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Increase Adoption and Shorten the Calendar:

A New Formula that Cultivates Innovators

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Introduction

Zara, ranked as the 46th world's most valuable brand in 2018 on Forbes[1] and, undoubtedly, one of the most successful fast fashion brands, launches new products twice each week and 10,000 new designs each year[2]. Other industries, though not as dramatic as the fast fashion industry, also have been accelerating new product launches (e.g., a new concept, new generations, new line extensions, etc.) to satisfy fragmented customer preferences. For instance, Apple has been launching new product series twice per year since 2011, and the number of new product varieties has enlarged significantly. New product launch acceleration is inevitable in the contemporary business landscape and, consequently, new product success immensely affects a company's survival. If a new product is not quickly accepted by an adequate group of pioneering customers, namely innovators, the majority would hardly consider it without deep discounts in the future. Simply, thousands of new products are launched every day, especially in non-technological product categories (i.e., the fast-fashion industry) competing for customers' attention. Competitors are too aggressive to wait for the focal brand to penetrate the market gradually and customers are excited about new products just launched. Thus, companies are compelled to invest an enormous amount of marketing effort and resources in incentivizing customers to adopt their new products quickly. That way, they can grab more or at least maintain their market share, stay relevant in consumers' minds, and obtain sufficient revenue to proceed future business cycles.

However, the efficacy of company-initiated marketing communications on customer purchase decisions is limited, not as optimistic as marketers would like to see. As customers

[1] https://www.forbes.com/companies/zara/#72f777717487
[2] https://www.forbes.com/sites/gregpetro/2012/10/25/the-future-of-fashion-retailing-the-zara-approach-part-2-of-3/#46105ed77aa4

become more powerful and “seize control of the [purchase] process and actively ‘pull’ information”(pp. 5), customer-driven activities account for two-thirds of the touchpoints during the evaluation phase of purchase journey (Court et al. 2009). Firms seem to have much less control over the customer journey (Lemon and Verhoef 2016). Customers rely on self-discovered information more than ever, e.g., monitoring sales of current stocks and referencing “typical” marketing mix offerings (i.e., product features, pricing). Many comments and online reviews like the following vignettes hint this fact. “I have purchased many types of products from XXX [brand]. Now it has a new edition of lipsticks, it must be good”; “I am not buying XXX [brand] unless it is on sale, usually 30% off”; “So many people have bought this brand, it can’t be bad.” Apparently, these commetns suggest that the information is learned from customers’ past experiences and leveraged in their upcoming adoption decisions. That is, customers’ prior responses to marketing mix are not only outcomes but can serve as mechanisms to ease the uncertainties of their next purchase. Simply put, customers are smart and they utilize what learn throughout the entire customer-company touchpoints to make wise decisions in the future (e.g., Cheng, Zhang, and Nesllin 2016; Gaur and Park 2007; Sriram, Chintagunta and Manchanda 2015), reflecting the fundamentals of the theory of transfer of learning (Thorndike and Woodworth 1901).

Taken all together, companies are now confronting more impediments and complications when launching new products due to the inevitability of accelerating new product launches and the decrease in power from company-initiated activities. Knowing that customers rely significantly on what they have learned when making purchase decisions, can companies leverage customer learning to succeed in new product launches? The so-called customer learning behavior has been recognized as a critical factor for successful marketing and organizational effectiveness (Hibbert, Winklhofer, and Temerak 2012). It is because as customers learn, they are able to gain confidence and reduce uncertainties in making decisions (Kang, Hahn, and De 2017). This research defines *customer learning* from the perspective that customers accumulate experiences through past touch points with the focal brand. We assert that customers draw inferences from, and transfer and synthesize the learned information to make their next purchase. If firms are able to *guide* customer learning in ways that benefit new product adoptions, such customer-directed behavior can become an asset of companies and be converted into a significant ingredient in the receipt of new product success. The primary research question of this study is whether customer learning affects an individual's new product adoption in terms of adoption likelihood and duration to adoption.

Learning literature has documented various aspects of customer learning. There are *self-directed learning* (Hibbert, Winklhofer, and Temerak 2012) and *social learning* (e.g., Cheng, Wang and Xie 2011; Lee and Bell 2013; Zhang 2010). Self-directed learning is that customers initiate and control their learning practices. For instance, customers can learn a brand's product features (i.e., Anderson and Simester 2013; Cheng, Zhang, and Neslin 2016) pricing strategy (i.e., Anderson and Simester 2013) from their own purchase experiences. Social learning refers to that customers learn from either what others say (i.e., word of mouth (WOM) and online reviews: Zhao et al. 2013) or what others do (i.e., observational learning: Zhang 2010). The learning behavior can be triggered by avoidance motivation (i.e., "I am not going to buy this new product until others buy it") or approach motivation (i.e., "I am going to buy this new product, but at the best price"). To firms, the selection, motivation, and utilization of different aspects of customer learning result in the complexity of contingent effects. However, prior research has been scattered on this topic. In the absence of such integrated empirical evidence, managers are unable to grasp what and how customers really learn about their brands, let alone cultivating their learning habits that benefit new product success. Thus, we propose the second research question: whether and how various aspects of learning influence new product adoption decisions differently and/or jointly? This research not only extends customer learning literature by presenting a more comprehensive understanding of the phenomenon but delivers avenues that firms can engage in to streamline and enhance the efficiency of a customer learning process. Altogether, rather than heavily relying on promoting new products with advertisements and discounts, we suggest firms facilitate and guide customer learning from the beginning of customer journey and nurture innovators for their new products.

Additionally, this research also contributes to the consumer new product adoption literature significantly. Prior research has studied consumer-related factors that drive new product adoptions, with a concentration on those that are relatively constant in nature or hard to change such as personality traits (i.e., Faraji-Rad, Melumad, and Johar 2017; Kuester et al. 2015; see details in Tabl 1). However, this research investigates a newly uncovered customer-related factor, customer learning about the brand, which is amendable and can be maneuvered by firms. As indicated, the merit of our propounded factor is that managers can proactively guide consumers' learning process by educating and training their customers to get ready for new products. In addition, this research extends the new product literature to non-technolgocial product categories, whearas much prior research only studies technological new products (i.e., Antioco and Kleijnen 2010). Non-technogolical categories, many times, compete for exciting and refreshing ideas or concepts to satisfy customers rather breakthrough technical advancement and thus launch new products more frequently. The success determinants of non-technological categories can be fundamentally different from those of technological ones, thus requiring dedicated research for them. Last but not least, our results deliver implications on a pair of critical outcomes of new product success: increasing likelihood of and decreasing duration to new product adoption, when literature has been silent on the latter aspect. We assert that understanding the drivers of adoption duration is vitally important because as indicated, neither customers nor competitors have the patience to wait for a new product to diffuse in the market gradually.

To address our research questions, we bridge the gap between consumer new product adoption and customer learning literature streams by the theory of transfer of learning (Thorndike and Woodworth 1901). We then utilize the data from one of the largest fast-fashion apparel companies in China and construct various types of customer learning. They are self-directed learning—product-feature learning (how well customers are familiar with product features of the focal brand) and price-strategy learning (how well customers grasp the focal brand's price and promotion strategies) and social learning (observing from others' purchases). To form these learning constructs, we monitored 98,185 customers starting from their first purchase and their following touchpoints with the brand. Then, we utilize split-population duration models to examine the independent as well as joint impacts of self-directed learning and social learning on new product purchases. The predictive validity and the results of model comparisons all favor the superiority of our model.

