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REVIEW PAPER

Consumer dynamics: theories, methods, and emerging directions

Jonathan Z. Zhang[1] · Chun-Wei Chang[2]

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Abstract
Consumer attitudes and behaviors are fundamentally dynamic processes; thus, understanding consumer dynamics is crucial for truly understanding consumer behaviors and for firms to formulate appropriate actions. Recent history in empirical marketing research has enjoyed increasingly richer consumer data as the result of technology and firms' conscious data collection efforts. Richer data, in turn, have propelled the development and application of quantitative methods in modeling consumer dynamics, and have contributed to the understanding of complex dynamic behaviors across many domains. In this paper, we discuss the sources of consumer dynamics and how our understanding in this area has improved over the past four decades. Accordingly, we discuss several commonly used empirical methods for conducting dynamics research. Finally, as the data evolution continues into new forms and new environments, we identify cutting-edge trends and domains, and offer directions for advancing the understanding of consumer dynamics in these emerging areas.

Keywords Consumer dynamics · Behavioral evolution · Dynamic models · VAR · Dynamic linear model · CRM · Hidden Markov model

Introduction

A fundamental principle in marketing and business is that consumer preferences and behaviors are always changing; that is, consumers are *dynamic*. Consumers can change due to a variety of factors such as individuals' natural life stages, contacts and relationship formation with firms, learning and experiences, and shifts in macro environments. These changes can occur in both business-to-consumer (B2C) and business-to-business (B2B) contexts.

The principle that all consumers change can represent either opportunities or threats, depending on how the firm understands and manages it. Managers developing marketing strategies must not only account for static variation in consumers' needs due to their inherent differences but also account for the dynamic variation that arises as their needs evolve. At any point in time, firms could conduct a segmentation study and place consumers into segments. However, even after consumers are assigned to a segment, their needs continue to evolve at different rates and in different directions—at some future point, the consumers in a once homogeneous segment will develop very different preferences.

Despite the voluminous empirical research which has studied consumer dynamic behaviors in a variety of B2B and B2C product and service contexts over the years, there is surprisingly no succinct definition for "consumer dynamics." By examining some of the most highly cited papers in top marketing journals that contain "dynamics" or "dynamic" in either author-provided keywords or abstracts, we quote the various elements in the main texts that shed light to the nature of the concept:

- "Relational contract between a buyer and a seller" (Dwyer et al. 1987).
- "Consumers can be affected by the observable choices of others" (Bikhchandani et al. 1992).
- "Duration and strength of the customer-firm relationship" (Bolton 1998).
- "Elements of the marketing mix, such as price, influence customer usage levels and customer satisfaction over time." (Bolton and Lemon 1999).

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✉ Jonathan Z. Zhang
jonathan.zhang@colostate.edu

Chun-Wei Chang
chunwcha@amazon.com

[1] Colorado State University, Fort Collins, CO 80523, USA

[2] Amazon.com, Seattle, WA 98109, USA

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- "Customers' future orientation towards services and products" (Lemon et al. 2002).
- "Prior customer experiences will influence future customer experiences" (Verhoef et al. 2009).
- "Prediction models that ignore the possibility that current low-profit customers might evolve to become higher-profit customers would provide biased profitability predictions" (Rust et al. 2011).
- "Service exchanges are dynamic, and actors learn and change their roles within dynamic service systems" (Edvardsson et al. 2011).
- "Consumers are always changing" (Neslin et al. 2013).

The convergent theme from the above quotes is the existence of time dimension and elements of change to consumer preferences and behaviors. Furthermore, consumers' experiences and the marketing environment are responsible for these changes.

Accordingly, we define the term *consumer dynamics* as "temporal changes in consumer attitudes and behaviors." Note that in this article, we use the broader term "consumer" instead of "customers," as the former term encompasses firms' current as well as potential customers, and as dynamics apply to consumer behaviors in general.

Over the past 40 years, plenty of models have been developed and applied to consumer dynamics in empirical research. However, there has been a paucity of review in this domain. There were some efforts either using one method (Pauwels et al. 2004) or through papers presented at a particular conference (Leeflang et al. 2009). Given the fundamental importance of this topic in marketing and in business, a holistic approach with a historical perspective and a future orientation is needed.

In general, the evolution of marketing models in consumer dynamics has been fueled by the data explosion over the past decades, which in turn led to the better understanding of consumers. In recent years, consumer-level data have become increasingly richer and granular due to the rapid developments in information technology and firms' conscious data collection efforts. Consequently, researchers have been able to achieve a deeper understanding of how consumers' behaviors change in a variety of domains. Also, thanks to the development in social networks, platform technologies, mobile computing, and AI marketing implementation, the entry barriers to start new businesses that target emerging consumer needs have also lowered. Just in the past decade, innovative firms such as Warby Parker, Blue Nile, Harry's, eBay, Amazon, Netflix, Airbnb, Uber, Tiktok, and Stitch Fix, have all disrupted established industries, redefined paradigms, and altered consumers' buying and consumption behaviors, all in a fraction of the time it would normally take in past eras. These business trends create pressing needs for companies to seek faster responses to changes and create a better fit with the needs of ever smaller groups of consumers.

The theme of "richer consumer data lead to richer insights" underlies the development of consumer dynamics research over the past four decades and constitutes the basic premise of this study. As marketing researchers and managers are both interested in (1) developing a deep understanding of their customer base and consumers in general and (2) understanding the temporary (short-term) and lasting (long-term) impact of marketing actions, these two objectives necessitate the studies of how and why consumer dynamics takes place.

The rest of the paper is organized as follows. First, we discuss the sources of consumer dynamics and the importance of accurately accounting for them for managerial decision making. Second, we study historical citation trends in consumer dynamics research in the past four decades, summarize the evolution of research interests, and discuss the commonly used empirical approaches for modeling consumer dynamics. In the interest of space, we will not venture deeply into each method but rather will introduce each method's main characteristics, the appropriate contexts in which they can be applied, and the seminal papers and readily available software packages. Finally, we consult research priorities of established global organizations to identify trends and cutting-edge domains in business and technology, and offer future directions for advancing consumer dynamics research in these emerging contexts that are of interest to academics, practitioners, and policymakers.

Why do consumers change?

The economics and psychology literature have documented the various reasons for consumer attitudinal and behavioral changes, such as inertia and state dependence (Frank 1962; Seetharaman et al. 1999), variety seeking (Kahn et al. 1986), consumer learning (Erdem et al. 2004), switching cost (Wirtz et al. 2014), and trust-building (Morgan and Hunt 1994). Drawing from these fundamental psychological processes, the marketing domain has discussed reasons of why consumers change, such as consumer lifecycle (Du and Kamakura 2006), engagement and consumer journey (Lemon and Verhoef 2016), satisfaction (Bolton and Lemon 1999), and loyalty (Watson et al. 2015).

To appropriately address consumer dynamics in empirical research, it is useful to first understand the factors that cause individuals to change in different directions and at different rates. Only through first identifying the sources of consumer dynamics will it be possible to understand and manage these changes.

Consumer behaviors change due to both macro and micro factors that encompass consumer, firm, social interaction, product/market, and macro environment levels that range from specific to broad. We identify the major sources of dynamics within each level as follows: (1) individual level: discrete life events, customer lifecycle; (2) social interaction level: peer influences and observational learning; (3) firm level: customer–firm interactions and experiences, customer–firm relationship stages and quality, firms' marketing actions; (4) product/market level: customer learning, product lifecycle, competitive response; and (5) macro environment level: economy, culture, institutions, technological norms, and governmental policies. Each source will cause customers to change at different rates. Table 1 outlines them.[1]

Individuals change due to *discrete life events* such as graduation, a new job, marriage, parenthood, divorce, financial windfalls, catastrophes, and retirement. These factors can have immediate impacts on many aspects of their brand choices and consumption patterns due to changes in roles, lifestyles, psychological states, and income. On the other hand, through a person's *natural lifecycle* (Du and Kamakura 2006), consumers' product and service priorities and their willingness to take on risks and try new things shift as they mature, albeit at a much slower pace. Young consumers are relatively open to trying new brands and experiences to enrich their "experiential CV" and are more influenced by the hottest current trends. As they age and gain more wisdom, they become less tempted by the ever-shifting tides and focus more on relationship security and financial safety. In the later stages of consumers' lives, they tend to become fixed in their habits and worldviews, are less open to learning new technology, more risk-averse to new experiences, and place stronger values on nurturing existing relationships compared to starting new ones. At the same time, they might also experience a renewed sense of freedom unconstrained by the social pressure and worries of their early years.[2] *Lifestyle and interests* represent changes in activities, brands and product categories associated with changes in income, social status, and exposures to new cultures. These changes do not occur as quickly as discrete life events and are not as predictable as natural lifecycles.

As social networks become more prevalent in the modern economy, *social interaction effects* play an increasingly larger role in shifting consumer preferences. In both offline and online settings, consumers' tastes form through observations of and interactions with peers, friends, neighbors, and influencers. As tastes and brand preferences are formed very early on by one's family members, the evolution of family members' preferences will continue to exert influence on the focal consumer.

At the firm level, repeated *customer–firm interactions* allow customers to better understand firms' offerings, their prices, as well as service quality and policies should disagreements happen (Lemon and Verhoef 2016; Petersen and Kumar 2009). These interactions impact customers' satisfaction, perceptions of how products fit in their lives, and eventually customer loyalty (Watson et al. 2015). *Customer–firm relationship stages and relationship quality* play important roles in longer-duration relationships. Early stages of relationships (i.e., acquisition stage) are characterized by word-of-mouth, trial, and limited purchase. As relationships progress into expansion and retention stages, existing customers make their decisions based on their experiences and firms' new offerings. They are also more open to firms' novel sales and communication channels (Pauwels and Neslin 2015; Valentini et al. 2011). Depending on the context, some existing customers may exhibit variety seeking and switch to other brands, while others would remain loyal. *Firms' marketing actions* could alter the brand image and reputation, thereby changing consumers' perception of the firm and its offerings. For example, a niche luxury brand's decision to expand to mass-market with a lower entry price point may deter previous customers who valued its high levels of exclusivity. More fundamental firm actions such as digital transformation efforts not only change consumers' perceptions but can also alter the way consumers interact with the firm and unlock new values (e.g., smart devices with in-use updates and usage recommendations).

At the product market level, right after consumers try a new product category, they undergo a *learning process* in which they become familiar with the product by using it. The learning changes their weighting of the relative importance of attributes as the result of their enhanced knowledge and experience (Erdem and Keane 1996; Li et al. 2011). The type and speed of learning depend on the *product lifecycle* (Arora 1979; Day 1981). For example, whenever a new product concept is first introduced to the world (e.g., laptops, smartphones, virtual reality, sharing economy, smart devices, self-driving cars), extensive in-person demos and education are often needed. As these products reach maturity stages, consumers develop general proficiency to make decisions with minimal sales support. When *competitors respond* with new offerings focusing on particular features such as lower price and new material (Dekimpe and Hanssens 1999), customer attention and preference also shift along these features.

Finally, consumers live in an ever-changing *macro environment* consisting of cultural, institutional, and technological norms. Societal shifts toward healthier living, the prevalence of mobile computing, the "digital native" mindset that characterizes younger consumers, environmental sustainability, widening inequality, and the changing perceptions toward issues such as ownership, family composition, privacy, and cultural identity all gradually yet surely redefine the functions and benefits that consumers seek in products and services.

[1] These are the common sources that emerge from decades of extant research. Although the list is comprehensive, it is not exhaustive.

[2] The concept that people's attitudes and worldviews change over their natural lives has been rooted in cultures and philosophies across the world. One notable example is the following passage from *The Analects of Confucius* (circa 400 BC):

"Confucius said, 'Since the age of 15, I have devoted myself to learning;

At 30, my ways of thinking have matured;

At 40, I was no longer confused and easily influenced by others; At 50, I have known my fate and the unspoken rules of the world;

At 60, I was able to calmly listen to diverse voices and understand the perspectives of others;

At 70, I could follow what my heart desired, without transgressing what was right.'"

