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Digital Analytics: Modeling for Insights and New Methods☆

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Abstract

Firms are increasingly turning towards new-age technologies such as artificial intelligence (AI), the internet of things (IoT), blockchain, and drones, among others, to assist in interacting with their customers. Further, with the prominence of personalization and customer engagement as the go-to customer management strategies, it is essential for firms to understand how to integrate new-age technologies into their existing practices to aid seamlessly in the generation of actionable insights. Towards this end, this study proposes an organizing framework to understand how firms can use digital analytics, within the changing technology landscape, to generate consumer insights. The proposed framework begins by recognizing the *forces* that are external to the firm then lead to the generation of specific *capabilities* by the firm. Further, the firms capabilities can lead to the generation of *insights for decision-making* that can be data-driven and/or analytics-driven. Finally, the proposed framework identifies the creation of *value-based outcomes* for firms and customers resulting from the insights generated. Additionally, we identify moderators that influence: (a) the impact of external forces on the development of firm capabilities, and (b) the creation of insights and subsequent firm outcomes. This study also identifies questions for future research that combines the inclusion of new-age technologies, generation of strategic insights, and the achievement of established firm outcomes.

Keywords: Digital analytics; Internet of things; Artificial intelligence; Drones; Blockchain; Firm capabilities

Introduction

Consider the case of credit scoring. This important financial activity has become one of the primary ways for financial institutions to assess credit risk, improve cash flow, reduce possible negative outcomes, and make managerial decisions (Huang, Chen, & Wang, 2007). In this regard, research has investigated the use of various statistical models and data mining tools such as linear discriminant models, logistic regression, decision trees, neural networks, and support vector machines, among others (Chen & Liu, 2004). Recent developments show the rise of artificial intelligence (AI) as a useful tool for credit analysis. For instance, ZestFinance, an AI developer for credit analysis, combines typical credit information (e.g., types of credit used, amount of debt, duration of credit history, etc.) with thousands of data points collected from consumers' offline and online activities. Using big data and machine learning techniques, they analyze a large volume of individual-level data to arrive at a final credit score (Hurley & Adebayo, 2017). The ZestFinance credit-scoring model considers how carefully a loan applicant reads the terms and conditions section (using cookies).

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According to the company, this was indicative of how serious the applicant was in taking a loan, and not just in a rush to get the money. Similarly, an applicant who moved residences was found to be risky (Lippert, 2014). More recently, this company has linked up with several companies such as Microsoft and Discover to create and deliver personalized financial technology (fintech) products. In addition to ZestFinance, the fintech industry is changing the face of the financial industry with several new companies and business models being launched (Hudson, 2018).

New approaches using digital analytics are not just limited to select industries but are emergent across a wide range of industries. For the purpose of this study, we refer digital analytics as the technology-enabled analyses of data and processes using new-age technologies (such as AI, machine learning (ML), internet of things (IoT), blockchain, drones, etc.) and other online and offline data sources to design and deliver continuous, one-on-one personalized engagement in real-time. In this regard, a broad consensus prevails among marketers on the importance of using data to drive marketing actions. Further, with the increased adoption of digital technologies in companies, the need for establishing meaningful differentiation among competitive offerings has become more pronounced. In a recent survey of chief marketing officers (CMOs) by the IBM Institute for Business Value, most respondents have expressed their inclination to focus on customer experiences rather than products (Baird, Dasgupta, Mooney, Schwartz, & Winans, 2018). The majority of CMOs conveyed the importance of developing a customer-focused culture in their respective organizations that can deliver personalized experiences as identified by data-driven analytics.

From the earlier discussed CMO survey and similar data-oriented initiatives in other industries, the emergent picture suggests that new technologies serve as the springboard to collect and (simultaneously) analyze pertinent data to create personalized offerings. This is different from an earlier period wherein the data were first collected, and then analyzed to gain insights. Currently, new technologies allow firms to derive superior insights from advancements in data and in analytics. Therefore, we distinguish between data-driven insights and analytics-driven insight and emphasize that synergies are achieved when newly developed analytical methods give access to previously unavailable and unique data sources. In other words, as technology evolves, firms are channeling new-age technologies towards customer-centric data that will then inform the creation of offerings that are most aligned with their customer's needs and preferences. Consider the earlier credit-scoring example. By developing a cookie mining algorithm, ZestFinance can collect data about the time spent on the terms and condition section and use it to calculate a credit score. Towards this end, this study proposes an organizing framework to understand how digital analytics, within the changing technology landscape, can be used to generate consumer insights.

Several frameworks reflect this increasing interest in data-driven analytics. Focusing on big data and marketing analytics, Wedel and Kannan (2016) discuss the evolution of the new data sources, data types, and analytical methods to leverage those data in support of marketing decisions. Big data revolution is already happening in retailing, as large amounts of data about customers, products, purchase channels, locations, and time are collected every day. Bradlow, Gangwar, Kopalle, and Voleti (2017) outline research opportunities whereby integrating multiple data sources leads not only to "bigger" but to "better" data and better models. Reinartz, Wiegand, and Imschloss (2019) show how digital transformation changed the role of institutional retailers in the customer purchase journey, which now involves multiple touchpoints and interactions with manufacturers, third parties, as well as online and stationary retailers. Further, Lamberton and Stephen (2016) point to the rising prominence of social media and mobile marketing (SMMM) in customer–firm communications and identify several promising future research themes. In contrast to above, this framework looks at digital analytics considering the influencing external forces, capabilities that firms need to develop, resulting insights for decision-making and outcomes related to value-creation.

This study is organized as follows. In the next section, we propose the organizing framework for understanding digital analytics. We begin the framework by identifying four motivational forces that operate in the current marketplace that impact technological progress in the firm–customer interaction context. We believe these four factors collectively influence the growth and usage of technologies, specifically new-age technologies such as AI and big data. Then, we identify how these factors influence the creation of customer insights through firm, customer, and environmental factors. The resultant outcome of customer insights is value creation for both firms and customers. Following the description of the framework, we identify future research questions that can spur future research.

An Organizing Framework for Understanding Digital Analytics

To develop an organizing framework for understanding digital analytics, we adopt a macro view by observing external influences that result in firm-wide changes and development of competencies (see Fig. 1, "Forces" and "Capabilities"). Further, we track how capabilities that firms develop (in response/anticipation to external forces) can benefit them in generating insights for decision-making that subsequently results in value-creating firm outcomes (Fig. 1, "Insights for decision-making" and "Outcomes"). Additionally, we identify moderators that: (a) influence the impact of external forces on the development of firm capabilities, and (b) influence the creation of insights and subsequent firm outcomes (Fig. 1, "Moderating conditions" and "New innovative methods").

Forces

We explain the following four major marketplace forces that provide the context, constraints, and opportunities to efficiently integrate AI and big data technologies in firm–customer interactions: (a) technological evolution, (b) firms' shift from traditional to digital media, (c) consumers' preferences for digital media, and (d) data privacy and security.