Our results show that product-feature learning is the most influential driver for increasing the likelihood of new product adoption, followed by social learning. However, price-strategy learning adversely affects the likelihood. As for the duration to adoption, product-feature learning is again the most influential driver to decrease the duration to adoption, following by price-strategy learning and social learning. Synergy effect appears between social learning and product-feature learning, whereas social learning and pricing-strategy learning counteract with each other which together harms new product success. Thus, we suggest that firms need to facilitate different types of learning to cater to their new product marketing goals: market penetration (likelihood of adoption) vs. market expansion (duration to adoption). Given the nature of our research questions are empirical, we will elaborate on extant literature and the theory of transfer of learning before we demonstrate our data and method. Then, we discuss our results in detail, followed by theoretical and managerial implications.

Literature and Theory

Consumer New Product Adoption

This research is specifically interested in what drives a consumer to adopt a new product. The extant research has studied three domains of drivers for consumer adoption: *marketing-related drivers* (i.e., WOM: Hennig-Thurau, Wieta, and Feldhaus 2015; price: Kuester et al. 2015; direct marketing: Risselada, Verhoef,, and Bijmolt 2014) , *product-related drivers* (product originality and usefulness: Li, Zhang, and Wang 2015; product longevity: Langley et al, 2012; relative advantage and compatibility: Kim and Park 2011), and *consumer-related drivers* (desire for control: Faraji-Rad, Melumad, and Johar 2017; price fairness judgment: Kuester et al. 2015; status: Hu and Bulte 2014). This research focuses on consumer-related drivers, in particular. We summarize the empirical research on this specific topic in Table 1. It also delineates the scope of our study relative to the prior studies.

-----Insert Table 1 about here----

Looking into the literature, we find that previous research has only studied consumer-related drivers that are constant or static such as consumer characteristics and/or personality traits, which makes it difficult for firms to proactively influence and alter those drivers, leaving firms very few options to improve customer new product adoption. These actions include simply targeting customers with the desirable traits and characteristics or adapting retail environments to cope with psychological barriers to consumer adoption (i.e., de Bellis and Johar 2020). Thus, it is highly desirable from managerial perspectives to identify manageable and amendable consumer-related drivers, which marketing actions can cultivate. Another theme we observe from the literature is that research intensively studies how to persuade consumers to adopt (high) technological products (i.e., Antioco and Kleijnen 2010; Langley et al. 2012) but shies away from the non-technological products. For non-technological products such as clothing and many others, technology advancement, innovation, and organizational governance do not play a significant role in new product adoption, compared to technological products such as cell phones. These fundamental differences between the two types of categories make the extrant research on drivers that facilitate technological product adoption inapplicable to the non-technolgical product adoption. The fact that every business launches new products to survive and thrive calls for dedicated research on what drives customers to adopt a non-technoglical new product. Lastly, it is almost unified that this literature steam concentrates on predicting new product adoption likelihood (i.e., Faraji-Rad et al. 2017; Kuester et al. 2015). The likelihood to adopt a new product or adoption intention is indeed an important indicator of new product success. However, facing the fast-changing and competitive business environments, in addition to adoption likelihood, another refined success indicator—adoption duration (speed to adopt a new product) urges the attention of researchers and firms. Understanding factors that increase the speed to new product adoption is of paramount importance, because fast market penetration not only deters competitive market entries but also attracts prospective customers from existing competitors.

To fill the stated gaps in the literature, this research identifies a cultivatable consumer-related driver, *customer learning* about the brand, which, by definition, is amendable as each consumer accrues experiences and touchpoints with the brand throughout the journey. Then, we examine consumer learning's impact on both the likelihood of and duration to consumer new product adoption, utilizing data from a fast-fashion company that produces and sells non-technological products.

Transfer of Learning

Given the factor this research propounds that drives new product adoption is customer learning about the brand, this research draws vital inferecnes from the theory of transfer of learning. The theory states that the knowledge learned in the past can be reused when completing a new but related task later. Hence, this learned knowledge can influence the process of performing the new task (Perkins and Salomon 1992; Yang, Hanneke, and Carbonell 2013). It is quite intuitive that people utilize and draw inferences from their past experiences when facing a situation later in their life that is similar to what occurs before. Two criteria are needed for learning transfer taking effect: 1) the upcoming task is *new* in a way that is not a simple repetition of the previous experiences; 2) the past experiences and the new task are *adequately similar* (Perkins and Salomon 1992; Yang, Hanneke, and Carbonell 2013). Applying the theory to our research context, as consumers accumulate their purchase experiences from a brand, they learn knowledge about the brand from various aspects, e.g., quality, size, pricing, etc. All the information stored in their mind is readily available to reutilize when customers encounter a relatively new but still similar situation in the future.

In our context, this *new* comes from buying a new product from the brand, where almost no one or only a few people have purchased this product along with higher financial and performance risk. The *similarity* comes from the fact that the new product is sold by the same brand the consumers have purchased from previously. Transfer of learning is thus appropriate to address a customer's new product adoption decision when considering the individual's longitudinal purchase behavior with the same brand. The theory prediction applies, suggesting that consumers would utilize their learned knowledge accumulated from past purchase experiences when they purchase a new product from the same brand. The theory further suggests that there may be positive and negative transfers, indicating that learning in one context can improve or harm performance in another context (Perkins and Salomon 1992). One empirical evidence pertaining to the harm aspect of learning is that consumers who took a lesson from overage payments at retail banks later switched to a plan with large monthly allowances and high fixed payments, which is *not* a cost minimized choice (Alter and Landsman 2013). A literatue review on various types of customer learning is presented below.

Customer Learning

We propose that customer learning is a new driver that affects new product adoption, and different types of customer learning may impose differential impacts. Particularly, this research examines self-directed learning (i.e., Hibbert, Winklhofer, and Temerak 2012), social learning (i.e., Chen, Wang, and Xie 2011; Zhang 2010; Zhao et al. 2013) and their inter-relationships. Table 2 summarizes representative studies in customer learning and its implications.

-----Insert Table 2 about here----

Self-directed learning: There are mainly three aspects in the domain of self-directed learning (learning from a consumer's own experiences) that align with marketing mix: learning about a firm's pricing strategy, product/service features, and distributions. One of the earliest empirical evidence documented that pricing learning might explain why established (vs. new) consumers reduce future purchases after being offered deep discounts (Anderson and Simester 2004). In this vein, Yu, Debo, and Kapuscinski (2015) also identified that strategic customers strategize their purchase timing and frequency based on a firm's dynamic pricing. To best cope with pricing structures, consumers learn their own consumption usage to achieve a win-win situation (Iyengar, Ansari, and Gupta 2007), while learning is not always rewarding such that consumers who experienced overage payments at retail banks may exhibit "overage aversion" and make suboptimal decisions (Alter and Landsman 2013). In addition, consumers also learn about product/service features. Research shows that customers learn which apparel brands offer standardized sizes and sizes that fit them well (Anderson and Simester 2013). Similarly, customers who have experienced fit-product purchases are more likely to migrate to a trusting state where they also buy other product types online (vs. offline), buy more, and buy more frequently (Cheng, Zhang, and Neslin 2016). Most recently, studies show that consumers also learn how a brand strategizes its product distribution and leverage it in purchase decisions. For instance, a decrease in the availability of Amazon lighting deals attracts more future sales (Cui, Zhang, and Bassamboo 2019); the opening of a new distribution center leads to increases in both online and offline sales, where customer learning is considered the main driver of the observed dynamics in the short-run (Fisher, Gallino, and Xu 2019).

