS & q_{itNS1} & q_{itNS2} & q_{itNS3} & \cdots & q_{itNS-1} & q_{itNSNS}
\end{array} \tag{2}
$$

In line with prior research (Kumar et al., 2011), we used a multinomial logit specification to formulate this transition process. Therefore, as demonstrated in Eq. (3), the transition probabilities ($q_{itss'}$) denoted in Eq. (2) are influenced by a vector of the customer experience dimensions (recency, peak, trend, and fluctuation effects) that affect the transition from state s to s' at time t.

$$
q_{itss'} = \frac{\exp(\phi 0ss' + \phi 1ss' \; Xit + \phi 2ss' \; XHit + \phi 3ss' \; XLit + \phi 4ss' \; XTIit + \phi 5ss' \; XDit + \phi 6ss' \; XFLit)}{1 + \sum_{s=1}^{s-1} \exp(\phi 0ss' + \phi 1ss' \; Xit + \phi 2ss' \; XHit + \phi 3ss' \; XLit + \phi 4ss' \; XTIit + \phi 5ss' \; XDit + \phi 6ss' \; XFLit)} \tag{3}
$$

In Eq. (3), $\phi_0^{ss'}$ is the intercept which represents the baseline log-odds of transitioning from state s to s' when all customer experience dimensions are absent or set to zero. This intercept reflect the intrinsic transition dynamics and capture structural tendencies and unobserved factors, such as general customer inertia or systemic propensities to upgrade or downgrade along the expansion journey, not explained by the observed variables. Parameters $\phi_1^{ss'}$, $\phi_2^{ss'}$, $\phi_3^{ss'}$, $\phi_4^{ss'}$, $\phi_5^{ss'}$, and $\phi_6^{ss'}$ are the response coefficients that measure the impact of each customer experience dimension on the transition probability $q_{itss'}$, thereby capturing how these dimensions influence both the direction and rate of the customer expansion journey. A positive in these parameters indicate that a particular customer experience dimensions increases the likelihood of transitioning from state s to s', while a negative suggests that it slows such a transition. The direction is observed as a transition from one state to the subsequent state (e.g., from S1 to S2). Meanwhile, transitions along the customer expansion journey may span more than one state (e.g., from S1 to S3 or S2 to S4), thus representing the rate, as they quantify the magnitude of change in the expansion journey. A positive sign of $\phi^{ss'}$. X_{it} is the customer experience most recently encountered by customer i at time t. XH_{it} and XL_{it} represent high and low peaks of customer experience, respectively. The increasing and decreasing trends of customer experience are denoted as XTI_{it} and XTD_{it}. Finally, XFL_{it} indicates customer experience fluctuations.

4.2.3. State-dependent choices

In line with prior research (Luo & Kumar, 2013), in Eq. (4) we express the latent utility U_{its} that customer i derives from the customer expansion behaviors at time t in state s. S_{it} indicates the customer expansion state to which customer i belongs at time t. The set of control variables include customer-, firm-, and context-related characteristics, which are denoted as $Customer_{it}$, $Firm_t$, and $Context_t$, respectively. Thus, the parameters θ_s and β_1–β_3 capture the influence of the customer expansion states and control variables in different customer expansion behaviors. As a component of HMM, the state-dependent choices should be developed according to the distribution of the observed outcome (Schweidel et al., 2011). Given the categorical nature of cross-buying Y_{imt}^{CR} and service usage Y_{ijt}^{SU}, their state-dependent choice probabilities follow multinomial logit models. In Eqs. (5.1) and (5.2), Pr ($y_{imt}^{CR} | S_{it} = s$) and Pr ($y_{ijt}^{SU} | S_{it} = s$) represent the possibility of observing the choice profile that in a given state s customer i would choose cross-buying (service usage) alternative j (m) across the J (M) alternatives at time t. The other two behaviors, new product adoption and product upgrading, are dichotomous. To model the probability of a dichotomous choice of new product adoption Y_{it}^{AD} and product upgrading Y_{it}^{UP}, we used the binary logit models (Netzer et al., 2008) in Eqs. (5.3) and (5.4), respectively. Consequently, Pr ($y_{it}^{AD} = 1 | S_{it} = s$) and Pr ($y_{it}^{UP} = 1 | S_{it} = s$) indicate the probability of customer i in state s adopting an innovative product category and choosing the upgraded offering at time t.

$$
U_{its} = \alpha_0 + \theta_{sSit+}\beta_1 Customer_{it+}\beta_2 Firm_{t+}\beta_3 Context_t \tag{4}
$$

$$
\Pr\left(y_{imt}^{CR} \middle| S_{it} = s\right) = \frac{\exp^{Uitsm}}{1 + \sum_{m=1}^{M} \exp^{UitsM}} \tag{5.1}
$$

$$
\Pr\left(y_{ijt}^{SU} \middle| S_{it} = s\right) = \frac{\exp^{Uitsj}}{1 + \sum_{j=1}^{J} \exp^{UitsJ}} \tag{5.2}
$$

$$
\Pr\left(y_{it}^{AD} = 1 \middle| S_{it} = s\right) = \frac{\exp^{Uits}}{1 + \exp^{Uits}} \tag{5.3}
$$

$$\Pr\left(y_{it}^{UP} = 1 \middle| S_{it} = s\right) = \frac{\exp^{Uits}}{1 + \exp^{Uits}} \tag{5.4}$$