Table 1 Why consumers change

Sources of dynamics	Descriptions and examples	Examples of managerial implications
Individual level		
Discrete life events	A major life event such as parenthood or divorce often changes people's consumption priorities, such as preferences for cars, vacations, and restaurants.	• Newly married couples are better off financially than when they were single. The combined income boost, the excitement of the new family, and the free time before children allow them to spend substantially on clothing and leisure activities such as dining out and travel. • The arrival of the first child and often the associated purchase of the first house change perspectives and place emphasis on home maintenance and expenses for the child. These requirements immediately reduce the family's disposable income and time, and changes the family's purchase priorities.
Natural lifecycle	Younger consumers are interested in collecting more experiences. As people age, they become more focused on risk reduction and are less willing to change.	• Young singles have free time and are more variety seeking. They are getting exposed to many new product categories and consumption contexts for the first time, so their preferences are more malleable and are more open to new technology. • Empty nesters usually have stabilizing financial position, free time, and the lack of expense for children allow them to enjoy pursuit of hobbies and luxuries.
Life-style changes	New hobbies and interests can be developed as a result of travel, moving to new neighborhoods, and exposure to new cultures. Income shifts also affect lifestyle changes. These changes occur not as immediately as discrete life events but also not as gradually as in natural lifecycles	• Changes in income, social status, and self-image shift consumers' requirement for quality and preferences for brands that are consistent with their new self--images. • Development of a new hobby (e.g., skiing) would exhibit periods of heightened engagements with the hobby and purchases of related products. Engagement intensity and purchases would wane over time as lifestyle restabilizes and/or attention shifts.
Social interaction level		
Peer and family influences	Tastes form through exposures and interactions on social media, product forums, and micro influencers. Offline observational learning can take place from peers, friends, and neighbors. Preferences and values are often shaped by family members, and the evolution of family members' preferences will continue to influence the focal consumer throughout her life.	• Spending patterns converge as people attend more social events together. The effect is further magnified if the attendees are of the same age and come from the same background (Zhang 2019). • Exposure to network neighbor's defection will increase the probability of defection, especially for those consumers that are highly connected (Nitzan and Libai 2011).
Firm level		
Customer–firm interactions and experiences	Repeated customer-firm interactions and positive experiences allow customers to understand firm's prducts, prices, and service qualities, which generate satisfaction, loyalty, and purchase fluency.	• Product returns provides learning and builds engagements (Petersen and Kumar 2009) • Successful attaining rewards in the past affects consumers' future efforts (Drèze and Nunes 2011)
Customer–xzfirm relationship stages	During early relationship stages, consumers are driven by trial and word-of-mouth, and buy in smaller quantities. In later relationship stages, they are driven by crossselling and are open to more purchase channels. Relationships are especially important in B2B as establishing and switching channel relationships are costly.	• How much the customer is currently priced relative to her reference price affects perceived relationship quality with the firm (Zhang et al. 2014). • Firms' efforts in increasing communication and in establishing norm are important early in the relationship, but relationship-specific investments to build dependence is more important later in the relationship. (Zhang et al. 2016)
Firm's marketing actions	As firms change their image, reputation, marketing actions such as advertising and promotion (e.g., celebrity endorsement), distribution (e.g., from exclusive to intensive), pricing (e.g., from price consistency	• Advertising has much larger long-term effects than immediate effects on sales. The insight can help

Table 1 (continued)

Sources of dynamics	Descriptions and examples	Examples of managerial implications
	to offering hi/lo pricing), and product (e.g., design and material changes), consumer's perception of the firm and its product will accordingly change. For example, when a niche brand decides to go mass-market, those consumers who value exclusivity will shift to other niche brands.	guide short and long-term allocations of marketing communication resources (Köhler et al. 2017). • Firm-initiated channels have significant spillover effects to customer-initiated channels at visit and purchase stages (Li and Kannan 2014).
Product market level		
Product learning process	A consumer might learn, after using a new product (e.g., a new phone) for a period of time, that she only uses certain features. As the result, she weighs these features more and ignore the rest of the features in her usage and in her future product choices.	• Exposures to decision aids can increase online store loyalty and reduce the pressure of price and promotion competitions over time (Shi and Zhang 2014). • For credit cards, customers' repayment behaviors change over time as a result of the learning about the features, policies, and usage experiences of the creddit cards (Zhao et al. 2009).
Product lifecycle	When a new technology category is introduced, consumers need extensive education from the brand in order to be acquired. When the category matures, consumers are able to find the information on their own.	• Price elasticities decrease over time with product lifecycle (Parker 1992). • When launching an innovative brand, the cross-price elasticities increases after the launch which implies the existing brand is closer to substitutes. The own-price elasticities of existing brand also increase. Those elasticities change gradually over time to adapt to the new environment (Van Heerde et al. 2004).
Competitive response	Competitive offerings focusing on particular features such as cheaper price and newer designs could shift consumers' attentions and preferences along these features.	• Consumers' brand preference changes over time with entry and exit of product models. The changing brand preference has a greater impact than prices, product attributes, and the length of the product line on brand performance (Sriram et al. 2006). • Switchers and repeat shoppers show significant differences in the timing of "shopping trips" and the timing of "switching trips" (Leszczyc et al. 2000).
Environmental level		
Economy, culture, and institutions	Societal shifts towards healthier living change people's eating behaviors and preferences for ingredients and food. The ride-share culture changes people's car buying attitudes and their socializing behavior. The rise in nationalism can influence people preference for the product's country of origin.	• Consumers become more wary of sharing data and privacy concerns with reports of high-profile data breaches. • Sustainability concern shift consumers' attention towards new product attributes such as firms' manufacturing process, supplier diversity, and environmental footprint. • How much consumers value relationships and how fast relationships evolve vary internationally as a function of cultural and business institutions.
Technology norms	As retail becomes increasingly onine and mobile, it creates pressure for technology laggards to adopt online and on mobile platforms. Consumer's aversion to oncedisruptive technologies such as cloud-computing and AI marketing will diminish over time as these technologies become norms	• The accessibility of health information online increases the self-diagnosis ability of consumers and affects how consumers search for and engage with health-care providers. • The ubiquity of mobile devices encourages sharing behaviors and facilitates the explosion of user-generated contents. • The prevalence of content recommendation systems could create siloed and sticky preferences and echochambers.
Government policies and intervention	Governmental regulations, interventions, taxes have immediate effects on how businesses are conducted in both B2B and B2C settings and could encourage switching, substitution, and potential product and	• Interventions such as soda tax, vaping laws, in-door smoking ban, cleaner energy laws not only make it more costly for consumers, but also raise the

Table 1 (continued)

Sources of dynamics	Descriptions and examples	Examples of managerial implications
	business model innovations. These interventions also create longer-term effects of changing consumers' attitudes and preferences by raising the salience of the various issues.	awareness of the associated potential harms and reinforce the cultural shifts in consumption. • Trade wars and tariffs can cause switching behaviors in brands and product categories. They also have long-term implications on changing consumer attitudes towards products' countries-of-origin. • Data privacy regulations and the related media discussions can increase consumers' awareness of how their data might be mis-used, alter how they interact with firms and share their data, and change firms' business processes of

Likewise, technological norms influence how consumers learn, search, and purchase. For example, the emergence of online forums and educational blogs have democratized information and "freed up" consumers from the traditional influence of brands, salespeople, and the limited number of experts. This democratization has enabled consumers from all over the world to connect, discuss, and learn about a variety of product domains ranging from wine to mechanical watches. Governmental regulations, interventions, and taxes have immediate effects on how businesses are conducted in both B2B and B2C settings and can encourage switching, substitution, and product and business model innovations. These interventions also create longer-term effects of changing consumers' attitudes by raising the salience of the various issues.

As Table 1 illustrates, these sources of dynamics operate simultaneously, at different speeds, and sometimes in conflicting directions. Understanding and accounting for these sources are important for firms. Although these sources offer some generalizations on how they impact consumers, assuming that they affect all consumers equally would be naïve—one needs to account for consumers' inherent differences as well as dynamics.

Managerial implications of consumer dynamics

As marketing decision making relies heavily on an accurate understanding of consumers, ignoring the temporal aspects of consumer behaviors and focusing only on a snapshot of the present will have devasting managerial effects. Furthermore, the aggregation of individual behavioral shifts also constitutes shifts in market taste and market-level responses to firms' marketing actions. At the micro tactical level, not accurately accounting for consumer dynamics will result in misvaluation of the customers and mistargeting of marketing actions. At the macro strategic level, it will result in misallocation of marketing resources and biased strategic planning. For instance, as the recent meta-analyses on marketing communication carry-over illustrate (Köhler et al. 2017; Sethuraman et al. 2011), most of the marketing communication effect is long term instead of near term, and the personal selling effect could last for over a year. Ignoring the long-term and gradual impact of marketing communication could result in underinvestment of long-term marcom budgets by as much as 35%, resulting in millions of dollars of wasted resources.

Accordingly, we highlight in the third column of Table 1 some of the managerial implications of accounting for consumer dynamics that correspond to each of the sources of dynamics. The examples listed are illustrative and by no means exhaustive. We elaborate on some of the examples below.

Example 1: Product returns can facilitate customer learning and engagement

An e-commerce retailer might treat product returns as negative, view those customers who return products as unprofitable, and accordingly segment them based on product return rate as a lower-value segment. However, product returns are not necessarily evil—they can provide additional touchpoints for customers to learn about the firm's offerings and services (Petersen and Kumar 2009). Returns, if handled professionally, could encourage learning and be treated as a goodwill stock variable that might lead to higher future purchases. This can be especially true for product categories that exhibit high consumer need for idiosyncratic fit. For instance, Warby Parker bases its business model on establishing consumer learning through easy trials and returns. Thus, not accounting for future customer behavioral changes from returns would cause firms to misjudge the role of return, segment customers using the wrong metrics, and design unnecessarily harsh return policies.

Example 2: Sales promotion can lead to stock-ups and increased consumer price sensitivity

Price promotion for a branded consumable can achieve an immediate lift in sales; however, customers will stock up as the result of the discount and will not buy in the next few periods (Slotegraaf and Pauwels 2008). Therefore, the effect of promotion is positive in the short run but negative in the next few periods, and the long-run net effect of the promotion can be nil. Furthermore, frequent sales promotion can increase consumers' price sensitivity and erode brand equity in the long run.

Example 3: Reference price effects can shift consumers' price perceptions

Price judgment does not occur in absolute terms—consumers judge the attractiveness of the current prices based on their past experiences and reference prices (Hardie et al. 1993; Kalyanaram and Winer 1995). A price discount will be effective in the short run in generating sales as it will be perceived as a "gain" relative to the consumer's current reference price. However, the discount lowers the consumer's reference price, making future discounts difficult for the firm to implement. Likewise, a price increase is considered a "loss" relative to the consumer's reference price, which can adversely affect short-term sales. However, if the product offers compelling value or if the firm has certain degrees of monopolistic pricing power (e.g., dominant tech services such as Uber and Netflix, or high switching cost contexts such as in B2B channels), price increases will shift consumers' reference prices upwards, making the higher price the new market norm (Zhang et al. 2014). Thus, pricing strategy is a double-edged sword and firms should consider both the short-term and long-term effects of pricing.

Example 4: Recency and onboarding effects can determine the efficacy of marketing contacts

When consumers have recently searched or purchased a brand or category, they may be in a heightened state of interest attention towards the category. Marketing communication is more effective during this state of arousal compared to when the consumer has shifted attention away (Montoya et al. 2010). Therefore, uncovering a customer's interest state from observed search and purchase data and selectively targeting marketing can be fruitful.

Similarly, when a customer is first onboarded to the brand, the firm should devote more time to educate and "hand hold" the customer during this onboarding window to take advantage of her heightened interest—forming the right impression can result in lasting virtuous effects in enhancing consumer value.

Example 5: B2B relationship stages should be matched with different types of relationship marketing efforts

While the above examples illustrate various B2C settings, B2B consumers also exhibit significant dynamics in channel relationships. Repeated transactions and the resulting performance outcomes can lead to channel members' attitudinal changes with respect to trust, norms, commitment, and dependence on each other. These relational changes can subsequently inform how relationship marketing efforts should be timed (Dwyer et al. 1987; Luo and Kumar 2013). For example, communication efforts are essential early on in the relationship as they can quickly develop norms, whereas mutual and irrevocable investments are far more important in later stages in order to establish relational mutual dependence and to signal long-term commitment (Zhang et al. 2016). Ignoring the differential effects of investment types at different stages of the channel relationship will result in wasted relationship marketing resources.

