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ORIGINAL EMPIRICAL RESEARCH

Seller marketing capability, brand reputation, and consumer journeys on e-commerce platforms

Jifeng Mu[1,2] · Jonathan Z. Zhang[3]

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Abstract
Seller marketing capability and brand reputation are central to firm performance and customer behaviors. However, little is known about how these two dimensions matter in the increasingly important domain of e-commerce platforms, where sellers are diverse and brand reputations are challenged. This research examines the effects of marketing capability and brand reputation on key customer purchase journey outcomes on e-commerce platforms, from click to browsing time, purchase, and post-purchase frustration. Using smartphone category data from a leading e-commerce platform, the authors demonstrate the positive and increasing effect of marketing capability on consumer journey outcomes. This research also paints a more nuanced view of brand reputation in e-commerce platform environments and illustrates nuanced U-shaped effects of brand reputation on consumer journey outcomes. These findings provide implications for brands and sellers on e-commerce platforms.

Keywords E-commerce platform · Marketing capability · Brand reputation · Consumer journey

Introduction

The proliferation of e-commerce platforms in recent years has transformed and democratized the retail landscape. E-commerce platform technologies and the resulting business models such as Amazon and eBay in the U.S. and worldwide, Cdiscount in Europe, Mercado Libre in Latin America, Flipkart in India, Jumia in Africa, Rakuten in Japan, and Taobao in China have shaken traditional retail giants around the world. The successes of these platform-based businesses lie in the large numbers of entrepreneurial sellers who participate and the massive value created by enabling communication and transactions that otherwise would not occur. In 2019, the top e-commerce platforms sold $1.8 trillion of goods globally, comprised of 52% of total global e-commerce volume, and are currently experiencing high annual growth of 23% (DigitalCommerce360, 2019a). In the U.S., Amazon alone accounts for 40% of the country's e-commerce sales and is experiencing an annual growth rate of 15% compared to less than 5% of overall US retail growth (DigitalCommerce360, 2019b). Such global trends are expected to continue well into the next decade as emerging economies begin to participate in such online business models and as industry-specific platforms such as Etsy, Wayfair, and Chrono24 emerge.

E-commerce platforms have tremendous implications for the livelihood of the vast number of participants. According to IDC,[1] selling on platforms is supercharging growth for U.S. small- and medium-sized businesses. For example, in 2019, American small- and medium-sized businesses (SMBs) selling on Amazon had more than 15,000 businesses surpassing $1 million in sales and nearly 25,000 surpassing $500,000 in

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✉ Jifeng Mu
jifengmu@gmail.com; microfoundation@outlook.com

Jonathan Z. Zhang
jonathan.zhang@colostate.edu

1 Microfoundation Institute, Madison, AL 35758, USA

2 School of Business, Alabama A&M University, Box 429, Normal, AL 35762, USA

3 College of Business, Colorado State University, Fort Collins, CO 80523, USA

[1] Source: International Data Corporation (IDC) InfoBrief, SMB Success in the Multichannel Era, January 2020. Methodology: Survey of small and medium business owners, executives and managers across multiple industries, currently selling or planning to sell online, fielded August–September 2019.

sales. Independent sellers on Amazon are selling an average of 4000 products a minute, and they have created more than 800,000 jobs.[2] Globally, 225,000 SMBs have surpassed $100,000 in sales on Amazon in 2019. As such, e-commerce platforms create a business environment that benefits millions of independent sellers (selling generic and branded products and producing firm-generated content), consumers (buying on the platform and creating user-generated content), and suppliers (i.e., brands and products). The buyers, sellers, suppliers, and the information exchanges among these players compose the e-commerce platform ecosystem.

Because of their surging popularity and economic importance, economists and marketing scholars have examined platform economies from various angles such as cross-network platform competition, pricing structure, and business model determination (e.g., Armstrong, 2006; Rochet & Tirole, 2006), cross-market network effects on marketing budgeting (Sridhar et al., 2011), types of social platforms (Perren & Kozinets, 2018), marketing efforts and advertising revenue on B2B platforms (Fang et al., 2015), and the nature of platform value creation (Ramaswamy & Ozcan, 2018).

What is unique about e-commerce platforms, in contrast with mono-brand retailers such as Warby Parker or single-seller retailers such as Nordstrom, is that there are many sellers offering the same or similar products and competing in the same categories. The sellers differ in size and capabilities, and each has full control over its pricing and promotion decisions. Unlike single-seller retailers, there is no centrally coordinated brand and product curation strategy on platforms—well-known brands are sold alongside discounted generic products of similar attributes. Traditionally, sellers' marketing capability and brand reputation are differentiating factors in the crowded marketplace. However, given its complex ecosystem with diverse participants and the nuanced customer decisions on platforms, identifying the roles of marketing capability and brand reputation remains challenging (Batra & Keller, 2016). Thus, we currently lack an understanding of how these two factors affect consumer behaviors on e-commerce platforms and in digital environments in general (Moorman & Day, 2016; Perren & Kozinets, 2018; Ramaswamy & Ozcan, 2018; Swaminathan et al., 2020).

Yet, as marketers' online spendings on marketing capability and brand reputation continue to grow, they also harbor concerns about the return on digital marketing investment and face significant pressure in justifying these investments to senior management and shareholders (CMO Survey, 2018; Delloitte, 2020; Delmulle et al., 2015). This important area has prompted several recent calls to action for the investigation of the roles of marketing capability and brand reputation at various stages of the customer journey (Batra & Keller, 2016; Moorman & Day, 2016; Swaminathan et al., 2020). In this paper, we attempt to address these research gaps and managerial concerns. We aim to answer the following: *On e-commerce platforms, how do (1) seller marketing capability and (2) brand reputation affect customer journey outcomes, specifically, click likelihood, purchase likelihood, browsing time, and expressed post-purchase customer sentiments, namely customer frustration?*

To provide insights into these research questions, we employ data collected from different sources on one of the largest e-commerce platforms in North America, as measured by revenue and market capitalization. To the best of our knowledge, our research is the first to empirically investigate marketing capability and brand reputation that characterize e-commerce platform environments. We approach the challenge of understanding marketing capability and brand reputation from the perspective of customer journey, which decomposes decisions into a series of steps that constitute a path to purchase and post-purchase behaviors.

This research program offers the following contributions. First, our study adds to the marketing capability literature by demonstrating marketing capability's importance on e-commerce platforms. Extant research often suggests a linear positive effect of marketing capability on firm performance from the focal firm perspective, employing either survey or input-output stochastic frontier analysis in offline environments (e.g., Dutta et al., 1999; Feng et al., 2017). However, the roles of marketing capability on customer journey outcomes and in online environments are largely unexplored (Moorman & Day, 2016). As harnessing the power of platforms constitutes an essential marketing capability in the current digital age (CMO Survey, 2018), it is vital for researchers and practitioners to investigate marketing capability's role in digital environments. Likewise, research has called for novel frameworks in marketing capability development and deployment at different stages of the consumer journey (Hamilton et al., 2021). Our approach provides such an empirical framework that brings marketing capability from theory to practice at the customer journey level. As mentioned earlier, justifying digital marketing investment has been difficult for marketing managers. Our findings that marketing capability exhibits increasingly positive effects on consumer journey outcomes suggest that these investments can pay off handsomely. We estimate that sellers with marketing capability two standard deviations above the mean can achieve 80% higher customer purchase likelihood and 61% lower post-purchase frustration than those with two standard deviations below the mean. As marketing capability in other contexts has been found to have greater impacts on firm performance than operational and R&D capabilities (e.g., Krasnikov & Jayachandran, 2008), our findings provide especially strong support for marketers to prioritize resources for enhancing their marketing capability on e-commerce platforms. More generally, these results help marketing managers better communicate the financial implications of digital marketing

[2] Small businesses alone make up 99.9% of U.S. businesses and employ almost 60 million people; see https://cdn.advocacy.sba.gov/wp-content/uploads/2019/04/23142719/2019-Small-Business-Profiles-US.pdf.

investments to their non-marketing colleagues and other stakeholders in the organization.

While marketing strategy research in recent years has pushed for firm capability measures using user-generated content (UGC) (e.g., Melumad & Meyer, 2020; Netzer et al., 2012; Rust, 2019; Timoshenko & Hauser, 2019), there is surprisingly no analysis of the marketing capability employing UGC. The wealth of consumer textual information that exemplifies the current digital era can be extracted to analyze marketing capability. Leveraged unstructured consumer textual data from the e-commerce platform, we derive marketing capability from UGC—an approach that not only can increase the representativeness of the sellers measured but more importantly allows for real-time updating of capability measures.

Second, while marketers have demonstrated the importance of brand reputation in firm performance and consumer decision making (Batra & Keller, 2016; Erdem & Valenzuela, 2006; Hsu et al., 2016; Keller, 2003), recent research has suggested that the online environment might be diminishing the role of brands due to increased variety of products offered online and lowered search costs for discovering non-mainstream products (Anderson, 2006; Hollenbeck, 2018; Rosen & Simonson, 2014; Waldfogel & Chen, 2006). The coexistence of diverse brands on e-commerce platforms can thus shift consumption away from well-known brands to a much larger number of lower-selling niche and generic products (Brynjolfsson et al., 2011; Mu et al., 2018). Resolving this tension can offer new insights on brand management, and marketing scholars have thus called for new understandings of brand reputation in online consumer experiences before, during, and after purchase (Swaminathan et al., 2020).

Our empirical results suggest that despite the current concerns of brand value erosion online due to product proliferation, brand reputation continues to be a critical factor for products competing in the platform environment. However, the effects are nonlinear, nuanced, and can have opposing forces on different metrics—while brand reputation has an inverted U-shaped effect on customer click, browsing time, and purchase, it exhibits a U-shaped effect on post-purchase frustration. These results suggest that a strong brand reputation, while useful in the buying process with diminishing marginal returns, can set up high consumer expectations, which may lead to disillusionment and post-purchase frustration. For example, our findings suggest that while brands with reputation two standard deviations above the mean achieve 15% higher customer purchase likelihood than brands two standard deviations below the mean, the same comparison can increase post-purchase frustration by 44%. Sellers of premium brands should have a holistic view of brands that encompass both short-term (purchase phase) and long-term (post-purchase phase) effects of brands. For example, sellers should devote sufficient attention to setting the right expectations and address customer issues in a timely manner to prevent post-purchase frustration. For brand owners, the results suggest that seller behaviors on these platforms can influence the relationship between brands and their end-users, potentially disrupting the value of brands and their perceptions by the consumer. Therefore, well-crafted, well-coordinated, and well-enforced channel partner policies are crucial in maintaining brand equity in the online environment.

The rest of the paper is organized as follows: We begin by presenting our conceptual framework and hypotheses. Next, we discuss the institutional details and the data used for this study, followed by the models and estimation results. We conclude with theoretical and managerial implications.

Conceptual framework and research hypotheses

Our framework is based on consumer journeys on e-commerce platforms with a focus on the roles of seller marketing capability and brand reputation. As stated earlier, a significant body of work has found support for positive effects of marketing capability (e.g., Dutta et al., 1999; Feng et al., 2017; Krasnikov & Jayachandran, 2008; Mishra & Modi, 2016; Vorhies & Morgan, 2005; Xiong & Bharadwaj, 2013) and brand reputation (e.g., Barone & Jewell, 2013; Hollenbeck, 2018; Erdem & Valenzuela, 2006; Hsu, Fournier, & Srinivasan 2016; Aaker & Keller, 1990) on performance outcomes. Despite these insights, research has yet to demonstrate the value of these two constructs in consumer journey and in e-commerce platform environments, which differ significantly from many offline business environments.

In essence, we showcase the curvilinear effects of marketing capability and brand reputation on the customer journey outcome variables, while providing a novel approach to extract marketing capability measures from unstructured consumer textual data often found in digital contexts. We first introduce, in our context, the four focal dependent variables of the consumer journey, followed by discussions of the two independent variables and how they affect these dependent variables.