4.2.4. HMM likelihood function

To derive the HMM likelihood function of the sequence of observations, we combined the three components of the HMM, namely the initial state distribution, the states transition matrix, and the state-dependent distribution. Conditional on being in state s at time t, a customer responds to the level of service usage, cross-buying, new product adoption, and product upgrading. Given the Markovian structure of the model, the likelihood of observing a set of joint customer responses at time t depends on all the responses prior to that event. If customer i at time t is in a latent state $S_{it} = s$, we can use multivariate normal distributions to model the joint distributions on the four dependent variables. Following Zucchini and MacDonald (2009), the likelihood of a customer's responses over T periods (Y_{i1}, Y_{i2}, …, Y_{iT}) can be expressed using Eq. (6), where π_i is the initial distribution, Q is the state transition matrix, M is an S × S diagonal matrix with the elements Pr (y_{imt}^{CR}| $S_{it} = s$), Pr (y_{ijt}^{SU}| $S_{it} = s$), Pr ($y_{it}^{AD} = 1$| $S_{it} = s$), and Pr ($y_{it}^{UP} = 1$| $S_{it} = s$) from Eq. (2) on the diagonal, and 1' is an S × 1 vector of ones.

$$LL = P\left(Y_{i1=yi1,}\ldots YiT{=}_{yit}\right) = \pi_i M_{i1} Q_{i,1\rightarrow 2} M_{i2\ldots} Q_{i,T-1\rightarrow T} M_{Ij} 1' \tag{6}$$

4.2.5. Identification strategy

It is necessary to identify not only the model parameters of the HMM but also its states. In our HMM, latent expansion states are determined by each customer's time-varying levels in the four behavioral manifestations considered (i.e., cross-buying, service usage, new product adoption, and product upgrading). The model simultaneously identifies the number of latent states, allows customers to migrate freely across different states, and assesses the role of each dimension of the customer experience dimensions (the recency, peak, trend, and fluctuation effects) in the migration path alongside the customer expansion journey in terms of direction and rate.

5. Study findings

In this section, we report the results of the estimation of the multivariate HMM using the data collected from the telecom industry. We started by comparing the fit of a set of benchmark models. For model estimation, we applied the Baum–Welch or forward backward algorithm (Baum et al., 1970; Paas et al., 2007), which is a special variant of the expectation-maximization algorithm for latent Markov models. This algorithm enables the estimation of models with long time series and can easily handle incomplete data (Baum et al., 1970; Paas et al., 2007).

5.1. Model comparison

We began by assessing the fit of our model in comparison to four benchmark models. Given that we had no prior knowledge of the exact number of expansion states, we estimated a set of HMM models. We estimated models A–C by taking the recency, peak, trend, and fluctuation effects of customer experience as the key variables influencing the direction and rate of state transitions within the matrix across two to four states alongside the customer expansion journey, keeping the emission probabilities and the initial distribution the same as in the models estimated above. Model D is a latent growth curve model that ignores the dynamic transition across customer relationship expansion states, focusing instead on the static customer relationship expansion clusters. Latent growth curve analysis is usually applied to determine whether the sample relationship (here, customer relationship expansion) follows a common developmental path by testing the latent growth constructs (here, number of acquired product categories, service usage, and others) that emerge from the longitudinal data (Bollen & Curran, 2006; Palmatier et al., 2013). Lastly, as a nested version of model C, we estimated model E, in which no variable was computed in the state transitions matrix.

To choose the model with the best performance, we compared the fit statistics for the set of estimated models (i.e., models A–E). In addition to the log-likelihood ratio, the traditional Bayesian information criterion (Schwarz, 1978), and Akaike's information criterion (AIC) (Akaike, 1974), we used the consistent AIC (CAIC) (Bozdogan, 1987) and the AIC with a per parameter penalty factor of three (AIC3) (Bozdogan, 1994). Table 4 presents the model fit measures for the benchmark models. The model with a four-state HMM (model C) fitted the dataset better than the two-state and three-state HMM models (models A and B). Importantly, we found that model C gave better performance than models D and E, which indicates the importance of accounting for the dynamic nature of customer relationship expansion and the key roles of customer experience dimensions in transitioning customers across the states in the expansion

Table 4
Model fit statistics.

	Model A	Model B	**Model C**	Model D	Model E
LL	-747,054.958	-603,453.845	**-530,716.593**	-671,952.706	-553,516.466
BIC	1,494,810.588	1,207,731.452	**1,062,401.428**	1,344,691.301	1,107,904.037
AIC	1,494,257.916	1,207,081.689	**1,061,624.699**	1,344,071.412	1,107,216.931
AIC3	1,494,331.916	1,207,168.689	**1,061,728.699**	1,344,154.412	1,107,308.931
CAIC	1,494,884.588	1,207,818.452	**1,062,505.428**	1,344,774.301	1,107,996.037
SABIC	1,494,575.423	1,207,454.975	**1,062,070.926**	1,344,427.535	1,107,611.670

journey. Finally, following standard practice, to infer whether our estimates could have been affected by multicollinearity, we computed the variance inflation factor (VIF) scores for each regression. Each VIF score was below the recommended cutoff of 10 (the maximum score was 5.70), which suggests that multicollinearity did not have a serious effect on the model results (Hair et al., 1998). In addition, the correlations between the key variables shown in Web Appendix A do not signal multicollinearity.