Social learning: Another broad classification is social learning, in which consumers learn from others rather than their own experiences. Social learning can resolve uncertainties by transferring information on experience attributes (Lee and Bell 2013), but may also lead to contagious switching (Hu, Yang, and Xu 2019). Primarily, social learning includes learn from what others say (i.e., WOM, peer reviews, and experts' opinions) and what others do (i.e., observational learning). The former has been extensively documented in the WOMs and online reviews literature (i.e., Kubler et al 2018; Motyka et al 2018) along with the potential credibility issues (i.e., fake reviews, Malbon 2013)). Using a novel data set from the U.S. kidney market, perhaps the "cleanest environment", Zhang (2010) empirically demonstrated the existence of observational learning. Cai, Chen, and Fang (2009) also show that observational learning is distinctive from the saliency or conformity effect, acknowledging the informational content of observations that customers would purposely rationalize the reasoning from others' behavior and transfer it to other decisions. Other studies demonstrate that observational learning affects choices (Tucker and Zhang (2011), motivates group-buying deals purchases (Luo et al. 2014), and increases cart add-ins of lightning deals (Cui, Zhang, and Bassamboo 2019).

This research emphasizes observational learning to best align with the theory of transfer of learning, which suggests that people transfer what they learn in the past and apply it in a new situation. Due to the suggested sequential manner between learning beavhior and its impact on other decsions, we view observational learning as the accomplished sales level (how many customers have purchased a certain product) that a customer refers to when making purchase decisions regarding the product in the past, which in turn would affect their subsequent adoption decsions. In contrast, the influence of online reviews is product specific and dedicated to the current purchase decision. Though by no means would we deny that a customer may rely on reviews for the purchase decision of a product, the knowledge does not seem readily transfer to the adoption decision of their next purchase. Thus, learning from online reviews in the past is not suitable for transferring and reutilizing in future purchase decisions.

Differences and interrelationships between types of learning: One obvious distinction between self-directed vs. social learning is whose action produces learning materials. Another one is the dynamism of learning efficacy. For self-directed learning, a customer is expected to be wiser if s/he has a longer relationship with the focal brand, all else being equal (i.e., with the same level of learning sensitivities to different occasions). In contrast, for observational learning, a customer acts wiser if all the predecessors' choices reflect "true" or "unbiased" quality inference. When mistakes occur, the customer has to be self-motivated to correct it and incorporate the occasions into learning. Thanks to informational cascades where prospective customers may ignore their own preferences and follow their predecessors' decisions (Bikhchandani, Hirshleifer, and Welch 1992; Zhang 2010), mistakes may cause and develop into systematically biased information to the followers. Thus, the efficacy of observational learning is less controlled and may take longer to benefit decision making compared to types of self-directed learning. Though different, it is almost affirmative that various learning aspects jointly influence consumers' minds when making future decisions. Information search theories provide the foundation for such joint impacts, as they articulate that people tend to integrate information from various sources and utilize them altogether when making decisions (citation). However, only a few studies have examined how observational learning varies across a consumer's prior purchase experiences (Luo et al. 2014; Zhao et al. 2013), and they mainly deem customer learning as product quality inference. To provide a better understanding of interactive effects between self-directed learning (i.e., learning about the product features and pricing strategy) and observational learning (i.e., learing about what others do), this research empirically demonstrates how these aspects of learning jointly influence consumers' decisions on buying a new product.

Examine the Impact of Customer Learning on Consumer New Product Adoption

Data and Variables

In the main study, we obtained the data from one of the largest fast fashion women apparel companies in China. This company launches more than 20 new products every week. During the peak season, they launch new products in a larger quantity with a shorter time window. Our empirical context is extremely suitable for our research question due to the following reasons. First, fast fashion industry launches new products at a higher speed along with larger quantities than any other industries, thus in more need of guidance on how to identify customers who are ready to purchase new products and especially those who can purchase sooner. Second, given the nature of this industry, customers' purchase frequency is high enough that it is possible to observe learning experience gradually accumulated within a reasonably short time window. Third, when buying clothing, consumers especially learn from their past purchases of a given brand and leverage the learned knowledge in their future purchases (Anderson and Simester 2013). Thus, the learning impact in the clothing product category is more prominent.

We utilize six-month transactional-level sales data from October 2014 to March 2015 to examine each type of learning and their interactions in influencing customers' first new product purchase. To do so, leveraging the first nine-month of 2014 data, we first identified new customers of the brand whose first purchases were in the time window of our study period (October 2014 to March 2015) and monitored their learning experience starting from their first purchases. As we are interested in customer learning, we form our sample with customers who at least purchased twice during the study period. Also, following the premise of transfer of leanring, and to capture the learning experience accrued in the past and leveraged in the current order ($order_j$), we form all learning variables in the manner of a cumulative value from the first order until $order_{j-1}$ (the order before the current order). Specifically, we compute the number of product categories $customer_i$ has purchased until $order_{j-1}$ as the product-feature learning. We define price-strategy learning as the number of products customer$_i$ has purchased with a deeper discount compared to the average discount of the same product until order$_{j-1.}$ Lastly, we compute the sum of unit sales of all the products cusotmer$_i$ has purchased until order$_{j-1}$ as social learning. The unit sales accomplished were captured right before customer$_i$ made his or her purchase. This is a valid measure because on the online platform in which this company operates, people are able to see how many items a product has been sold while they browse and search for products. Table 3 details the operationalization of these variables.

In addition, we also collected data on media mentions of the focal brand on Baidu.com[3] (news post) and data on its own social media posts (social media brand post) during the study period to have a more complete set of information sources that customers potentially can utilize to gain knowledge about the focal brand. To further strengthen the rigor of our analyses, we also control for *customer-level characteristics* such as customers' overall cumulative experience with the brand (cumulative spending) and where they are from (rural, east, west, south and north of China); *order$_j$'s characteristics* such as regency between order$_{j-1}$ and order$_j$ (recency), how difficult to examine product fit for products in order$_j$ (fit[4]), how many customers have purchased the products in order$_j$ (unit sold), how many days those products have been on the market (days on market) ; *brand-level characteristics* such as how many new products launched during the week of order$_j$ occurred (new product launched). All variables' operationalization is shown in

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3 The largest search engine in China.

4 We asked two coders to assign a value on a scale of 1-6 to each product category that the focal brand carries in terms of to what extent a product category would be classified as fit vs. non-fit products. 1 is non-fit products and 6 is fit products. The concept of product fit coined in Nelson (1970). A fit product requires physical inspection and is complex, and also, people may evaluate it differently depending on their preferences and may need salesperson and experts' inputs (Chang, Zhang, and Neslin 2016). Thus, the dimensions of product fit include complexity, require physical inspection, generate preference heterogeneity, and need sales help, which were considered in the coding process. The discrepancies between the two coders were resolved by the third coder.

Table 3. Also, all continuous variables included in the analyses are standardized for efficient comparison.