Example 6: Consumers evolve differently due to institutional diversity

Diversity among consumers across different cultures and economic institutions can affect the drivers of dynamics and the rates of change. For example, how much consumers value established relationships and how fast relationships are established vary internationally as a function of cultural and business institutions (Samaha et al. 2014). Marketing in emerging countries also exhibits different long-term effects due to unestablished market structures and an abundance of new customers. For example, whereas promotion often has a temporary impact on sales in established markets, emerging markets exhibit higher potential for marketing to persistently shift baseline sales (Osinga et al. 2010; Slotegraaf and Pauwels 2008).

Incorporating consumer dynamics into marketing models

From an empirical modeling perspective, dynamic behaviors suggest two aspects that researchers should incorporate into their modeling approaches. First, consumers' coefficients (i.e., the "betas") concerning inherent preferences (e.g., category, brand, and channel preferences) and responses to marketing actions (e.g., pricing, communication) change over time. Second, consumers rely on past experiences and brands' goodwill when making decisions, so these factors need to be incorporated into the set of explanatory variables. One can imagine that a consumer faced with the new brand might initially be influenced by the firm's marketing communication (as she has no prior experience with the brand). As she accumulates more experiences from repeated interactions with the brand in terms of purchases, advertising exposure, and service encounters, she would shift her decision weights towards these past experiences. Therefore, properly accounting for past experiences and brand goodwill as explanatory variables is important—firms' actions today not only impact consumers' immediate decisions but also can have longer term consequences.

Also, as patterns and rates of behavioral changes vary depending on individual differences and consumption contexts, researchers with sufficient customer data should also account for customer heterogeneity in addition to dynamics. Not accounting for both sources of variation might confound heterogeneity as dynamics and therefore bias theory building and constrain the model's ability as a managerial decision support tool.

Next, we study historical citation trends in consumer dynamics research and examine how research interests evolved in the past four decades. We then discuss several commonly used empirical approaches for modeling consumer dynamics that emerged during this time.

Evolution of consumer dynamics research in marketing

"Richer consumer data lead to richer insights" has been the central trend in empirical marketing for the past four decades. This trend continues at an accelerated pace in recent years and into the future. In this section, we review consumer dynamics research from 1977 to 2018 and describe the evolution of data, research interests, and modelling approaches.

Review method and sample

To ensure the representativeness of high-quality studies in our review, we identified the top seven marketing journals that have relevance in empirical consumer dynamics research—*Journal of Marketing*, *Marketing Science*, *Journal of Marketing Research*, *Management Science*, *Journal of the Academy of Marketing Science*, *International Journal of Marketing Research*, and *Journal of Retailing*.

We determined the time span of our analysis and the universe of keywords by following a snowball sampling approach used in meta-analyses and review papers. We began with a small set of obvious keywords identified through the various elements of the definition for consumer dynamics definition in the beginning of the Introduction such as "dynamic," "dynamics," "temporal," "relationship," "evolution," and "evolving," as well as keywords related to the sources of dynamics mentioned in Table 1 such as "lifecycle," "peer influence," "learning," and "experiences." Next, based on the relevant papers from this initial search, we further expanded our keywords by looking at the author-provided keywords in those papers as well as their synonyms. This approach not only led us to include other terminologies in dynamics such as "transition" and "inertia" but also to identify substantive themes related to dynamic processes such as "trust" and "loyalty." Using the snowball sampling approach of enlarging of our keyword pool, we iterated the process until the number of keywords becomes too general and irrelevant for our scope.

To avoid a biased sample of methods a priori, the empirical methods emerged naturally from the process. We picked the six most commonly employed models, namely "dynamic linear model," "vector auto-regressive model," "hazard model," "hidden Markov model," "state-space model," and "negative binomial model," from the literature review and then gathered variations on their names.[3]

To further bolster the keyword searches, we enlisted a research assistant to separately add similar keywords to our list and assess whether the effort yields additional studies and citations.[4] We then combined the studies from these searches and identified the appropriate papers by examining title, abstracts, and author-provided keywords. Finally, we screened the combined list of keywords on methods and topics for relevance.

To assess the evolution of consumer dynamics research from both substantive topic and method perspectives, we identified the topics and methods with the greatest impact according to the annual relative citation percentage. The annual relative citation percentage for a particular topic was determined by dividing the number of citations on the topic published in a given year by the total number of citations for all relevant topics (Mela et al. 2013; Watson et al. 2015).

Figure 1 and Fig. 2 respectively illustrate the evolution of topics and methods over the past 42 years. We find very sparse empirical research that addressed dynamics before 1980, which is not surprising, given the paucity of data availability and limited computing power. Therefore, we believe the period spanning 1977 to 2018 safely encompasses the vast majority of empirical research in consumer dynamics.[5]

Trends in data, substantive domains, and methods

Over the past four decades, the general trend was that of increased data richness. Data have evolved from the aggregate market and brand-level data to consumer-level transactional data and more recently to even more granular and varied consumer journey measures such as browsing, response to marketing, engagements, and social interactions. Accordingly, Fig. 1 illustrates that research focus has evolved from examining the overall effectiveness of marketing instruments such as sales promotion and advertising, to understanding the

[3] Although there are other econometrics models that studied dynamics and lagged effects (e.g., goodwill stock of Nerlove and Arrow 1962, Koyck model of Clarke 1976), given the space constraint and the present and future orientations of the study, we give emphasis to (1) the most common methods, (2) the relatively more recent methods, and (3) methods that are adapted for consumer behaviors rather than firm or industry-level dynamics.

[4] Using Webster's thesaurus to generate synonyms to our selected keywords, we obtained a total list of 178 keywords and conducted literature searches based on them. The keyword list was intentionally broad and inclusive and that many of these words have resulted in no citations. A complete list of keywords is included in the Web Appendix Table A.

[5] Although our literature review is comprehensive and achieves our goal of highlighting the evolution of topics and methods as the result of better data, we admit that it is not exhaustive.

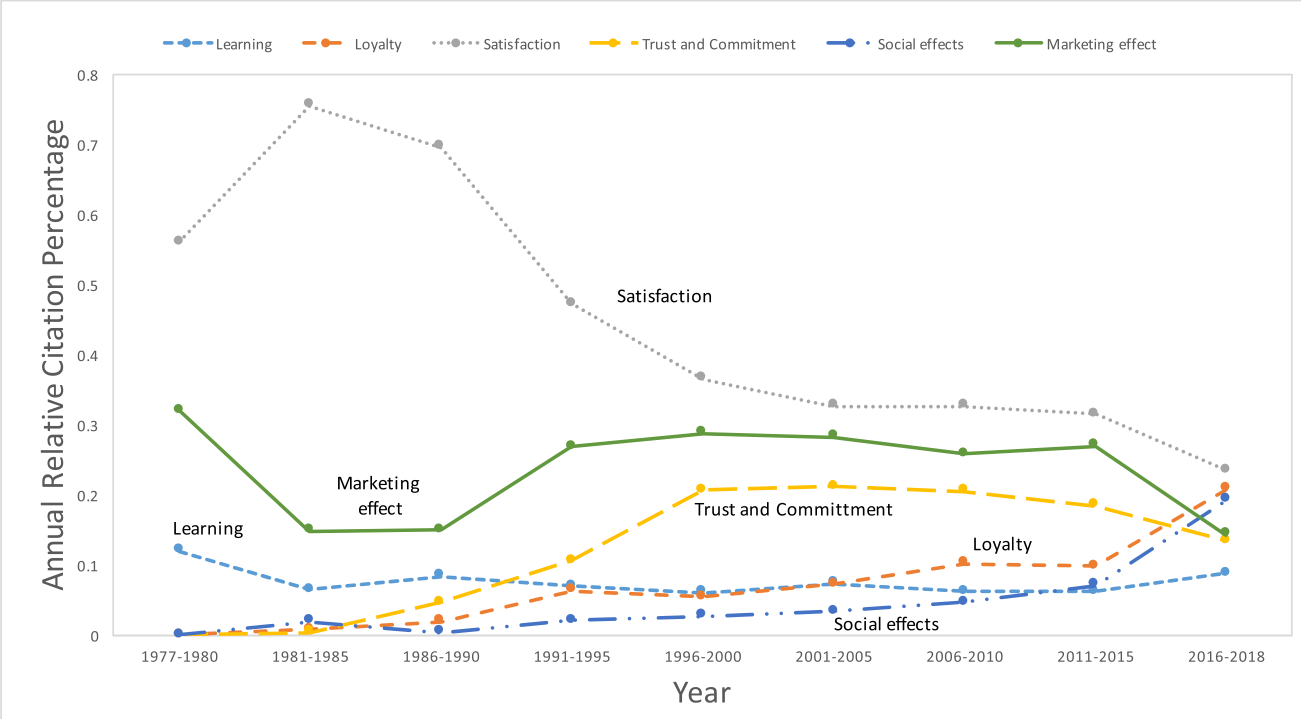

Fig. 1 Trend of top topics in dynamics from 1977 to 2018

differential roles of marketing on different types of consumers at different points in time. We discuss the evolution below.

Using product- and market-level data to investigate marketing mix effectiveness Until the early 2000s, researchers were primarily interested in separating short- and long-term effects

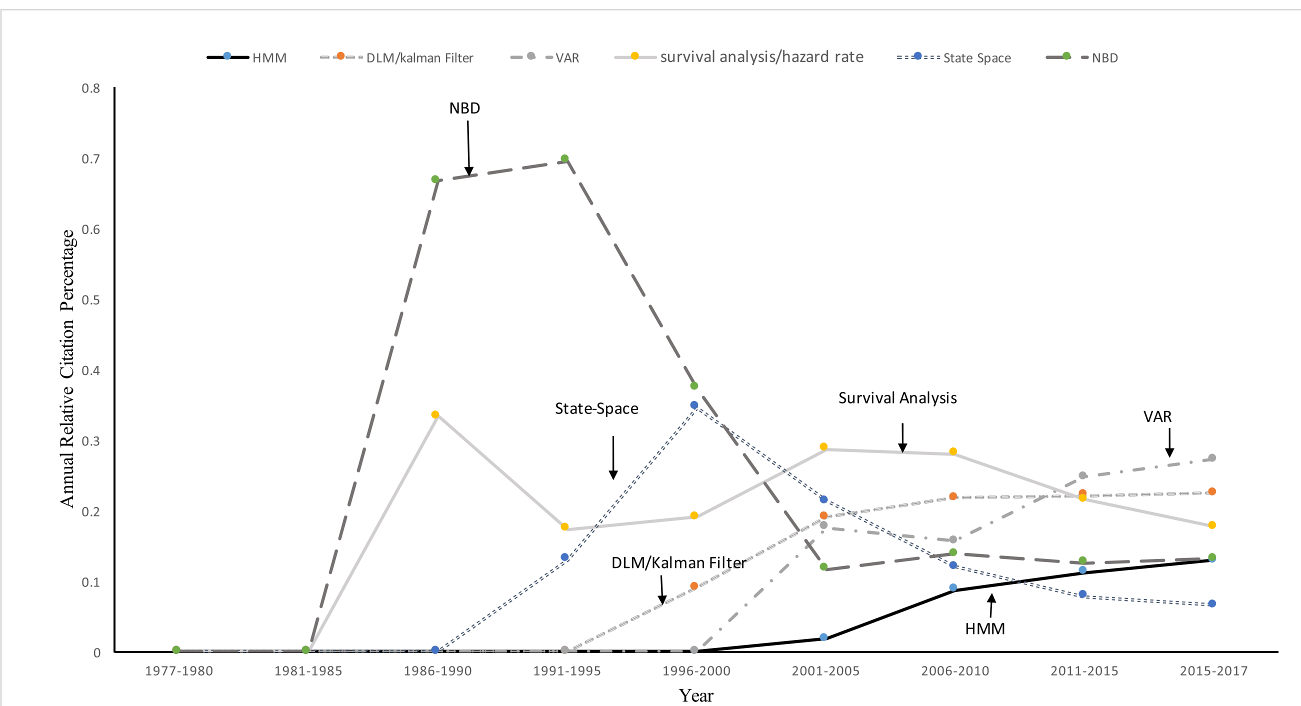

Fig. 2 Trend of top empirical methods in dynamics from 1977 to 2018

of marketing actions such as advertising on the brand's market performance in terms of brand sales and market share. Research settings focused on frequently purchased household items and typically employed supermarket scanner data. For example, Pedrick and Zufryden (1991), using yogurt scanner data, proposed a negative binomial distribution (NBD) model to use brand choice, purchase incidence, and advertising viewing behavior to predict and measure brands' market performance. Papatla and Krishnamurthi (1992) explored dynamic choices by incorporating loyalty, variety seeking, inertia, repeated consumption, and the similarities of choice alternatives. During this time, short- and long-term effects of advertising and other marketing mix variables were explored (Bronnenberg et al. 2000; Dekimpe and Hanssens 1995a; Dekimpe and Hanssens 1999; Nijs et al. 2001; Pauwels 2004).