Customer click

Click-through rates have been examined in advertising research. Edelman et al. (2007) propose a model where the ad click-through rate depends on ad and position effects and does not depend on other ads. Other research studied how keyword characteristics relate to clicks, such as the popularity of keywords, whether the search phrase includes the name of a brand or a retailer, the difference between organic and sponsored links, and the length of the search phrase (e.g., Agarwal et al., 2011; Jerath et al., 2014). On e-commerce platforms, after searching, the customer can see in the search results information related to brands and sellers, product names, and short product descriptions. They can then click an offering if they are interested in the results presented after the search. The rich information environment allows us to investigate how marketing capability and brand reputation affect clicks conditional on the search results.

Customer browsing time

Customer browsing time reflects consumers' efforts involved in information search and uncertainty reduction (Lallement & Gourmelen, 2018). While consumer search has been a topic of interest in marketing as it relates to the fundamental domain of uncertainty reduction, relatively little research has investigated consumer browsing on e-commerce platforms. Understanding how marketing capability and brand reputation affect customer browsing behavior allows sellers to optimize the customer journey through the use of improved information presentations.

Customer purchase

Customer purchase likelihood (or conversion) is directly related to revenue. Conversion rates are low across e-commerce sites, and small increases of even 1% in conversion rate on platforms such as Amazon can translate into millions of dollars in incremental revenue.

Post-purchase customer frustration

Customer frustration is an unpleasant state of emotional response to opposition or conflict, which arises when a customer has competing or interfering goals (Smith & Ellsworth, 1985). Feelings of frustration occur when customers expect a product to have certain features or value, but the product, in reality, does not fit with the expectation (Patrick & Hagtvedt, 2011). As negative sentiments loom larger than positive sentiments as suggested by prospect theory, customers' feelings of frustration may particularly adversely affect their overall evaluations of purchase experiences. The resulting negative review expressing their frustration can negatively affect future customers and be detrimental to sellers and brands. However, this negative emotion is rarely studied in marketing compared to other customer emotions such as happiness and satisfaction (Patrick & Hagtvedt, 2011), and it is particularly under-studied in online and e-commerce settings, despite its important implications in these contexts. For our analysis, we extract post-purchase customer frustration from online reviews of verified purchasers.

Marketing capability

Marketing capability is a foundational capability for selling firms to succeed. We define marketing capability as *a firm's ability to efficiently convert available customer feedback into outputs*. Extant research has often employed either an input-output stochastic frontier approach (Dutta et al., 1999; Feng et al., 2017) or managers' evaluation (e.g., Mu, 2015; Vorhies & Morgan, 2005) to measure marketing capability from the focal selling firm's perspective. While both approaches provided insights on the linkage between marketing capability and firm performance, data availability, and timeliness of obtaining such data limit the ability of marketers and researchers to understand the impact of marketing capability in a timely fashion. For example, results based on archival data and survey data typically lag the actual marketing practice by months and years, and marketers and researchers can find themselves working off old data and insights to address current problems. As online environments and the attendant marketing actions are increasingly dynamic, this lagged approach may not be relevant to the current market conditions and may result in missed opportunities.

In the present online environment, UGC can provide rich alternative measures of sellers' marketing capability. Customer comments regarding customer order fulfillment, purchasing process, customer service, and product delivery reflect the marketing capability of the seller (Day, 2011; Moorman & Day, 2016; Mu, 2015). While this approach is different from extant methods of measuring marketing capability, it can shed light on "the efficiency with which sellers convert marketing resources (in our case, customer input) into sales," the working definition of marketing capability in the literature (Mishra & Modi, 2016). The approach can offer advantages in helping marketers quickly understand and respond to customers' evolving requirements in digital contexts.

Marketing capability is not fixed and should be updated regularly. UGC provides an abundance of data for researchers to leveraging this unstructured, customer-centric data to evaluate marketing capability and understand its impact on performance outcomes. The massive amount of data permits marketers to "listen," allowing them to replace slow and costly traditional marketing research with timely and crowdsourced intelligence (Netzer et al., 2012). Moreover, UGC is updated continuously, enabling the firm to agilely sense changes in marketplaces and consumer preferences. For example, customer comments can serve as a tool for sellers to directly gauge customer reactions to its offering and services, and rapidly take actions to respond to complaints. These actions can prevent customer switching, enable sellers to address the inadequacies quickly for the focal and future customers, and limit future negative comments. Therefore, extracting information from UGC that reflects sellers' marketing capabilities from customers' perspectives can provide a novel approach to marketing capability analysis. This approach also speaks to the future of real-time analysis of customer conversations through AI deployment (Rust, 2019). Accordingly, in this study, we use a text mining approach based on customer comments to measure marketing capability, similar to other examples of uncovering managerially meaningful constructs such as customer needs and customer sentiments (Archak et al., 2016; Büschken & Allenby, 2016; Lee & Bradlow, 2011; Melumad & Meyer, 2020; Timoshenko & Hauser, 2019).

While prior studies have established the overall positive link between marketing capability and performance outcomes, they are silent on marketing capability's potential to exhibit non-linear impact. Although a linear relationship can serve as the first approximation, failures to account for non-monotonic patterns may oversimplify the relationships between the focal variables (Cameron & Trivedi, 2009). E-commerce platforms attract large numbers of visitors. Yet, because of the ease of comparison, the environment is also more competitive than in the physical world. Success on the platforms especially depends on sellers' ability to grab the attention of site visitors and convert them into buyers and references for future customers. As seller comparisons are easy, customers can sort on seller performance metrics. Likewise, platforms have incentives for highlighting high-performing sellers, and the default "best matches" sort on many platforms (e.g., eBay and Amazon) are often directed to strong sellers. These mechanisms can positively differentiate the superior sellers from the rest, making marketing capability especially salient on platforms. Thus, sellers with strong marketing capabilities could take the lion's share of benefit in terms of increased clicks, purchases, and decreased customer frustration, and we expect the relationship between marketing capability and these customer outcomes to be positive and non-monotonic.

For example, sellers with strong marketing capabilities can continuously gauge customer reactions to their offerings and rapidly address customer issues. The timely monitoring and the consequent agile customer service can have an especially strong payoff on e-commerce platforms - it not only engenders loyalty for the focal customer but can also increase the likelihood of eliciting additional positive comments about the seller, resulting in a virtuous cycle for resolving uncertainty for future customers and positively differentiating the focal seller from the rest of the competition. Similarly, sellers with strong marketing capability can proactively adjust their inventories and service terms in a timely manner in the presence of customer comments (negative or positive), increasing the match between firm inventory and customer orders (Bharadwaj et al., 2007). Therefore, sellers with high marketing capability should achieve superior customer outcomes in click, purchase, and post-frustration reduction. In terms of browsing time, sellers with low levels of marketing capability cannot adequately engage the attention of the customers. Sellers with medium levels of marketing capability can engage customers, but the information might be too much, disorganized, and might not fit with customers' preferences, resulting in high browsing time (akin to information-rich but poorly designed webpages). Sellers with high marketing capability are efficient in terms of attracting customer attention and matching information presentation with customer needs, and customers need not spend unnecessary time browsing. Thus, we expect as marketing capability increases, browsing time increases, but at high levels of marketing capability, browsing time actually decreases. We hypothesize:

H1: As marketing capability increases, (a) click likelihood increases at an increasing rate; (b) browsing time first increases, then decreases; (c) purchase likelihood increases at an increasing rate, and (d) customer frustration decreases at an increasing rate.

Brand reputation

Brand reputation—how a brand is viewed by others—is often referred to as an important source of the brand and product value (Hollenbeck, 2018). Brand reputation can provide awareness, perceived quality, specific mental associations, uncertainty reduction, and customer loyalty in the customer purchase process (Aaker & Keller, 1990; Keller, 1993, 2003). Extant research on brand reputation suggests a linear positive effect on customer purchasing behavior (Erdem & Valenzuela, 2006). Brands with higher reputation command higher prices, so the focal question is: can stronger brands with their associated higher prices induce more favorable consumer behaviors on e-commerce platforms?

Four areas of discussion formulate our hypothesis development. First, on platforms, customers are faced with more noise, higher awareness of competitive offerings, other customers' comments, and more rapid expertise accumulation. These factors dampen the focused message from the brand and reduce customer reliance on brand reputation as a quality signal. Some researchers suggest that brands tend to lose their value in the online environment (Rosen & Simonson, 2014; Waldfogel & Chen, 2006). This could occur due to the convergence of product features across different products on the platform and that online customer comments have produced an influx of detailed product quality information through reviews and opinions. Hollenbeck (2018) thus suggests that as more information becomes available, customers should rely less on brand reputation for quality signals. On the supply side, there is a growing tendency for companies to come up with the same market insights and launch products with similar attributes with similar messages. Therefore, firms' ability to leverage brand reputations in online settings is limited.

Second, in order to provide a consistent customer experience, e-commerce platforms restrict product presentation customization, which creates difficulties for branded products to build strong relationships with their customers. Brands thus have mostly become trademarked goods in the context of limited exposure to customers (Swaminathan et al., 2020), and the roles of brands acting as an avenue for the excitement of consumption are diminishing. E-commerce platforms facilitate the search and comparison of products of similar functions from a diverse set of options. This drives consumption away from well-known brands' products to a much larger number of lower-selling niche products (Brynjolfsson et al., 2011; Mu et al., 2018).

Third, sellers on e-commerce platforms are increasingly pushing their private labels (Geyskens et al., 2010) and engaging in marketing activities designed to enhance their profits with little or no regard for the interests of brand owners. This misalignment of interests between sellers and brands may lead to a downward spiral of brand image and brand equity (Gielens & Steenkamp, 2019).

Fourth, high product variety increases market fragmentation, which erodes brand loyalty. This occurs because consumers can use low prices as a reference point to judge the value of similar products and thus distort consumers' price perceptions, potentially jeopardizing the value of premium brands in favor of economy brands and private labels (Sotgiu & Gielens, 2015). Price competition among sellers also erodes brand value. Unlike in offline settings where price discovery takes effort, and unlike with single-retailer sites that have coordination and consistency when it comes to price discounts, sellers on e-commerce are "every man for himself"—they are not coordinated and can compete fiercely on price because prices are readily observable. A tempting strategy to stand out from the competition is to race to the bottom in price. Although this strategy can benefit individual sellers, it can be detrimental to the perceived brand value.

Taken together, brands are useful, but their roles are limited on e-commerce platforms and should exhibit curvilinear effects—after a certain point, a stronger brand reputation no longer matters for click and purchase. For browsing, it should have the same inverted U logic as in marketing capability in reducing uncertainty. Furthermore, although brand reputation can resolve some uncertainty and facilitate purchases, a strong brand can also set up high and sometimes unrealistic expectations, resulting in more post-purchase frustration stemming from the increased dissonance. We hypothesize:

H2: Brand reputation has inverted U-shaped effects on (a) click likelihood, (b) browsing time, and (c) purchase likelihood; and a U-shaped effect on (d) customer frustration.

Figure 1 depicts the hypothesized relationships between marketing capability, brand reputation, and the four customer journey outcomes.

Research methodology

Data

In this section, we describe the data and industry setting. One of the largest e-commerce platforms in North America, as measured by revenue and market capitalization, has provided part of the data for this research from its 2017 and 2018 databases. The company sells a comprehensive list of items ranging from apparel, books, household items, to electronics and many other categories. The company also allows third-party independent sellers to sell products on its website, with over 50% of the sales generated by independent sellers. The independent sellers can offer a variety of merchandise of their own selections on the platform, and they can advertise their products independently of the platform owner's activities.