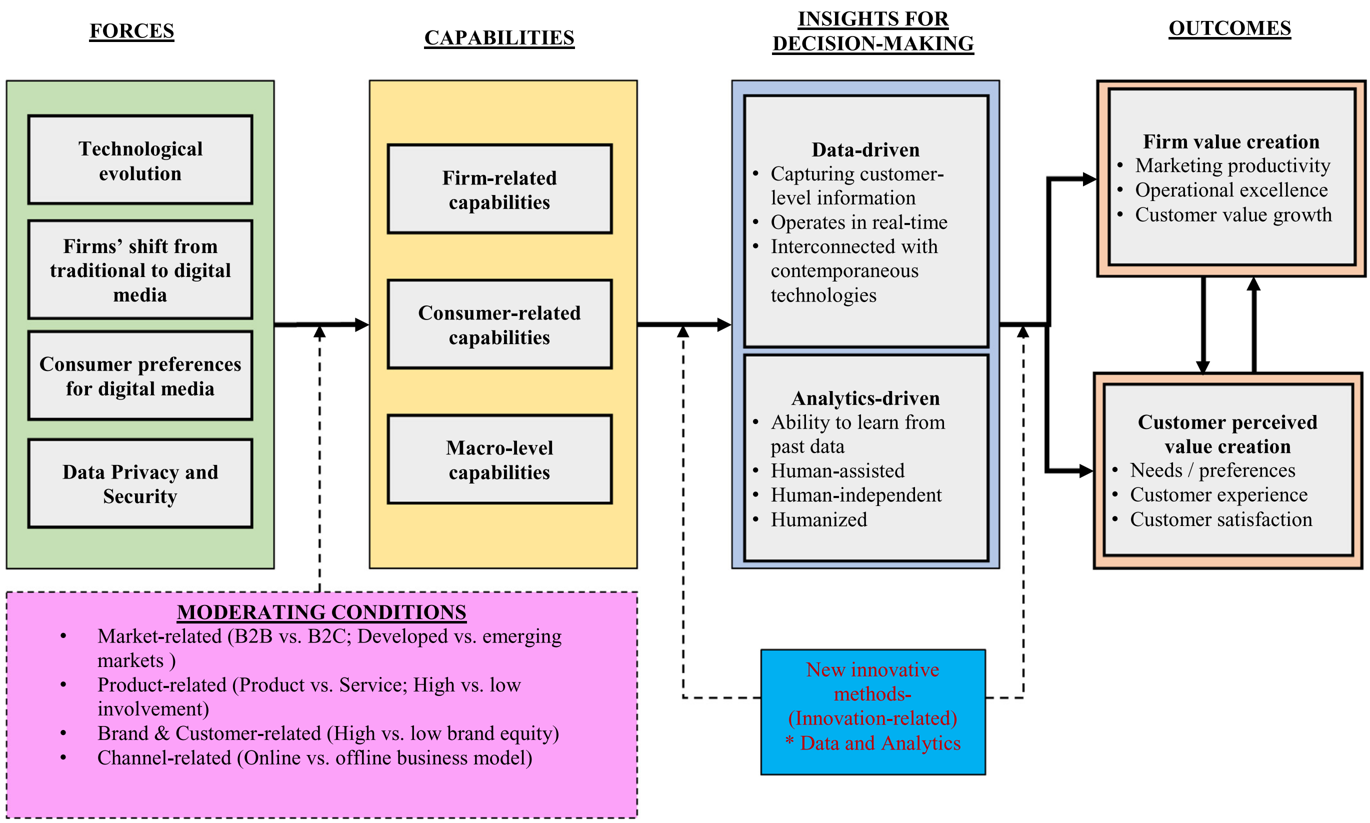

Fig. 1. Understanding digital analytics: An organizing framework.

Technological Evolution

The World Economic Forum defines the current industrial stage as a Fourth technological revolution, also named Industry 4.0. Characterized by a "fusion of technologies," this "revolution is blurring the lines between the physical, digital, and biological spheres" including business contexts.[1] The adoption, usage, and diffusion of new-age technologies by the businesses contribute to enhanced firm–customer interactions. Two key characteristics of this evolution are technology diffusion and marketplace disruption.

Technology diffusion

New-age technologies such as big data, AI, drones, and robotics effortlessly diffuse across industries and markets.[2] For example, drone technology exhibiting its significant benefits in form of effective monitoring, building vast communication networks, and delivering goods, and is affecting not only just technology companies but all the industries such as agriculture, retail, construction, transportation, security in a big way (Floreano & Wood, 2015). Another example of pervasive penetration of new technologies refers to AI and big data that have become the universal driver of business productivity and success across markets and industries. Research from McKinsey lists four ways that AI can improve efficiency and create value (Bughin et al., 2017). These four ways amount to: (a) project enlightened R&D, real-time forecasting, and smart sourcing; (b) higher productivity, lower cost, and better efficiency of operations; (c) promotion of products and services at the right price, with the right message, and to the right targets; and (d) providing enriched, tailored, and convenient user experience. This suggests that "firms that combine strong digital capability, robust AI adoption, and a proactive AI strategy see outsize financial performance" (Bughin et al., 2017; p. 20).

Marketplace Disruptions

Recent digital technologies serve as catalysts for innovations, thereby increasing their speed and expanding scope. The digital setting enables experimentation opportunities for firms, firmly entrenching the digital approach as the core of innovations, and realizing outcomes that are vivid, fast, and reliable for the firm. Now firms can develop products and test marketing hypotheses based on the evidence from their customer responses. Companies like Uber use elaborate experimentation platforms for product testing, sometimes conducting 1,000+ field experiments simultaneously.[3]

[1] https://www.weforum.org/agenda/2016/01/the-fourth-industrial-revolution-what-it-means-and-how-to-respond/

[2] https://www.wsj.com/articles/every-company-is-now-a-tech-company-1543901207

[3] https://eng.uber.com/xp/

In addition to enabling product and service innovations, cutting-edge technologies create business model innovations that subsequently bring even higher value to a company's success.[4] These technology-enabled business models can be classified in four broad categories: e-commerce, digital platforms, models that turn data into assets, and automation-enabled services (Johnson, 2018). Their separate or joint introduction to the market allows firms to match demand and supply with value-generating outcomes. Airbnb and Amazon are examples of companies that have disrupted industries with new technology-based business models.

Firms' Shift from Traditional to Digital Media

Firms' increasing spend on digital ads and e-commerce dynamics are worthy of research attention. In 2019, digital ad spending in the U.S. was forecast at 129 billion USD, exceeding traditional ad spending for the first time.[5] For the last five years, worldwide B2C e-commerce shows three times growth and strives for 3.5 trillion USD in 2019, which accounts for more than 12% of global sales. Moreover, more than 40% of internet users made at least one purchase on the internet, which equates to more than 1 billion people around the globe.[6] This tremendous shift from traditional to digital media in the market place reflects on two major factors: the changing nature of firm–customer interactions and the economics of communication.

Changing Nature of Firm–Customer Interactions

From the outset of information search stage, users are provided with the most relevant results for their query by firms. The Nielsen Global Connected Commerce survey[7] suggested that searching for product information, checking/comparison of prices, and looking for deals/promotions/coupons are the most popular activities of internet shoppers. Likewise, in another survey by Burke,[8] it was found that nearly 80% of internet users utilize search engines as the top medium to search for offline local products and services. At the information search stage, search engines, social media, and geo-location services are powered by big data and machine-learning algorithms to provide the precise information customers are seeking for.

Integrating new-age technologies allows firms to influence customer behavior during the purchase stage. In an online setting, recommendation systems significantly influence consumer decision/choice and willingness to pay (Adomavicius, Bockstedt, Curley, & Zhang, 2017). Similar outcomes have been observed in offline settings also. For instance, Mystore-E, a Tel Aviv-based clothing store, has designed their stores to mimic the experience of a website within a store (Windyka, 2018). Using digital displays and augmented reality, customers can virtually try on products. With AI capabilities, employees then receive notifications that match customers' choices to provide highly personalized and curated offerings. Such initiatives provide customers and firms the ability to respond immediately to communication messages initiated by either party.

At the post-purchase stage, AI helps to automate communications and effectively collect feedback. Zendesk,[9] in the segment of customer support and communications, determines how AI enables the efficiency of its service by providing “smart” self-service experience, customized content to customers, automation of suggestions, and data-driven customer experience improvement to increase quality and speed of services, and improve customers' satisfaction.

A key aspect of the changing nature of firm–customer interaction across all stages is observed in the personalization of content and offerings. A recent Harvard Business Review survey of 600+ business executives emphasizes that personalization has become a critical factor to improve business performance.[10] More than half of the respondents mentioned that personalization significantly contributes to the revenue growth and 81% of them expect this trend to continue. Moreover, providing a personalized customer experience has been reported as a top application of machine learning in the current business environment.[11] Further, recent research in new-age technologies aim to support and automate most of the marketing decisions to fulfill specific customers' needs and expectations in addition to allowing firms to provide personalized experiences to consumers (e.g., Kopalle, Kumar, & Subramaniam, 2020; Kumar, Rajan, Gupta, & Pozza, 2019; Gupta, Kumar, & Karam, 2019; Kumar, Ramachandran, & Kumar, 2020).

Economics of Communication

According to Statista Report (2017), around 2.7 billion people use smartphones worldwide and the number continues to grow by 10% annually.[12] The lower-priced devices integrated with wireless expansion and 3G/4G/LTE coverage equips consumers with 24/7 internet connection at a reasonable cost. At the same time, investments in developing apps and transaction costs of functional apps (e.g., WhatsApp in communications) are also decreasing significantly. Thus, the swift transmission of relevant information forces and enables firms to act appropriately in a timely and fiscally responsible manner (Tiago & Veríssimo, 2014). For instance, using big

[4] https://blogs.wsj.com/cio/2018/11/02/its-all-about-business-model-innovation-not-new-technology/

[5] https://www.emarketer.com/content/us-digital-ad-spending-will-surpass-traditional-in-2019

[6] https://www.statista.com/statistics/261245/b2c-e-commerce-sales-worldwide/

[7] https://www.nielsen.com/us/en/insights/report/2016/global-connected-commerce/

[8] https://www.emarketer.com/Article/Most-Internet-Users-Prefer-Search-Engines-Find-Local-Products/1015737

[9] https://www.zendesk.com/blog/artificial-intelligence-customer-experience/

[10] *The Age of Personalization: Crafting a Finer Edge*. (2018). *Harvard Business Review Analytic Services*.