5.2. Customer relationship expansion states

As noted above, the model with four states outperformed the other benchmark models. We refer to the four states, ordered from less to more expansion, as (1) the basic state S1, (2) the intensified state S2, (3) the widened state S3, and (4) the supreme state S4. To characterize each of these customer expansion states, drawing from Zhang et al. (2016), we assessed the mean value of each of the customer expansion behavioral manifestations (i.e., cross-buying, service usage, new product adoption, and product upgrading) conditional on being in each state. We describe each of them in turn.

Basic state Customers in the basic state typically exhibit low levels of cross-buying (mean = 1.000) and service usage (mean = .004). Additionally, customers in this state are less likely to upgrade from their current product category (mean = .023) or to adopt a new one (mean = .008). These combined characteristics suggest that the customer–firm relationship has developed to a limited extent only.

Intensified state Transitioning from the basic state to the intensified state, the customer relationship expands primarily by increasing cross-buying (mean = 2.046) and service usage (mean = .903). However, customers in this state continue to show modest levels of adoption of new product categories (mean = .014) and upgrading to advanced offerings (mean = .027), similarly to those in the basic state. The intensified state is defined by two key features. First, heightened service usage indicates that customers in this state are more inclined to broaden their relationship with the firm compared to those in the basic state. Second, customers in this state tend to follow a cautious approach to relationship expansion, starting with familiar product categories rather than immediate upgrades or new category adoption.

Widened state The widened state is marked by a notable increase in cross-buying (mean = 3.013). Customers in this state typically engage with three product categories from the focal firm, showcasing a strong tendency for cross-buying. In contrast to those in the intensified state, their service usage is slightly higher (mean = 1.347) and they are more inclined to accept upgraded offerings (mean = .026). The significant rise in cross-buying reflects a transformative shift in the possibilities for expanding customer relationships. Therefore, we employ the term “widened state” to symbolize a dynamic evolution between the customer and the firm, signifying a process of expansion.

Supreme state Lastly, in the supreme state, customers advance their relationship with the focal firm through cross-buying (mean = 3.718). The service usage within the main category experiences a slight uptick (mean = 1.627). Customers in the supreme state exhibit a highly positive attitude toward adoption of new product categories (mean = .997). Although the likelihood of customers upgrading their current product category remains moderate (mean = .028), it surpasses that of customers in the other relationship expansion states. This proactive inclination of customers to expand the relationship suggests a stronger willingness on their part to engage with the firm and increase the benefits from the relationship.

5.3. Roles of customer experience dimensions in the transitions between expansion states

An important feature of our estimated model is the ability to reveal how different customer experience dimensions influence transitions along the customer expansion journey, both in terms of direction and rate. The detailed parameter estimates for these transition probabilities (derived from Eq. (3)) and state-dependent choices (Eqs. (5.1), (5.2)) are presented in Table 5. The top section of Table 5 presents how customer experience dimensions influence directional transitions between adjacent states (i.e., one-level state shifts), while the bottom section focuses on transitions that span multiple states, reflecting the rate of transitions. These results are visually summarized in Fig. 1. The color intensity in Fig. 1 corresponds to the magnitude and direction of the coefficients in Table 5, with blue shades indicating positive effects and green shades representing negative effects. This visualization highlights the customer experience dimensions that most strongly shape specific transitions, offering an intuitive complement to the numerical results.

The recency effect primarily serves as a stabilizing force, helping to prevent downward transitions and slow their rate. Specifically, recent positive experiences decrease the probability of moving the intensified state S2 to the basic state S1 (ϕ_1^{21}= -.087, $p < .10$), from the widened state S3 to the intensified state S2 (ϕ_1^{32} = -.153, $p < .01$), and from the supreme state S4 to the widened state S3 (ϕ_1^{43} = -.115, $p < .05$). Moreover. as shown in the bottom section of Table 5, the recency effect significantly slows rapid regression from the supreme state S4 to the basic state S1 ($\phi_1^{41} = -.098, p < .05$) and from the supreme state S4 to the widened state S2 ($\phi_1^{42} = -.125, p <$ .01). These findings highlight that recent experiences help maintain relationship stability, particularly by mitigating both the likelihood and speed of decline, but have limited influence on driving upward progression.

In contrast, positive peak experiences act as powerful drivers of upward transitions and accelerators of expansion journey. Customers exposed to peak positive experiences are more likely to move from the basic S1state to the intensified state S2 ($\phi_2^{12} = .539, p <$ .10) and from the widened state S3 to the supreme state S4 ($\phi_2^{34} = .804, p < .01$). Additionally, they are prone to serve as catalysts for accelerating upward progress, facilitating transitions from the basic state S1 to the supreme state S4 ($\phi_2^{14} = .499, p < .05$) and from the intensified state S2 to the supreme state S4 ($\phi_2^{24} =. 770, p < .01$). However, these peaks do not significantly affect downward movement in the expansion journey. This suggest that while memorable positive events can drive relationship progression, they may not necessarily prevent relationship deterioration. Conversely, negative peaks are particularly detrimental to upward movement, significantly hindering progress from the basic state S1 to the supreme state S4 ($\phi_3^{14} = -.337, p < .01$) and from the intensified state S2 to the

Table 5
HMM model estimation results.