The company provided us with part of the data in the smartphone category, which constitutes our research setting. We believe that smartphones are a good category for our research purpose for the following reasons. First, smartphones are economically important as an industry as well as the role they play in consumers' lives. Smartphones are ubiquitous in North America, have impacted almost all walks of consumers' lives; even relatively novice consumers would have some familiarity with the category (Grewal et al., 2019; Melumad & Meyer, 2020). In the US, there are more than 260 million smartphone users, with annual sales exceeding 70 billion U.S. dollars.[3] Globally, the smartphone market was valued at USD 715 billion in 2019 and is expected to reach USD 1.35 trillion by 2025.[4] Second, because of the prices, attributes, the infrequency of purchase,[5] diversity of choices,[6] symbolic social status implications (van de Ven et al., 2011), and cognitive effort required for using the device (Melumad et al., 2019), smartphones are relatively high-involvement products that make many consumers engage in extensive problem solving, where they spend time and effort processing the diverse information and researching the products during the buying process (Tong et al., 2020). Due to these reasons, consumers might experience cognitive dissonance and post-purchase frustration often seen in higher-involvement purchases. Third, although they are high in involvement, smartphones do not need deep physical inspection (e.g., as in clothing or glasses) where many consumers cannot readily purchase in e-commerce settings. This balance of smartphones' high involvement as well as their digital attributes allows us to observe and investigate the nuanced aspects of the consumer journey in e-commerce. Finally, as consumers are in-

[3] https://www.statista.com/topics/2711/us-smartphone-market/

[4] https://www.mordorintelligence.com/industry-reports/smartphones-market

[5] https://arstechnica.com/gadgets/2019/12/fewer-than-10-of-americans-are-buying-1000-smartphones-report-says/

[6] https://www.wsj.com/articles/upgrade-no-thanks-americans-are-sticking-with-their-old-phones-1540818000?mod=rss_Technology

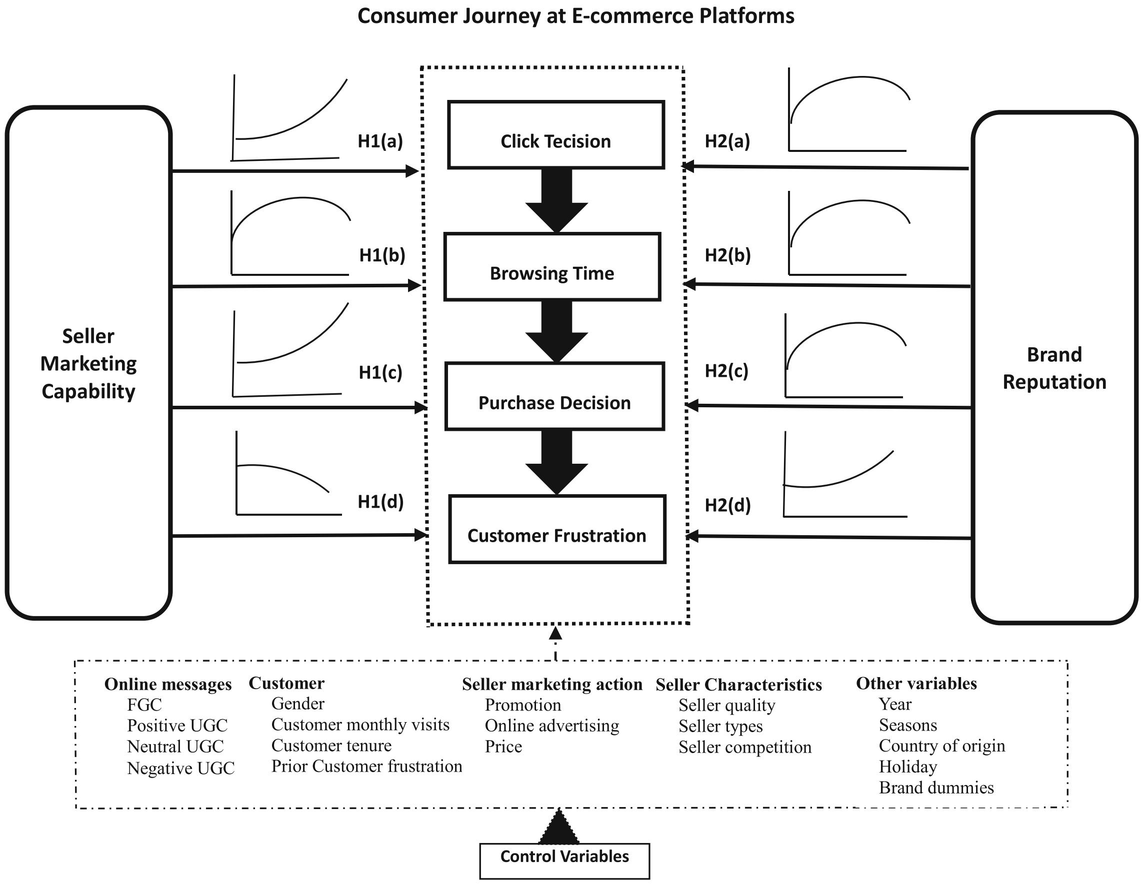


Fig. 1 Conceptual framework: the impact of marketing capability and brand reputation on customer journeys at e-commerce platforms

creasingly comfortable buying higher-ticket items online,[7,8] insights from smartphones can have implications for many other medium- to high-involvement categories.

When customers search for smartphones on this e-commerce platform, their online behaviors are recorded in the database. After the search, customers are shown the detailed product lists that provide information with several product photos, product title, short description, as well as seller information and ratings. This rich information at the search level is typical of many e-commerce platforms that try to promote clicking. Then, customers might click on an offering if they are interested in the search results (alternatively, they can either leave, or search again), browse the offering, purchase the product after browsing, and share post-purchase experiences. Figure 2 graphically depicts this process and the information environment presented at different stages of the journey that we use in the model.

The company randomly selected 1 % of samples from its database for our research purpose. The sample represents 87 brands of smartphones[9] manufactured by smartphone producers such as Apple and Samsung, and offered for sale by 3917 independent sellers of smartphones at the platform. Within the 87 brands, there are 1658 different models, with prices ranging from \$49.99 to \$1599.99, with the median price of US \$538.95, and 25th percentile at \$227.69 and 90th percentile at \$893.62. There's a diversity of reputation - with the number of awards ranging from 0 to 5 (with the median number of awards being .305) and rankings ranging from 0 to 30 (most rankings are from 1 to 10 by the majority of ranking organizations for phone brand and its models). The dataset contains 714,860 observations of customer visits for smartphones in a non-panel data structure. The variables were aligned at the time of the customer visit.

Our final dataset of the platform information environment is constructed from three different sources. The company provides data on click and purchase decisions, browsing time, sales, information about the customers such as gender and tenure, the types of smartphones, and advertising and sales promotion activities. We then extract information from the company's e-commerce platform and construct seller marketing capability, customer frustration, as well as control variables such as UGC, FGC, and seller type. The third data source includes an online ranking of brands, mainstream media sources on brand reputation, and online sources on the brands' country of origin.

[9] We count an umbrella brand only as one brand, and house of brands as different brands, e.g., Apple, Samsung, Google, Sony, Motorola, Xiaomi, LG, Nokia, OnePlus, Oppo, Asus. In our analysis, we use brand fixed effects to capture specific brand effects.

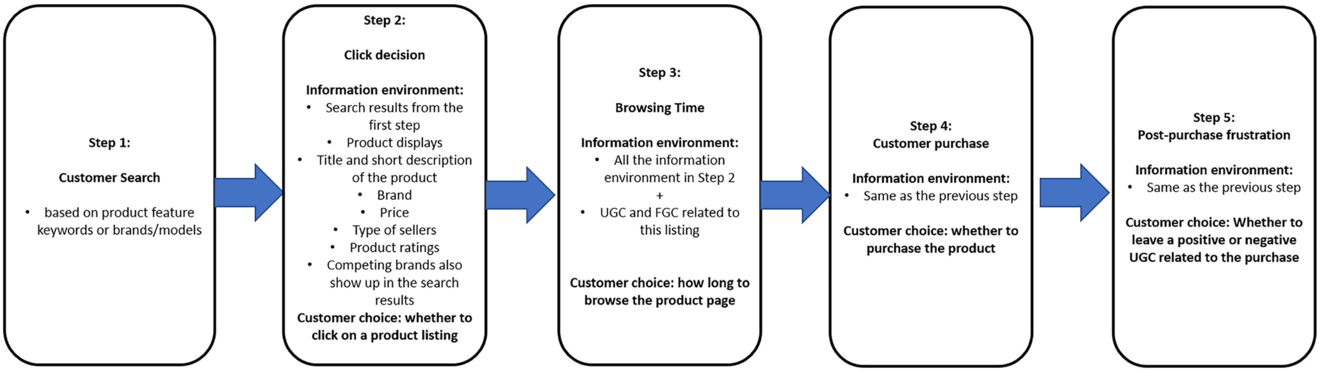


Fig. 2 Customer journey on the e-commerce platform

Variables and measurements

Table 1 details the operationalization of the dependent, independent, and control variables that correspond to our conceptual model. We detail below measurements of key variables.

Dependent variables

Customer clicks, customer browsing time, customer purchase, and customer frustration Customer clicks and customer purchases are binary variables, coded as 1 or 0. Customer browsing time is time spent on looking over one specific smartphone offered by a specific seller at the time of the visit on the platform for the smartphone.

Customer frustration is measured by the number of words related to feelings of frustration posted by those customers who made verified purchases on the platform, divided by all words used in comments for that product.[10] We use the following formula to calculate customer frustration:

$$Customer\ Frustration_{ijkt} = {\sum_{ij=1}^{n} \mathrm{CA}_{ijkt}}\Big/{\sum_{ij=1}^{n} N_{ijkt}} \tag{1}$$

where *customer frustration*$_{ijkt}$ represents the overall customer frustration in user comments for the smartphone *i* of brand *j* from seller *k* on day *t*; $\sum_{ij=1}^{n} \mathrm{CA}_{ijkt}$ is the sum of customer frustration content words (CA) across all comments (1 to n) posted about product *i* of brand *j* from seller *k* on day *t*; and $\sum_{ij=1}^{n} N_{ijkt}$ represents the sum of all words used in comments of the smartphone *i* of brand *j* from seller *k* on day *t*. We distinguish prior customer frustration and post-purchase customer frustration. We employ the same formula to calculate prior customer frustration and post-purchase customer frustration. Prior customer frustration calculates the frustrated feelings prior to this study and is used as a control covariate in our analysis to address the influence of prior customers on current customers. Post-purchase customer frustration calculates the frustrated feelings of only those focal customers who made post-purchase comments in this study and is the dependent variable. Our approach for measuring customer frustration is consistent with research in marketing for mining unstructured textual data to address managerial questions through word groupings (Archak et al., 2016; Büschken & Allenby, 2016; Lee & Bradlow, 2011; Ordenes et al., 2017; Timoshenko & Hauser, 2019). Appendix 1 presents the robustness tests for our measures.[11]

Focal explanatory variables

Marketing capability Because marketing capability is not directly observable, the literature proposes two major approaches to measure marketing capability: either using surveys to solicit managers' knowledge or opinions towards their firms' marketing activities (e.g., Vorhies & Morgan, 2005) or using an input-output stochastic frontier approach. To align our measure with the definition of marketing capability in our research context and the extant literature (e.g., Dutta et al., 1999; Feng et al., 2017; Xiong & Bharadwaj, 2013), we measure marketing capability employing an input-output stochastic frontier approach. The difference between our approach and the extant approach is that we use customer feedback as input, whereas extant research employs marketing spending and accounts receivables as input.

The stochastic frontier approach allows researchers to decompose the error term to recover firm-specific (in)efficiency, which is considered a proxy for firm capability. One major advantage of the stochastic frontier approach is that it takes the relationship between inputs (e.g., customer input) and outputs (e.g., sales) into account, thus allowing a more comprehensive benchmarking across different sellers. This is useful because

[10] Examples of customer frustration words include irritate, disappointment, angry, blow, discontent, upset, annoyed, discomfort, terrible, disappointed, extremely disappointing, worst ever, waste of time, waste your money, super annoying, horrible, chokes, troublesome, wearing on my patience, unbearable, nightmare, frustrating, unacceptable, suck, buyer beware, very disappointed, robbed, bricked, most regrettable purchase, problematic, hate, and major loss.

[11] The result using scale by Patrick and Hagtvedt (2011) has 0.86 correlation with our approach; the result from the Linguistic Inquiry and Word Count (LIWC) (Pennebaker et al., 2015; Tausczik & Pennebaker, 2010) has a correlation of .85 with our approach.