[11] Artificial Intelligence: The End of the Beginning. (2018). Harvard Business Review Analytic Services. https://doi.org/10.3167/armw.2013.010103

[12] https://www.statista.com/statistics/330695/number-of-smartphone-users-worldwide/

data, AskRail (a mobile app) helps firefighters and other first responders get instant access to critical and real-time scene assessment data to save lives in the event of accidents (Violino, 2018).

Consumer Preferences for Digital Media

As firms turn to digital media, so do consumers. The three principal reasons behind this drift include: solution orientation, social networking, and generational factor.

Solution Orientation

The digital age conditions customers to relentlessly look for memorable experiences with the firm/brand they are with or want to associate (Kumar, 2018). Compared to traditional media, digital media puts the consumer at center of communication exchanges. Apart from the benefit of integrating multiple channels, media options, and devices, the customer focus enables firms to offer a solutions-focused approach to marketing messages. It shortens customers' purchase journey and makes it more efficient and convenient. Customers also like their options to be narrowed down and curated to fulfill their specific needs. For instance, in a B2C context, ski-equipment retailer Black Diamond realized the value of using AI for personalized engagement.[13] Skiers often do not know exactly what kind of equipment they need to remain competitive and safe. Using AI, Black Diamond predicts skiers' needs and proactively suggests the right products to its e-store visitors, rather than waiting till shoppers submit the order.

Solution orientation is further critical in the B2B context. A survey conducted by Salesforce (CRM tool) across 6,700 business buyers reveals two top expectations towards their suppliers:[14] (a) contractors should deeply understand the focal firm's products and processes, and (b) contractors need to provide contextualized engagement based on earlier interactions and needs. To meet such expectations, Salesforce utilizes AI technology (called Einstein) and machine-learning algorithms to analyze customer conversations in real-time. The software then immediately alerts the managers, giving them an opportunity to enhance customer experience, to introduce new solution to customers problems, and cross-sell or up-sell.

Social Networking

The fascinating diffusion of social networks worldwide invigorates consumers' preference for digital media. In 2018, around 2.65 billion people operated an account in at least one social network, spending more than two hours per day.[15] Joinson (2008) identifies seven unique motivations and gratifications that Facebook users experience, such as social connection, shared identities, content, social investigation, social network surfing, and status updating. Based on a recent study among 3,665 U.S. respondents, Hubspot (a marketing automation platform) classifies users' motivations for employing social media channels into five distinct categories: [16] bridging, bonding, communicating, discovering, and taking actions which differs across platforms. YouTube, for example, is an appropriate place for discovering new content but provides fewer opportunities in bonding and communication. In contrast, Instagram works well for bonding but less so for discovering new content. Therefore, understanding consumers' motivations to choose a social media platform, as well as their activity on it, can help companies create a social media strategy by targeting the right segment, on the right outlet, and with the right content. Although social media have the potential to increase the efficiency of communication strategies, they also make firms more dependent on consumers. The network-based power owned by consumers allows them to influence the marketplace through the distribution, remixing, and enhancement of digital content (Labrecque, Esche, Mathwick, Novak, & Hofacker, 2013).

Generational Factors

Among the users of digital devices, the consumption of technology by younger consumers is high. From a coverage perspective, for instance, a 2018 Pew Internet research shows that 88% of U.S. adults between 18 and 29 years use some form of social media, the most among all age groups (Smith & Anderson, 2018).[17] Additionally, millennials score high in technology usage with nearly 92% of them owning smartphones in 2018, compared to 85% of Gen Xers (ages 38–53), 67% of Baby Boomers (ages 54–72) and 30% of the Silent Generation (ages 73–90) (Jiang, 2018). From a usage intensity perspective, younger generations (tweens: ages 8–12 and teens: ages 13–18) consume entertaining media between 6 and 9 hours per day, respectively, including the most popular formats like online videos, mobile gaming, and social media. Moreover, mobile devices account for 41% of their screen time. These demographic changes in media consumption enforces companies to adjust their digital marketing capabilities and strategies to acquire new customers and brand adopters during their early ages.

Data Privacy and Security

Customer-level personal information has become a valuable currency for firms as it provides an opportunity to personalize their marketing offerings and bring better one-to-one relationships with customers, thus increasing their satisfaction and loyalty (Huang & Rust, 2017). But this positive effect is highly intertwined with customers' concern for the security of their personal information (Malhotra, Kim, & Agarwal, 2004). Customers' negative perception about data collection, storage, and the high probability of misuse of their data may adversely affect their privacy concerns (Beke, Eggers, & Verhoef, 2018; Smith, Milberg, & Burke, 1996). New-age technologies

[13] https://www.pointillist.com/blog/role-of-ai-in-customer-experience/

[14] Trends in Customer Trust. The future of personalization, data, and privacy in the Fourth Industrial Revolution. Salesforce Columbus 2018.

[15] https://www.statista.com/topics/1164/social-networks/

[16] https://blog.hubspot.com/news-trends/social-media-framework

[17] https://www.commonsensemedia.org/about-us/news/press-releases/landmark-report-us-teens-use-an-average-of-nine-hours-of-media-per-day

introduce three “new” problems for consumer privacy: (a) firms are increasingly informed about future customer buying patterns using their focal transaction data; (b) firms may not fully internalize the potential harms to the customers due to the inability to trace the source of data; and (c) firms may promise a consumer-friendly data policy at the time of data collection but renege afterwards because it is difficult to detect and penalize it after the fact (Jin, 2019). In this situation, customers may choose to manipulate their personal information by using careful privacy calculus (weighing the costs and benefits from private information disclosure) to prevent identity theft threats or inappropriate data usage (Dinev & Hart, 2006; Mothersbaugh, Foxx, Beatty, & Wang, 2012). Beke et al. (2018) summarize that firm, consumer, and environmental characteristics influence the balance of consumer privacy calculus and should be considered when firms elaborate their privacy practices.

As firms increasingly collect numerous individual-level data points, including private data, the threat of security breaches intensifies. In 2016, U.S. firms and government agencies suffered over 1,000 security breaches, an increase of 40% compared to the year before (Kharif, 2017). It affects both small and large companies, e.g., in period 2011–2017, Yahoo was under several data attacks affecting billions of users' accounts.[18] Martin, Borah, and Palmatier (2017) show that such incidents negatively affect consumers' attitudes and companies' financial outcomes. Transparency and control in firms' data management practices can reduce the vulnerability of customer data.

Capabilities

The evolving forces in the environment serve as a positive force in making all the concerned stakeholders build required capabilities to adequately prepare them for responding to the future challenges and be future-ready. We identify these capabilities as: (a) firm-related capabilities, (b) consumer-related capabilities, and (c) macro-level capabilities. Fostering these capabilities are critical for any future-focused firms to own competitive advantage and make the best decision in the environment of future uncertainty. Research has recognized that future-focused firms need to adopt technologies to build capabilities and manage future needs (Kopalle et al., 2020; Srinivasan, Lilien, & Rangaswamy, 2002). Next, we discuss each capability in detail.

Firm-Related Capabilities

To address the emerging environmental forces, firms must build the required capabilities for a sustainable future. Firm capabilities are defined as a “complex bundle of skills and accumulated knowledge that enables firms to coordinate activities and make use of their assets,” (Day, 1994) that boosts the productivity of other resources. Firm capabilities can also be viewed as integration, building, and reconfiguration of the internal and external resources to build a sustainable competitive advantage (Teece, Pisano, & Shuen, 1997, p. 516). However, it is the firm who decides the way it wants to respond to the given technological evolutions, and behavioral shifts at the firm' and customers' end. The importance of firm capabilities was appropriately captured by a recent Bain survey of 325 multinational companies (MNCs). This survey found that 59% of those organizations believe they lack the capabilities to generate meaningful business insights from their data.[19] In another Bain survey of 250 MNCs, 85% said they require substantial investments to update their existing data platform, which includes consolidating and cleaning data, simplifying access and rights management, and improving access to external data sources.[20]

In this study, we suggest that acquiring four capabilities—technology, marketing, human resources, and firm agility—can provide firms a head start towards the path of accomplishing the required competitive edge. Technological capabilities encompass the firm's extent of responding to the need of updating/upgrading technological infrastructure. Marketing capabilities comprise of the firm's ability to respond to the market forces with their accumulated market-based knowledge. Human resource capabilities provide resilience and strength to firms in responding to the unpredictable market forces. Finally, firm agility deals with the firm's operational swiftness in its processes and procedures in responding to external changes. Next, we discuss all these required capabilities in detail.