Aside from NBD models and hazard models that predicted product purchase timing, vector autoregressive (VAR) models and other time-series econometric models have been utilized to leverage information on firms' marketing mix and competitive response and examined the differential effects of various marketing mix on sales over time. A classic example is Pauwels et al. (2004), where the author used the frozen dinner category to explore how consumer response, competitor response, and marketing actions contribute to long-term marketing effectiveness. The study used a VAR model to measure dynamic interactions between sales and marketing actions by including endogenous variables which are impacted by their own past actions and past sales variables, and found that the net effect of marketing does not depend on competitive reactions but on its own actions. In the new product adoption domain, Van Heerde et al. (2004) studied the demand for frozen pizza and modeled dynamic market responses that resulted from the entry of an innovative product. Using a dynamic linear model that can handle non-stationary time series of sales or marketing mix instruments, they found cross-price elasticities increase after the launch of the innovative brand, implying that the existing brand is closer to substitutes. The own-price elasticities of existing brands also increase, and those elasticities change over time to adapt to the new environment. These results highlight the fact that the changes do not occur instantaneously but over time.

During this time, researchers were able to (1) disentangle the short- and long-term effects of marketing mix on brand performance, and (2) identify the reasons why certain market performances evolved while others stayed stationary (see Dekimpe and Hanssens 1995b; Pauwels 2001). These empirical findings broadened our understanding of the duration of marketing actions from a firm's strategic perspective. However, the limitation during this time was that data were generally available and analyzed at the aggregate level. Although the results were insightful for firms at a product and market level, they offered limited insights on individual behavior evolutions and lacked prescriptions on how best to target and manage consumers.

Availability of customer-level data and the emergence of customer-centric research Beginning in the early 2000s, as the result of more sophisticated and automated data collection systems, we started to observe richer data on customer-level transactions across domains beyond just consumer packaged goods and data on other measures of firm–customer contacts. These factors prompted customer-centric research focus and greatly advanced the domains of customer relationship management (CRM) and customer lifetime value (CLV).

Accordingly, the research focus has evolved to micro-level consumer dynamics issues such as predicting customer churn, customer profitability, satisfaction, and repurchase. A notable example was that of Reinartz and Kumar (2003), who used direct-marketing data from a catalogue retailer and utilized the Pareto/NBD model to predict the probability that a customer's relationship with the firm is "alive" (i.e., the customer has not churned) in a non-contractual setting. Explanatory variables that drive the customer relationship duration include exchange characteristics such as purchase frequency, purchase amount, and types of communication—variables that were getting collected with increasingly more powerful CRM systems. Fader et al. (2005) addressed similar issues of customer churn prediction in a non-contractual relationship setting using the simplified and more easily applicable BG/NBD model.

Better data collection in service industries allowed for empirical studies in the relationship marketing and loyalty domains. For instance, we saw during this time research that examined retention decisions of interactive TV services (Lemon et al. 2002), loyalty in financial services (Bell et al. 2005), repurchase intention and recommendations in cell phone services (Johnson et al. 2006), churn in telecommunication services (Gustafsson et al. 2005; Schweidel et al. 2008), customer repayments on credit cards (Zhao et al. 2009), and customer value changes across industries (e.g. banking, telecom, pharmaceutical, chemical) due to transactional and customer characteristics (Homburg et al. 2009).

E-commerce and social media emerged as new substantive topics during this period. Early papers in these domains looked at how customers adjusted their behaviors in these new digital environments. For example, Montgomery et al. (2004) studied e-commerce product choices using clickstream data. Manchanda et al. (2006) modeled repeat purchase for online beauty products as a function of advertising exposure. Ansari et al. (2008) studied the effect of email marketing on purchase channel migration. Villanueva et al. (2008) and Trusov et al. (2009) studied online word-of-mouth referrals.

With richer consumer panel data, a prevailing managerial theme during this time was the understanding of the variability in consumer decision-making, which allows for individual-level targeting through mixture models and hierarchical Bayesian specifications. As we will see next, the trends on data granularity and the empirical focus on behavioral variability continue to flourish well into the present. Accordingly, researchers are able to address more flexible patterns of dynamics that enable not only individual targeting but also dynamic targeting.

Higher-dimensional behavioral data, digital and social domains, and more flexible dynamic patterns Towards the end of the 2000s and into the present, with rich individual panel data becoming the norm, empirical researchers became more interested in understanding dynamics in more nuanced ways that could further disentangle heterogeneity from dynamics. Furthermore, with detailed customer data beyond transactions such as customer referrals (Kumar et al. 2010) and social media posting behaviors (Ma et al. 2015), researchers moved beyond purchases to study how marketing impacts the various other customer outcomes over time, how these outcomes translate to future sales, and how the various outcomes are interrelated.

One theme that emerged during this time was the ability to perform dynamic targeting. State-space models and hidden Markov models (HMM) were often used where the customer's response parameters are not only individual-specific but also time-varying. In particular, with hidden Markov models, researchers can flexibly allow these response parameters to change over time as customers move in and out of the empirically determined latent "states" (akin to latent segments in a dynamic context). The movements of customers in and out of the latent states and the identification of different drivers of the state migration push forward the marketing domain in two directions. First, it provides a fertile modeling context for theory building and theory testing of dynamic behaviors. Second, the differential effects of marketing actions in various latent states provide managers with tools to tailor marketing actions to customers in a just-in-time fashion. The latter contribution is especially useful in the current era where information environments are richer, product lifecycles become shorter, and consumers evolve at a faster pace.

Along this line, Netzer et al. (2008), using the context of university alumni donation and the theory of customer engagement, employed a HMM to classify alumni into dynamic relationship states based on their changing propensities for donation. Montoya et al. (2010) explored dynamics in physician prescription behaviors and found that detailing is effective for acquisition whereas sampling is more effective for retention.

Two substantive trends have emerged in the last ten years. First, with the advances in technology and data integration across advertising and sales channels, substantive interests of consumer dynamics have intensified in the domains of technology (Schweidel et al. 2011; Ascarza and Hardie 2013), social media (Ma et al. 2015; Kozlenkova et al. 2017), multichannel retail (Shi and Zhang 2014; Chang and Zhang 2016), and mobile marketing (Wang et al. 2015; Park et al. 2018). In contrast to previous research that examined dynamics in generalized terms, studies during this time looked at customer–firm or customer-to-customer relationships with finer detail that allowed for individuals to exhibit different product learning rates, different probabilities of relationship revival, different purchase journeys, and different channel adoption trajectories.

Second, detailed longitudinal data collection in B2B domains, combined with flexible dynamic models, allowed for the empirical understanding of B2B decision-making dynamics—a domain that was largely dominated by conceptual frameworks and survey methods. For instance, Zhang et al. (2014), using data from a B2B metal seller, provided an individual and dynamic pricing decision support framework for the seller to balance the tradeoff between short- and long-term effects of pricing in order to optimize long-term profit. Luo and Kumar (2013) examined the short- and long-term effects of marketing contacts for customers in a B2B high-tech firm. Zhang et al. (2016), using six years of detailed senior manager survey data from 552 B2B relationships, identified four evolving latent relationship states and offered relationship marketing strategies tailored for each state.

As the B2B space becomes increasingly digitized, we expect to uncover more decision dynamics (e.g., multichannel negotiation process, customer referencing marketing, value co-creation dynamics) in B2B in the near future. Given that B2B accounts for over 90% of the world's commerce, empirical insights into this massive yet once "black-box" will provide tremendous contributions to the marketing discipline.

Methods for modeling consumer dynamics

Just as new research areas have emerged in the past four decades as the result of richer data, so have the empirical methods used for modeling dynamics. Plenty of empirical methods have been utilized to measure consumer behavioral changes, such as the straightforward logic of comparing the results before and after a certain time period or a marketing intervention (Mittal et al. 1999; Jap and Anderson 2007; Wirtz et al. 2014), including past behaviors as independent variables in the regression model (e.g., Papatla and Krishnamurthi 1992; Bolton and Lemon 1999; Heilman et al. 2000; Gustafsson et al. 2005; Sridhar et al. 2012), Markovian state dependence model where past states are explicitly defined based on observed behaviors (e.g., Pfeifer and Carraway 2000; Homburg et al. 2009), survival analysis (e.g., NBD) models for predicting customer behaviors (e.g., Bolton 1998; Manchanda et al. 2006; Moe and Trusov 2011; Kozlenkova et al. 2017), change-point models for identifying

Table 2 Popular models for customer dynamics

Methodology	How the model captures dynamics	Data and execution requirements	Appropriate contexts	Software/package	Illustrative studies
VAR/VAR-X	• In a market system with multiple brands, VAR can describe the evolution of a set of dependent variables over the period (t = 1, ..., T) as a linear function of their past values. • For example, a p-th order dynamic system with k dependent variables (e.g., sales of k brands) indicates that sales of each brand i is affected by its past sales as well as that of the competitor's up to the past p periods. Augmenting the model with exogenous variables X_it such as marketing would arrive at the VAR-X model. • After running the VAR model, one can derive the impulse-response function (IRF) which traces the incremental effect of a one-unit shock to one of the exogenous variables (e.g. price promotion) on the future values of the other endogenous variables (e.g. sales).	• Panel data structure on the focal brand performance and marketing, and performance of competitive brands and their marketing efforts (if competitive responses need to be measured). • Often utilizes product- and brand-level scanner data	• Useful to quantify short- and long-run marketing effectiveness and can incorporate the chain reaction of consumer response, marketing, and competitive reaction through its system's approach. • Suitable for gaining an understanding of the aggregate impact of marketing on sales and is a decent tool for forecasting. • Potential drawback: there are inflexibilities for incorporating richer customer level data, heterogeneity and error specification, and interaction terms. Hence VAR is often used at the market and product-level and not flexible to address nuanced specification of consumer dynamics.	• STATA package-var • Eviews package-var • SAS-VARMAX • R package-vars	Dekimpe and Hanssens (1995a); Villanueva et al. (2008); Trusov et al. (2009); Tirunillai and Tellis (2012); Reimer et al. (2014); Pauwels and Neslin (2015); Srinivasan et al. (2016); Hewett et al. (2016).
Dynamic Linear Model (DLM) / Kalman Filter	• Captures dynamics through two equations – the observation equation that captures changes in behavior (e.g., changes in "y"), and the state equation that captures evolution of baseline preference and sensitivities (i.e., the changes in beta) • Captures unobserved trends in consumers' behaviors by making the baseline behavior and marketing response coefficients time-varying (e.g., baseline brand preference and pricing sensitivity may shift over time, depending on the industry context and the popularity of the brand).	• Consumer-level panel data on outcome variables (e.g., transactions or other outcome variables) and responses to marketing (e.g., price promotion, email, communication)	• Offers a continuous form of dynamics where the response coefficient changes gradually over time, and it is useful in situations where one would expect consumer behaviors to change gradually (e.g., product lifecycle, consumer lifecycle, and changes in lifestyle) instead of sudden regime shifts (e.g., discrete life event, or sudden heightened interests from a new hobby). • DLM can also accommodate latent cumulative variables such as advertising goodwill and customer experience. For example, current advertising may have an	• Matlab Kalman Filter Toolbox • Matlab DLM toolbox • R Package-dlm	Erdem et al. (2004); Van Heerde et al. (2004); Akçura et al. (2004); Sriram et al. (2006); Zhao et al. (2009); Osinga et al. (2010); Osinga et al. (2010); Aravindakshan et al. (2012).