Table 1 Variable descriptions and definitions

Definitions and operations	
Dependent variables	
Customer click	Whether the customer clicks or not on an offering; it is a binary variable coded as 0 for not click and 1 for click.
Customer purchase	Binary variable indicating whether the customer purchases the product or not; coded as 1 for purchase and 0 for not purchase
Customer frustration	Customer unease feeling content about the smartphone, buying process and post-purchase behavior in their purchase journey. It is measured by using customer frustration words scaled by the total number of words used in comments of the smartphone *i* of brand *j* in the day *t* from the platform site.
Customer browsing time	The duration of customer web browsing time (hours) after clicking an offering on the e-commerce platform in this study.
Independent Variables	
Brand reputation	Brand reputation - how a brand is viewed by others, is often referred to as an important source of the brand and product value (Hollenbeck, 2018). We measure brand reputation as the number of awards and top ten product rankings accumulated average each year in the past nine years (for year 2017) or ten years (for year 2018).
Seller marketing capability	Marketing capability is defined a firm's overarching ability to efficiently convert available customer feedback into outputs. We use a stochastic frontier equation based on extant research (e.g., Dutta et al., 1999; Feng et al., 2017; Xiong & Bharadwaj, 2013) to measure marketing capability.
Control variables	
Positive UGC	Customer-generated positive comments of the smartphone at the time of visit
Negative UGC	Customer-generated negative comments of the smartphone at the time of visit
Neutral UGC	Customer-generated neutral comments of the smartphone at the time of visit
FGC	The number of seller-generated messages about the smartphone at the time visit
Gender	The gender of the customer, coded as 0 for female and 1 for male
Customer tenure	The duration of time (years) since customer registered at the e-commerce platform at the time of visit
Monthly visits	The times of customer visiting the e-commerce platform in a month to the e-commerce platform
Promotion	Binary variable indicating whether there is promotion for the smart phone by the seller when customers browse the website of the e-commerce platform coded as 0 for no and 1 for yes.
Online advertising	The number of times the product is advertised at the platform website by the seller in a week.
Price	The seller listed price of the smartphone
Seller quality	The average ranking of the seller at the time of the visit, level one to four, and four is the highest level.
Seller types	Four binary variables indicating the following four types of sellers: Platform seller, foreign sellers, domestic firm sellers, and domestic individual sellers
Seller competition	The number of sellers sells the same type of smartphones at the time of visit
Year	A binary variable indicating the years: 0 for 2017 and 1 for 2018.
Seasons	A dummy variable, four seasons of the year
Holiday	A binary variable indicating holiday or not
Countries of origin	Binary variables indicating the countries of origins of the smartphones
Brands	Binary variables indicating the brand names of the smartphones

adopting inputs (output) alone as benchmarking criteria would overlook the nuances in output (inputs). In our context, marketing capability is based on the ability of sellers to handle customer feedback. Using information from daily customer comments in the input-output stochastic frontier model can capture dynamics in seller marketing capability. Seller marketing capability can vary over time as it reflects firms' learning from customer feedback, changes in the marketing environment, and changes in competition. The efficient frontier approach estimates the marketing capability as the residuals from a model with seller fixed-effects, exploiting the within seller variation. Specifically, we write the frontier equation in Cobb–Douglas production function as the following to measure marketing capability:

$$\begin{aligned}\ln(\mathrm{Sales})_{\mathrm{kt}} &= a_0^m + a_1^m \ln\left(\sum_{s=1}^{\mathrm{P}_k} \mathrm{MW}_{\mathrm{sijkt}}\right) \\ &+ a_2^m \ln\left(\sum_{s=1}^{\mathrm{P}_k} \mathrm{W}_{\mathrm{sijkt}}\right) + \ln(\mathrm{Sales})_{\mathrm{kt}-1} \\ &+ \sum Seller_k + \varepsilon_{kt}^m - \eta_{kt}^m \end{aligned} \quad (2)$$

where $Sales_{kt}$ is the total sales for seller k at time t, $\sum_{s=1}^{\mathrm{P}_k} \mathrm{MW}_{\mathrm{sijkt}}$ indicates the total number of positive marketing capability words contained in customer review s for seller k's sales of smartphone i in brand j at time t, $\sum_{s=1}^{\mathrm{P}_k} \mathrm{W}_{\mathrm{sijkt}}$ is the negative marketing capability words contained in customer comment s for seller k's sales of smartphone i in brand j at t, and P_k is the total number of customer review for seller k.[12] $Seller_k$ is seller dummies, ε_{kt}^{m} is idiosyncratic error, and η_{kt}^{m} is a marketing inefficiency error component. We derive the maximum likelihood estimates of the inefficiency term and use its inverse to capture seller marketing capability.

To assess the reliability of our marketing capability measure, with the help of the focal platform company, we asked a representative sample of 95 independent smartphone sellers on the studied platform about their marketing capabilities based on Vorhies and Morgan (2005), and then compared with the results from our approach using our stochastic frontier approach on the same set of sellers. The two approaches for measuring marketing capabilities yield a correlation of .86.

Brand reputation Past research has often used consumer ranking or rating (e.g., Barone & Jewell, 2013) to measure brand reputation. In this research, we adopt a similar and aggregate approach to measure brand reputation by using third-party publicly available information. As consumers often use reputable third-party sources such as Consumer Reports to evaluate brands, using third party information can capture brand reputation as perceived by consumers (Hollenbeck, 2018). We measure brand reputation as the number of awards and top ten product rankings accumulated in the past ten years. Awards and ranking information are extracted from major report outlets such as Customer Reports, New York Times, Washington Times, Forbes, Fortune, Economists, CNET, brandindex.com, yougov.com, marketwatch.com, ranker.com, thedailyrecords.com, and manufacturingglobal.com. Specifically, (1) we assigned 1 for each major award that a brand received; (2) we assigned value 1, .9, .8, .7, .6, .5, .4, .3, .2, and .1 corresponding with ranking orders 1 to 10; (3) we then added up the scores from awards and ranking order value to get the total brand reputation score for each brand.

To triangulate our measure, we employ another approach: monthly social media reach (the number of people who are talking about the brand, log-transformed) of each phone brand on Facebook. Social media reach as a brand reputation metric can illustrate the awareness, influence, and popularity of the brand. This metric has a correlation of .76 with our approach of using major awards and rankings.

[12] Examples of marketing capability words include polite, responsive, resolved issues satisfactorily, fast delivery, good customer service, great transaction, excellent service, consistent with advertisement, satisfied customer, great price, smooth return, nice packaging, fast shipping, exceptional value, as promised, matching needs, easy check-out, top notch, easy to deal with, dependable, pleasure to deal with, great communication, good price, excellent value, everything is nice, delighted, on time delivery, everything as expected, earlier than the expected delivery, sealed as advertised.

Control variables

Our models control for a large set of control variables to partial out confounding effects.

Online content Online content refers to user/customer-generated content (UGC) and firm/seller-generated content (FGC), which can affect customer attitudes and behavior throughout their purchase journeys (e.g., De Vries et al., 2017; Kumar et al., 2016; Tang et al., 2014). Online content can be a good source of product-related information because it offers customers diverse perspectives, allowing potential buyers to better gauge the fit of the product with their own needs and preferences (Johnen & Schnittka, 2019). In accordance with the literature, UGC is classified into "positive," "negative," and "neutral" sentiments (e.g., Gelper et al., 2018). We employed a lexicon-based sentiment analysis tool, SentiStrength, to capture the sentiment of UGC (Tang et al., 2014; Thelwall et al., 2012), indicating one of the three sentiment natures. We use the log-transformed total volume of customer positive, negative, and neutral reviews to measure sentiments. Consistent with the literature, FGC is measured by the number of messages that the seller posted for the smartphones on the platform's website (De Vries et al., 2017; Kumar et al., 2016).

Customer characteristics: gender, tenure, and monthly visits Customer gender is recorded as a binary variable (0 = female, 1 = male). Customer tenure is measured in years since the customer first registered on the platform and can be an indicator of loyalty. Customer monthly visit is measured by the number of visits a customer makes to the e-commerce platform in a month and controls for the overall level of customer engagement with the platform.

Seller marketing actions We take into account three factors of seller actions: Seller sales promotion, pricing, and online advertising. Sales promotion creates salient stimuli to attract customers to the discounted products (Pauwels et al., 2002) and thus should have a positive effect on the customer journey. Sales promotion is measured in a binary fashion, indicating whether there is a promotion for the product when the customer visits the platform.

Price is measured as the seller's listed price at the time of the customer's visit. E-commerce platforms are competitive and lead to a steeper and more price-sensitive customer response curve and demand (Dost et al., 2014; Stigler, 1961). Sellers offering lower prices generally will achieve higher sales.

Advertising on e-commerce platforms often takes the form of sponsored and highlighted listing with the purpose of attracting customer attention. However, platform advertising space is often restricted, and the lack of visual appeal and interactivity may limit the effectiveness of online advertising on e-commerce platforms (e.g., Belanche et al., 2017; Steele et al., 2013). Online advertising is measured by the number of times the product is advertised on the platform website by the seller in a week.

Seller characteristics variables The seller characteristics we consider in this study include seller type, seller quality, and competition among sellers. On e-commerce platforms, small business owners often compete side by side with major retailer accounts (e.g., major "featured retailers" on eBay) and the platform seller (e.g., "selling-by-Amazon"). Unfortunately, many small business owners could be disadvantaged because of their relative lack of business and technological expertise. Although competition among sellers generally makes platforms more attractive for buyers (Rochet & Tirole, 2006), competition among sellers on a variety of options adds noise and could also overwhelm customers in their decision making (Scheibehenne et al., 2010).

We use four binary variables to represent the four types of sellers based on origin and scale of business as provided by the platform: Platform seller, foreign sellers (primarily small foreign retailers), domestic large retailer sellers, and domestic individuals or small retailers. E-commerce platforms usually reveal quality information about independent sellers through customer ratings, which serve as quality information signals. Seller quality is measured by the average ranking of the sellers at the platform from level one to four at the time of the customer visit on the platform's website, where four represents the highest seller quality. Seller competition is measured by the number of sellers that sell the same model of smartphones at the time of customer visits.

Other control variables Other control variables include year, seasons, holiday, countries-of-origin, and brands. Year is an indicator variable indicating the year of customers' visit (0 = 2017, 1 = 2018). Season is a dummy variable with Spring coded as the base season. Holiday indicates if the day of the visit is a holiday or not. Countries of origin are coded as a series of indicator variables the smartphones brands' countries of origin. Similarly, brands are coded as a series of indicator variables to capture specific brand effects.

Analysis and results

Model specification

We use a set of fixed effects to control concerns for unobserved heterogeneity effects (Germann et al., 2015; Papies et al., 2017). We use brand-level fixed effects to control for unobserved time-invariant smartphone quality variables such as camera, design, architecture, and major attributes. We use seller fixed effects to control for unobserved time-invariant seller characteristic effects.

We build four regression models to explore the relationship proposed in our research framework. Our model for click is based on the full dataset of 714,860 customers who had visited and searched on the platform. Out of 714,860, 420,720 customers clicked on an offering. Out of the 420,720 customer who clicked, 70,921 made a purchase. Finally, 4113 out of the 70,921 verified purchases generated reviews. A review can only be left after a verified purchase, so the risk of fake reviews is minimized.

We specify and estimate the remaining journey outcomes conditional on clicks and post-purchase comments; that is, we estimate the browsing time and purchase models for the 420,720 customers who clicked an item, and the post-purchase frustration model based on the 4113 customers who generated post-purchase reviews. We model customer frustration by examining the "frustration content" of the focal customer reviews in this study as the dependent variable and use prior customer frustration as a covariate throughout the models.