-----Insert Table 3 about here----

Preliminary Empirical Evidence

This research articulates that customer learning imposes a significant impact on new product adoption. Before we analyze our data using split-population duration models, it may be helpful to visualize the differential new product adoption propensities between orders purchased by customers with high-learning level vs. those with low-learning level by plotting our data. Specifically, we split our sample into high vs. low product-feature learning, high vs. low price-strategy learning, and high vs. low social learning, based on the median values of these three types of customer learning. As shown in Figure 1, the Y-axis is new product adoption percentage which is the ratio of the number of orders containing new products to the total number of orders. The X-axis is customer purchase experience which is operationalized as the number of orders a customer has purchased. Orders purchased by customers with less learning experience (i.e., product-feature learning) are associated with a lower probability of containing new products, especially for product-feature learning and social learning, demonstrating their more prominent roles in driving new product adoption. In the high-level learning group, the new product adoption propensity is increasingly augmented as customers purchase more orders. The opposite is true for the low-level learning group where the propensity is decreased as customer purchased more orders. Moving forward, we employ split-population duration models to rigorously test our research question.

-----Insert Figure 1 about here----

Method

The outcome of our analyses is the time until the occurrence of a customer purchasing a new product from the focal brand. The definition of a new product is a product on the market for less than or equal to 30 days[5]. In particular, we are interested in not only the likelihood a customer eventually adopts a new product but also the duration for a customer to actually purchase a new product. Thus, we employ a split-population duration model, one type of duration analyses. The advantage of this model is threefold. First, based on the work of Schmidt and Witte (1989), this model simultaneously demonstrates the probability and timing of new product adoption, two research interests of ours. It is critical to distinguish these two effects because some factors may positively influence the probability of eventual adoption but adversely affect the timing of adoption. Knowing adoption drivers' specific effects on adoption rate and speed helps promote a more complete understanding of what really drives adoptions. More importantly, this model delivers more managerial implications. As indicated, firms have accelerated their new product launches, thus in more need of understanding how to convert more customers to be new product adopters, and more importantly, how to induce those adopters to purchase new products sooner. This model is able to answer both questions.

Second, this model allows for incorporating time-varying explanatory variables (i.e., Beger et al. 2017). The variables of our interests are various types of customer learning which are inherently time-varying factors. Third, this model takes into account that not all individuals have the same underlying risk to experience a specific outcome and may not even be at risk at all. In our context, this model relaxes the assumption that customers will eventually buy new products, unlike the traditional duration models. In fact, we have two underlying populations: those who will purchase a new product and those who will never do. Thus, this model reduces

[5] During the interviews with managers of three fashion brands, we found that they considered a product that had been on the market for less than 30 days as a new product.

the probability of having biased estimates and inaccurate predictions (Chandrasekaran and Tellis 2011).

To demonstrate the superiority of our model, we first utilize a standard survival analysis—Cox Proportional-Hazards Model which assumes that all population will eventually adopt a new product, and then implement Weibull and Loglogistic forms for the duration component using our split-population duration models, and finally contrast all three models' model fits. Prior to model comparisons, we split our sample into an estimate sample (n=202,467 orders by 68,441 customers) and a holdout sample (n=89,639 orders by 29,744 customers) which is used for model validation. In the estimate sample, the average number of orders purchased by customers during the six-month study period is 3 orders (minimum 2 orders per customer and maximum 8 orders per customer). Given the focal brand is a fast fashion brand, we deem the order frequency pattern we observe in our data is reasonable compared to the industry average[6]. The average number of orders purchased by customers in the holdout sample is 3 orders as well. In the typical duration model, time is utilized to measure duration, however, in our context, we employ number of orders a customer has purchased from the focal brand as duration. We built a profile for each customer when they made their first purchase with the focal brand and started measuring all their learning indicators and other covariates as they continued their journey with the brand. The reason that we chose number of orders purchased rather than time is that purchasing products from the brand is how a customer learns about the brand which is more accurate than the cumulative time for measuring learning.

Endogeneity

[6] https://blog.salecycle.com/featured/online-fashion-retail-11-essential-statistics/

We also note that the three types of learning in our model are potentially endogenous as customers are self-motived to learn about the brand and its products in various aspects. In this research, we control for their potential endogeneity using the Gaussian Copula method (Park and Gupta 2012) which does not require instrumental variables. It is extremely helpful when valid instruments are hard to find (Rossi 2014) as this method is able to directly model the joint distribution of the endogenous regressors and the error term. One critical requirement of this method is that endogenous variables are not normally distributed. Using Shapiro-Wilk tests, we find that all three types of learning are not normally distributed (product-feature learning, W = .954, p < .001; price-strategy learning, W = .824, p < .001; social learning, W = .675, p < .001). Following Park and Gupta (2012), we add the following regressors (in Equation 1-3) in the tested models:

$$Copula_{product_{ij-1}} = \Phi^{-1}\left(H_{product}\left(poduct\_learning_{ij-1}\right)\right) \quad (1)$$

$$Copula_{promotion_{ij-1}} = \Phi^{-1}\left(H_{price}\left(price\_learning_{ij-1}\right)\right) \quad (2)$$

$$Copula_{social_{ij-1}} = \Phi^{-1}\left(H_{social}\left(social\_learning_{ij-1}\right)\right) \quad (3)$$

where $\Phi^{-1}$is the inverse of the normal cumulative distribution function (CDF), and $H_{product}(\bullet)$, $H_{price}(\bullet)$, and H_{social} $(\bullet)$ are the empirical CDFs of product-feature learning, price-strategy learning, and social learning, respectively.

Model Development

The conventional duration models' likelihood follows Equation 4 where all subjects will eventually experience the event (i.e., new product adoption).

$$\mathcal{L} = \prod_{i=1}^{N}(f((t_i))^{\delta_i} \times (S(t_i))^{1-\delta_i} \quad (4)$$

where a customer$_i$ with survival time t (in our research, time t is operated as number of orders customer$_i$ has purchased since their first order with the focal brad) is the failure rate f(t) at the time or the probably of survival beyond t, S(t), depending on whether the customer has already purchased a new product (δ_i) or is right-censored (1-δ_i). Researchers need to choose a function form (i.e., popular choices are Weibull or log-logistic) describing the underling hazard rate h(t) = $\frac{f(t)}{S(t)}$ over time.

The cumulative failure rate (adopting a new product- F(t) = 1-S(t)) over time converges to 1. However, as we indicated earlier not all customers will eventually purchase a new product (or are at risk), and thus, a sub-population is not at risk for new product adoption. To incorporate the presence of this sub-population, following Beger et al. (2017), we label the sub-population at risk with π, and the new likelihood as:

$$\mathcal{L}\{\{\theta|(t_1, \dots, t_n\}\} = \prod_{i=1}^{N}(\pi_i f(t_i))^{\delta_i} \times ((1-\pi_i) + \pi_i S(t_i))^{1-\delta_i} \qquad (5)$$

We then model membership in the sub-population with its covariates through a logistic link function:

$$\pi_i = \frac{1}{1+e^{-z_i\gamma}}$$

where z_i is a vector of covariates for a customer at a given time, which can include time-varying covariates. Details of the covariates we include in our analysis are in Table 3. All covariates are standardized for better interpretation and comparison and their correlation matrix is shown in Table 4.