Table 2 (continued)

Methodology	How the model captures dynamics	Data and execution requirements	Appropriate contexts	Software/package	Illustrative studies
	• Offers the advantage of accounting for both dynamics and cross-sectional heterogeneity • Estimated using a common approach based on Kalmanfilter and maximum likelihood.		immediate effect on current sales, but it can also contribute to an "advertising stock" and affect future sales. • Potential drawbacks: Given its parametric nature, there exists limitations with respect to distribution assumptions. More importantly, from a managerial perspective, this continuous form of dynamics creates difficulties for firms to segment customers.		
BG-NBD	• Models repeat-buying behavior in non-contractual settings (e.g., e-commerce) and uses only recency and frequency data to predict customer churn, while allowing for some degrees of customer heterogeneity in both purchase rate and retention.	• Data requirements are few (only recency, frequency, and monetary (RFM) measures are needed, essentially only one data point per customer)	• Elegant and easy to implement for predicting future purchase likelihood for customers in non-contractual settings. Low data requirements. • Potential drawbacks: 1) the model assums that once a customer drops out, the customer is gone for good – the model does not allow for customer revival. 2) the heterogeneity parameters are common across all customers and the analysis has to conducted on the same cohort; 3) the model does not take into account the effect of marketing or influences from any exogenous variables	• R package -BTYD	Schmittlein et al. (1987); Pedrick and Zufryden (1991); Reinartz and Kumar (2003); Fader et al. (2005); Abe (2009).
Hidden Markov Model (HMM)	• Captures consumers' evolving latent attitudinal states (e.g., relationship strength, shopping attitudes, trust towards the brand) through any observed actions (e.g., browsing, purchase, response to marketing actions, postpurchase behaviors, survey response). The number of latent states can be empirically determined based on model fit.	• Individual-level panel data structure. To be able to reliably estimate state migrations or individual-level parameters, need longer panel: generally at least 6 data points per individual needed, the more the better. Bayesian pooling allows for fewer data points	• Well-suited for understanding B2B vendor–supplier relationships or B2C brand-engagement, interest development, or learning which take time and effort to either develop or decay. State transitions take time, but once a consumer get into a new state, her behavior should be markedly different empirically and theoretically from the previous state.	• R packages "HMM", "HiddenMarkov", and "depmixS4" • Latent Gold	Montgomery et al. (2004); Netzer et al. (2008); Montoya et al. (2010); Li et al. (2011); Schweidel et al. (2011); Park and Gupta (2011); Ascarza and Hardie (2013); Romero et al. (2013); Luo and Kumar (2013); Mark et al. (2013); Van der Lans et al. (2008); Shi et al. (2013); Shi and Zhang et al. (2014); Zhang et al. (2014); Ma et al. (2015); Zhang et al. (2016); Chang and Zhang (2016).

Table 2 (continued)

Methodology	How the model captures dynamics	Data and execution requirements	Appropriate contexts	Software/package	Illustrative studies
	• Consumers can transition between the latent states over time, akin to "dynamic segmentation". Explanatory variables can be included in the transition equation to guide understanding of what drives latent attitudional changes • The same explanatory variables can be placed in both the outcome equation and transition equation, to disentangle the variable's short and long-term effect (e.g., pricing can affect the customer's immediate outcome such as "buy or not buy, but can also impact future behaviors by transitioning the customer to a more price sensitive state) • Can incorporate heterogeneity specification in HMM (i.e., either through latent class or continuous heterogeneity in a hierarchical Bayesian fashion) in order		• Illustrates how "transient" or "sticky" different states are, allows for both gradual migrations in relationship states as well as quick jumps from one state to all other states. • The semi-parametric approach offers distributional flexibility (compared to the normal distributional assumptions of DLM). • Potential drawback: 1) not suitable if there is the context offers no theory to support regime changes. Too many states and quick fluctuation between states make the states difficult to interpret. In those cases, one should use DLM. 2) Not as useful for predictions as it is a probabilistic model and thus under predicts dynamics.		

large changes (e.g., Fader et al. 2004; Park and Park 2016), VAR models for addressing marketing's short- and long-term effects (e.g., Dekimpe and Hanssens 1995a; Pauwels and Neslin 2015; Hewett et al. 2016), hazard models for predicting customer behaviors with limited information especially in non-contractual CRM settings (e.g., Reinartz and Kumar 2003; Fader et al. 2005; Abe 2009), and models that allow for evolving customer response coefficients such as state space models (e.g., Van Heerde et al. 2004; Osinga et al. 2010; Aravindakshan et al. 2012) and hidden Markov models (e.g., Netzer et al. 2008; Zhang et al. 2014; Ma et al. 2015).

Fig. 2 highlights the various methods in terms of their relative citation percentages over time. We can see that richer data have led to the developments of VAR, dynamic linear models, and HMM in recent years.

Given the space constraint and the goal of present and future orientation, this section focuses on the common and relatively more recent methods. We focus on four models: VAR model (for measuring short and long-term effect of marketing actions), dynamic linear model (for capturing gradual unobserved trends in behaviors), BG/NBD model (for predicting customer churn with limited information), and hidden Markov models (for capturing latent behavioral regime shifts). Accordingly, Table 2 lists how each of the four models captures consumer dynamics, the data requirements, the appropriate contexts and research questions, software packages, and representative papers.

It is important to note that all the methods are still being utilized, and depending on the research contexts and data structure, some are more appropriate than others. Given the long list of methods, we further elaborate on them in Web Appendix Table B1 and B2 that include other discussions on properties, data requirements, and pros and cons of usage. Given the nuances of the approaches (each one is worthy of an entire monograph) and in the interest of space, we will briefly describe them and refer interested readers to seminal papers and the various applications in the tables. Web Appendix A further discusses these models in textual details.

Vector auto-regressive model (VAR)

Firms are often interested in finding out how marketing affects performance over time in a competitive environment. The goal is to disentangle the short-term (temporary) from the long-term (persistent) marketing effects and competitor actions. Time series models such as VAR are useful for this purpose. VAR can quantify short- and long-run marketing effectiveness and can incorporate the chain reactions of consumer response, marketing, and competitive reaction through its systems approach. It is suitable for gaining an aggregate understanding of the impacts and is a decent tool for forecasting. However, VAR is often applied at a product level as sales of competitor products are not available at the individual level and does not directly address consumers' dynamics due to its various inflexibilities with heterogeneity, interaction terms, and error specification.

Dynamic linear model (DLM)

DLM captures unobserved trends in customer behaviors by making the baseline behavior and marketing response coefficients time-varying (e.g., baseline brand preference or pricing sensitivity may shift over time). DLM can accommodate latent cumulative variables such as advertising goodwill and customer experience. For example, current advertising not only may have an immediate effect on current sales but can also contribute to an "advertising stock" and affect future sales. DLM is commonly estimated using the approach based on Kalman-filter and maximum likelihood. DLM offers the advantage of accounting for both dynamics and cross-sectional heterogeneity. However, from a managerial perspective, this continuous form of dynamics creates difficulties for firms to segment customers and accordingly design strategies at a segment level. Hence, if there are theories to support that customers change over time not in a gradual fashion but due to qualitatively different "regime shifts" (e.g., variety seeking mindset vs. habitual mindset), then dynamic segmentation frameworks such as the hidden Markov model might be more appropriate.

Survival models and BG/NBD models

Predicting customer churn and future purchases are two central academic and managerial interests in CRM. In contractual settings such as subscriptions where customer attrition is observed, one can model customer relationship duration using survival analysis or hazard model (Bolton 1998; Reinartz and Kumar 2003; Manchanda et al. 2006). Hazard functions such as exponential, Weibull, and log-logistic distributions can be used with various degrees of flexibility. Software packages such as "survival" in R and "PHREG" in SAS could be used.

For non-contractual situations where customer attrition is not observed and customer purchase frequency is not fixed (e.g., in virtually all retail situations), an elegant and widely applied model with little data requirement is the BG/NBD (Beta-Geometric/Negative-Binominal Distribution) model (Fader et al. 2005) which describes repeat buying behavior in non-contractual settings and uses only recency, frequency, and monetary value data (i.e., RFM) to predict customer churn. This approach allows for certain degrees of customer heterogeneity in both purchase rate and retention. However, BG/NBD has limitations when it comes to incorporating marketing actions and more flexible forms of heterogeneity. Furthermore, the model assumes that once a customer drops out, he is gone for good—the model does not allow for customer revival. As we will see next, these concerns could be alleviated by leveraging richer customer-level data with more flexible models such as the HMM.

Hidden Markov models (HMM)

With granular panel data such as online browsing, clicks, multichannel choices, negotiation, product returns, and post-purchase behaviors, firms can dynamically segment consumers and shed light on their evolving latent attitudes. A representative method that achieves this goal is the hidden Markov model (HMM) approach which has been used to model how a sequence of customer observations is governed by transitions among a set of customer latent states. Such efforts are useful for building new theories and empirically testing existing theories of how and why consumer behaviors evolve (e.g., reference price effects, hedonic adaptation, effects of conflict on channel relationship).

In an HMM model setup, consumers migrate over time among a set of latent states. As we only observe consumers' choices and not their latent states, one objective of HMM is to infer the latent states from the observations. The observations provide a noisy measure of the underlying states, which are more stable and better reflect customers' longer-term behaviors. As the consumer may change her states over time, an HMM can estimate the transition probabilities between states, which indicate the stickiness of the relationship. Additionally, marketing actions can be incorporated into the transition to nudge consumers towards desirable states—a useful feature for dynamic targeted marketing. For further details on HMM specifications, please refer to Zucchini and MacDonald (2009).

The merits of employing HMM to study consumer dynamics in both B2C and B2B domains include flexibility and multifaceted richness. First, aside from the distributional flexibility of its semi-parametric approach and the ability to identify the number of states empirically, HMM can show how "transient" or "sticky" different states are and allows for both gradual migrations in relationship states as well as for quick jumps from one state to all other states. These flexible properties are well-suited for B2B vendor–supplier relationships or B2C brand engagement states which take time and effort to either develop or decay but could also experience a sudden increase or deterioration of relationship in extreme circumstances (e.g., conflicts and injustice in channel relationships). Second, although states can be inferred from a single behavior such as brand choice or purchase frequency, states can also encompass multiple behaviors that might move in different directions and measure the various facets of a richer state construct, hence providing the ability to advance consumer dynamics theory. Finally, relative to continuous dynamic models such as DLM, HMMs in marketing are attractive because they are easily interpretable and often lead to easy-to-communicate managerial insights, akin to segmentation studies.

However, HMM should not be applied in all contexts. In situations where there is no theory for the existence of discrete underlying attitudinal regimes that govern the observed behaviors and the observed behaviors are expected to gradually change, then HMM might not be appropriate. In those situations, the number of states recommended by the model selection criteria might become large, in which case we suggest the use of DLM. Furthermore, while HMM is useful in describing customer behaviors and in informing theories, it might not be useful for predictions as it infers the states probabilistically and then averages them in prediction tasks, resulting in lower predicted consumer dynamics compared to the reality.

Dynamic structural modeling approaches

Consumer dynamic decision making also exists in the structural modeling world (Chintagunta et al. 2006; Dube 2019). The structural approach assumes a priori that consumers are forward-looking based on the economic theory relevant to the study's context. In the previously listed models, consumers maximize current utility based on the current environment, past experiences, and past marketing contacts. The structural approach assumes that consumers are always forward-looking based on the assumptions made to maximize a stream of discounted future expected payoffs. For example, consumers' current purchases of storable goods depend on their future expectation of prices, and consumers' warranty purchase decisions depend on their future expectations of product usage and quality (Dube 2019).

Dynamic structural models present a fundamentally different class of models than the ones presented so far in terms of assumptions and estimations. All the models presented previously essentially take a reduced form, statistical, and largely agnostic approach—they describe the observed empirical relationships of the data, let the data uncover patterns of dynamics and identify drivers of dynamics. In contrast, the nature of the dynamic decision process requires strong assumptions along many dimensions: individuals' utility functions, their information set, their ability to make accurate forecasts about the future, and the extent to which they trade off future versus current utility. Whereas the various decay parameters in reduced form statistical models can generally be estimated from the data based on model fit, structural approaches often assume the discount rate for the future payoffs because this parameter typically cannot be identified.