Customer click and purchase likelihood

We represent the customer's clicking and purchasing decisions via logistic regressions as these two dependent variables are dichotomous. Specifically, we use the following model for customer click and purchase likelihood:

$$
\begin{aligned}
&Y\left(\frac{\Pr\left(Y_{cijkt}=1\right)}{1-\Pr\left(Y_{cijkt}=1\right)}\right)=a_0+b_1\text{MarketingCapability}_{kt}+b_2\text{BrandReputation}_{jt}+b_3\text{MarketingCapability}_{kt}{}^2+\\
&b_4\text{BrandReputation}_{jt}{}^2+b_5\text{PositiveUGC}_{ijkt}+b_6\text{NegativeUGC}_{ijkt}+b_7\text{NeutralUGC}_{ijkt}+b_8\text{FGC}_{ijkt}+\\
&b_9\text{Gender}_c+b_{10}\text{CustomerTenure}_{Ct}+b_{11}\text{MonthlyVisits}_{Ct}+b_{12}\text{PriorCustomerFrustration}_{ijt}+\\
&b_{13}\text{CustomerBrowsingTime}_{Ct}+b_{14}\text{Promotion}_{ijkt}+b_{15}\text{OnlineAdvertising}_{ijkt}+b_{16}\text{Price}_{kijt}+\\
&b_{17}\text{SellerQuality}_{kt}+b_{18}\text{SellerTypes}_k+b_{19}\text{SellerCompetition}_{ijt}+\eta+\varepsilon
\end{aligned}
\tag{3}
$$

in Eq. (3), Y_{cijkt} is an indicator of customer c's response to offer i of brand j at time t by seller k. If customer c clicks or purchases offer i of brand j by seller k, then Y_{cijkt} = 1, and 0 otherwise; b_n is the coefficient, η represents a vector of country-specific, seller-specific, brand-specific, season- and year-specific fixed effects, and ε is the error term. However, fixed effect estimators of nonlinear logit models suffer from the incidental parameter problem (Neyman & Scott, 1948) under asymptotic sequences where T is fixed as N → ∞(Cruz-Gonzalez et al., 2017; Fernandez-Val and

Weidner (2016)). We deal with the incidental parameter problem by using the bias corrections in Fernandez-Val and Weidner (2016), applying STATA code developed by Cruz-Gonzalez et al. (2017). This approach produces corrected estimates of the coefficients and average partial effects in the logit models.

Customer browsing time and post-purchase customer frustration

We specify the following models for customer browsing time and post-purchase customer frustration via normal distribution:

$$\begin{aligned}Y_{cijkt} &= a_0 + b_1\text{MarketingCapability}_{kt} + b_2\text{BrandReputation}_{jt} + b_3\text{MarketingCapability}_{kt}{}^2 + b_4\text{BrandReputation}_{jt}{}^2 + \\ &b_5\text{PositiveUGC}_{ijkt} + b_6\text{NegativeUGC}_{ijkt} + b_7\text{NeutralUGC}_{ijkt} + b_8\text{FGC}_{ijkt} + b_9\text{Gender}_c + \\ &b_{10}\text{CustomerTenure}_{Ct} + b_{11}\text{MonthlyVisits}_{Ct} + b_{12}\text{PriorCustomerFrustration}_{ijt} + b_{13}\text{Promotion}_{kijt} + \\ &b_{14}\text{OnlineAdvertising}_{kijt} + b_{15}\text{Price}_{ijkt} + b_{16}\text{SellerQuality}_{kt} + b_{17}\text{SellerTypes}_k + b_{18}\text{SellerCompetition}_{ijt} + \eta + \varepsilon\end{aligned} \tag{4}$$

where the specifications are similar to those of click and purchase as in Equation (3) except that dependent variable Y is continuous for customer browsing time and customer frustration.

Estimation results

Table 2 presents the descriptive statistics and correlations among variables. All correlations are less than .50. Moreover, in all regression models, VIF is below 5 (the highest VIF 2.153 is the brand reputation squared), indicating that no significant multicollinearity problems exist (Hair et al., 2010). Table 3 reports the regression results for each model using Eq. (3) or (4). To test our U-shaped hypotheses, we follow the widely used procedure recommended by Haans et al. (2016). All U-shaped relationships are of the right sign and within the data range.

Customer click likelihood

The logistic regression in Table 3, Model 1 has a classification rate of 81%. In order to determine how well the model discriminates between click and not click, we use the receiver operating characteristic (ROC) curve[13] and the area under the curve (AUC)[14] (Witten & Frank, 2005). In Model 1, the area under the curve (AUC) is .83, indicating good discrimination (Hosmer Jr. et al., 2013).

Model 1 presents the results on customers' click likelihood, and demonstrates that seller's marketing capability increasingly improves the likelihood of customers clicking an offering (b = .023, odds ratio = 1.023, $p < .001$ for marketing capability; b = .005, odds ratio = 1.005, $p < .001$ for marketing capability squared). This supports H1(a). This finding extends extant research that suggests marketing capability has a linear effect on performance outcome variables (e.g., Dutta et al., 1999; Feng et al., 2017). The results also show that brand reputation has an inverted U-shaped effect on customer click likelihood (b = .053, odds ratio = 1.055, $p < .001$ for brand reputation; b = −.004, odds ratio = −1.004, $p < .001$ for brand reputation squared). This supports H2a. Figure 3 graphically illustrates this relationship.

Customer browsing time

Model 2 shows the results for customer browsing time and indicates that as marketing capability increases, customer browsing time decreases (b = .004 for marketing capability, $p < .05$; b = −.008, $p < .001$ for marketing capability squared). This supports H1b. Figure 4 graphically shows this inverted U-shaped effect of marketing capability on browsing time.

The analysis also suggests that brand reputation initially increases customer browsing time, but this positive effect decreases as we find a significant yet negative squared brand reputation on customer browsing time (b = .101, $p < .001$ for brand reputation; b = −.009, $p < .001$ for brand reputation^2). This supports H2b. Figure 5 demonstrates this inverted U-shaped relationship.

Customer purchase likelihood

The logistic regression Model 3 on customer purchase has a classification rate of 88%. In Model 3, the area under the curve

[13] ROC curve provides a way to represent the trade-off between false positives and true positives for different values of the rejection threshold by showing the relation between the sensitivity and specificity of the forecast. This curve is obtained by plotting sensitivity (proportion of times the model predicts a positive when it is actually a positive) versus 1- specificity (proportion of times the model predicts a negative when it is actually a negative) for all possible values of cut-off points.

[14] The AUC summarizes the area under the ROC in the entire range [0, 1] false positive rate. The higher the AUC value, the lower the false positive rate for a given true positive rate (i.e., the model performs better because it identifies true positives more frequently with fewer false positives).

Table 2 Descriptive statistics and correlation table

Variables	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	
1. Purchase	.148	.355	1.00															
2. UGC positive	3.147	1.363	.005***	1.00														
3. UGC negative	6.787	4.279	−.326***	.004***	1.00													
4. UGC neutral	.490	.350	.005***	−.004***	−.011***	1.00												
5. FGC	4.955	2.685	−.001	−.001	.013***	.005**	1.00											
6. Brand reputation	.446	1.198	.011***	.088***	−.008***	−.019***	−.063***	1.00										
7. Gender	.552	.497	−.040***	−.011***	.007***	.005***	−.003*	.019***	1.00									
8. Customer tenure	5.066	4.408	.009***	.091**	−.006***	−.008***	.016***	.022***	−.009***	1.00								
9. Prior customer frustration	.084	.031	.010***	.025***	.018	−.021***	.019***	−.001	.001	−.220***	1.00							
10. Post-purchase customer frustration	.059	.012	.008**	.013**	.011	−.013***	012***	−.003	.002	−.153***	.348***	1.00						
11. Customer browsing time	.964	.845	.006***	.001	−.008***	.392***	.112***	.042***	.002	.038***	.016***	.011***	1.00					
12. Promotion	.718	.450	.008***	.010***	.001	−.009***	.065***	−.071***	−.188***	−.038**	.010***	.002	.009*	1.00				
13. Advertising	.791	2.225	.000	.070***	.001	.007***	.000	.064***	−.073***	.002*	.007***	.009***	.007***	.00	1.00			
14. Price	.894	.248	−.012***	−.004***	.012**	.022***	.131***	−.188***	.016***	−.135***	−.005***	.011***	−.073***	−.023***	.001	1.00		
15. Competition	.921	1.983	−.006***	.103***	.002	.001	−.032	−.032***	−.002	.041***	−.005***	−.216***	.007***	.000	−.007***	−.003*	1.00	
16.Marketing capability	3.57	1.386	−.002	.071***	−.000	−.006***	−.079***	.009***	.046***	−.000	−.005***	.105***	.007***	.000	−.007***	−.070***	.019*	1.00

†$p < .1$; *$p < .05$; **$p < .01$; ***$p < .001$

Table 3 Regression estimation results

	Customer click	Customer browsing time	Customer purchase	Post-purchase customer frustration
Main Predictors	Model 1	Model 2	Model 3	Model 4
Seller marketing capability	.023***	.004*	.075***	−.005***
	(.002)	(.001)	(.009)	(.0002)
Seller Marketing capability^2	.005***	−.008***	.007*	−.007***
	(.001)	(.0004)	(.002)	(.0003)
Brand Reputation	.053*	.101*	.069***	−.091***
	(.017)	(.003)	(.005)	(0002)
Brand reputation^2	−.004***	−.009***	−.008**	.012***
	(.001)	(.0003)	(.002)	(.0002)
Control Variables				
UGC positive		−.003*	.025***	−.0009***
		(.001)	(.004)	(.0001)
UGC negative		−.004***	−.641***	−.00021***
		(.0007)	(.004)	(.00004)
UGC neutral		.985***	−.013	.939***
		(.004)	(.015)	(.002)
FGC		.041***	.008***	.0006***
		(.003)	(.002)	(.00005)
Customer gender	−.182***	.004	−.533***	−.013***
	(.005)	(.003)	(.010)	(.00008)
Customer tenure	.004*	.002***	.012***	.00001
	(.0006)	(.0004)	(.001)	(.00001)
Monthly visits	.017	.025	.014***	.015
	(.014)	(.018)	(.004)	(.013)
Prior customer frustration		−.221***	−.182***	.141***
		(.039)	(.031)	(.023)
Customer browsing time			.009***	.0006*
			(.002)	(.00005)
Promotion	.011*	.007*	.047**	−.003***
	(.004)	(.002)	(.011)	(.0001)
Online advertising	.001	.002	−.002	.0005*
	(.001)	(.004)	(.002)	(.00001)
Price	−.107***	−.041***	−.241***	.0005**
	(.012)	(.003)	(.022)	(.0001)
Seller quality				
2	−.203***	.023***	−.128***	.002***
	(.005)	(.003)	(.011)	(.0001)
3	.253***	−.037***	−.241***	.003***
	(.008)	(.004)	(.017)	(.0001)
4	.762***	−.026	3.027***	.007
	(.057)	(.017)	(.693)	(.009)
Foreign seller	−.021*	.011	−.135***	.0009*
	(.007)	(.007)	(.031)	(.0002)
Domestic firm seller	.026***	−.007	−.003	−.00007
	(.008)	(.008)	(.012)	(.0001)
Domestic individual seller	.045*	−.005	.041	.0009*
	(.019)	(.007)	(.034)	(.0003)
Seller competition	.017***	.004***	−.012***	.005***
	(.001)	(.0005)	(.003)	(.00002)
Year (2018)	−.003	−.006*	−.041*	−.002***
	(.002)	(.001)	(.012)	(.00007)
Fall	.041***	.005	.026†	.010
	(.005)	(.002)	(.014)	(.008)
Winter	.053***	.006*	.036*	.008

Table 3 (continued)