-----Insert Table 4 about here----

The last component to complete the likelihood is the choice of a distribution for the shape of the hazard rate (h(t)) and we decide to contrast two most frequently implemented shapes: Weibull and log-logistic and select the better model fit for our analyses:

Weibull

$$f(t) = \alpha\lambda(\lambda t)^{\alpha-1}e^{-(\lambda t)^{\alpha}} \quad (6)$$

$$S(t) = e^{-(\lambda t)^{\alpha}} \quad (7)$$

$$h(t) = \alpha\lambda(\lambda t)^{\alpha-1} \quad (8)$$

Log-logistic

$$f(t) = \frac{\alpha\lambda(\lambda t)^{\alpha-1}}{(1+(\lambda t)^{\alpha})^{2}} \quad (9)$$

$$S(t) = \frac{1}{1+(\lambda t)^{\alpha}} \quad (10)$$

$$h(t) = \frac{\alpha\lambda(\lambda t)^{\alpha-1}}{1+(\lambda t)^{\alpha}} \quad (11)$$

where $\lambda = e^{-x_i\beta}$ is a parameter of covariates.

Results

Model Fit: By contrasting the three models (the Cox Proportional-Hazards model, split-population duration models: one with Weibull distribution, and the one with log-logistic distribution), we find that the log-logistic form outperforms the rest in terms of fitting our data (see Table 5). Thus, we report the results of the split-population duration model with the log-logistic form.

-----Insert Table 5 about here----

Results: As shown in Table 6, the results suggest that with respect to probability of eventual adoption (adoption rate), product-feature learning is the most effective and positive factor (b = 1.80, p < .00), following by social learning (b = 0.21, p < .05). Intriguingly, price-strategy learning lessens the probability of customers adopting new products (-0.68, p < .10). The product term of social learning and price-strategy learning also adversely affects the probability (b = -0.04, p = .06). In terms of duration-to-event (adoption speed), the results indicate that product-feature learning is again the most effective factor in reducing the duration ($b = -0.20$, $p < .00$), following by price-strategy learning ($b = -0.13$, $p < .00$), and then social learning ($b = -0.01$, $p < .10$). The product term of social learning and product-feature learning is also negative and significant ($b = -0.01$, $p < .00$). However, the product terms of social learning and price-strategy learning ($b = 0.01$, $p < .00$) as well we product-feature learning and price-strategy learning ($b = 0.01$, $p < .00$) are positive and significant. The prediction accuracy of our log-logistics form model using the holdout sample is 88.7 %, indicating a satisfactory prediction power of our model. All our control variables reveal reasonable effect signs as well. For instance, the more news about the brand and the more social media posts the brand shares, the more likely customers purchase a new product. When a product is hard to examine product fit, it will lengthen the duration to new product purchase (see more details in Table 6).

-----Insert Table 6 about here----

Result Discussions: Our results suggest that customer learning is a multi-faceted construct. Learning about different aspects of a brand/product or from different sources generates differed impacts on new product adoption. The phenomenon is more intricate when considering the interacting effects among these learning aspects. For firms to leverage customer learning in their new product marketing strategy, they are better off acknowledging various aspects of customer learning along with their varied impacts. It seems that learning product features of many product categories is a strong driving force for customer adopting new products (adoption likelihood and duration). Namely, when customers have tried many product categories of the brand, they are more confident in accepting new products. Social learning is also in favor of new product success since it also increases the likelihood of purchase and reduces the time to purchase, although not as efficient as product-feature learning. This result accurately manifests the differences between two types of learning that is the efficacy of observational learning is less controlled, thus less efficient in enhancing decision making compared to self-directed learning (Zhang 2010).

Price-strategy learning is tricky in that it hurts the likelihood of new product purchase but reduces the duration to new product purchase. The interpretation is when a customer learns the focal brand's pricing patterns (i.e., when is the brand more likely to offer more discounts?) and becomes a strategic customer (Yu, Debo, and Kapuscinski 2015), they are less likely to adopt a new product. This is reasonable since new products are rarely promoted as intensively as products that have been on the market for a while. Also, for price sensitive customers, they do not care about having the most newly launched products or experiencing new products eagerly right after they are launched (citation). Additionally, our split-population duration model splits the population into two camps, those who eventually purchase the new product and those who do not. For those who will eventually adopt a new product, the model further studies their duration to the event. The results show that if a customer belongs to the first camp, grasping in-depth knowledge about the brand's price strategy can actually reduce the time to adoption. We surmise that when a customer is likely to adopt a new product who also understands the pricing pattern of the brand, he may feel more confidence when making his purchase decisions which leads to new product adoption sooner. For example, this consumer knows that the brand won't discount the new product anytime soon and it is wise to purchase the new product sooner than later to enjoy the new features or designs of the new product.

Additionally, various types of customer learning also jointly influence new product adoption. For customers who have obtain high social learning (i.e., purchased many established products), getting exposed to more product categories is helpful in reducing the time to adoption but the opposite (i.e., less likely to adopt and longer time to adoption) is true if they obtain more knowledge on brand price strategy (i.e., purchasing products with more discounts than average). Customers who have gained high-level social learning are more risk averse since when they first interact with a brand, they intend to purchase the products that have been validated by other cusotmers and proved to be great already. However, we suggest these customers actually more likely to purchase new products and purchase them sooner as products that have been sold a lot normally give those new customers good notion of the brand, which can be transferred to the new products and foster positive image of the products in the mind of customers. They then feel confident to purchase the new products. Another merit of buying those established products is that they are likely associated with deep discounts. Thus, if customers are high in both social learning and price-strategy learning, they are both risk averse and price sensitive, who, logically, may not be good candidates for new product adoption. Nevertheless, this is also plausible when customers with high-level social learning have had experience with many product categories, their knowledge and understanding in terms of product fit of those categories can be generalized to other products including those new ones. Eventually, they feel assertive to purchase the new products. We will discuss the corresponding managerial implications of these results below.

Robustness Check: Alternative Definitions of New Products

To test the stability and robustness of our results, we alter the definition of new product and re-run the split-population duration model with log-logistic distribution. Instead of defining it as on the market for less than or equal to 30 days, we employed two additional sets of analyses, one for new products on the market for less than or equal to 45 days and one for those on the market for less than or equal to 10 days. The results are largely consistent with our main analyses (shown in Appendix 1).

Discussions

This research provides the first empirical evidence pertaining to that customers learn various aspects of a brand and then leverage their learning in new product adoption decisions. Particularly, we consider customer learning from both customers' own experiences and others' experiences in this research. We examine three types of customer learning: self-directed learning (i.e., learning from own past experiences) that includes product-feature and price-strategy learning, as well as social learning (i.e., learning from others). Specifically, we investigate and compare the independent impacts of these three types of customer learning on new product adoption (likelihood and duration) and, more importantly, how they interact and jointly influence a customer's new product adoption decision. Our research delivers significant contributions to consumer new product adoption and customer learning literature and offers guidance on how to lever customer-driven activities and stored transactional information to boost new product success, especially in non-technological categories.

Theoretical Contributions

Consumer new product adoption. Our research sheds light on consumer new product adoption literature by identifying an unexplored driving force—customer learning, which is more generalizable and cultivatable by conscious marketing efforts. Drivers of new product adoption have possessed a prominent standing in the new product literature (i.e, Hirunyawipada and Paswan 2006; Langley et al. 2012). However, many of them are not always applicable, such as technology advancement (Kim and Park 2011) for non-technological categories, which account for a significant proportion of new product launches in business. If we look exclustively into customer-related drivers, many refer to either personality traits or innate characteristics (e.g., Faraji-Rad, Melumad, and Johar 2017; Li, Zhang, and Wang 2015), which are usually unobservable and hard to alter, thus limiting marketers' maneuverability of promotion tactics of new products. To directly address these gaps, we uncover a new customer-related driver—customer learning about the brand, which can be tracked, supervised, and amended by companies when they interact with customers with more mindful marketing offers. This is especially suitable for firms competing in the non-technological categories.