From an estimation perspective, dynamic structural models are often difficult to estimate—the associated Bellman equations have no closed-form and often need to be solved numerically. As every structural model is different depending on the environment of study, all pieces need to be custom-coded and there are no readily available software packages.

The state of knowledge in consumer dynamics

The past several decades of dynamics research have yielded insights across different substantive domains. In Table 3, we list 15 substantive areas (though not an exhaustive list) in which looking at customer behaviors through a dynamic lens has enabled the field to understand customers better, has led to the development of new theories and empirical validation of existing theories. For each area, Table 3 highlights the key variables studied, a representative set of papers, and the key findings.

Emerging directions for consumer dynamics research

The future of consumer dynamics research is far more exciting. It allows us to (1) understand behavioral changes in rapidly evolving environments in current business paradigms, (2) study new behaviors in emerging contexts, and (3) study those customers in previously unexamined economies.

As we look into the future, we search beyond published academic research for inspirations in identifying emerging domains. We first consult the research priorities and trends of proposed by six established business and public organizations, namely, Marketing Science Institute research priorities 2018 to 2020 (MSI 2018), McKinsey Global Institute (McKinsey Global Institute 2019), Deloitte 2020 tech trends (Deloitte 2019), Gartner's strategic technology trends (Gartner 2019), AT Kearney's global trends 2018–2023 (AT Kearney 2018), and United Nations' 2030 sustainable development goals (UN 2019). Next, based on the many topics mentioned by these organizations, we then use judgment to select the relevant topics to include within the current paper's scope—essentially, the focus on (1) consumers, (2) consumer attitudinal and behavioral changes, and (3) potential implications for businesses with these changes.

Continuing with the theme that "richer data lead to deeper insights," the opportunity for deeper learnings about consumer dynamics arises due to (1) increase in more detailed consumer touch-point data in novel contexts; (2) increase in unstructured data formats such as text, videos, sound, and advances made in methods that can extract structures from them; and (3) the opportunities to fuse diverse data sources such as forum reviews and

Table 3 The state of marketing knowledge through the dynamic lens

Domain	Topics of interest	Key variables of interest	Representative papers
Customer engagement	Encourage customers' direct and continuous involvement in sharing experiences and interacting in the community.	• relationship, customer decision • donation incidence • purchase incidence • voice decision • purchasing and posting activities	• Customer-firm interactions affect the relationship evolution (Netzer et al. 2008). • Engagement has an impact on customer behaviors on social media. A customer's relationship with the firm influences the voice decision of whether to complain or compliment. Social factors and service intervention affect voices as well (Ma et al. 2015). • There is a correlation between a customer's purchasing and posting activities until a churn happens. Customers are less likely to become inactive when they are active with other activities (Schweidel et al. 2014).
Switching cost	• The costs of changing brands, products, services, and suppliers. • There are two types of switching costs: monetary and nonmonetary (e.g., time and effort spent searching for information and evaluating alternatives) switching costs.	• switching behavior • choice • lifetime duration • share of wallet • retention • relationship • channel choices in consideration • purchase stage	• Overall customer satisfaction, perceptions of relative competitors' performance, nonmonetary switching costs, and marketing mix show significant influences on actual switching behavior (Wirtz et al. 2014). • Calculative commitment such as lack of alternatives and switching cost has a negative effect on churn and captures the competitiveness of the value proposition (Gustafsson et al. 2005). • Switching cost reduces the effect of functional service quality on customer loyalty. Higher switching cost increases the importance of technical service quality on customer loyalty (Bell et al. 2005).
Learning, uncertainty and perceived risk	• Perceived risk is an important concept in the social sciences and relevant to human behavior and consumers' evaluations of products. • Consumers' perceptions of risk are crucial to their evaluations, choices, and behaviors. • Perceived risk can be considered as a function of the uncertainty about the potential outcomes and the possible disappointment for the outcomes. • Six types of perceived risk: financial, product performance, social, psychological, physical, and time/convenience loss (Brooker 1984). • The decision process is being learned because of motivation and ability, lack of familiarity, and unsatisfying experiences (Valentini et al. 2011).	• channel choice • path to purchase • brand choice • paid search clicks, website visits, and Facebook likes/unlikes • payment decision • ratio of repayment amount • purchase decisions • lifetime value • customer desired value	• The decision process evolution is a result of learning (Valentini et al. 2011). • The path to purchase has three stages - learning, feeling, and behavior (Srinivasan et al. 2016). • Customer learning, perceived risk, and consumer attitude toward risk, quality, and price have significant impacts on store-brand and national-brand choices (Erdem et al. 2004). • Customers' repayment behavior changes over time because the behavior evolves as a result of the learning about the features, policies, and usage experiences of the credit cards (Zhao et al. 2009). • Customers who are new to the market may go through three stages. Initially, customers are in an information collection stage and focus on low risk and big brands. Later, they may switch to lesser-known brands. In the stage of information consolidation, customers will choose the brands that provide the highest utility (Heilman et al. 2000). • Consumers update the perceptions of the mean product quality level and the precision of the information from use experience and advertising about product quality over time (Zhao et al. 2011).

Table 3 (continued)

Domain	Topics of interest	Key variables of interest	Representative papers
			• Risk has an impact on customer values of different segments and the switching probabilities between segments (Johnson and Selnes 2004). • The consumption in the past period impacts the purchase incidence in the current time period. Consumers update their quality beliefs over time and show significant cross-category learning (Sridhar et al. 2012).
Habit & variety seeking	• Habit persistence is an effect of prior propensities to select a brand on current selection probabilities (Roy et al. 1996). • Habit is a learned response to a stimulus that has become routine and requires little or no cognitive effort (AMA). • Habit buying is usually associated with low involvement products. • Variety seeking: Customer's desire to search for alternatives. It happens when there is a significant difference between brands and when customers do not have high involvement with the products.	• number of orders • order rate • hazard rate • purchase incidence • brand choice • timing of shopping trips • store choice • stock keeping unit choice	• Brand-loyal customers are not necessary to be variety-avoiders (Papatla and Krishnamurthi 1992). • Variety seekers and repeat shoppers show significant differences in the timing of shopping trips and the timing of switching trips (Leszczyc et al. 2000). • Customers may show reinforcing behavior like repeated purchases on some attributes and variety-seeking behavior on other attributes (Inman et al. 2008). • Customers tend to buy habitual items that they have purchased before and buy less unfamiliar products to minimize potential regret (Wang et al. 2015). • Customers develop habits of makeing purchases through mobile devices (Wang et al. 2015).
Loyalty	Customer loyalty is a favorable attitude toward a brand or a commitment to repurchase a preferred product over time (Kotler).	• relationship • repurchase intentions • purchase incidence • recommending to others • lifetime duration • timing of shopping trips • store choice • share of wallet	• Switching cost reduces the effect of functional service quality on customer loyalty. Higher switching cost increases the importance of technical service quality on customer loyalty (Bell et al. 2005). • The influence of perceived value on loyalty intentions is positive and decreases over time (Johnson et al. 2006). • The loyalty program reduces the relative risk of defection and thus increases share or wallet (Meyer-Waarden 2007). • Customer loyalty reduces the likelihood of being affected by others' defections (Nitzan and Libai 2011). • Customers in the low switching segment tend to switch to similar alternatives, whereas customers in the high switching segment are more likely to switch to dissimilar alternatives (Papatla and Krishnamurthi 1992).
Exchange characteristics	• A mechanism for creating value through coordination of production, consumption, and related economic variables between a customer and a supplier (Johnson and Selnes 2004). • Exchange characteristics are frequency, amount, and communications between the firm and the customer (Reinartz and Kumar 2003).	• customer portfolio • customer lifetime value • form of collaboration • commitment velocity • relationship duration	• The theory of exchange relationships captures the trade-offs between economies of scales and customer lifetime value (Johnson and Selnes 2004). • The firm which builds closer relationships creates more value through relationships over time. It is more difficult to lose customers to competitors when there is a deep customer-supplier relationship (Johnson and Selnes 2004).

Table 3 (continued)

Domain	Topics of interest	Key variables of interest	Representative papers
Satisfaction	Satisfaction is a fulfillment response and a customer assessment of performance and expectations (Oliver 2014).	• service usage • relationship • behavioral intention • repurchase behavior • switching behavior • relationship duration • customer value • retention	• Satisfaction leads to high usage level in the subsequent periods (Bolton and Lemon 1999) • Satisfaction changes over time and then affect consumption goals. Service satisfaction is more important initially, but product satisfaction becomes more important during later consumption periods (Mittal et al.). • Prior cumulative satisfaction and assessments of service influence relationship duration (Bolton 1998). • Customer satisfaction has a positive effect on retention (Gustafsson et al. 2005).
Trust and commitment	• Trust is defined as "confidence in an exchange partner's reliability and integrity (Morgan and Hunt 1994). • Commitment is "an enduring desire to maintain a valued relationship" (Moorman et al. 1992). • Trust leads to commitment (Morgan and Hunt 1994).	• relationship • desire for revenge • desire for avoidance • perceived betrayal • relationship quality • lifetime duration • share of wallet • usage and retention • patronage behavior • lifetime value • commitment velocity	• 60% of the customers who churn show low commitment level a long time before they canceled their subscription (Ascarza and Hardie 2013). • Trust has a direct and positive impact on service usage and cross-buying. Trust plays an important role when customers make decisions in uncertain situations. Relationship commitment enhances customer retention and is critical for relationship maintenance and long-term customer relationship (Aurier and N'Goala 2010). • Investment capabilities are more important than trust and communication capabilities as a relationship matures. Communication capabilities are the most important in a highly turbulent industry (Palmatier et al. 2013).
Construal level theory	When the event is hypothetical or distant, people tend to focus more on the "central" aspects of the event such as outcomes or desirability (better price/service). When the event is near, customers will focus on the procedure involved in the action (time/effort).	• switching behavior • choice	• Consumers' self-reported intentions are usually inaccurate because customers cannot predict their future behavior accurately. Customers overweight outcome and desirability-related variables, and underweight nonmonetary switching costs and advertising when expressing their switching intent. (Wirtz et al. 2014). • The different focus on concrete aspects of near-future events or abstract aspects of distant-future events lead to preference inconsistency (Zhao et al. 2007).
Information search	The stage of the decision-making process where the consumer is motivated to search for more information (Kotler).	• number of stores visited • perceived integrity of the store • product comparison • decision of stopping search • purchase intentions • purchase choices	• When search costs are high, the types of store-price signals will not affect consumers' search behavior (Ho et al. 2011). • The product recommendations can affect product search decision and consideration sets, which further affects the product choice. Customers tend to make broader comparisons with previous consideration sets when inspecting a new product with recommendations. With recommendations, customers' decision shifts to a more thorough comparison among alternatives that are already inspected. With

Table 3 (continued)

Domain	Topics of interest	Key variables of interest	Representative papers
		• duration of purchase deliberation	recommendations, greater variability causes consumers to end the search earlier (Dellaert and Häubl 2012). • The "cue-of-the-cloud" can help customers assess the information seen in the store and thus enhance confidence and positive feelings about the purchase decisions (Bhargave et al. 2016).
Social fairness (Conflict & Conflict resolution)	Customers may revise their preferences in the subsequent purchase decisions if they have incongruent preferences about a purchase.	• choice	• The spouse with stronger preference may use strong influence behavior to get his/her way. The family decision process is dynamic and adaptive to the other's reactions. Prior spousal decisions, spouses' influence, and spouses' satisfaction with decision outcome have carry-over effects on spousal subsequent decisions (Su et al. 2003).
Social influence, information sharing, and imitation	• A person can be influenced by another person by word of mouth and information from people who have used the products. It occurs through information transmission which reduces uncertainty and search effort as a result of network externalities. (Peres et al. 2010, Van den Bulte and Lilien 2001) • The nature of social effects (Nitzan and Libai 2011): -tie strength: how closer of the relationships of the network -homophily: similarity between people -degree of connectivity -average degree of defecting neighbors.	• relationship duration • product ratings • online ratings and opinions • user-generated content metrics • stock market performance • customer acquisition • customer value	• Customers who acquired by word-of-mouth contribute twice as much long-term value to the firm than who acquired by marketing actions (Villanueva et al. 2008). • Word-of-mouth referrals have longer carry-over effects than traditional marketing actions and higher response elasticities than average advertising elasticities (Trusov et al. 2009). • Exposure to network neighbor's defection will increase the probability of terminating the relationship with the service provider. Defections in social networks affect more on highly connected customers than on loyal customers (Nitzan and Libai 2011). • The dynamics in average ratings has direct and immediate effects on sales and indirect effects on future sales through the influence on future ratings (Moe and Trusov 2011). • The volume of chatter has a positive effect on returns and trading volume. The negative user-generated content (UGC) has a stronger negative effect on returns than the positive effect caused by positive UGC. The volume of chatter and negative chatter influence the trading volume positively. TV advertising increases the volume of chatter and decreases negative chatter (Tirunillai and Tellis 2012). • Sequential ratings are declining when reviewers are highly heterogeneous (Godes and Silva 2012).
Persuasion & argument (e.g. sales force)	Persuasive argument theory is an informational influence perspective to describe group polarization.	• choice	• Preferences shift toward the initially most preferred alternative. People dropped positive beliefs on the initially less-preferred alternatives (Chandrashekaran et al. 1996).
Marketing mix exposure & marketing shock (e.g. pricing exposure, reference price, advertising exposure)	"Marketing mix consists of everything the firm can do to engage consumers and deliver customer value," (Kotler).	• repeat purchase probability • purchase incidence	• Number of exposures, number of web visits, and number of pages viewed have a positive impact on repeat purchase probabilities (Manchanda et al. 2006).