	Customer click	Customer browsing time	Customer purchase	Post-purchase customer frustration
	(.006)	(.002)	(.012)	(.006)
Summer	−.009	−.003	−.004	−.007
	(.022)	(.006)	(.007)	(.006)
Holiday	−.003	−.041***	.071***	−.0005***
	(.004)	(.003)	(.010)	(.00006)
Country of origin				
2	.889***	−.018***	−.589***	.0009***
	(.009)	(.004)	(.017)	(.0002)
3	1.913***	−.011***	−.979***	−.0001
	(.022)	(.004)	(.034)	(.0003)
4	.156***	.017***	.115***	.003***
	(.007)	(.003)	(.014)	(.00002)
5	.821***	.002	.728***	.005***
	(.017)	(.003)	(.027)	(.0001)
6	1.692***	.026***	.251***	.003***
	(.014)	(.007)	(.023)	(.0001)
7	.003	.016***	.246***	.004***
	(.016)	(.004)	(.025)	(.0002)
8	.662***	.014***	.237***	.005***
	(.017)	(.005)	(.025)	(.0003)
9	1.419***	−.003	−.571***	.006***
	(.016)	(.003)	(.031)	(.0002)
10	−.618***	.024*	−.411***	.005***
	(.017)	(.011)	(.035)	(.0004)
11	.259***	.053***	−.205***	.007***
	(.022)	(.007)	(.033)	(.0003)
12	1.187***	.018*	−.781***	.007***
	(.024)	(.006)	(.039)	(.0003)
Brand fixed effect	Yes	Yes	Yes	Yes
Seller fixed effect	Yes	Yes	Yes	Yes
Intercept	3.295***	.369***	.931***	.113***
	(.033)	(.014)	(.062)	(.0004)
Model Properties				
Akaike's Information Criterion (AIC)	718,905	982,193.85	236,782.49	845,732
Bayesian Information Criterion (BIC)	719,203.8	983,895.62	241,692.75	853,691
Likelihood Ratio Chi-square	45,781.29		11,788.51	
Log-likelihood	- 364,522.18		- 127,568.42	
Pseudo R^2	.115		.322	
Classification Rate	.81		.88	
Area Under the Curve (AUC)	.83		.91	
F		812.56***		429.55***
R^2		.179		.212
Sample size	714,860	420,720	420,720	4113

1. Columns contain estimated coefficients and their associated standard errors (in parentheses)

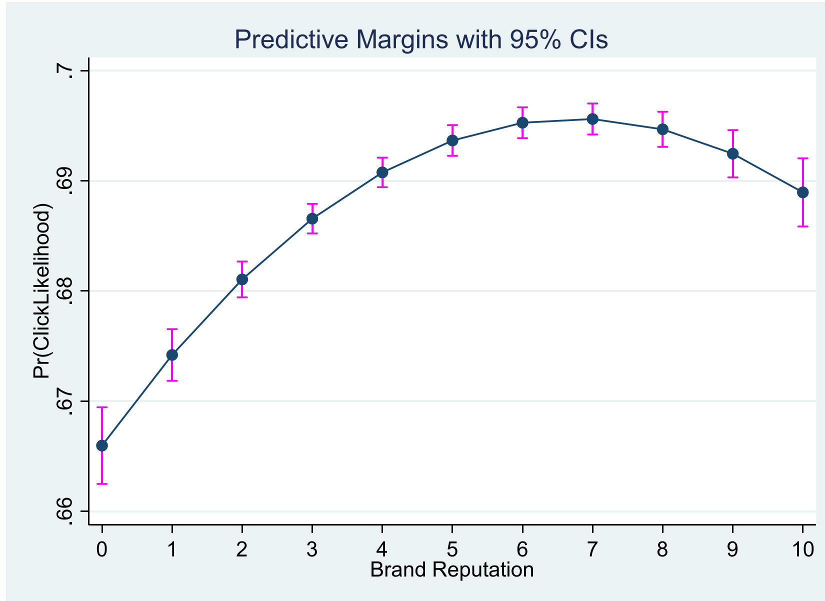
2. †$p < .1$;*$p < .05$;**$p < .01$;***$p < .001$

3. For simplicity of presentation, we do not show brand coefficients in the table

(AUC) is .91, indicating excellent discrimination (Hosmer Jr. et al., 2013).

Model 3 indicates that marketing capability (b = .075, odds ratio = 1.078, $p < .001$ for marketing capability; b = .007, odds ratio = 1.007, $p < .001$ for marketing capability squared) increasingly improve the likelihood of customer purchase. This supports H1c. Fig. 6 graphically illustrates the influence of marketing capability on the likelihood of customer

Fig. 3 The effect of brand reputation on customer click likelihood



purchase. This is a novel finding as prior research demonstrates that marketing capability has a linear effect on performance outcome variables (e.g., Dutta et al., 1999; Feng et al., 2017). The results suggest the increasing importance of marketing capability in the online environment.

Model 3 suggests that brand reputation (b = .069, odds ratio = 1.072, $p < .001$ for brand reputation; b = −.008, odds ratio = −1.008, $p < .001$ for brand reputation squared) has an inverted U-shaped influence on purchase. This supports H2c.

Post-purchase customer frustration

The results in Model 4 show the effects of marketing capability on and brand reputation on customer post-purchase frustration. Model 4 indicates that marketing capability makes customers increasingly less frustrated as the coefficient is negative and significant (b = –.005, $p < .001$ for marketing) capability and b = −.007, $p < .001$ for marketing capability squared). This supports H1d. The results in Model 4 suggest that as brand reputation increases, customers get more and more frustrated (b = −.091 for brand reputation, b = .012 brand reputation^2, $p < .001$). This supports H2d.

Robustness check

To check for the robustness of our results, we randomly split our samples into half; the results from the two samples are consistent with the results from the full dataset. Also, adding or deleting variables does not change the direction of the

Fig. 4 The effect of marketing capability on customer browsing time

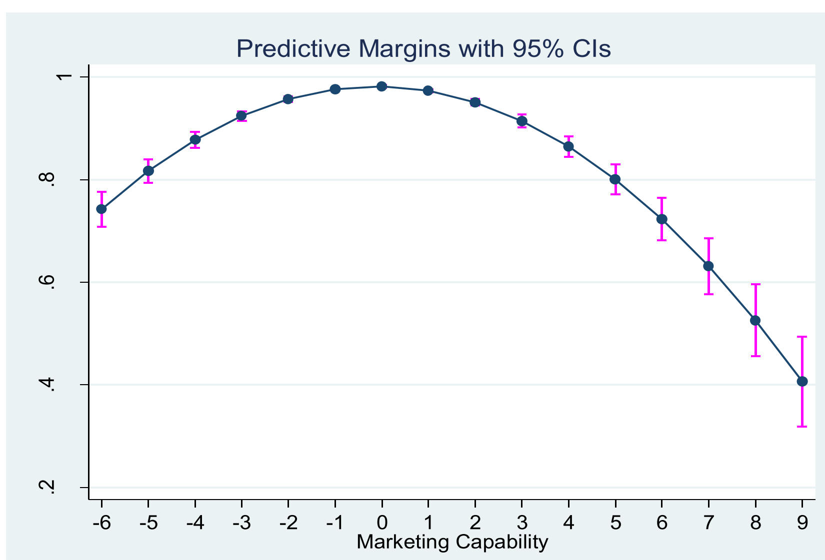
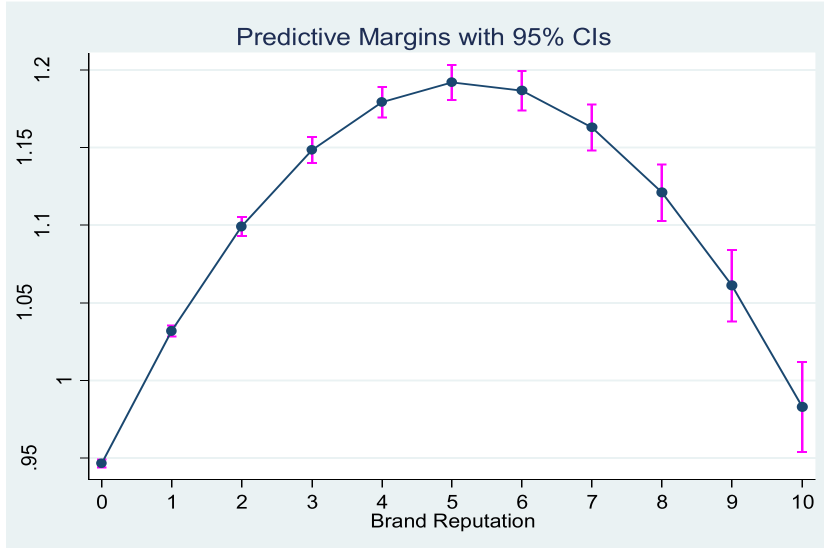


Fig. 5 The effect of brand reputation on customer browsing time



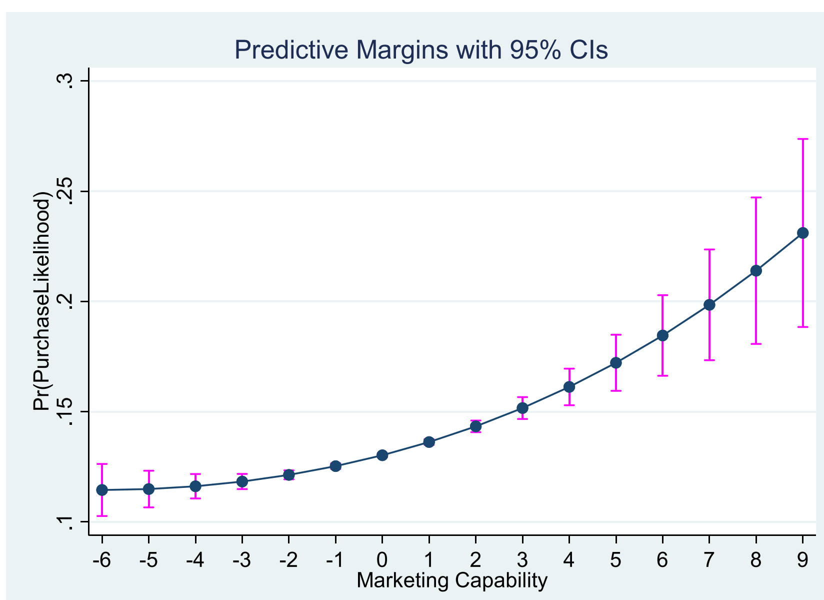
coefficients of the estimation. In order to mitigate the threat of omitted variables, we conduct a control function analysis. Appendix 2 presents the results of the control function approach and confirm the robustness of our main analysis.

Discussion

Theoretical implications

Our research has several theoretical implications. First, this study contributes to the literature on the impact of digital marketing activities and assets on firm performance (Moorman & Day, 2016; Perren & Kozinets, 2018; Ramaswamy & Ozcan, 2018; Swaminathan et al., 2020). Our results demonstrate the paramount importance of sellers' marketing capability on e-commerce platforms. Whereas extant research demonstrates the linear positive effect of marketing capability on outcome variables in offline settings (e.g., Dutta et al., 1999; Feng et al., 2017), the results from this study suggest marketing capability has increasing effects on customer clicks and purchases. Moreover, it is effective in reducing post-purchase consumer frustration. The findings suggest that firms with higher marketing capability would reduce the uncertainty and complexity of consumers' buying process. These can be especially important for higher-involvement product categories where consumers conduct extensive problem solving

Fig. 6 The effect of marketing capability on customer purchase



and rely on sellers' quality signals for confidence. The findings provide a new understanding of the marketing capability and illustrate the virtuous cycle of investing in marketing capabilities, where the capable sellers not only can obtain the lions' share of the buyers' attention and business, but are also well positioned for future buyers. Furthermore, we leverage the availability of consumer textual data to derive a user-generated content approach to seller marketing capability, which, in addition to having many benefits, map well with traditional approaches.

Second, our results reveal rather complicated relationships between brand reputation and consumer journey outcomes in the online environment. While some scholars highlight the importance of brand reputation in customer decision making in the online space (e.g., Batra & Keller, 2016), other commentators suggest that the online environment might erode the value of brands (Hollenbeck, 2018; Rosen & Simonson, 2014; Waldfogel & Chen, 2006). Our results reconcile these two views and suggest a more nuanced view of brand value in the online environment—strong brand reputation helps to reduce uncertainty to a certain extent, but it also sets up customer expectations, which can result in higher post-purchase frustration. Our results suggest that brand reputation increases click and purchase likelihood with diminishing effects, and that it has an inverted-U relationship with browsing time. However, a higher brand reputation makes consumers less frustrated initially but more frustrated when the brand reputation increases beyond a certain threshold. We believe that this U-shaped relationship between brand reputation and frustration takes place because consumers initially use brand reputation to resolve conflicts, but a high reputation sets up high expectations, and any service or product performance deviation from this high expectation is more likely to cause frustration. Therefore, one needs to be careful when balancing the opposing effect of brand reputation on e-commerce platforms, and that sellers of premium brands should especially devote attention to properly set up expectations and timely address customer issues to prevent frustration.