		Top Section: Customer Expansion Journey Direction (∇Δ = one state)					
		S1 → S2 (Upward)	**S2 → S1 (Downward)**	**S2 → S3 (Upward)**	**S3 → S2 (Downward)**	**S3 → S4 (Upward)**	**S4 → S3 (Downward)**
CX Dimensions	**CX Recency**	.062 (.054)	**-.087(.050)** *	.081 (.061)	-.153 (.029) ***	.068 (.074)	-.115 (.046) **
	CX Positive Peak	.539 (.200) *	.272 (.250)	.627 (.153)	-.363 (.258)	.804 (.204) ***	.235 (.295)
	CX Negative Peak	-.406 (.116) ***	.251 (.119) **	-.116 (.116)	.355 (.075) ***	-.224 (.168)	.162 (.119)
	CX Positive Trend	.259 (.339)	-1.337 (3.635)	-.319 (1.476)	-1.670 (3.062)	-7.959 (3.727)	8.600 (1.999)
	CX Negative Trend	-10.366 (2.288)	.706 (.253) ***	-.456 (.552)	-.176 (.430)	15.115 (82.179)	8.600 (1.998)
	CX Fluctuations	-.825 (.234) ***	.812 (.213) ***	-1.082 (.296) ***	.040 (.229)	-.495 (.385)	.248 (.348)
	Intercepts	-4.882 (.461) ***	-4.341 (.411) ***	-5.464 (.501) ***	-3.553 (.238) ***	-4.373 (.632) ***	-3.942 (.395) ***
		Bottom Section: Customer Expansion Journey Rate (∇Δ> one state)					
		S1 → S3 (Upward)	**S3 → S1 (Downward)**	**S2 → S4 (Upward)**	**S4 → S2 (Downward)**	**S1 → S4 (Upward)**	**S4 → S1 (Downward)**
CX Dimensions	**CX Recency**	-.029 (.046)	-.084 (.056)	.022 (.081)	-.125 (.041) ***	.081 (.075)	-.098 (.047) **
	CX Positive Peak	.509 (.248)	.260 (.199)	.770 (.174) ***	.062 (.299)	.499 (.206) **	-.008 (.311)
	CX Negative Peak	.260 (.199)	.102 (.129)	-.298 (.165) *	.031 (.095)	-.337 (.115) ***	.008 (.311)
	CX Positive Trend	-.250 (1.042)	.240 (.343)	-.420 (1.821)	-16.940 (3.407)	.225 (.380)	-.229 (1.109)
	CX Negative Trend	.442 (2.170)	-.118 (1.290)	.057 (2.564)	13.654 (7.442)	.167 (2.919)	.314 (1.972)
	CX Fluctuations	-.252 (.349)	.167 (.428)	-.277 (.490)	.427 (.240) *	-.150 (.477)	.580 (.260) **
	Intercepts	-4.197 (.381) ***	-4.819 (.453)	-4.939 (.662) ***	-3.928 (.348) ***	-4.394 (.619) ***	-4.557 (.383) ***
	States	.643 (.015) ***	.570 (.015) ***	-.451 (.021) ***	-.762 (.023) ***		
		S1	**S2**	**S3**	**S4**		
State Dependence Choices							
	Cross-buying	Service usage	New product adoption	Product upgrading			
Basic state (S1)	.198(.011) ***	-4.246(.055) ***	-3.850(.039) ***	-.072 (.020) ***			
Intensified state (S2)	-14.81(.727) ***	1.478(.019) ***	.233(.029) ***	.104 (.020) ***			
Widened state (S3)	1.774(1.000)	1.765(.019) ***	3.350(.041) ***	.059 (.023) ***			
Supreme state (S4)	12.838 (1.000)	1.003(.019) ***	6.967(.076) ***	.091 (.027) ***			
Gender	.006(.007)	-.036(.005) ***	-.236(.014) ***	.041 (.024) *			
Age	-.004(.0002) ***	-.0001(.0002)	-.001(.001)	-.009 (.001) ***			
Social class (low)	-.433(.009) ***	-.122(.007) ***	-.536(.020) ***	-.143 (.032) ***			
Social class (high)	.277(.010) ***	.045(.006) ***	.808(.017) ***	.077 (.030) ***			
Household size	.023(.003) ***	-.040(.002) ***	.083(.006) ***	.033 (.010) ***			
Adver commu (Log)	-.318(.004) ***	.014(.002) ***	.069(.006) ***	-.016 (.008) *			
Conflict frequency	-.159(.007) ***	.015(.004) ***	.116(.006) ***	.017 (.022)			
Conflict length	.005(.0003) ***	-.004(.0002) ***	.001(.001)	-.004 (.001) ***			
Product innovation (Log)	.076(.002) ***	.029(.001) ***	.050(.003) ***	-.001 (.005)			
Market share	.003(.024)	-.015(.017)	.030(0.049)	-.063 (.084)			

(*continued on next page*)

Table 5 (*continued*)