Table 3 (continued)

Domain	Topics of interest	Key variables of interest	Representative papers
		• expenditure • sales • advertising • category demand • price • advertising spending • competitive marketing • merchandising variables • customer acquisition • average weekly spending • brand choice • exposure behavior • expenditure • number of visits • number of product types purchased	• Free shipping is preferred for re-acquiring lapsed customers, whereas price promotion is more effective for active customers (Khan et al. 2009). • When there is a new product introduction in the same category, the short-term effectiveness of price promotion is lower. In perishable product categories, both shortrun and long-run promotion effectiveness is high (Nijs et al. 2001). • Shocks from marketing mix impact the dynamics of the retail system (Bandyopadhyay 2009). • WOM referrals have longer carryover effects than traditional marketing actions and higher response elasticities than average advertising elasticities (Trusov et al. 2009). • 1/3 of the explained sales variance can be attributed to advertising awareness, brand consideration, and brand liking (Srinivasan et al. 2010). • Marketing contacts have long- and short-term effects on customer purchasing behavior through the dynamic relationship states (Luo and Kumar 2013). • The relationship strength moderates the impact of direct mails on purchase behaviors (Gázquez-Abad et al. 2011). • Marketing carryover and saturation interact with customer recency. Direct mail interacts with recency positively and has more carryover, whereas email has saturation effects (Neslin et al. 2013). • Firm-initiated channels have significant spillover effects to customer-initiated channels at visit and purchase stages. E-mails and display ads encourage visit through search and referral channels. E-mails encourage customers to purchase through search channels (Li and Kannan 2014).
Signaling	Use observable marketing tools to signal unobservable quality to customers. Observable marketing tools may include price, brand, etc.	• consumer search • store image • probability of relationship formation	• Always low price (ALP) discourages consumer search, whereas low price guarantee (LPG) encourages consumer search. When price signals are credible, LPG creates favorable store image while ALP discourages consumer search. When LPG is not credible, consumers visit fewer stores relative to a credible LPG (Ho et al. 2011). • Buyers use signals such as bilateral communications, seller's reputation, and buyer's observation to identify suitable partners and manage the risk. The importance of these signals reduces when buyers gain experience. When buyers are forming more committed reciprocal relationships, these signals become more important (Kozlenkova et al. 2017).

just-in-time surveys with behavioral data. We first list the research opportunities arising from future data trends, followed by opportunities in emerging substantive domains, which are respectively listed in Tables 4 and 5.

Opportunities from emerging data trends

1. Data variety and customer touchpoints beyond transactions

More detailed consumer touchpoints such as cross-device data, location-based data, social data, and more recently in-store browsing and facial recognition data can capture rich information value of consumer hobby developments, statements, learning, and information search. Diverse touchpoints across channels allow for understanding how customer preferences evolve across channels (e.g., linking in-store browsing behaviors with online purchase, as can be identified by Amazon's Go stores). While multichannel touchpoints are ideal for studying consumer dynamics in a connected world, marketers are confronted with numerous challenges such as missing data and the identification and matching of consumers from separate datasets. Therefore, there exists strong demands for advanced imputation techniques to overcome these data integration issues.

2. Unstructured data and data fusion

Geospatial, video, voice textual (i.e., user-generated from online brand communities, forums, and consumer-to-consumer interactions) data and continued development in data-summarizing techniques to fuse and place structures on these data types (e.g., natural language processing) can scale up traditional qualitative research and identify consumer conversations, emotions, and help firms to market-sense. Massive amount of unstructured data can be handled via machine learning methods such as latent Dirichlet allocation (LDA), random forests, deep learning, and natural language processing to first obtain structure and then subsequently modeled to examine dynamics.

3. Faster survey technologies

Data fusing from real-time surveys allows us to understand consumer attitudes and behaviors beyond their interactions with the focal firm, thus expanding the scope of CRM research. As surveys become much easier and faster to administer online and on mobile devices, these data can supplement companies' existing CRM data to get a broader view of customers' behaviors outside of the company and better link intentions to behaviors.

4. Information on prospective customers

Companies' databases almost always consist of existing customers, which creates self-selection sampling issues when it comes to analysis and insights. Various online communities can inform the characteristics of prospective customers from different channels and address important issues such as how much CLV is determined at the acquisition stage versus later stages.

5. Faster field experiments and richer lab experiments

Online field experiments are faster to conduct and to scale up, allowing for adaptive personalization. Online lab experiments can now collect audio, video, eye-tracking, facial recognition, and emotion data through cameras and EEG devices. These affect-rich data could capture deeper levels of latent consumer preferences that consumers often fail to verbalize in surveys, and can inform a deeper understanding of what drives behaviors.

6. IoT and natural user interface

Data from customer interactions with increasingly prevalent IoT devices provide novel and detailed customer consumption outcomes, and enable researchers to study how consumption across all aspects of a consumer's life is interrelated and how these interrelationships evolve as the boundaries of consumption and purchase channels become blurred. Data from consumer–device interactions such as voice, gaze, facial expression, and motion control allow for the studies of how habits form and how attention and interests evolve.

Opportunities from emerging domains

Several cutting-edge substantive domains emerge that are of interest to marketing academics, practitioners, and policymakers. As novel consumer data are currently getting collected in these areas, we state the following research opportunities. Details are tabulated in Table 5.

1. Digitization allows for expanded industry insights

New data from new industries will likely shift research focus away from fast-moving consumer goods, subscription-based services, and durable goods, which consisted of the bulk of research settings in the past due to data availability. Digitization and digital transformation of industries allow for empirical models of consumer behaviors including Fintech, the merging and finance and e-commerce platforms (e.g., JD.com and JD finance), healthcare, entertainment, higher education, the arts, philanthropy, and luxury markets. Continued digital transformation of B2B allows for more empirical research of the consumer buying process into the

Table 4 Future research in consumer dynamics: Emerging data trends

Emerging data trends	Description	Research opportunities
Data variety and richer consumer touch-points	• Collection of consumer touchpoints beyond transactions such as cross-device data, mobile and location-based data, and social data.	• Touchpoints beyond transactions allow for the understanding of the additional underlying consumer decision processes. • Can capture rich information value of consumer hobby developments, statements, and information search offline and online and across platforms.
Unstructured data and data fusion	• Placing structures on unstructured data types such as geo-spatial, video, voice, and textual data can scale up traditional qualitative research and generate deep insights.	• Using natural language processing to identify consumer conversations, emotions, and help firms to market-sense. • Crowdsourcing for innovation. • Advances in machine learning algorithms combined with marketing theories can resolve the disconnect between industry practice and academiah and improve managerial applicability of academic research. For example, compared to the topic models by academics, industry practitioners often use much larger numbers of latent topics to identify long-tailed, yet potentially insightful traits for market-sensing.
Faster survey technologies	• Surveys become much easier and faster to administer online and on mobile devices.	• Real-time surveys can supplement companies' existing CRM data to achieve a broader view of customers' behaviors outside of the focal firm. • Real-time surveys can better link intentions to behaviors. • Mobile devices can be used to track customer experiences in real-time by surveying customers about competitive offerings, attention, and other environmental factors during the shopping trip. • Understand how customer preferences are fine-tuned during offline shopping journeys. • Address share-of-wallet for the focal product category as well as trade-offs between categories.
Information on prospective customers	• The prevalence of user-generated contents from different online channels allows firms to observe preference and behavioral characteristics of potential customers beyond their existing customers.	• Information on prospective customers can address how much customer-lifetime-value is determined at the acquisition stage vs. later stages. • Observing the needs and characteristics of both existing customers as well as potential customers allow firms to resolve sampling and self-selection issues when forming strategies.
Faster field experiments and richer lab experiments	• Online field experiments are faster to conduct and to scale up. • Online lab experiments can collect audio, video, eye-tracking, facial recognition, and even emotion data (e.g., through EEG device).	• Using online field experiments for adaptive personalization. • Affect-rich data from experiments could capture deeper levels of latent consumer preferences that consumers often fail to verbalize in surveys, and can inform deeper understandings of behavioral drivers.
IoT and natural user interfaces	• Detailed and dynamic consumption outcomes across devices in all aspects of the consumer's life (e.g., at home, during transit, at work, during leisure). • Natural user interfaces collects consumer voice, gaze, facial expression, and motion control.	• How consumptions across all aspects of a consumer's life are interrelated. How do consumption patterns (e.g., brand preference, price sensitivity) change during different consumption contexts (e.g., at home vs. on vacation). • How consumptions evolve as the boundaries of consumption and purchase channels become blurred. • Using consumer attention analysis through IoT interaction data to study how attentions evolve.

traditional "black box" of B2B, which comprises the majority of the world economy.

2. Product and experiential personalization

As digitized manufacturing processes make product personalization more prevalent and as AI-enabled IoT devices provide dynamic experiential personalization, future research can study the appropriate levels of personalization in various contexts. Future research can also determine the appropriate level of personalization needed for each consumer and how the need for personalization evolves (e.g., tradeoffs between brands' core DNA and consumers' self-identity, preference for customization due to the accumulation of experience and

Table 5 Future research in consumer dynamics: Emerging domains

Emerging domain	Description	Research opportunities
Digitization of traditional industries	• Data from new industries (e.g., fintech, healthcare, entertainment, education, philanthropy, art) allow for empirical studies of consumer behaviors in diverse domains.	• Behavioral changes with novel payment platform options adoptions. • Companies that integrate e-commerce with financial services (e.g., JD.com + JD finance) can address the evolutions of consumer product preferences in tandem with their investment preferences and possibly real-estate preferences (through mortgage data). The goal is to achieve a holistic view of consumers' life over time. • Empirically examine industries such as healthcare, entertainment, higher education, and provide decision-support to industries that traditionally have not emphasized quantitative analysis, such as the arts, philanthropy, and luxury markets. For example, linking detailed firm-hosted offline event attendance activities (i.e., from PR agencies) to the firm's purchase data will allow luxury firms to optimize the design of offline group marketing strategies (Zhang 2019). • Continued digital transformations of B2B allow for empirical research of the consumer buying process (e.g., negotiation) into the traditional "black box" of B2B.
Product and experiential personalization	• Digitized manufacturing processes make personalization more prevalent across a variety of product categories. • IoT and AI allow for dynamic experiential personalization.	• Study the appropriate level of personalization for different contexts and how the level evolves (e.g., trade-offs between brand's core DNA vs. the consumer's self-identity, preference evolution for customization due to accumulation of experience and expertise). • As personalized products currently cost more than those from off-the-shelf, with data integration across multiple categories, investigate how consumers form idiosyncratic preference in different categories and how they decide to "trade up" in some categories while "trading down" in others. • How to use AI and attention analysis systems to deliver dynamic and personalized experiences? • How to balance the benefit of personalization vs. perceptions of creepiness?
Online influencer marketing and micro-targeting	• Increasingly heterogeneous consumer preferences and the democratization of communication platforms give rise to online influencers. The power of influencers changes the way brands reach consumers and how consumers perceive brands.	• How do brands choose and value influencers given the brand's overall positioning, desired message outcome, and customer acquisition objective, without damaging the brand's reputation? • With faster consumer feedback loops and crowdsourcing, how do influencers, lead-users, and new segments of consumers provide ideas for brands to innovate and reposition? • How do consumers' brand perceptions evolve as the result of interactions with the brand and its influencers?
Consumers' evolving attitudes toward AI vs. human experiences	• AI continues to play a prominent role in society spanning service automation to product recommendations. • AI offers increased efficiency and precision albeit with the potential drawback of offering a more siloed experience (e.g., product recommendations are often based on the consumer's past preferences), while humans satisfy our social needs and serendipity,	• How consumer preferences for AI vs. human service providers evolve for different types of consumers across various product domains and consumption contexts? • How will consumers manage their algorithm aversion and anxiety? • When do consumers prefer analog vs. digital experiences? • Is efficiency and consistent experience the right metrics that determine consumer happiness? What are the roles of serendipity and discovery in enhancing consumer happiness? • How do consumers engage with conversational agents? • How do consumers and companies design and adapt to a balanced world in which there is "tech in the background with humans in the foreground"?