Third, it is worth noting that extant empirical marketing research has not looked much into customer frustration. However, we believe that understanding the strong negative emotion of customer frustration, especially in the information-rich online environment, is diagnostic of service issues and can guide firms to better engage with customers. Our research provides initial insight into this issue and demonstrates that prior customer frustration negatively affects current customers' buying behaviors. The results also offer factors leading to customer frustration. Traditionally, firms rely on customer interviews and surveys to identify factors associated with customer service so they can design better approaches for customer experience management. Our approach of extracting customer frustration illustrates that UGC, with its extensive rich textual content, can be a promising source from which to identify customer emotions and for designing optimal consumer experiences.

Managerial implications

Our research provides several managerial implications for sellers and brands in the platform environment. First, many senior executives still argue that the return on investment (ROI) from marketing is hard to assess (Delmulle et al., 2015). While businesses are able to provide anecdotal evidence or monitor key metrics to approximate digital marketing success, very few are able to directly link digital marketing with customer outcomes (CMO Survey, 2018). As a result, these companies choose to focus on tactical efforts that provide quick, visible results instead of building sustainable marketing capability. That is a mistake. Our results demonstrate that in the competitive e-commerce platform environment, marketing capability not only exhibits increasingly positive effects on purchases but also acts as a buffer against customer frustration. Marketing capability transforms customer experience and how sellers serve their customers (i.e., the traditional customer-supplier experiences can be significantly improved by the digital marketing capability). Our results suggest that firms should develop expertise in targeting stakeholders and communicate the importance of investing in digital marketing capability.

To illustrate the effect of marketing capability, holding the value of other variables at the mean, we show how marketing capability at ± 1 standard deviation (SD) and ± 2 SDs from the mean, as exhibited by the range of sellers in our data, affects customer journey outcomes. The results are reported in Table 4. For example, sellers with marketing capability 2SD above the mean can achieve 80% higher purchase likelihood (0.292 vs. 0.057) and 61% lower post-purchase frustration (0.035 vs. 0.089) than those with 2SD below the mean. This example shows the importance of marketing capability in promoting tangible business metrics such as increased consumer purchases and reduced customer frustration. Our findings show that enhanced digital marketing capability can benefit both firms and customers in terms of improved sales performance and improved shopping experiences, and can enable marketers to demonstrate the impact of increasing marketing capability investment to their more finance-oriented executives (Katsikeas et al., 2016).

Second, we demonstrate that although brand reputations might be diminished in the online environment, firms can still benefit from increased brand reputation on e-commerce platforms as it can still increase clicks and purchases. Table 5 illustrates the positive yet diminishing effect of brand reputation. We calculate different levels of brand reputation at ± 1SD and 2SD on customer journey outcomes while holding the value of other variables at the mean. For example, while 2SD above the mean in brand reputation can achieve a 15%

Table 4 Different levels of marketing capability on customer journey

Levels of marketing capability	Customer click	Customer browsing time	Customer purchase	Post-purchase customer frustration
−2 SD	.511	.902	.057	.089
−1 SD	.629	.958	.119	.083
Mean	.701	.939	.131	.069
+ 1 SD	.738	.718	.194	.061
+ 2 SD	.802	.415	.292	.035

higher customer purchase likelihood than brands with 2SD below the mean, the same comparison can increase post-purchase frustration by 44%. The results illustrate that while brand reputations are still useful on e-commerce platforms, they might asymmetrically set up high expectations, which may lead to post-purchase frustration. Sellers of premium brands should accordingly have a holistic view of brands that encompass both short-term (purchase) and long-term (frustration) effects of brands, and devote attention to setting up the right expectations and timely address issues to prevent frustration.

For brand owners, our findings suggest that sellers on e-commerce platforms may offer large discounts for branded products or communicate in a manner inconsistent with the brands' positioning. These misalignments between sellers and brands' goals are detrimental to brand image and value. The results suggest that brand owners should select distributors and e-tailers based on shared long-term vision, mandate enforceable channel contracts (e.g., retail price maintenance), and offer regular brand code training to maintain and improve brand equity. Otherwise, brand equity can quickly erode with various channel conflicts.

Finally, the Customer Rage Survey shows that more companies have customers experiencing frustration than they may think (Morgen, 2017). The survey also reports that when respondents have a problem with the product or service, 56% fall into the "rage" category of being very upset to extremely upset. In an online environment especially, the broadcasting ability of customer frustration puts businesses at risk in a vicious cycle. For example, we demonstrate that frustrating posts made by previous customers can negatively affect current customers' click and purchase likelihoods. However, that there are ways to prevent frustration. Our results suggest that firms can improve their marketing capability to reduce customer frustration. We also show that browsing time makes customers frustrated, suggesting that sellers and platforms should design their online product offerings with reducing customer browsing time in mind, in order to improve the buying experience and reduce frustration.

Limitations and future research

This research is subject to several limitations. First, due to the limitation that our data is non-panel at the customer level, we cannot capture customer dynamics. We were not able to collect more customer level variables and past behaviors in order to address micro issues such as learning. Our research is thus aimed at marketing strategy implications. Future studies with richer customer-panel data structures could offer additional insights into such micro behaviors. Second, we focused on the focal purchase of smartphones, which is a relatively high-involvement and infrequent purchase. Our model could be extended to the area of related products to examine how marketing capability and brand reputation affect cross-buying and repeat purchases.

Third, as typical in CRM datasets, our measures for marketing capability are based on existing customers, and we were unable to observe those consumers that the firm was unsuccessful in attracting, i.e., our data is censored. Thus,

Table 5 Different levels of brand reputation on customer journey

Levels of brand reputation	Customer click	Customer browsing time	Customer purchase	Post-purchase customer frustration
−2 SD	.665	.932	.121	.084
−1 SD	.683	1.125	.153	.081
Mean	.742	1.296	.197	.074
+ 1 SD	.696	1.415	.172	.096
+ 2 SD	.668	1.342	.139	.151

we were not able to evaluate the extent of lost customers on our measure of marketing capability, and can only logically infer that those sellers with lower observed capabilities and lower sales should also have higher numbers of lost customers. We believe that this data limitation should not pose a threat to the validity or generalizability of the construct, or to sellers' goal of fine-tuning their marketing practices. Future research can develop methods to evaluate the magnitude of censored customers on our results. Fourth, the current study only has data on a single dominant e-commerce platform, and we were unable to investigate the moderating role of platform characteristics in our analysis. Future research with data from multiple platforms can examine how platform characteristics can moderate our results. Lastly, as with most research on UGC and FGC, we analyzed text data. In online environments, text data, images, and sometimes video data co-exist. Future research can investigate how these data types work together to influence consumer journeys.

Appendix 1

Robustness tests for customer frustration

To test the robustness of our measure, we employed two approaches. First, we asked two research assistants to assess the degrees of customer frustration ("To what extent, do you think that the customer feels frustrated" on a scale of 1 to 7, 1 = "not at all," and 7 = "extremely" based on Patrick & Hagtvedt, 2011) for each of the 300 randomly selected comments. The inter-coder agreement is 0.83, and the averaged assessment from the two assistants has 0.86 correlation with our measures, suggesting that our continuous measure can robustly capture the degree of customer frustration for large scale data. We did similar tests for post-purchase customer frustration. Second, Kübler et al. (2020) show that the results of sentiment analyses for marketing models are prone to category effects. Consistent with their recommendations, we use an automated text analysis tool to quantify consumers' frustrated emotions (e.g., disappointed, frustrated). The Linguistic Inquiry and Word Count (LIWC) program provides the scale score of frustrated emotions using the LIWC2015 Dictionary, which contains a list of 6400 words, word stems, and selected emoticons (Pennebaker et al., 2015). The LIWC is an appropriate and robust tool for textual sentiment analysis, as it can accommodate numbers, punctuation, short phrases, and informal languages, and its internal reliability and external validity are well supported in the literature (Pennebaker et al., 2015; Tausczik & Pennebaker, 2010). The result from LIWC has a correlation of .85 with our approach.

Appendix 2

Robustness check for endogeneity

Although we use a large set of control variables and fixed effects to partial out alternative explanations, our analysis can be subject to endogeneity. For example, current marketing capability can be a function of sellers' current responses to competitors. Likewise, current brand reputation can be a function of brands' current marketing campaigns and spending. These unobserved factors potentially impact these independent variables as well as the current consumer journey. Therefore, omitting unobservable factors may result in endogeneity (e.g., Wooldridge, 2010). Accordingly, we use instrumental variables (IV) to account for the possibility that there may be unobserved factors affecting customer journey variables that may be correlated with marketing capability or brand reputation.

The current IV approach for two-stage least squares hinges on the system being linear in the parameters and variables. When they can be applied, IV methods can mitigate omitted variable bias, reverse causality, selection bias, and errors-in-variables in our efforts to estimate casual relationships using observational data. The question of identification in nonlinear models is complex and little can be said about global identification, although conditions for local identification sometimes yield useful insights. While numerous empirical and econometric studies explore the implications of parameter heterogeneity for IV estimation, very few studies focus on the implications of nonlinearity when the estimated model is assumed to be linear. However, in many applications in marketing, there is no particular reason to expect the true relationship to be linear. In our case, theory suggests models that are nonlinear rather than linear. Standard instrumental variable approaches for linear models, such as two-stage least squares, would provide inconsistent results for our nonlinear models (Abrevaya et al., 2010). Therefore, we employ a control function variable approach, which has been used in extant nonlinear marketing models (Jindal, 2020; Srinivasan et al., 2018).

The first step is to find valid instruments. For the instruments to be valid, they must meet the requirements of the relevance and exclusive restrictions. We use the percentage of focal seller's net marketing capability words (positive marketing capability words minus negative marketing capability words) scaled by the total number of customer review for focal seller six months prior to the actual observation period, and six-months brand social media reach prior to the actual observation on Facebook to instrument current brand reputation.

Our selection of instruments takes advantage of the sequential nature of the key variables (Wooldridge, 2010, 2015). This approach could apply to very old lags which would have no direct effects on current customer behaviors. Logically, using lagged marketing capability words alleviates the concern for sellers' current competitive response and strategic intent. Likewise, lagged social media reach alleviates the concerns for brands' current marketing campaigns and spending. These lagged variables are thus not prone to the current observed temporal shocks. However, they reflect the sellers' and brands abilities to address the marketing and competitive environment of the time, and thus are correlated with current marketing capability and brand reputations. Thus, our instruments satisfy the relevance criteria for instrument variables. As reported in Appendix Table 7, the coefficient estimates for the associated instruments in each of the first-stage regressions are significant (p < .001), indicating that the instruments are relevant.

In practice, older UGC is not salient on e-commerce platforms as customers seldom go through many pages of UGC to get to the old UGC. Given the fast-moving nature of e-commerce platforms (in social media time), sellers also are less likely to go through UGC of six months old to extract insights to improve their current marketing capability. Net marketing capability words derived from older UGC comments therefore have less influence on current customer behavior, and any possible influence of marketing capability derived from UGC will thus be reflected in the latest UGC. The same logic applies to the lagged brand social media reach. These practical considerations thus make our instruments ecologically valid. Thus, our instruments satisfy the exclusion restriction for instrument variables.

We estimate marketing capability and brand reputation as follows:

$$\begin{aligned} \mathit{Marketing\ capability}_{kt} = a_{0,} + a_1 * \frac{\Delta \mathit{Marketing\ capability\ words\ (six\ months\ prior\ to\ the\ observation\ period)}}{\mathit{Total\ number\ of\ customer\ review\ words\ (six\ mont\ priosr\ to\ the\ observation\ peroid)}} + \\ a_2 * \mathit{social\ media\ reach\ (six\ months\ prior\ to\ the\ observation\ peirod)} + \varphi * \mathrm{Exogenous} + \vartheta. \end{aligned} \tag{1}$$

$$\begin{aligned} \mathit{Brand\ reputation}_{jt} = b_{0,} + b_1 * \mathit{social\ media\ reach\ (six\ months\ prior\ to\ the\ observation\ period)} + \\ b_2 \frac{\Delta \mathit{Marketing\ capability\ words\ (six\ months\ prior\ to\ the\ observation\ peroid)}}{\mathit{Total\ number\ of\ customer\ review\ words\ (six\ months\ prior\ to\ the\ observation\ period)}} + \varphi * \mathrm{Exogenous} + \vartheta \end{aligned} \tag{2}$$

where φ is a vector of coefficients that captures the impact of the set of exogenous variables, Exogenous is the vector of exogenous variables including the control variables, and ϑ is the residue.