Second, this study examines the two critical new product outcomes: adoption likelihood and speed to adoption, simultaneously. Consumer new product adoption literature dominantly focuses on new product adoption likelihood but overlooks speed to adoption. Speed to adoption of innovators is important in itself because it can accelerate the entire new product diffusion process, maintain market attractiveness of companies, and bring financial returns from new product launches efficiently for ongoing business. Moreover, we depict the differential impacts of customer learning on adoption likelihood and speed to adoption. Conventional wisdom supports the positive association between adoption likelihood and speed to adoption, but it is also plausible that the same set of drivers may affect them in either consistent or opposing directions (Sinha and Chandrashekaran 1992). Our results demonstrate that most aspects of customer learning predict the two outcomes consistently, where product-feature and social learning both increase new product adoption likelihood and speed to adoption. An intriguing finding is that price-strategy learning reduces adoption likelihood but increases speed to adoption.

Last, our employed split-population duration model not only examines the effects of various aspects of customer learning on the two new product adoption outcomes (i.e., adoption likelihood and speed to adoption) simultaneously but also accounts for customer heterogeneity in adoption decisions. That is, our approach is not constrained to the assumption that all the studied customers will eventually adopt a new product. We believe this approach is more realistic and rigorous for studying new product adoptions.

Customer learning. The customer learning literature acknowledges the importance of different aspects of customer learning and identifies their marketing implications. The behavioral outcomes of customer learning include progressing decisions in a purchase journey (Cui, Zhang, and Bassamboo 2019; Luo et al. 2014; Zhao et al. 2013), acting strategically to minimize cost (Anderson and Simester 2004; Iyengar, Ansari and Gupta 2007), and responding favorably to competitive actions (Anderson and Simester 2013). Consequently, at the aggregate level, customer learning serves as mechanisms to explain fluctuations in sales performance (Chen, Wang and Xie 2011; Fisher, Gallino and Xu 2019; Lee and Bell 2013) and retention rate (Hu, Yang, Xu 2019). New products not only bring more excitement and uncertainties to customers but also cost marketers more investments with less certainty in returns. With new products' benefits and chanllenges in mind, this research explores how customer learning drivers new product adoption, uncovering a new domain in the marketing implications of customer learning.

Second, the literature documents that customers learn from their own past experiences （i.e., self-directed learning—learning about product features, pricing structures, and learning distribution strategies) and from others' experiences (i.e., social learning). A customer may rely on multifaceted learning aspects simultaneously when s/he makes a purchase decision. The extant studies on joint effects between self-directed and social learning deem self-directed learning as an overall purchase experience that a customer has with the company (Luo et al. 2014; Zhao et al. 2013). Consequently and consistently, these studies find positive joint effects. That is the benefit of social learning is enhanced as a customer becomes more experienced, implying that these two kinds of learning convey complementary information that helps customers make better decisions. However, we articulate that because the motivations and the underlying mechanisms of various learning aspects differ in influencing subsequent purchases, both synergistic and antagonistic interactions can occur. Inconsistent with the literature, our results suggest that self-directed and social learning can also be counteractive, evidenced by the negative interactive effects between price-strategy and social learning on both adoption likelihood and speed to adoption. Thus, not only compares the independent effects of various aspects of customer learning, this research documents synergistic and counteractive interaction effects between self-directed and social learning by dissecting the former in detail.

Third, customers' reactions to economic incentives are intricate and hard to predict. As such, the customer learning literature documents mixed findings that price-strategy learning can guide both wise (Anderson and Simester 2004; Ansari, and Gupta 2007) and suboptimal decisions (Ater and Landsman 2013). Our results also reflect and confirm this complexity. We show that price-strategy learning is considered a double-edged sword even in new product adoption. Specifically, though price learning reduces the likelihood of new product adoption, it fastens the adoption speed according to its main effects. The interactive effects are consistently negative. That is it weakens the benefit of social learning in adoption likelihood as well as puts off the driving force of product-feature learning and social learning in adoption speed. By and large, our findings indicate that customers who engage in price-strategy learning tend to avoid the risk of buying a new product, however, if other motivating drivers are strong enough to persuade customers to adopt a new product, these customers are probably more sensitive to economic incentives and act faster. This study adds another empirical evidence on customer price-strategy learning with regards to its intricately mixed and/or double-edged effects.

Managerial Implications

To fully potentialize the market, firms have accelerated their new product launches to fulfill the ever-changing and fragmented consumer preferences and outperform competitors. In the phase of a new product launch, companies eagerly look for resources and capabilities to reach out to customers. In a customer-centric business world, new product launching strategies sometimes even contribute more to success than the product itself. As marketers are using up every possible platform to communicate with their consumers, it becomes even more challenging to make a new product stand out when consumers are facing a barrage of commercial messages. This research identifies an unexplored customer-driven recipe for new product success: customer learning. Customers learn as they interact with a brand. Information on what a customer purchases, when, and for how much is automatically recorded for most companies. Using such customer data, companies can characterize each customer by learning behavior. It can be a valuable guidebook for companies to answer key questions when promoting new products. Who are the target customers with higher potential to adopt new products? How to manage new-in calendars based on adoption tempo? When will be the best moment of markdowns to induce adoption and to whom? In short, firms can identify, and more importantly, train their own innovators (the first 2.5 % adopters, Mahajan, Muller, and Srivastava 1990).

Identify innovators: Using our model, managers can identify a group of customers who have a greater propensity for buying a new product and who will buy a new product more quickly. Leveraging firms' CRM data, managers can screen customers who have purchased more product categories (high in product-feature learning) and/or those who tend to purchase more popular products (high in social learning). Firms can also use customer learning to personalize new product promotion tactics to reconcile the heterogeneity that some customers prefer popular products, and some are more into unique styles. Companies can communicate to customers who engage in social learning that the promoted new products are popular, viewed and/or purchased by other customers. In contrast, firms should emphasize “being the latest” to customers who do not participate in social learning. Moreover, if a customer has purchased many products with deeper discounts than average, she might not be a good candidate for an innovator. Firms should not waste space on product suggestions or other formats of personalized recommendations for new products to price-strategy leaners.

Cultivate innovators: This research provides an alternative concept for new product marketing strategy: instead of waiting for customers to adopt new products or pushing new product information to them, managers can cultivate their own innovators. The idea is similar to the engagement marketing coined in Harmeling et al. (2017) that firms should guide customer engagement to favor firm performance even though customer engagement has been deemed as a customer-directed behavior. In the same vein, firms can guild or facilitate the types of customer learning that favors new product adoption. For instance, firms can launch marketing campaigns that aim to encourage customers to try more product categories such as bundle promotions where customers need to buy two or more categories to receive a discount and/or even free samples. This way, customers’ product-feature learning is motivated by firms’ marketing tactics, and then customers are more likely to be ready for new product purchases. Similarly, firms can launch email marketing campaigns suggesting that customers purchase some established products (i.e., popular products) to accelerate customers’ social learning. This suggestion is opposite to firms who spend most of their marketing efforts on “being the latest” of a new product and leave popular products with very little promotion attention. However, this unattended practice delays customers’ social learning and attenuates their new product adoption probability and speed.