Technological Capabilities

This refers to a firm's capacity to acquire and build the necessary technological eco-system and infrastructure that is in sync with the existing firm capabilities, in order to improvise the existing offerings or develop a new one to swiftly responding to the marketplace shifts and evolving consumer preferences (Moorman & Slotegraaf, 1999). A firm's capability to absorb a new set of knowledge mainly depends on its existing processes and knowledge base (Saboo, Sharma, Chakravarty, & Kumar, 2017). Therefore, it is critical for a firm to regularly audit their existing knowledge and infrastructure base and then initiate the creation. Furthermore, the emergence of various digital platforms compels firms to audit and develop their technological capabilities in the form of updated technological infrastructure such as hardware, software, and service integration. The robust technological infrastructure enhances customer–firm interactions, thereby enriching the firm with comprehensive customer level data in real-time and engaging the use of new-age technologies in an effort to generate greater firm and customer value.[21]

[18] https://www.statista.com/statistics/290525/cyber-crime-biggest-online-data-breaches-worldwide/

[19] https://www.bain.com/insights/most-cios-dont-think-their-companies-can-handle-big-data-forbes/

[20] https://www.bain.com/insights/most-cios-dont-think-their-companies-can-handle-big-data-forbes/

[21] https://www.forbes.com/sites/forbescommunicationscouncil/2019/06/20/is-ai-ready-to-transform-the-marketing-industry/#3dab9e8a2d1d

Marketing Capabilities

Based on the firm capability theory, a firm that best utilizes its accumulated knowledge over time gains a sustainable competitive advantage (Barney, 1986). This organizational learning theory indicates that a firm can improve its marketing capabilities via two basic “adaptive processes,” i.e., exploitation and exploration. Also, organizational learning theory suggests marketing exploration and marketing exploitation as two ways in which firms can enhance its market knowledge and respond to the available external environmental forces (Kyriakopoulos & Moorman, 2004).

Market exploitation refers to a firm's capability of improving and refining its existing skills, processes, procedures, and marketing capabilities and consequently ability to produce desired valued outcomes. Market knowledge acquired via marketing exploitation capabilities is mostly consumed to incrementally alter the existing marketing-related capabilities to achieve improved outcomes concerning all stakeholders (Levinthal & March, 1993; Slater & Narver, 1995). Market exploitation best applies to a situation where incremental innovation is sought (Vorhies, Orr, & Bush, 2011) with minimum disruption to existing processes and provides quick efficient output. This approach provides an opportunity to continue modifications and iterations of marketing capabilities until the desired downstream output is received.

Market exploration is useful when basic assumptions and fundamentals related to customers and competitors are fast changing and the ability to respond to a dynamic market and environmental variations becomes a unique capability (Slater & Narver, 1995). A firm with high explorative capabilities can better avoid missed-out market opportunities and can act upon them ahead of its competitors. Explorative marketing capabilities prepare a firm to deal with future uncertainties and build its learning curve to best utilize its existing market-based resources (Vorhies et al., 2011). However, firms achieving a balance between both types of capabilities are more resilient in the long run.

The prominence of new-age technologies has encouraged firms to build a newer set of capabilities by investing in research and development and building a new set of firm knowledge capital that eventually bodes well for the exploitation of existing marketing capabilities. Whereas new-age high-tech firms like Google and Facebook originally grounded in the digital world focus more on exploration strategies, legacy firms tend more to exploitation. In disrupting the marketplace, this conjuncture threatens the latter to fail in competition. As a counter strategy, it is recommended that legacy firms adopt a digital ecosystem based on digital customer orientation (Kopalle et al., 2020).

Human Resource Capabilities

The organizational capability theory refers to “the ability of an organization to perform a coordinated set of tasks, utilizing organizational resources, for the purpose of achieving a particular end result” (Helfat & Peteraf, 2003). Relatedly, the adaptive structuration theory (AST) describes the role of social structures, rules, and resources facilitated by technologies and institutions as the fundamental for human activity in the firm (DeSanctis & Poole, 1994). The AST explains the interplay between advanced technologies, social structures' and human interactions.

With the emergence of digitization and new-age technology in businesses, firms need to develop the most critical resource (i.e., human resource). Until employees are prepared to deal with entrusted environmental forces such as changing nature of firm–customer interactions, it will be challenging for a firm to create sustainable value for itself and its customers. Employees exhibiting a high level of adaptability and flexibility are more likely to empower the firm to be ready for the future uncertainties. Such empowered firms would tend to be solution-oriented and better equipped to respond to social media dynamic, and technological and marketplace disruptions.

Firm Agility

Agility refers to the dynamic capability of the firm to recognize and respond swiftly to the external forces (Ghasemaghaei, Hassanein, & Turel, 2017). Hyper-competitiveness brought about by the availability of new-age technologies, big data, and consumers preferences to go digital have placed agility among firms' strategic capabilities (Chakravarty, Grewal, & Sambamurthy, 2013; Roberts & Grover, 2012). Agile firms can better extract value from the available external forces and turn threats into valuable opportunities. Grounded in the resource-based view, dynamic capability theory (DCT) suggests that to achieve congruence with the fast-changing environment, firms should develop the capability to renew its competence. In the context of digitization and data analytics, it is suggested that when adopting DCT, firms should analyze and leverage its IT capabilities to enhance its agility. Additionally, it is expected that firms that can effectively collect, synthesis, and analyze huge volume data by adopting powerful analytical tools would be in a better situation to make critical decisions in a timely manner (Brynjolfsson & McAfee, 2012; Gillon, Brynjolfsson, Griffin, Gupta, & Mithas, 2012).

Consumer-Related Capabilities

In the wake of digitization and the presence of social media and big data, not just firms but consumers too have to enhance their capabilities to absorb the tremor of these transformative forces. Rooted in the Theory of Reasoned Action (TRA) (Ajzen & Fishbein, 1988), the Technology Acceptance Model (TAM) explains that individuals are prepared to accept the technology when they perceive that the new structure will bring about better performance while expending less efforts. Under such state, consumers express the willingness to equip themselves with the desired capability in the form of learning and working on new technology platforms. Further, TAM suggests that at large, the degree of consumers' acceptance and readiness for new technology affects their intention to adopt new technology, which is mediated by the perceived usefulness and perceived ease of use of the given technology.

At the same time, technology readiness index (TRI), which measures people's general beliefs about technology, proposes four dimensions, (i.e. optimism, innovativeness, discomfort, and insecurity) in explaining individuals' propensity to embrace and use new technologies to accomplish their desired goals (Lin, Shih, & Sher, 2007; Parasuraman, 2000). Optimism exhibits the positive attitude towards technology indicating increased control, efficiency, and flexibility. Innovativeness refers to the sense of being pioneered to adopt the new. Discomfort relates to the migration uneasiness from inertia. Insecurity is the feeling of distrust and skepticism towards new technology and its application. However, TAM is a more system-focused approach. Research suggests a correlation between an individual's technology readiness and their propensity to engage with the technology (Parasuraman, 2000).

Though TAM and TRI suggest that individuals' acceptance and readiness for technology is contingent upon their beliefs and attitude, individuals develop capabilities in response to the external forces. For example, during the 2016 demonetization in India, e-wallet platforms emerged as a rescue; however, it was initially available only to a limited number of users with internet access, a smartphone, and an online bank account. The financial survival of individuals, especially in the low-income segment, was depended on their ability to promptly develop new technological skills and accept the e-wallet as a new payment method. Therefore, given that the major forces evolving from digitization enforce dynamism in all the spaces, consumers often express the need for productive solutions that also provide value.