We tested whether the instrumental variables met the requirements of the relevance and exclusive restrictions. First, Cragg–Donald Wald F-statistics on our instrumental variables for each of the first stage equations demonstrates are all above the rule-of-thumb threshold of 10 (Staiger & Stock, 1997), with the lowest being 375.68 as indicated by Appendix Table 7. Therefore, the null hypothesis of weak instrument can be rejected, and our instruments satisfy the requirement for relevance (i.e., strongly correlated with the endogenous variables). Second, Sargan test (Sargan, 1958) for overidentification could not reject the null hypothesis that the focal instrument was uncorrelated with the error term in the second-stage equation as suggested by Appendix Table 7. These tests suggest the validity of the instrumental variables.

After estimating Eqs. (1) and (2), we corrected for endogeneity bias by entering the residual values into the model specified in Eqs. (3) and (4) described in our model specification section as additional covariates to test for the presence of endogeneity using the standard z-test, after bootstrapping the standard errors (Papies et al., 2017). Appendix 2 Table 6 presents the second stage estimation results and Table 7 presents the first stage results. The second stage regression results are consistent with our main analysis.

Table 6 Control function estimation results (Second stage results)

	Customer click	Customer browsing time	Customer purchase	Post-purchase customer frustration
Main Predictors				
Seller marketing capability	.015***	. 006***	.067***	−.003***
	(.002)	(.001)	(.004)	(.0002)
Seller Marketing capability^2	.004***	−.008***	.005***	−.006***
	(.001)	(.0003)	(.001)	(.0004)
Brand Reputation	.047*	.019*	.014*	−.089***
	(.018)	(.006)	(.006)	(0002)
Brand reputation^2	−.003***	−.004***	−.005**	.007***
	(.001)	(.0006)	(.002)	(.001)
Control Variables				
UGC positive		−.032***	.024	−.0007***
		(.004)	(.023)	(.0002)
UGC negative		−.005***	−.511***	−.00001
		(.0009)	(.008)	(.00003)
UGC neutral		1.875***	−.012	.002***
		(.008)	(.015)	(.0004)
FGC		.131***	.007**	.0005***
		(.002)	(.002)	(.00007)
Customer gender	−.187***	.011***	−.544***	−.017***
	(.005)	(.003)	(.012)	(.00008)
Customer tenure	.003*	.004***	.009***	.00001
	(.0007)	(.0002)	(.002)	(.00002)
Monthly visits	.016	.022	.013*	.016
	(.014)	(.017)	(.004)	(.015)
Prior customer frustration		−.218***	−1.179***	.143***
		(.041)	(.182)	(.025)
Customer browsing time			.009*	.0004*
			(.004)	(.00005)
Promotion	.009*	.006***	.043**	−.003***
	(.002)	(.001)	(.011)	(.0001)
Online advertising	.0005	.00002	−.004	.0005*
	(.002)	(.0004)	(.003)	(.00002)
Price	−.113***	−.051***	−.239***	.0006***
	(.011)	(.006)	(.021)	(.0001)
Seller quality				
2	−.171***	.022***	−.136***	.002***
	(.007)	(.004)	(.025)	(.0002)
3	.332***	−.021***	−.241***	.001***
	(.015)	(.002)	(.023)	(.0003)
4	.819***	−.288	6.835***	.007
	(.058)	(.181)	(1.162)	(.008)
Seller types				
Foreign seller	−.029*	.006	−.063	.0006*
	(.008)	(.010)	(.041)	(.0002)
Domestic firm seller	.016***	−.014***	−.006	−.00009
	(.006)	(.003)	(.015)	(.0002)
Domestic individual seller	.045*	−.003	.026	.0009*
	(.017)	(.008)	(.040)	(.0003)
Seller competition	.021***	.003***	−.010***	.005***
	(.002)	(.0004)	(.002)	(.00003)
Year (2018)	−.005	−.007***	−.039*	−.003***
	(.006)	(.001)	(.012)	(.00008)
Fall	.041***	.003	.026†	.015
	(.008)	(.004)	(.015)	(.009)

Table 6 (continued)

	Customer click	Customer browsing time	Customer purchase	Post-purchase customer frustration
Winter	.042*** (.007)	.011* (.004)	.036* (.011)	.007 (.006)
Summer	−.010 (.019)	−.004 (.006)	−.004 (.005)	−.006 (.004)
Holiday	−.004 (.006)	−.039*** (.004)	.071*** (.013)	−.0005*** (.00008)
Country of origin				
2	.872*** (.010)	−.017*** (.004)	−.585*** (.021)	.015*** (.003)
3	1.873*** (.027)	−.016*** (.004)	−.977*** (.036)	−.016*** (.004)
4	.149*** (.008)	.021*** (.003)	.121*** (.015)	.016*** (.004)
5	.809*** (.013)	.004 (.005)	−.389*** (.024)	.003 (.004)
6	1.713*** (.015)	−.015*** (.003)	−.726*** (.030)	.019*** (.003)
7	.006 (.012)	.011*** (.003)	.242*** (.025)	.014* (.004)
8	.659*** (.013)	.015*** (.004)	.237*** (.024)	.006*** (.0002)
9	1.421*** (.018)	−.003 (.005)	−.548*** (.027)	.029* (.011)
10	−.619*** (.017)	.027*** (.008)	−.397*** (.035)	.055*** (.008)
11	.259*** (.020)	.054*** (.007)	−.189*** (.034)	.007*** (.0002)
12	1.186*** (.022)	.021* (.006)	−.767*** (.041)	.018*** (.006)
Brand fixed effect	Yes	Yes	Yes	Yes
Seller fixed effect	Yes	Yes	Yes	Yes
Intercept	.373*** (.029)	.462*** (.019)	.992*** (.079)	.679*** (.015)
Model Properties				
Akaike's Information Criterion (AIC)	697,283.6	942,885.83	218,792.65	962,319.51
Bayesian Information Criterion (BIC)	705,262.7	954,829.62	223,847.25	9,687,513.36
Likelihood Ratio Chi-square	44,198.39		10,396	
Log-likelihood	−337,582.86		−107,682.35	
Pseudo R^2	.112		.318	
Classification Rate	.79		.85	
Area Under the Curve (AUC)	.81		.87	
F		929.85***		885.93 ***
R^2		.229		.198
Sample size	714,860	420,720	420,720	4113

1. Columns contain estimated coefficients and their associated standard errors (in parentheses)

2.†$p < .1$;*$p < .05$;**$p < .01$;***$p < .001$

3. For simplicity of presentation, we do not show brand coefficients in the table

Table 7 Control function estimation results (First stage results)

	Customer click equation		Customer browsing time equation		Customer purchase equation		Post-purchase customer frustration equation	
	Marketing capability	Brand reputation	Marketing capability	Brand reputation	Marketing capability	Brand reputation	Marketing capability	Brand reputation
IV for marketing capability	.016*** (.002)	. 021*** (.005)	.038*** (.007)	.011*** (.002)	.021*** (.006)	. 019*** (.004)	.049*** (.008)	.009*** (.0002)
IV for brand reputation	.002 (.002)	.031*** (.007)	.003 (.002)	.013*** (.0004)	.014 (.012)	.016*** (.003)	.003 (.005)	.013*** (.0008)
Customer gender	−.002 (.011)	.013 (.027)	.033 (.029)	.022 (.031)	.019 (.018)	.012 (.011)	.022 (.017)	.011 (.016)
Customer tenure	.011 (.013)	.009 (.011)	.011 (.015)	.0003 (.0004)	.004 (.011)	.002 (.003)	.011 (.008)	.0004 (.0006)
Monthly visits	.011 (.013)	.019 (.017)	.013 (.013)	.015 (.017)	.023 (.018)	.019 (.016)	.015 (.017)	.013 (.012)
Promotion	.011* (.002)	.015*** (.003)	.029** (.008)	.013*** (.004)	.016* (.003)	.015*** (.003)	.039** (.008)	.011*** (.0002)
Online advertising	.013*** (.002)	.002*** (.0003)	.008* (.003)	.004*** (.0003)	.017*** (.003)	.0005*** (.0001)	.007* (.003)	.0008* (.0001)
Price	.085*** (.009)	.131*** (.012)	.219*** (.017)	.023*** (.003)	.075*** (.011)	.051*** (.007)	.017*** (.005)	.0009* (.0003)
Seller quality								
2	−.119*** (.003)	−.024*** (.005)	−.107*** (.012)	−.015*** (.001)	−.102*** (.002)	.038*** (.004)	−.105*** (.021)	.013*** (.0007)
3	.285*** (.013)	.018*** (.003)	.219*** (.020)	.001*** (.0002)	.128*** (.013)	.092*** (.011)	.105*** (.013)	.106*** (.005)
4	.472*** (.038)	.219*** (.026)	.495*** (.016)	.018* (.006)	.315*** (.021)	.208*** (.015)	.301*** (.019)	.019*** (.004)
Foreign seller	−.019 (.008)	−.005 (.009)	−.036 (.052)	.016 (.042)	−.009 (.012)	.003 (.006)	−.017 (.023)	.0007 (.0004)
Domestic firm seller	.025*** (.006)	.017*** (.003)	.019* (.007)	.001 (.002)	.008 (.006)	.009 (.006)	.007 (.011)	−.002 (.015)
Domestic individual seller	.013 (.007)	.011 (.009)	.019 (.028)	.003 (.004)	.017 (.018)	.005 (.008)	.002 (.009)	.007 (.0003)
Seller competition	.015*** (.002)	.007*** (.0003)	.028*** (.004)	.009*** (.002)	.013*** (.002)	.009* (.003)	.011*** (.003)	.004*** (.00002)
Year (2018)	−.004 (.005)	−.005 (.007)	.021 (.018)	.014 (.016)	−.001 (.003)	−.003 (.005)	−.005 (.004)	−.002 (.0003)
Fall	.011 (.013)	.023 (.013)	.011 (.013)	.012 (.017)	.025 (.019)	.001 (.002)	.003 (.007)	.009 (.012)
Winter	.013 (.010)	.005 (.004)	.005 (.011)	.004 (.005)	.021 (.025)	.003 (.007)	.007 (.012)	.008 (.006)
Summer	−.005 (.016)	−.006 (.008)	−.006 (.009)	−.008 (.007)	−.013 (.009)	−.001 (.005)	−.001 (.005)	−.009 (.007)
Holiday	−.002 (.006)	.021 (.018)	.018 (.022)	.007 (.005)	−.012 (.007)	−.011 (.009)	.013 (.011)	.003 (.004)
Brand fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Seller fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	.253*** (.019)	.431*** (.025)	.835*** (.061)	.639*** (.021)	.385*** (.029)	.522*** (.029)	.851*** (.038)	.731*** (.019)
F	741.65***	939.79***	751.29 ***	895.63 ***	629.31***	817.25***	679.33***	871.45***
R^2	.108	.129	.115	.131	.116	.105	.117	.109
Cragg–Donald Wald F-statistics	382.78	396.04	495.72	375.68	435.69	651.38	433.19	569.88
Overidentification test	.158 (.231)	.175 (.273)	.253 (.209)	.247 (.615)	.192 (.580)	.199 (.351)	.295 (.425)	.282 (.641)

Table 7 (continued)

	Customer click equation		Customer browsing time equation		Customer purchase equation		Post-purchase customer frustration equation	
	Marketing capability	Brand reputation	Marketing capability	Brand reputation	Marketing capability	Brand reputation	Marketing capability	Brand reputation
Sample size	714,860	714,860	420,720	420,720	420,720	420,720	4113	4113

1. Columns contain estimated coefficients and their associated standard errors (in parentheses)

2.†$p < .1$;*$p < .05$;**$p < .01$;***$p < .001$

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