	Top Section: Customer Expansion Journey Direction (∇Δ = one state)			
Social media mention	.003(.0003) ***	.001(.0002) ***	-.002(.001) **	.005 (.001) ***
Acquisitions	-.111(.019) ***	-.016(.011)	.015(.032)	-.019 (.059)
iPhone release	.032(.011) ***	-.048(.008) ***	.066(.023) **	-.122 (.040) ***
New entrants	.234(.017) ***	-.020(.012) **	.007(.037)	.396 (.052)
Intercepts		3.996(.048) ***		
	1.694(.186) ***	2.449(.025) ***		
	1.7395(.182) ***	1.135(.006) ***		
	3.659(.182) ***	-1.766 (.025) ***	.980(.026) ***	1.755 (.036) ***
	-7.093(.546) ***	-5.813(.050) ***	-.980(.026) ***	-1.755 (.036) ***

Note: S1, S2, S3, and S4 represent the basic state, the intensified state, the widened state, and the supreme state, respectively.
Significance levels:
* $p < .1$;
** $p < .05$;
*** $p < .01$

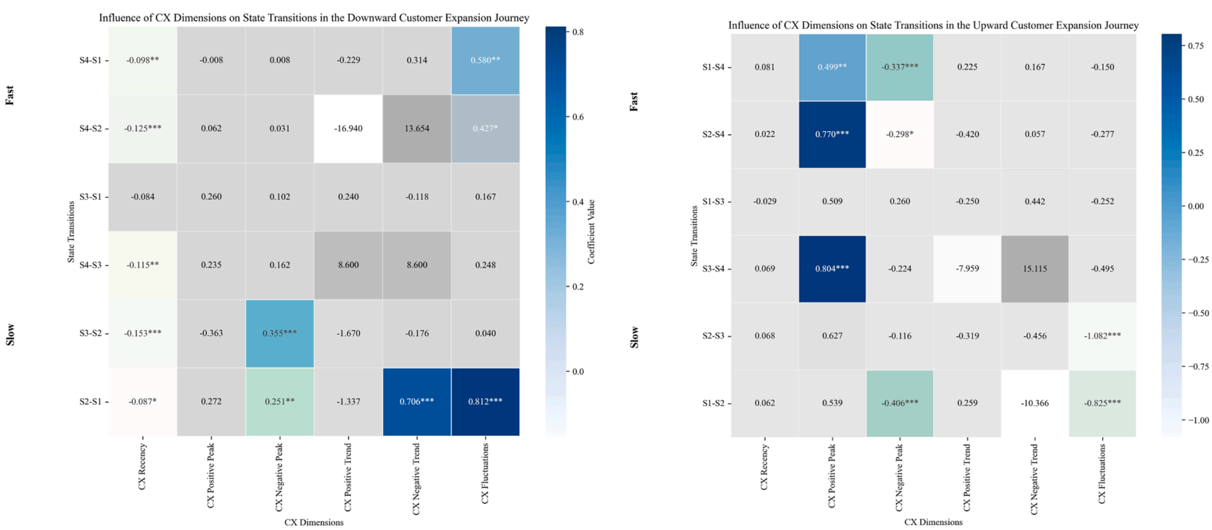

Fig. 1. Illustration of influence of CX dimensions alongside customer expanion journey.
Note: CX means customer experience.

supreme state S4 ($\phi_3^{24} = -.298$, $p < .10$), underscoring how vivid negative events can create lasting barriers to relationship development.

Trend effects, whether positive or negative, show limited impact on the direction of the customer expansion journey. Most coefficients associated with trends are statistically insignificant. Similar to the direction findings, trend effects do not significantly influence the rate of transitions along the customer expansion journey. This suggests that the subtle and gradual nature of trends may prevent them from being strongly encoded in customer memory, making them less likely to trigger immediate behavioral shifts or accelerate changes in customer–firm relationships.

Finally, fluctuations in customer experiences have a particularly pronounced and destabilizing impact, influencing both direction and rate of customer expansion journey. High variability in customer experience not only significantly hinders upward movements (e.g., ϕ_6^{12} = -.825, p <.01; ϕ_6^{23} = -1.082, $p < .01$), but more importantly, it facilitates downward shifts, such as transitions from the intensified state S2 back to the basic state S1(ϕ_6^{21} =.812, p <.01). Moreover, fluctuations significantly accelerate rapid regressions, particularly from the supreme state S4 to the basic state S1 ($\phi_6^{41} = .580$, $p <. 05$) or to the intensified state S2 ($\phi_6^{42} = .427$, $p < .10$) at a notably high rate. These results highlight the disruptive nature of inconsistent experiences, which can erode customer trust and trigger a reversal in the relationship expansion trajectory.

5.4. Robustness check

We performed several additional analyses to verify the robustness of our findings. First, we assessed predictive performance of benchmark models (Gelman & Rubin, 1995; Park & Yoon, 2022; Schwartz et al., 2014) by calibrating them with data from the first three years and validating them with data from the final year. The model with a four-state HMM (i.e., model C) demonstrate the best out-of-sample performance in predicting customer expansion behaviors, outperforming other benchmarks in both hit rate and mean absolute error (MAE). Second, using hierarchical Bayes estimation (Netzer et al., 2017), we accounted for heterogeneity in brand preferences and customer characteristics. The results reveal that brand preferences exhibit substantial effects across transitions. Several customer characteristics are significantly related to the propensity for transition between states. Third, we addressed missing LTR data with large language models (LLMs) and machine learning techniques (Li et al., 2024; Nazir et al., 2023). We re-estimated the model and found that the key variables retained the same directional effects as in our original analysis, which relied on mean replacement approach (Kamakura & Wedel, 2000). This consistency indicates that our results are robust across different imputation methods and that missing data are unlikely to have introduced significant bias. Fourth and finally, we performed a sensitivity analysis based on established methods (Kleijnen, 1997; Shang et al., 2009) to further validate the robustness of our findings. The results further confirm the stability of our conclusions. Further details are provided in Web Appendix B.