Macro-Level Capabilities

Some core capacity building blocks of skills and resources need to be in place at a macro-level, i.e., the ecosystem where the firm is operating. The capability of any nation can be classified in three interlinked categories: physical investment, human capital, and technological effort (Lall, 1992). *Physical investment* capability refers to the availability of the financial resources, plant, and equipment for any industry to exist in the given ecosystem. *Human capital* refers to the skillset of the individuals generated by formal education and training, on-the-job training, and experience of technological activity and the legacy of inherited skills, attitudes, and abilities that aid to the nation's development. Literacy and primary education are basic requirements for an efficient industrialization dealing with simple technologies (McMahon, 1987). However, advanced and specialized skills are required for the adoption and diffusion of sophisticated technologies. The larger the gap between the learned skills and skills that are required to use new technologies, the slower the society's response to environmental changes. National *technological effort* includes the production, design, and research work to facilitate firms working knowledge, it also comprises technological infrastructure that delivers basic scientific knowledge and various facilities such as data storage and retrieval, encouragement of in-country innovation, their patent and copyright guidelines and control. Briefly, technology effort at the national level comprises of capabilities that are generally too significant to be possessed by private firms. Apart from building in-country technological capabilities, the extent to which a country depends on foreign technologies also influences the nation's technological capabilities.

The exclusive contribution of any one of these macro-level capabilities is usually challenging to measure (Nelson, 1981). An appropriate sync between all three capabilities is required to respond to the external forces and to achieve an efficient output. For example, trained and skilled human capital and physical capital would be fully productive only when combined with relevant technology efforts.

Insights for Decision-Making

Advances in data availability and in analytics both have the potential to generate superior insights for decision-makers. Hence, new customer insights can be based (primarily) on data-driven or analytics-driven advancements. However, these two types of advancements are not necessarily on opposing ends but oftentimes positive synergies can be observed. For example, as discussed in the Introduction, the credit analysis by ZestFinance is based on a broad and new set of data (data-driven) and modern AI analysis techniques (analytics-driven). In the following two subsections, we discuss data-driven and analytics-driven advancements with a focus on possible synergies, wherever applicable.

Data-Driven

Firms with strong data capabilities enjoy the competitive advantage, thus increasing the amounts of data collected about the market, the customer, and purchase and communications channels. Furthermore, thanks to social media, customers voluntarily share their opinions about products, service received, and personal data. As a result, multiple data sources can be integrated to uncover the information about the consumer at the individual level. Furthermore, even with stronger privacy regulations and customers' growing need for data protection, the anonymized and fragmented event data sources can be can be merged and approximate individual-level heterogeneity (Kakatkar & Spann, 2019). While new and unique data sources are uncovered and mined for intelligence, the systematic data collection processes efficiently gather and analyze the data for real-time insights. Data-driven insights are interconnected with contemporaneous technologies, so that the marketing instruments become increasingly context specific, and firms can reach the right individual customer with the right message, through the right channel, at the right time and location.

Capturing Customer Level Information

Automation and learning aspects of AI-based algorithms give an undisputed potential for this technology to handle vast amounts of customer-level information (Libai et al., 2020). For example, recommender systems, which allow for consumer targeting with individualized content, are widely accepted by firms and customers alike. Ansari, Essegaier, and Kohli (2000) review different types and methods used in online personalized recommendation systems, which are commonly used by Netflix, Amazon, and many others. They propose a method that combines customers' stated preferences, preferences of other customers, expert evaluations, product attributes, and individual characteristics.

The personalized marketing concept presents the conceptualization of customers' response to technology-enabled devices (Kumar, Rajan, Gupta, & Pozza, 2019). Specifically, the study establishes that AI enables firms to interact with customers in a personalized way and in real-time. Thus, favorable attitudes towards technology-enhanced connections lead to the higher feeling of connectedness between customers and the firm, and ultimately engagement. Further, Summers, Smith, and Reczek (2016) focus on customers' response to online advertising that is person specific. Behaviorally targeted ads are unique to each customer since they are created based on their online behavior, such as search or purchase. The authors propose that behaviorally targeted advertising act as implied social labels. When customers know they see a behaviorally targeted ad, their self-perceptions adapt to match the implied label, which then impacts their purchase intentions and other behaviors towards the advertised product.

Operates in Real-Time

New smart technologies allow firms and customers to be connected 24/7/365. Therefore, firms put in place systems of real-time tracking and automated response without human agents, which lead to additional data-driven opportunities. For example, a negative comment posted online can go viral and damage a firm's reputation and undercut customers' trust. To prevent potential firestorms and to mitigate ongoing ones, firms need to monitor closely their online brand communities and respond quickly and fittingly to each negative message (Herhausen, Ludwig, Grewal, Wulf, & Schoegel, 2019). An automatized text analysis of comments posted on Facebook brand communities can be used to predict which messages are more likely to go viral and suggest actionable strategies to engage with and disengage from complaining customers. Furthermore, AI algorithms can be used to automate the process of handling customer complaints in real-time during the interactions between a customer and a customer service agent (Galitsky & De La Rosa, 2011).

Interconnected with Contemporaneous Technologies

Technology facilitates the connections between people, objects, and the physical world (POP framework), and it also intensifies the interactions between them (Verhoef et al., 2017). In response to these data-driven advancements, existing and new methods can extract enhanced marketing insights from such interactions. Lu, Xiao, and Ding (2016) develop a video-based automated recommender (VAR) system that is customizable for different retailers. This algorithm registers customers' reactions to tried on garments to generate recommendations about products. The authors collect unique data from the shopper's product trial and evaluation in front of store mirrors and record facial expressions and "eye-tracking" to specific garment parts. Recommendations are based on the preferences, purchase history, and consideration set of similar consumers. Parssinen, Kotila, Cuevas Rumin, Phansalkar, and Manner (2018) focus on blockchain technology and its potential to improve the efficiency of the online advertising market. They review specific requirements of blockchain that are necessary for successful applications in online advertising, as well as compare specific solutions and platforms in terms of their potential in this area. Rese, Baier, Geyer-Schulz, and Schreiber (2017) discuss the potential of augmented reality apps and investigate their acceptance by consumers. They use the opinion rating and reviews on four AR-based mobile apps as well as the data collected in laboratory experiments to show the validity of constructs of technology acceptance model in this context. Furthermore, the relative importance of the hedonic and utilitarian dimension of technology vary across applications.

Many firms see the potential of new technologies; however, uncertain benefits continue to be an obstacle for adoption. After reviewing the past, present, and future solutions in consumer-facing retail technology, Inman and Nikolova (2017) remark that these technologies are not always met with customers' enthusiasm. Therefore, the technology adoption decisions by retailers should also incorporate the anticipated consumer's response. They propose a decision calculus model that not only incorporates the retailers' value from new technology adoption, but also the customers utility from using it. The model identifies the sources of increased revenue and decreased costs to estimate the profits after technology adoption, as well as critical dimensions of consumer perceptions towards new technology (i.e., attitude, and privacy concerns).

Analytics-Driven

Ability to Learn from Past Data

Superior analytical methods, which have an ability to learn from past data (including unstructured data), are relevant for marketing when they lead to enhanced intelligence for business practice. Whereas firms traditionally used technology to integrate and analyze data to achieve specific marketing objectives and firm outcomes, recent changes indicate a more central role of technology among firms (Brady, Saren, & Tzokas, 2002; Kumar & Ramachandran, 2019a). Specifically, recent technological advancements such as IoT, big data, AI, and ML have rendered technology and consumer-level data inseparable. Here, we distinguish and describe learning algorithms that require expert input, are independent from such input, and can mimic human input.

Human-Assisted

Despite the apparent advantages of automation, the performance of learning algorithms can often be improved when they consider human input, such as expert judgements. Hartmann, Huppertz, Schamp, and Heitmann (2019) review 10 state-of-the-art supervised machine learning and lexicon-based methods for automatic text classification. They focus on sentiment analysis and content analysis of unstructured text data from social media, and emphasize the potential of automated text-mining for marketing discipline. However, even state-of-the art algorithms require either human coding to train supervised machine learning algorithms or linguistic dictionaries created by experts. D'Haen, Van Den Poel, Thorleuchter, and Benoit (2016) develop a decision-support system to qualify prospects as leads from web crawling data, explicitly introducing information from experts as variables in the model. They show that freely available web crawling data, combined with expert knowledge, can outperform models based on commercial business data. Liu, Lee, and Srinivasan (2019) apply a supervised deep learning natural language processing to extract price and quality features from review text, and next they estimate their impact on product sales. To this end, the authors use Amazon MTurk who coded 5,000 random reviews, indicating whether a feature is present in the review text or not. As a result, each feature is associated with human-tagged labels, which can be fed to the supervised learning algorithm to automatically extract features from large amounts of unstructured text review data. This approach shows high accuracy in more than 600 different product categories, and does not require hand-coding nor expert knowledge about different product categories.