Table 5 (continued)

Emerging domain	Description	Research opportunities
Virtual reality, augmented reality, and the new retail environment	• In addition to mobile and omnichannel retail technologies, the new retail environment is experimenting with VR, AR, smart display, embodied, and disembodied robots	• How can the various retail innovations be integrated to enhance behaviors such as engagement, customer-retailer relationships, and loyalty?
Linking evolving customer metrics to financial performance	• Customer-centric data scraped from the web can be used as explanatory variables for financial performance	• How data web-scraped proxies for retention rates and acquisition cost as well as consumer sentiments be used to identify mis-valuation in the equity markets. • Provides continuous updates of the marketing-finance data interface, aside from traditional announcements and quarterly filings.
Wearable devices, biometric data, and health marketing	• Wearable devices and the resulting biometric data create a "digital twin" that know about our health metrics before we do	• The wealth of health and activity data allow us to understand consumer lifestyles over time and provide health-related nudges and product recommendations in a personalized yet non-invasive fashion to improve health outcomes • If the biometric data are linked with a holistic information of the consumer's life such as types of work, work and travel schedule, budgets and other lifestyle constraints, a personalized health plan can be constructed and changed over time, akin to having a personal trainer, physician, and dietician at the consumers' fingertips.
Behaviors in international markets and "the bottom of the pyramid"	• Consumers in diverse international markets not only exhibit different budgets and product choices, but they also embody fundamental cultural differences that affect habits and relationship formation. • More data are collected from diverse regions, opening up large-scale empirical research opportunities for rarely studied consumer groups such as those at "the bottom of the pyramid".	• How do political, linguistic, religious, and socio-economic factors affect consumers' trust towards sellers and institutions, relationship-orientation towards each other, openness to new concepts, and the speed of attitudinal and behavioral change over time? • How are primarily demands formed? What are the attributes that affect primarily demand, and how do these attributes evolve when consumers move to secondary demand regimes (e.g., quantity-quality trade-off)? • How do consumers' shopping baskets and shopping channel preferences evolve with income? • How are "bottom of the pyramid" consumers' conversational interests, product concerns, and other topics related to brands and consumption different from those in the middle-class? • What are the behavioral changes rural consumers make when they migrate to urban areas and away from their social support networks?
Consumer Privacy	• Consumers globally are more aware of data privacy concerns, creating a new era of data collection challenges for firms.	• How do consumers deal with data sharing and privacy concerns in different consumption context, and how do they adapt over time? • How do consumers balance the need for authentication (e.g., hyper data-security especially in domains such as financial services and medical domains) vs. frictionless customer experiences (e.g., saved cookies and "one--click" check out in e-commerce)? • What are consumers' attitudes towards the balance between personalized recommendation vs. anonymity, and how do these attitudes evolve in the context of customer purchase journey and in the context of customer-seller relationships? • How do consumers' privacy preferences evolve based on their experiences and base on the environmental norms? • How do consumers' privacy preferences evolve as they grow? • How do consumers manage the needs for privacy vs. self-promotion?

expertise). As personalized products currently cost more than those from off-the-shelf, with data integration across multiple categories, research can look into how consumers form idiosyncratic preferences in different categories and how they "trade up" in some categories while "trading down" in others. Future research may also address related issues such as the usage of AI and attention analysis systems for delivering dynamic and personalized experiences, and firms' balancing of service personalization versus the perceptions of creepiness.

3. Online influencer marketing and micro-targeting

The increasingly heterogeneous consumer preferences and the proliferation of niche social platforms have given rise to online influencers, changing the way brands connect with consumers and how consumers perceive brands. In particular, how does a brand choose and value influencers, given the brand's overall positioning, desired message outcome, and customer acquisition objective, without damaging the brand reputation? With crowdsourcing and faster consumer feedback loops, how do influencers, lead-users, and new segments of consumers provide ideas for brands to innovate and reposition?

4. Consumers' evolving attitudes toward AI and human experiences

AI offers increased efficiency and precision albeit with the potential drawback of providing a more siloed experience (e.g., product recommendations are often based on consumers' past preferences), while humans satisfy consumers' social needs and serendipity. As AI continues to play a prominent role in society spanning service automation to product recommendations, future research can examine the consumer preference evolutions of AI vs human experiences across product domains and consumption situations. This research stream will be able to answer questions related to dynamic preferences such as: (1) How will consumers manage their algorithm aversion and anxiety? (2) When do consumers prefer analog vs digital experiences? (3) Is efficiency the right metric that drives happiness? (4) How will consumers and companies eventually adapt to a balanced world in which there is "tech in the background with humans in the foreground"? (5) How can this balanced world be achieved for different types of customers?

5. Virtual reality, augmented reality, and the new retail environment

In addition to mobile and omnichannel retail technologies that characterize the state of art in current research, the new retail environment is experimenting with VR (e.g., virtual test drive in car showrooms), augmented reality (e.g., virtual try-ons with cosmetics), public recommendations (e.g., clothing store recommendations based on one's facial and body-type recognition and past preference), smart displays, and embodied and disembodied robots to create convenience and vividness for consumers (Grewal et al. 2019). As these technologies mature and become more prevalent, how would these innovations be integrated into buying behaviors and influence key metrics of customer-retailer relationships?

6. Incorporating evolving customer metrics into "quantamental" financial research

Research on the marketing–finance interface has long investigated how announcements and marketing metrics from quarterly filings impact stock performance using event-study methods. In recent years, quantamental has emerged as a new approach to investing and firm valuation that leverages alternative data sources and machine learning techniques. Extending this development, future research can examine how scraped data such as retention rates, acquisition costs, consumer sentiments, product rankings on e-commerce platforms, and store traffic from mobile can be utilized to identify over- and under-valuations in the equity markets. As these data are continuous instead of discrete events, they can provide a continuous link and a new paradigm for marketing-finance interface research.

7. Wearable devices, biometric data, and health marketing

As wearable devices and the resulting biometric data become increasingly prevalent, there is the advent of "digital twin" that knows more about our state of health before we do. The wealth of health and activity data allows us to understand consumer lifestyles over time and provide health-related nudges and product recommendations in a personalized yet non-invasive fashion to improve health outcomes.

8. Behavioral diversity across cultures and geographies

Consumers in diverse international markets not only exhibit different budgets and product choices, but they also embody fundamental cultural differences inspired by historical, religious, political, linguistic, and socio-economic factors. These cultural differences can manifest in consumers' worldviews and behaviors such as group reliance in decision-making, trust toward sellers and institutions, relationship orientation, openness to new concepts, and the speed of attitudinal and behavioral changes. Data collection from different regions and cultures can provide deep understanding of these nuanced behavioral diversity instead of relying on the currently simplistic characterizations of "developed vs. emerging markets" or "East vs. West." Furthermore, with macro shifts such as globalization as well as the rise of populism and nationalism, consumers from different cultures might shift their brand and product preferences and overall consumption patterns in different ways and at different rates.

9. Behaviors of "the bottom of the pyramid"

As smartphones and associated services such as mobile payment and online interactions become more accessible globally, we will be able to observe and study consumers at "the bottom of the socio-economic pyramid." This broadening of data coverage could shift some of the focus away from the population samples in extant research which are predominantly middle-class consumers from the U.S. and Europe. Accordingly, we can ask new questions such as: (1) How are primarily demands formed? (2) What are the attributes that affect primarily demand and how do these attributes evolve when consumers move to secondary demand regimes such as quantity–quality tradeoff? (3) How do consumers' shopping baskets and shopping channel preferences evolve with income? (4) How do conversational interests, product concerns, and other topics related to brands and consumption differ between bottom of the pyramid consumers and those consumers in the middle class? (5) What are the behavioral changes rural consumers make when they migrate to urban areas and away from their social support network? As 70% of the world's population live in poverty (Brookings 2018), understanding their aspirations and preference evolutions will be of immense importance to the fields of marketing and international development.

10. Privacy

All of the potential insights mentioned above rely on detailed customer data. As consumers globally become more aware of data privacy concerns and as global legislation is evolving in this space (e.g., GDPR and California Consumer Privacy Act passed in 2018, with more regulation to come globally in the coming years), an important research stream is to investigate how consumers deal with data sharing and privacy concerns in different consumption contexts and how they adapt over time.

In addition to the broad inquiries on how data privacy impacts consumer–firm exchange relationships and novel retail technologies, future research could address: (1) How do different consumers balance the need for authentication (e.g., hyper data-security, especially in domains such as financial services and medical domains) versus frictionless customer experience (e.g., saved cookies and "one-click" check out in e-commerce)? (2) In the push for consumer data minimization, what is the appropriate "data lifecycle" that firms keep in order to provide good consumer experiences such as personalized recommendations? (3) Relatedly, what are the consumer attitudes toward the balance between personalized recommendation (but with more consumer data collection and usage) versus anonymity (but with less targeted and often less accurate recommendations), and how do these attitudes evolve with the various stages of the customer journey and within the context of buyer-seller relationships? (4) As privacy is an evolving domain with no clear current definition, how do consumers' perceptions of privacy evolve based on their experiences and environmental norms? (5) Privacy relates to self-identity and personal growth—how do consumers' privacy preferences change as they grow, and how do they manage the needs for self-promotion versus privacy online? If a negative article was posted about someone years ago online, how does this article anchor others' perceptions about this person's inherent characteristics vs her personal growth since then?

This research stream will not only address how consumers adapt to privacy concerns but will also determine the future nature of business processes, consumer–firm interactions, and data quality.

Concluding remarks

Consumers' attitudes and behaviors are changing all the time, and the pace of these changes is increasing with faster information and product dissemination through technology and globalization. We currently live in exciting times where firms of all types are keenly aware of the power of data, where richer consumer data from new exciting data sources are being captured in new industries across the globe, and where pervasive digitization is redefining business models and transforming how firms interact with consumers. The amalgamation of these trends will allow researchers to learn more deeply about consumer evolution across these emerging domains. These learnings will undoubtedly warrant empirical generalizations through meta-analyses in new substantive domains in the coming years.

As powerful econometric and statistical tools become increasingly user-friendly in the forms of readily applicable software packages, we believe that more marketing strategy researchers could tackle these issues and advance marketing strategy knowledge through an empirical and dynamic lens. The exciting intersection of data and method availability would allow more researchers to instill theories into the empirical analysis, synthesize perspectives across the quantitative and strategy marketing sub-disciplines, and ultimately advance our understanding of consumer dynamics in a theory-driven and empirically rigorous approach.

Just like the dynamic consumers, firms and managers should also adopt "dynamic mindsets", akin to the "growth mindset" advocated by the social psychologist Carol

Dweck (Dweck 2008), that enable them to evolve and thrive with the changing consumers and environments. "The best executives are made, not born. They absorb information, study their own experiences, learn from their mistakes, and evolve" (Schwarzman 2019). As the world changes, organizations, to survive, need to change their *worldview*, a term rooted in cognitive philosophy defined as "how one comprehensively sees the world—across political, social, and economic borders" (Nadella 2017). Understanding why, how, and when consumers change across micro and macro contexts, and also possessing the open-mindedness and the agility to adapt, are central for marketing and business excellence.

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