In terms of interacting effects of social learning and self-directed learning, we suggest that getting exposed to more product categories and more established products can enhance new product success. Thus, firms are better off bundling these two marketing efforts. However, when some customers have shown strong interests in buying established products with deep discounts, firms can selectively reduce marketing efforts on promoting new products toward them. Also, it is unwise to promote established products with deep discounts. Not only discounting popular products will disturb consumers' price expectations, but also demotivate customers as innovators.

Market penetration vs. market expansion: This research focuses on two critical goals for new product success—adoption likelihood and speed to adopt. While academic research has offered guidance to adoption likelihood, little is known to guide managers how to outpace their comeptitors and stay ahead of the pack in new product battles. In the fast fashion industry, and many other non-technological sectors, the speed to adopt new products is vital to keep the company stay in the game, keep up with the trend, and circulate the cash flow for operations. The split-population duration model grants us the privilege to test customer learning's impacts on the probability of the eventual event and the duration to the event, new product adoption likelihood and duration, repectively. This is especially informative to companies because when firms launch new products, they may have different goals: enlarge their target market (i.e., market expansion) or exploit their existing market (i.e., market penetration). If it is the former, managers can focus on the drivers of the probability of eventual event (adoption likelihood) and if it is the latter, managers may direct resources to drivers of adoption duration. For instance, price-strategy learning is a great lever for new products that aim to penetrate the existing market whereas it can detrimentally harm new products that aim to expand the target market. Hence, we suggest firms have to determine their marketing strategy goal for new products before they identify and cultivate their innovators.

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Table 1
Empirical Studies on Consumer New Product or Innovation Adoption (Consumer-related Drivers)

Reference	Consumer-related drivers		Context		Adoption Indicators	
	Constant	**Time-varying**	**Non-technological products**	**Technological products**	**Likelihood of adoption**	**Time to adoption**
Current research		Customer learning about the brand	×		×	×
Faraji-Rad, Melumad, and Johar (2017)	Desire for control		×		×	
Kuester et al. (2015)	Price fairness judgment			×	×	
Li, Zhang, and Wang (2015)	Consumer innovativeness		×	×	×	
Hu and Bulte (2014)	Status			×	×	
Risselada, Verhoef, and Bijmolt (2014)	Social influence			×	×	
Langley, Bijmolt, Ortt, and Pals (2012)	Consumer fecundity, fidelity, and longevity			×	×	
Antioco and Kleijnen (2010)	Perceived usage barrier; value barrier; performance risk, financial risk, tradition barrier, image barrier			×	×	
Huh and Kim (2008)	Age, adoption duration of first generation innovation; basic function usage; innovative function usage			×	×	
Hirunyawipada and Paswan (2006)	Consumer innovativeness and perceived risk			×	×	

Table 2

Representative Studies on Customer Learning

Article	Learning Aspect					Specifics	Context	Implications On
	Self-directed			Social	Interaction			
	Product/Service	Distribution	Pricing					
Current study	X		X	X	X	Product x pricing x observational learning	Online fashion retail	New product adoption rate and speed
Cui, Zhang, and Bassamboo (2019)		X		X		Percentage of claims (availability and observational learning)	Amazon lighting deals	Purchase consideration (in cart add-ins) and sales performance
Fisher, Gallino and Xu (2019)		X		X		Retail (unannounced) faster delivery	Apparel retail	Sales increase of both online and offline stores
Hu, Yang, and Xu (2019)				X		Social learning	Mobile network	Contagious Switching
Chang, Zhang and Neslin (2016)	X					Product fit	Retail	Multichannel shopping and customer value
Luo et al. (2014)	X			X	X[a]	Observational learning x past experience	Group buying deals	Deal purchase and time of redemption
Anderson and Simester (2013)	X					Product fit	Retail	Response to competitors' advertising
Ater and Landsman (2013)			X			Overage payment per service plan	Retail banking	Plan switching (selection)
Lee and Bell (2013)				X		Social learning	Online fashion retail	Customer trial and sales

Zhao et al. (2013)	X		X	X[a]	Product reviews x past experience	Experiential products (book)	Consumer purchase decision and profits
Chen, Wang and Xie (2011)			X	X	WOM and observational learning	Digital camera (Amazon)	Sales performance
Tucker and Zhang (2011)			X		Observational learning	Wedding service website	Website visits
Zhang (2010)			X		Observational learning	Kidney donation	Donation adoption
Cai, Chen and Fang (2009)			X		Observational learning	Restaurants	Consumer purchase
Iyengar, Ansari and Gupta (2007)		X			Service quality and self-consumption	Wireless service	Customer value
Anderson and Simester (2004)		X		X[a]	Price promotion	Retail	Future purchase and promotion sensitivity

Notes: X[a] indicates that the study examines customer learning varied across a customer's overall purchase experience.

Table 3

Operationalization of All Variables Included in Analyses

Variable Name	Operationalization
New product purchase	Whether $order_j$ contains a new product that has been on the market for less than or equal to 30 days. Assign 1 to new product purchase and 0 otherwise.
Cumulative spending	Cumulative dollar value spent by $customer_i$ until $order_{j-1.}$
Discount percentage	The ratio of discount to total spent for $order_j$
Order spending	Dollar value spent for $order_j$
Number of new products launched	Number of new products launched during the week of $order_j$ by the focal brand
Days on market	Average number of days the products in $order_j$ have been on the market
Unit sold	Average number of products sold of the products purchased by $customer_i$ in $order_{j.}$ The average unit sold was capture the day before $order_j$.
Recency	How many days apart between $order_j$ and $order_{j-1}$
Fit	To what extent products in $order_j$ can be classified as fit products, on a scale of 1-6, 1 being non-fit products and 6 being fit products. See more details in footnote 4.
Product-feature learning	Number of product categories $customer_i$ has purchased until $order_{j-1}$
Price-strategy learning	Number of products $customer_i$ has purchased with a deeper discount compared to the average discount of the same product until $order_{j-1}$.
Social learning	Sum of unit sold of all the products $customer_i$ has purchased until $order_{j-1}$. The unit sales were captured right before $customer_i$ made his or her purchase.
Social media brand post	Number of social media posts sent by the focal brand before $order_j$
News post	Number of ness posts regarding the focal brand before $order_j$
Rural	Whether $customer_i$ is from a rural area. Assign 1 to those from rural areas and 0 otherwise.
East	Whether $customer_i$ is from the east of China. Assign 1 to those from east and 0 otherwise.
West	Whether $customer_i$ is from the west of China. Assign 1 to those from west and 0 otherwise.
North	Whether $customer_i$ is from the north of China. Assign 1 to those from north and 0 otherwise. Customer from south of China is the reference group.
Holidays	Whether $order_j$ was placed during holidays or huge promoting events such as single day, double twelves, new year, Christmas, etc. Assign 1 to those placed during holidays and 0 otherwise.