Human-Independent

Modern AI algorithms behind the customer service interfaces can process vast amounts of difficult unstructured data in real-time such as video or text. For example, Li, Shi, and Wang (2019) develop an automated video mining method to predict crowdfunding success using information extracted from videos posted on a crowdfunding website. They use convolutional neural networks (CNN) to obtain measures of visual variation and video content, which are good predictors of a funding decision. Galitsky and de la Rosa (2011) developed an AI algorithm that extracts insights from natural language to handle various customer complaint scenarios in the interactions between a customer and a customer service agent, allowing customers seamlessly interact with technology. The adaptability of AI and ML also enables firms to refine their recommendations and promotions to consumers continuously, based on their behaviors over time. Recommendation engines are a popular application of ML, wherein users are matched with offerings that they liked in the past and/or may be interested in the future. Such curative actions by firms reduces consumer cognitive load and shifts the responsibility of finding the best options for a consumer's choice context to the search platform or the brand (Kumar, Rajan, Gupta, & Pozza, 2019).

Human-independent algorithms are still very imperfect. AI-powered face recognition systems used by London police have wrongly identified individuals in 81% of instances (Jee, 2019). In an open letter, Concerned Researchers (2019) called upon Amazon to stop selling their facial recognition software to law enforcement as it had shown racial and gender bias. The reported error rates for classifying the subject's gender were 31% for darker skinned women vs. 0% for lighter skinned men. Similarly, Lambrecht and Tucker (2019) explore the bias of fully automated algorithms for online display job offers in STEM. The results of a field test show that an advertisement which was designed to be gender neutral was viewed by fewer women than men because the ads displayed to them are more expensive. The algorithm optimizing solely on price proved to be discriminatory. More generally, human-independent automated algorithms are indeed free of human bias, but they can be biased due to implicit assumptions made consciously or unconsciously by software engineers or biases in past data used for algorithms training. Haenlein and Kaplan (2019) call for a moral codex for AI designers to improve firms' accountability for the mistakes their algorithms make.

Humanized

AI technology already can mimic the capabilities that intrinsically pertain to human intelligence. Huang and Rust (2018) discuss the huge impact AI technologies have and will have on the services industry. Although service tasks are generally difficult to automate, the authors theorize that as AI progresses towards handling higher intelligence tasks (i.e., mechanical, analytical, intuitive, empathetic), AI technology will first take over individual service tasks performed by humans and ultimately jobs performed by humans. Huang and Rust analyze various skills and tasks that are enabled at each level of intelligence and provide examples of existing AI technologies already able to perform those tasks. Interestingly, some types of chatbots and robots already exhibit empathy—the highest order type of intelligence. In the context of health care, Čaić, Avelino, Mahr, Odekerken-Schröder, and Bernardino (2019) examine whether social robots can evoke a similar social response as human agents. Specifically, the authors observe elderly patients during a physical exercise game and monitor their interactions with human coaches and robotic coaches that are programmed to appear friendly and social. The study provides evidence that the elderly humanize the robots and exhibit warmth and competence judgements in their interactions with them. However, the human agents are evaluated much more highly than robot agents when performing the same tasks. The authors conclude that social robots have a complementary role and can assist human care givers but not all the tasks should be automated and performed by robots. Mende, Scott, van Doorn, Grewal, and Shanks (2019) investigate how customers respond to humanoid service robots versus human service providers, giving empirical evidence of the uncanny valley—phenomenon that interacting with humanoid robots makes people uncomfortable. The insights from a series of experiments shows that customers interacting with humanoid robots engage in compensatory behavior (e.g., status signaling, social belonging, or increased food consumption) to reduce the threat to self-identity.

Outcomes

Despite the relatively high degree of uncertainty in implementation outcome and the associated costs, firms recognize the undisputed potential that new-age technologies bring. In order to justify the investments and speed up the adoption, there is an urgent need to understand how the use of novel tools contributes to actual marketing outcomes, key performance indicators (KPIs), and eventually the firm's bottom-line. In this section, we discuss how new-age technologies affect the firm's value through increased marketing productivity and operational excellence. When new-age technologies are used for targeting consumers, they can also become a source of customer value realized via various marketing mix decisions and the growth in customer base.

Firm Value Creation

Marketing Productivity

Schrage and Kiron (2018) focuses on the incredible potential of predictive ML algorithms in maximizing the impact of firm KPIs. Embedded in business processes, they will change the future digital dashboard and influence the way executives track and nurture growth. KPIs aligned with strategic objectives and business goals are most effective in organizations with a data-driven culture. The results from the survey of 4,500+ executives across various industries, countries, and job functions emphasize that modern KPIs will be even more customer-focused with 38% of the respondents citing customer-related metrics among top three most important KPIs. No other metric comes close, with sales taking second place (9%) and revenue third place (8%), respectively. Gong, Zhang, Zhao, and Jiang (2017) demonstrate the positive causal effect of microblogging on new product demand in the context of Chinese microblogging platform Weibo, a TV show, and a field experiment. The market outcome is TV show viewership. The results from the field experiment show a 77% increase in viewership due to a tweet and a 110% increase due to tweet + influencer retweet, compared to the control group. In the latter case, there is also increase in the number of followers by 35%.

Operational Excellence

Pagani and Pardo (2017) investigate the impact of digital technology on relationships between stakeholders in B2B settings. The study conceptualizes the digitalized business network exchanges as activity links, resource ties, and actor bonds. As a result, three types of digitalization appear, where the digital technology: (1) makes existing activities more efficient, (2) leads to new activities by existing actors, (3) creates new bonds between actors through the appearance of new actors in the network. Tarafdar, Beath, and Ross (2019) describe that AI can transform the way organizations operate, enhancing the organizational processes, speeding up information analysis, and the accuracy of their results. However, they acknowledge AI adoption by firms is low, and the benefits uncertain. The authors describe five capabilities (data science competence, business domain proficiency, enterprise architecture expertise, operational IT backbone, digital inquisitiveness) and four practices (developing clear, realistic use cases; managing enterprise cognitive computing applications; cocreating throughout the application life cycle; and thinking “cognitive”) companies need to develop to be able to realize the potential of AI technology. Chen, Preston, and Swink (2015) develop a theory of big data use in organizations by examining its antecedents and impacts. They propose that only firms which possess unique information processing capabilities can generate value from big data, and therefore gain competitive advantage.

Customer Value Growth (Acquisition, Retention, and Growth)

Gong et al. (2017) demonstrate that a firm can use microblogger influencers on social media to gain new followers, thus increasing the number of TV viewers. Ascarza (2018) proposed that retention programs should focus on those customers who are most sensitive to intervention instead of those who have the highest risk of churn. The method based on uplift modeling can be implemented as A/B testing. De Cnudde and Martens (2015) investigate a unique loyalty program in a public setting (city of Antwerp). They apply Naïve Bayes classifier and Support Vector Machine to predict the intensity and location user activities, as well as their churn hazard.

Meire, Ballings, and Van den Poel (2017) show that B2B acquisition process can be further improved with the use of social media data. This approach combines the information on prospects obtained commercially from a market research company, web crawling data, and the information about the prospect from their corporate Facebook page. The data from an experiment conducted at Coca-Cola's call-center suggests the complementarity of various data sources, with Facebook information having a slightly better predictive value, and being the most influential for the lead generation and classification DSS. Implementing such an acquisition system would yield Coca-Cola from $8 to $21 million without additional sales costs.

Customer Perceived Value Creation

Needs/Preferences

Technology has influenced the new product design process that is attuned to customer needs and preferences. One consistent need expressed by customers pertains to experiences that are effortless, intuitive, and seamless across touchpoints. Technologies such as AI, ML, and IoT are shaping marketing actions by enabling firms to acquire a holistic understanding of their customer's needs and behaviors across platforms, devices, and varied products and services.

One way of accommodating customer needs and preferences in developing meaningful offerings is including customers in the ideation process. Camacho, Nam, Kannan, and Stremersch (2019) investigate the role of feedback in customer ideation during innovation tournaments. They find that only negative and a combination of positive and negative feedback leads to updating of the submitted ideas. Furthermore, feedback with positive elements are more effective when administered early in the ideation tournament. Another way of addressing customer needs and preferences is in concept testing the offering before its launch. Joo, Thompson, and Allenby (2019) address the curse of dimensionality when designing meaningful product configurations for experimental concept testing. This method relies on the premise that potential customers sequentially evaluate most promising product concepts, and at each iteration a new product configuration maximizes the expected improvement in the market share. Such firm actions ensure that insights gained through analytics work towards connecting with customers via more interactions, and thereby create more value.