6. Discussion and implications

This study redefines the scope of the customer expansion process, introduces and conceptualizes the customer expansion journey, and develops an empirical application of the model. Building on the memory-based framework, we identify customer experience dimensions (i.e., the recency, peak, trend, and fluctuation effects) as key drivers of the changes along the customer expansion journey over time. From these foundations, we derive a number of important theoretical and practical implications.

6.1. Theoretical implications

Our research makes several key contributions to the literature on customer expansion. First, we refine the concept of customer expansion, offering a more comprehensive understanding of its scope. Although previous studies have devoted considerable attention to this topic (Bolton et al., 2008; Verhoef et al., 2007), understanding of customer expansion remains limited and fragmented, and, as revealed in Table 1, customer expansion has primarily been represented by cross-buying. In this study, we illustrate that customer expansion is multifaceted, shedding light on the notion that customer–firm relationships can be expanded through a diverse range of behaviors including cross-buying, increasing service usage, adopting new products, and upgrading to enhanced offerings. Building on these diverse behaviors, we identify four distinct customer expansion states: basic, intensified, widened, and supreme. Each state represents a unique pathway along which customers deepen their relationships with the firm. These states collectively illustrate the richness and complexity of customer expansion, underscoring the need for a broader framework that accounts fully for its multifaceted nature.

Second, we advance the literature on customer expansion (e.g., Li et al., 2011; Risselada et al., 2014; Verhoef et al., 2002) by moving beyond the static perspective commonly applied to it. Adopting a dynamic view, we introduce the concept of the customer expansion journey, which captures the evolving nature of customer expansion over time. This journey highlights two critical dimensions: direction and rate. Direction reflects the bidirectional nature of the journey, where customers can either move forward, deepening and strengthening their relationship with the firm (upward trajectory), or move backward, reverting to weaker states of engagement (downward trajectory). Rate, on the other hand, indicates the speed of progression or regression along the journey, reflecting the magnitude of changes in the customer relationship expansion. Overall, by integrating the multifaceted and dynamic perspectives, our research provides a more nuanced understanding of how customer–firm relationships expand over time.

Third, we identify and examine the key drivers of the customer expansion journey. The literature has paid significant attention to the customer experience and its central role in the development of customer–firm relationships (Lemon & Verhoef, 2016). However, the common approach in empirical research has considered the customer experience as a unidimensional construct. Adopting the memory-based framework as our theoretical basis, we comprehensively argue that the critical dimensions of customer experience—the recency, peak, trend, and fluctuation effects—influence the movement of customers along the customer expansion journey. Specifically, the recency effect acts as a stabilizer, preventing downward shifts and actively reducing the rate of such transitions, ensuring slower and more controlled declines when they occur. The peak effect demonstrates the dual impact of high-intensity experiences: positive peaks steer customers toward upward movements and accelerate progression to advanced states, while negative peaks hinder upward advancements and intensify downward shifts. The trend effect, by contrast, exhibits limited influence on both direction and rate. As suggested by Kahneman et al. (1993), customers tend to prioritize vivid or emotional moments over gradual trends, which limits the latter's role in shaping the expansion journey. Finally, the fluctuation effect, akin to the unpredictable ups and downs of a rollercoaster, evokes uncertainty and discomfort. It significantly accelerates downward transitions and hinders upward progress, particularly in the early stages of the journey, when consistency is critical. This volatility disrupts trust and reliability, making fluctuation one of the most critical challenges for firms seeking to sustain relationship expansion.

By presenting these insights, we provide a more fine-grained understanding of how customer experience influences the direction and rate of the customer expansion journey. Our work advances the literature by offering a multidimensional and dynamic framework for studying customer–firm relationships over time.

6.2. Managerial implications

In the contemporary landscape of heightened competition, where customers are exposed to a plethora of product offerings from numerous firms, it has become increasingly challenging for firms to expand their relationships with customers. Our findings enable us to address two managerially relevant questions for marketing practitioners. First, we illustrate how firms can comprehensively capture the customer expansion journey, taking into account the broad spectrum of expansion behaviors. Second, we offer actionable guidelines for firms to leverage customer experience dimensions proactively to ensure upward customer expansion trajectories, minimize the risk of downward shifts, and accelerate progress toward desired outcomes while slowing the rate of undesirable trends.