Table 4

Correlation Matrix of All Covariates Included in Analyses

Variable Name	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1. Duration until first new product purchase	1																		
2. New product purchase	.21**	1																	
3.Product-feature learning	.80**	.21**	1																
4.Price-strategy learning	.47**	.11**	.70**	1															
5.Social learning	.51**	.15**	.58**	.45**	1														
6.Cumulative spending	.76**	.20**	.85**	.66**	.57**	1													
7.Discount percentage	.10**	.05**	.13**	.22**	.04**	.08**	1												
8.Order spending	-.10**	.17**	-.03**	.03**	-.01*	.04**	.20**	1											
9.Number of new products launched	.00	.20**	-.01**	-.01**	.03**	-.02**	-.05**	.08**	1										
10. Days on market	.04**	.-31**	.03**	.03**	.05**	.01*	.01**	-.13**	-.06**	1									
11.Unit sold	.02**	-.14**	.01**	-.02**	.12**	.02**	-.07**	-.08**	-.00	.48**	1								
12.Recency	.28**	.20**	.30**	.12**	.15**	.28**	.01**	-.04**	.07**	.03**	.05**	1							
13.Fit	-.07**	-.12**	-.06**	-.02**	-.05**	-.03**	.00	.17**	-.07**	-.02**	-.01**	-.08**	1						
14.Social media brand post	.52**	.26**	.44**	.22**	.34**	.38**	-.02**	-.14**	16**	.09**	.11**	.50**	-.16**	1					
15.News post	.52**	.22**	.45**	.23**	.34**	.40**	.01**	-.16**	.03**	.11**	.11**	.48**	-.12**	.95**	1				
16.Rural	.00	-.01**	-.01**	-.02**	-.01**	-.01**	-.02**	-.01**	-.01**	.01*	.00	.01**	.02**	.03**	.03**	1			
17.East	-.02**	-.01**	-.01**	.00	-.01**	.01**	.02**	.04**	.02**	-.01**	.00	.01**	.03**	-.02**	-.03**	.00	1		
18.West	-.01**	.01**	-.01**	-.03**	-.00	.00	-.04**	.01**	.01**	-.01*	.01**	.01**	-.00	.02**	.01**	.12**	-.29**	1	
19.North	.01**	-.02**	-.01**	-.02**	-.02**	-.01**	-.00	-.03**	-.02**	-.00	-.00	-.01**	.01**	.01**	.02**	-.03**	-.41**	-.25**	1
20.Holidays	-.18**	-.07**	-.16**	-.07**	.11**	-.15**	.04**	.12**	.28**	-.02**	.01**	-.14**	.08**	-.24**	-.23**	.00	-.00	-.01**	-.01*

Table 5

Model Comparison

Model	**AIC**	**BIC**
Cox Proportional-Hazards Model	474,975.91	475,169.04
Split-population Duration Model - Weibull Distribution	73,782.39	73,813.04
Split-population Duration Model - Log-logistic Distribution	69,730.63	69,761.28

Table 6
Results of Split-population duration model - Log-logistic Distribution

Variable	At Risk (Probability of eventual adoption)		Duration (Time to adoption)	
	Coefficient	**Standard Error**	**Coefficient**	**Standard Error**
Product-feature learning	1.80***	.43	-.20***	.02
Price-strategy learning	-.68[a]	.39	-.13***	.02
Social learning	.21*	.10	-.01[a]	.01
Product-feature learning * Social learning	.03	.04	-.01***	.00
Price-strategy learning * Social learning	-.04[a]	.02	.01***	.00
Product-feature learning * Price-strategy learning	.07	.04	.01***	.00
Cumulative spending	-.11*	.06	.12***	.00
Discount percentage	.40***	.04	.00	.00
Order spending	6.53***	.48	-.07***	.00
Number of new products launched	.82***	.04	-.03***	.00
Days on market	-4.26***	.15	.19***	.01
Unit sold	.52***	.07	-.02***	.00
Recency	.00	.04	-.05***	.00
Fit	-.81***	.04	.04***	.00
Social media brand post	.35**	.13	.03***	.01
News post	.46***	.13	-.01	.01
Rural	.27*	.11	.01*	.00
East[b]	-.41***	.09	.00	.00
West	-.17	.11	-.01	.00
North	-.31***	.09	.00	.00
Holidays	.12	.08	-.01[a]	.00
$Copula_{product\text{-}feature\ learning}$	-2.79***	.60	.42***	.03
$Copula_{price\text{-}strategy\ learning}$	1.46[a]	.78	.12**	.04
$Copula_{social\ learning}$	-.36*	.15	.04***	.01

n = 202,467 orders by 68,441 customers. [a]: p < .10; *: p < .05; *: p < .01; ***: p < .001
b: customers from south of china are the reference group.

Appendix 1
Results of Split-population duration model - Log-logistic Distribution for Different New Product Definitions

Variables	New Product – 45 days					New Product – 10 days				
	At Risk		Duration		Replicate main analysis	At Risk		Duration		Replicate main analysis
	Coefficient	SE	Coefficient	SE		Coefficient	SE	Coefficient	SE	
Product-feature learning	2.22***	.03	-1.42***	.02		1.30**	.05	-.20***	.03	
Price-strategy learning	.21	.33	-.35***	.02		.25	.43	-.11***	.03	
Social learning	.12	.08	-.06***	.01		.07	.11	-.01	.01	
Product-feature learning * Social learning	.08**	.03	.01*	.00		-.00	.04	-.01*	.00	
Price-strategy learning * Social learning	-.06**	.02	.00**	.00		-.00	.03	.01**	.00	
Product-feature learning * Price-strategy learning	-.02	.04	.07***	.00		.01	.05	.01***	.00	
Cumulative spending	-.38***	.05	.09***	.00		-.07	.07	.12***	.00	
Discount percentage	.44***	.03	-.01***	.00		.52***	.07	-.00	.00	
Order spending	6.65***	.21	-.05***	.00		4.69***	.43	-.08***	.00	
Number of new products launched	.50***	.03	-.01***	.00		.49***	.05	-.08***	.00	
Days on market	-4.69***	.09	.16***	.00		-3.06***	.15	.28***	.01	
Unit sold	.36***	.05	.00	.00		.48***	.11	-.05***	.01	
Recency	.11**	.04	-.02***	.00		-.06	.04	-.06***	.00	
Fit	-.82***	.03	.03***	.00		-.33***	.04	.06***	.00	
Social media brand post	1.53***	.11	-.05***	.00		-.20	.18	.09***	.01	
News post	-.47***	.11	.06***	.00		.50**	.19	-.06***	.01	
Rural	.18*	.09	.00	.00		.31*	.13	.02^{a}	.01	
East^{b}	-.25***	.08	.00	.00		-.20^{a}	.11	.01^{a}	.01	
West	-.06	.10	.00	.00		-.19	.13	-.02**	.01	
North	-.20*	.08	.00	.00		-.32**	.12	.01	.01	
Holidays	-.12^{a}	.07	.00	.00		.31***	.11	-.02***	.00	
Copula$_{\text{product-feature learning}}$	-2.58***	.04	2.12***	.02		-.185**	.71	.40***	.05	
Copula$_{\text{price-strategy learning}}$	-.71	.66	.47***	.04		-.94	.85	.09	.06	
Copula$_{\text{social learning}}$	-.18	.13	.12***	.01		-.37*	.18	.03*	.01	

n = 202,467 orders by 68,441 customers. ^{a}: $p < .10$; *: $p < .05$; *: $p < .01$; ***: $p < .001$

b: customers from south of china are the reference group.

Figure 1

Preliminary Empirical Evidence