Customer Experience

Technology plays a critical role in providing memorable customer experiences leading to enhanced customer engagement. For instance, the Amazon Go store in Seattle combines machine vision, IoT sensors, and a mobile app for shopping. This allows the customer the convenience of shopping and leaving the store without needing to wait in long checkout lines. Further, Amazon captures the shopping behavior to develop shopping insights to enhance customer experiences further (Fierberg & Leswing, 2018). Additionally, with AI and ML analyzing IoT data continuously, consumers find themselves receiving personalized communication and relevant insights and having better experiences with the devices. For instance, IBM has developed a new AI-driven software offering based on deep learning that is scalable. By being able to connect to multiple servers at the same time to boost computing speed and power, the new AI offering can significantly scale up without any loss of accuracy in results, thereby enhancing customer experience. Pattabhiramaiah, Sriram, and Manchanda (2019) investigate how digital engagement of light and heavy readers changed after introducing a paywall for a New York Times' online content, showing that a paywall had an adverse effect on digital engagement, which was more negative for heavy users but does not impact subscribers as much as non-subscribers. On the other hand, the spillover effects of the digital paywall on print circulation share are positive, ranging from 0.32 to 0.52 share points.

Customer Satisfaction

Digital analytics gleaned via the use of new-age technologies such as AI, ML, and IoT among others enable firms to provide solutions that are intuitive, convenient, and engaging, thereby leading to enhanced customer satisfaction (Chung, Ko, Joung, & Kim, 2018). Further, such new-age technologies allow firms to simultaneously meet customer expectations and create value (Choi, Ko, & Kim, 2016). In retail settings, research has established that customers' shopping satisfaction is a key antecedent to shopping behavior and behavioral intentions (Cronin Jr, Brady, & Hult, 2000; Rose, Clark, Samouel, & Hair, 2012). While technology promises to deliver superlative experiences resulting in customer satisfaction, research shows that technology will have a positive impact on customer satisfaction when firms address customers' perceived privacy concerns (Mukherjee, Smith, & Turri, 2018). Another area where technology can make a big impact on customer satisfaction is the quality of customer interactions during a purchase event. Keeling, Keeling, and McGoldrick (2013) investigate the technology-enabled relationships between retailer staff (and their representations like online virtual sales assistants) and customers, and compare them to social relationships. They find that human-to-human relationships with retail staff are concentrated together and indicate low to moderate friendliness; however, human-to-technology relationships, is perceived with a low degree of hostility. While all types of retail relationships are perceived as rather superficial, human-to-technology relationships are perceived as more task-oriented and formal, while human-to-human relationships are more socio-emotional and informal.

Moderators

In proposing this organizing framework, we identify six moderators that influence the relationship between forces and capabilities. The rationale for the selection of the moderators is based on the fact that a firm's ability to create value is affected by internal and external environmental factors such as *market-, product-, brand & customer-, and channel-related* factors. Additionally, we propose that the relationship between the capabilities and insights for decision-making, and the relationship between insights for decision-making and outcomes are moderated by *innovation-related* factor such as new innovative methods pertaining to data and analytics. We discuss the effect of these moderating factors in this section.

Market-Related

B2B vs. B2C

The business context (B2C or B2B) play a vital role in the development of firm capabilities and resources. Consider the case of Red Roof Inn (B2C context). Recognizing that flight cancellations often leave passengers stranded, they developed a way to track flight delays in real-time and trigger targeted search ads for the Red Roof Inns near airports. The ads identified the critical moments of relevance to customers and delivered what people needed. This led to a 60% increase in bookings across non-branded search campaigns (Friberg, 2016). Even in the case of B2B relationships, buyers begin with an online search to inform themselves of the options. For instance, a survey has found that 78% of buyers in the pack and ship business and 82% of buyers in the industrial supplier business researched online and considered more than two brands for their purchase (Travis, 2018). Further, empowered by digital technologies, buyers are also making faster decisions with more than 70% of buyers researching and buying within a day (Travis, 2018). However, an area where new-age technologies falter is in accommodating human emotions. While emotions play an important role in decision-making (Schwarz, 2000; Shiv & Fedorikhin, 1999), new-age technologies, particularly robots, still must make much progress in terms of showing empathy for consumer needs (Prado, 2015). Further, social skills and networking are also essential for relationship building in a B2B setting, which new-age technologies such as robotics do not accommodate (Torres, 2015).

Developed vs. Emerging Markets

The type of market plays an important role in how firms handle new-age technologies to generate digital analytics. For instance, research finds that for firms offering IoT solutions, the struggle to maintain market share, initial reputation, and relevant business models involves competing in emerging markets, among other factors; in addition to posing difficulties in building uniform standards, regulations and policies (Nicolescu, Huth, Radanliev, & De Roure, 2018). Further, research shows that Chinese firms focused on developing AI solutions face considerable constraints in technological talents, compared to U.S. and Europe (Ransbotham, Gerbert, Reeves, Kiron, & Spira, 2018). However, research has also posited that the minimal regulations and compliance standards in the emerging markets allow firms to be agile and innovative in the adoption and application of new-age technologies such as AI and ML; eventually leading up to leapfrog innovation for the emerging market firms (Kumar & Ramachandran, 2019b). In comparison, firms in developed markets have to contend with long-established technologies, processes, and mindsets, as well as more stringent regulations and standards (Sarvepalli, 2016). Further, while developed market firms may be resource-rich and knowledge-rich, securing a managerial buy-in (from internal and external stakeholders) to deploy advanced technologies could be challenging.

Product-Related

Product vs. Service

The type of industry (i.e., product-oriented vs. service-oriented) that the firm operates in influences the development of firm resources and capabilities. with regard to products, we can expect products in this new-age technology space to yield firms the benefit of efficient resource usage – a key firm capability. For instance, firms can monitor the usage of their products (i.e., devices and equipment) and proactively conduct maintenance using sensors to manage productivity, efficiency, and operating costs. For example, BP uses sensors to communicate data about the conditions at each site to decision-makers and analyze the data to improve operations. Using a combination of sensors and cloud-based analytics software, the company can integrate operational data from oil and gas facilities and analyze more than 155 million data points per day in real-time, to prevent unplanned downtime (Hand, 2018).

With regard to service, we expect service in this new-age technology space to adequately capture consumer heterogeneity in transactions that are reflective of a customer's needs, attitudes, and emotions—a key consumer-related capability. Further, research has identified that a positive service experience can enhance satisfaction and emotional attachment when variations in service experience is lowered (Kumar, Rajan, Venkatesan, & Lecinski, 2019). In this regard, technology-driven solutions developed by firms focus on automating service delivery, such as Uber Eats' use of AI to optimize delivery times (Williams, 2018), and standardizing service delivery, such as the Keeko robot that teaches kindergarten kids in more than 600 schools in China (Low, 2018). Moreover, research shows that customers more often discuss their service experiences than their product usage experiences (Perry & Hamm, 1969). Whereas earlier internet-driven business practices used search engines powered by fixed “if-then” conditions to narrow the field of product options, newer business approaches focus on product curation using technologies such as AI (Kumar, Rajan, Gupta, & Pozza, 2019). Therefore, new-age technologies enable firms to hone their expertise in developing offerings, while also working towards building their capabilities and resources.

High vs. Low Involvement Offerings

Involvement refers to the level of perceived personal importance and/or interest evoked by a stimulus (or stimuli) within a specific situation (Antil, 1984). Further, the conceptualization of involvement identifies its influences as: (a) personal needs, values and references, and (b) the amount of product distinction within a product class (Zaichkowsky, 1986). Recent advancements in technology have bolstered customers' avenues of collecting pertinent information to aid in the decision process. This involves having access to devices capable of using advanced technologies such as AI and ML to communicate relevant offering-related messages, and design augmented service components. For instance, research shows that ensuring a consistent manner of communicating relevant content exerts a stronger influence on customer engagement for high-involvement products; whereas a convenient purchasing environment (e.g., buy online and collect in-store) exerts a stronger influence on customer engagement for low-involvement products (Lee, Chan, Chong, & Thadani, 2019). Further, Google uses natural language processing technology and ML-based search techniques to provide narrower content relevant to the user's needs (Li, 2017). Such advanced technologies could bridge the gap between high-involvement and low-involvement offerings that are relevant and timely to user needs.