With regard to the first question, our findings highlight the multifaceted nature of customer expansion, emphasizing that customer relationships can grow in diverse ways. To capture this complexity, firms should collect data on customer–firm relationships from various angles, including the number of product categories acquired, the depth of usage within the main product category, new product adoption, and product upgrading. These comprehensive data will enable firms to identify the distinct states of customer expansion: basic, intensified, widened, or supreme. Customers in a basic state are less interested in taking their relationship with the firm to the next stage. Therefore, they are likely to maintain their current number of product categories and their service usage in the main category. The intensified state, where customers encounter transitional changes internally, shows slightly augmented usage depth for the main product category. In the widened state, customers show a significant increase in their demand for other product categories from the focal firm, especially for innovative products. In the move from the widened state to the supreme state, customers are prepared to expand their relationship with the firm maximally. Timely collection and detailed analysis of such information are crucial for accurately inferring customer expansion needs and tailoring strategies for relationship growth. Frameworks that neglect any of these critical dimensions risk providing an incomplete or distorted understanding of customers' potential for future expansion (e.g., Zhang et al., 2016).

Regarding the second managerial question, from our findings we can suggest a number of customer expansion journey strategies in the form of the 2×2 matrix shown in Fig. 2. The customer expansion journey direction can be upward or downward, and its rate can be fast or slow. The four quadrants are named as follows: Momentum Growth (upward direction–fast rate), Sustainable Growth (upward direction–slow rate), Gradual Drift (downward direction–slow rate), and Freefall Decline (downward direction–high rate). In what follows, we outline specific strategies for effective management of each of the four quadrants.

- Momentum Growth represents a fast upward trajectory in the customer expansion journey. Exceptional and memorable experiences (positive peaks) significantly enhance this growth by creating excitement. Conversely, negative peaks can quickly disrupt

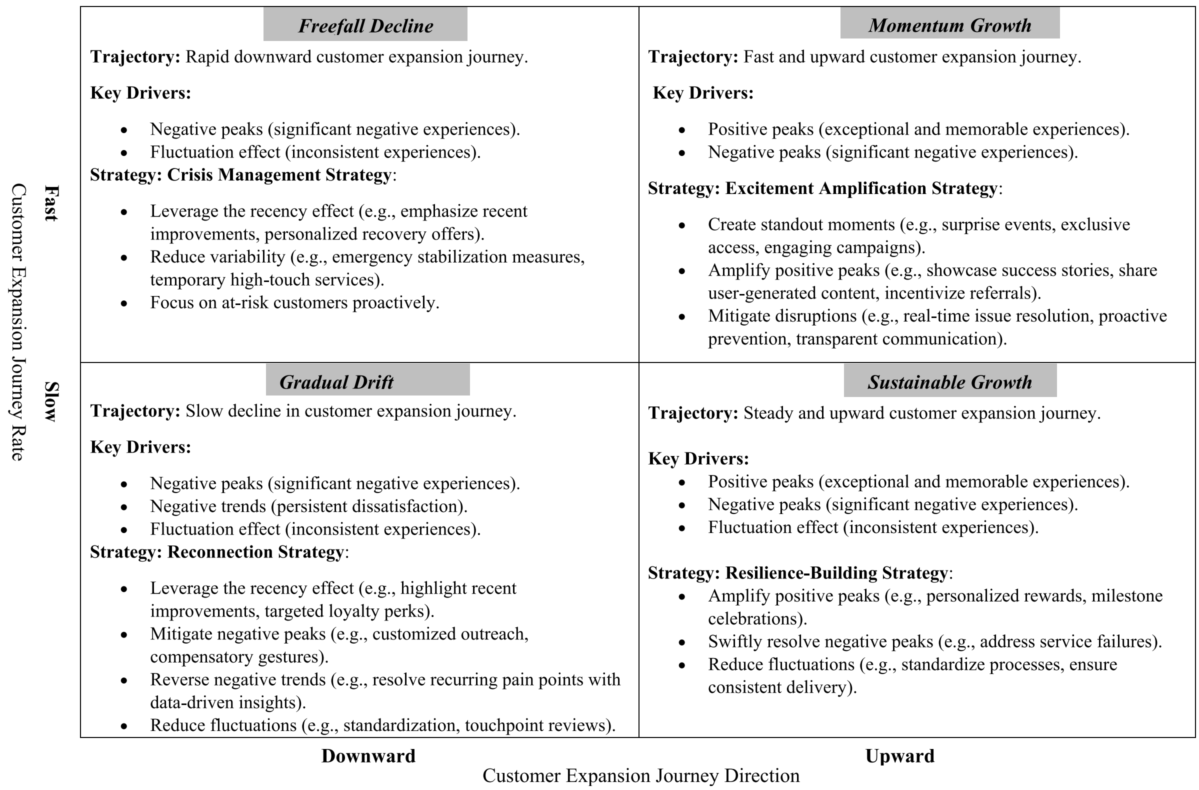

Fig. 2. Customer expansion journey matrix for managerial implications.

momentum, leading to a slowdown in growth. To amplify this trajectory, an *excitement amplification strategy* is employed, focusing on enhancing standout moments and maintaining customer enthusiasm by, for example, designing surprise events tailored to individual customers, providing exclusive access to premium services, and rolling out new features with engaging campaigns that drive advocacy. Positive peaks can also be amplified by showcasing success stories, sharing user-generated content, and incentivizing referrals. Mitigation of major disruptions (i.e., negative peaks) requires real-time resolution of issues via rapid response channels, proactive prevention of recurring issues, and transparent communication.

- Sustainable Growth represents a steady and upward customer expansion journey. To maintain steady progress, a *resilience-building strategy* combines amplification of positive peaks with swift resolution of negative ones while prioritizing reduction of fluctuations. Positive peaks, such as personalized rewards and milestone celebrations, reinforce satisfactory customer experiences, whereas negative peaks, like service failures, threaten to erode progress. However, it is variability in experiences (i.e., the fluctuation effect) that poses a unique challenge for Sustainable Growth, as variability amplifies the effects of negative peaks and dilutes the benefits of positive ones. The appropriate balance ensures long-term confidence. Together, these actions build a resilient foundation for sustainable growth.
- Gradual Drift is characterized by a slow decline in the customer expansion journey. Factors such as negative peaks (significant negative experiences), negative trends (persistent dissatisfactory experiences over time), and the fluctuation effect (inconsistent experiences) further accelerate this decline by eroding confidence. To counteract this, a *reconnection strategy* focuses on rebuilding confidence and reversing negative trends. The strategy starts with leveraging the recency effect by, for example, highlighting recent improvements or offering targeted loyalty perks to re-engage customers. It also mitigates negative peaks by addressing significant issues through customized outreach and compensatory gestures. Long-term improvement is emphasized by resolving recurring pain points via data-driven insights and visibly demonstrating care to customers. Finally, reducing variability in experience delivery through standardization and detailed touchpoint reviews ensures experience stability.
- Freefall Decline is characterized by a rapid downward customer expansion journey. Customers disengage quickly, creating a negative momentum that amplifies attrition, particularly when the fluctuation effect of variability in customer experiences is present. To address this, a *crisis management strategy* focused on stabilizing the decline and rebuilding customer trust is essential. This strategy leverages the recency effect, emphasizing recent positive experiences by, for example, highlighting recent improvements or offering personalized rewards to re-engage customers. Simultaneously, further losses can be minimized by reducing variability with emergency stabilization measures like deploying temporary high-touch services (e.g., dedicated account managers or proactive communications) and escalation support. This strategy not only prevents further decline in customer expansion but also establishes a foundation for long-term stability and recovery.

7. Limitations and future research

We acknowledge several limitations of our study which could be addressed in future research. First, we measured customer experience using a single-item metric, namely LTR. Although simple measures are easily understood by marketing practitioners (Lemon & Verhoef, 2016) and the superior predictive power of LTR for customer retention has been well demonstrated in the literature (De Haan et al., 2015), we recommend that future research consider other customer experience metrics. For example, enabled by the advances in machine learning algorithms, affective information (e.g., emotions, moods, and attitudes) can be extracted easily through sentiment analysis of large-scale written texts (Ashtar et al., 2023). Firms can use sentiment analysis (Mohammad, 2018) and latent Dirichlet allocation (LDA) topic modeling (Antons & Breidbach, 2018) to identify the recency, peak, trend, and fluctuation effects of customer experience and integrate them with customer expansion behavior-related information to obtain more general insights.

Second, we combined annually measured customer experience and monthly captured customer transactions. Given the stability of the customer experience over time (Roy, 2018), annual measurement should not be a concern. Nevertheless, more frequent measures may be preferable, albeit costly and difficult to execute. Future research may usefully collect monthly customer experience data and re-examine our proposed conceptual model to confirm its robustness.

The third limitation relates to missing data, which is a universal problem in survey-based and longitudinal studies (Patrician, 2002). The issue is likely to become much more serious if monthly measurements via surveys are undertaken in longitudinal contexts. We estimated the proposed conceptual model using both a commonly applied and well-performing method (mean imputation) (Kamakura & Wedel, 2000), in addition to state-of-the-art LLMs (Li et al., 2024; Nazir et al., 2023) and machine learning techniques. The consistency of the patterns captured in the two situations shows the robustness of our conceptual model. Nevertheless, we acknowledge that missing values can be a problem, not least because many companies in different industries (e.g., telecommunications, financial, retail, leisure, and online) aim to integrate so-called soft data, such as customer experience data, into their customer transaction records. Previous studies (Kamakura & Wedel, 2003; Kamakura et al., 2003) have recognized the value of a list augmentation or data augmentation approach for comprehensive inference (Petersen et al., 2018; Verhoef et al., 2016). Future studies may therefore seek to combine the captured customer experience with customer transactions using novel text-mining techniques (e.g., machine learning or natural language processing) in order to reduce the amount of data missing from the survey (Skiera et al., 2022).

Fourth, with the growth in prominence of digital communication technologies, social influence plays an essential role in driving customers' decisions to expand or reduce their relationship with a firm. Research (Landsman & Nitzan, 2020; Nitzan & Libai, 2011) has provided early empirical evidence about the significant impact of social influences on customers' adoption and defection decisions. We therefore encourage future research to explore further the links between social influence and customer expansion.

Fifth, while we accounted for brand heterogeneity in one of the robustness check model by incorporating brand-specific effects as random intercepts in the state transition matrix, we did not explicitly examine interactions between brand effects and customer experience dimensions. Future research could explore such interaction effects to uncover brand-specific customer experience strategies and deepen understanding of how brand positioning shapes the customer expansion journey.

Finally, the better to quantify the financial return on efforts dedicated to customer relationship expansion, it is important to establish linkages with customer profitability and customer lifetime value. We therefore encourage researchers to extend our proposed model by incorporating variables related to firm performance. This could be very helpful in enabling firms to allocate their financial resources optimally for expansion of customer relationships.

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Supplementary materials

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