Brand & Customer-Related

High vs. Low Brand Quality

Brand quality refers to consumers' perception of quality (i.e., subjective judgment) relative to the expectation of quality (Mitra & Golder, 2006). Therefore, it is not necessary to use or examine a product to assess brand quality. Research also shows that brand quality depends on objective quality (i.e., a higher or lower performance on all product attributes sought after by consumers) and prior expectations of quality (Boulding, Kalra, & Staelin, 1999; Parasuraman, Zeithaml, & Berry, 1985). Further, research has established the mediating role of brand quality in several investigations such as the importance of global brand purchases (Strizhakova, Coulter, & Price, 2011), corporate social responsibility (CSR) performance (Liu, Wong, Shi, Chu, & Brock, 2014), country of origin (Han & Terpstra, 1988), and product cues (Teas & Agarwal, 2000), among others. As businesses deal with fluctuating brand quality ratings, the presence of digital business formats also adds to the variation. For instance, Wang and Goldfarb (2016) examine the effect of brick-and-mortar store openings on sales in online and offline channels to identify the substitution and complementarity effects between two channels. They find evidence of both effects: in locations with brand presence prior to store opening, the online sales decreased post-opening (substitution); in locations without prior brand presence, the online sales and browsing increased (complementarity). It is found that complementarity is due to the billboard effect and the associated increased brand awareness, which resulted in attracting first-time shoppers from the area.

Channel-Related

Digital Natives vs Legacy Firms

Technology has a big impact on where customers can find information about products and purchase them, as evidenced by recent research (Kopalle et al., 2020). Customers now use multiple channels (online, offline, mobile) throughout the purchase journey, which makes omnichannel strategies more complex and difficult to design. Legacy firms dominated by traditional brick-and-mortar business model, need to conform with the needs and habits of digital natives. Zhang, Pauwels, and Peng (2019) on the other hand investigate the impact of adding the online-to-offline service platform (O2OSP) channel on firms' offline and total sales and profits, and find that adding the O2OSP channel hurts offline and total sales in the short run, but in the long run the sales increase by about 23% and 33%, respectively.

Innovation-Related

New Innovative Methods (Data and Analytics)

Technology now serves as a mainstay for many companies to drive the development of insights. How well companies can leverage capabilities to create insights is dependent on their readiness to develop and implement new analytical methods, as well as adapting existing ones to new data sources and/or changing consumer behavior. Such technology readiness will also impact the ability to extract value from insights. A survey of global firms found that nearly 71% of firms foresee their investments in data and analytics to accelerate in the next three years and beyond and that around 52% of firms are leveraging advanced and predictive analytics to generate insights and contextual intelligence into operations (Columbus, 2018). Further, researchers are developing novel approaches to make data more amenable to insights and strategy development. For instance, researchers are developing a cloud-based interactive data-science interface system called Northstar that supports any touchscreen device, including interactive whiteboards. By tapping into data feeds, the system lets users explore and investigate a wide variety of data transformations (using their fingers or a digital pen), to uncover trends and patterns (Matheson, 2019). Despite such developments, data quality concerns in firms remain. For instance, Nagle, Redman, and Sammon (2017) find that only 3% of companies' data meets basic quality standards. Such poor data quality causes significant problems and impedes prescient insight generation.

Agenda for Future Research

This study presents an organizing framework to understand the potential applications of digital analytics, within the changing technology landscape, to generate consumer insights. The proposed framework offers an approach geared towards eliciting strategic insights via digital analytics by tracking marketplace developments, specifically technological advancements such as AI, ML, among others. In doing so, the proposed framework illustrates the development of organizational resources and capabilities that can help firms better address changing business trends. Further, the approach also shows how firms can garner strategic insights for decision-making that can result in the achievement of established firm outcomes. Based on this proposed framework, we identify potential avenues for future research.

First, the marketplace forces – as exemplified by the emergence of new-age technologies (e.g., AI, ML, etc.), the shift from traditional to digital media, changing customer preferences, and regulations – continually shape the development of newer business models and offerings. However, for changes in business models and offerings to materialize, the development of firm- and customer-level capabilities are necessary. Moreover, the moderating factors cast important influences on the development of capabilities and resources. As a result, the various influences (from the forces and the moderators) warrants deeper examination, since they have the potential to build capabilities, automate smart and real-time decision-making, and enhance firms' abilities to achieve established outcomes. Therefore:

RQ1. What is the differential impact of the four forces and the moderating variables on firm- and consumer-related capabilities?

RQ2. How will the differences arising from the forces and moderators impact the choice of advanced technologies that a firm considers using?

Second, a firm may not have enough resources or may lack the expertise to implement the resources in a substantive manner to account for the marketplace forces affecting them. Similarly, there could be other factors both internal and external to the firm that could place further concerns in terms of generating essential capabilities. Moreover, the deployment of resources involves significant financial and human resource investments, while providing benefits across processes and departments. As a result, the determination of efficiency and effectiveness of resource allocation decisions that are conducive to developing the required capabilities is critical. Therefore:

RQ3. What optimal resource allocation decisions can firms implement to aid in the development of the required capabilities (e.g., in-house vs. buying; ROI)?

RQ4. What skills and resources should firms develop/acquire to account for all marketplace forces and moderators influencing the firm?

Third, customers are evolving, and their behaviors and demands are changing to be more technology oriented. The increased access to information about firms and offerings (enabled particularly by new-age technologies) allows customers to evaluate the alignment of the proposed offerings with that of their personal values. This creates a space for firms to know and observe more about their customers. Moreover, the transparency and traceability offered by new-age technologies provides vital information about customer needs and preferences, and the conditions in which they would require certain offerings. Further, customers share their personal data with firms in the course of using products and services based on new-age technologies. These data allow firms to provide customers with personalized experiences and offerings. Such developments could imply that various business units within a firm are likely to collect and deal with varying levels and volumes of customer data. These data-rich environment presents firms with an opportunity to glean insights on customer behaviors continuously, by ensuring all their business units remain and function in a connected manner. Therefore,

RQ5. What type of strategic and tactical approaches should firms pursue to bridge data silos and generate actionable insights?

RQ6. How can firms balance customer concerns regarding privacy and their expectations to collect information for marketing purposes? How would such a balance vary (or be similar) in light of the variety of new-age technologies such as AI, ML, drones, blockchain, and robotics, among others?

Fourth, the evolving business landscape indicates a current scenario where platforms and ecosystems are critical for firms to maintain strong direct relationships with their customers. This has created a challenge for firms in terms of making customers engage with them more than the platform while using the platform only as a facilitator. Further, this has also brought technology developers into prominence. The role served by technology developers is now vital, as they enable firms and intermediaries connect and engage with customers in real-time. Consequently, technology developers will have to be continually informed about all technological developments regularly. Alongside market dynamics and the prominence of technology developers, customer autonomy has also increased which provides customers greater control of the applications and devices. This new development of sharing control among firms, customers, and other related stakeholders necessitates technology developers to adopt a different approach to develop applications and programs. Therefore,

RQ7. How can the new-age technologies (e.g., AI, ML, drones, etc.) help firms foresee and/or cope with changes in the marketplace? Consequently, what firm-related aspects will the new-age technologies will not help firms foresee and/or cope with the marketplace changes?

RQ8. Under what conditions, technology platforms, technology developers and customers each have relatively greater control in the creation of applications and programs?

Finally, the new-age technologies (i.e., AI, ML, etc.) operate in a business milieu that focuses on personalization, delivering positive experiences, productivity enhancements, and value growth (for firms and customers). This implies that firms direct their attention to understanding individual customer preferences to determine marketing mix variables. Further, this calls for firms to ascertain the various offering combinations that delivers the expected level of personalization, which is typically delivered through the new-age technologies. Firms design personalized offerings to deliver positive experiences to customers, and the usage of new-age technologies offers firms the generation of real-time customer feedback and insights. With the growing reliance on new-age technologies to deliver positive experiences, firms also focus on monitoring and maintaining their devices/platforms, in an effort to increase productivity, improve efficiency, and reduce operating costs. Given data-driven insights via the new-age technologies, firms can potentially not only change the way they communicate with consumers in real-timew but also accurately measure the effectiveness of their marketing efforts, thereby increasing the opportunities for firm and customer value growth.

RQ9. How to optimize resources for maximizing multiple objectives of firm value and customer value?

RQ10. How can firms leverage these new-age technologies to adapt to new business models favoring platforms and ecosystems for direct firm–customer interactions in a profitable manner?

This study presents a framework that views the digital analytics and the generation of insights from an overall firm perspective. Of specific importance to the proposed framework is the key role played by the new-age technologies (e.g., AI, ML, robotics, etc.) that are growing in adoption and use by firms. To shape the academic discussion in a productive manner, this study also identifies potential research areas that merit deeper examination. By presenting this proposed framework and the future research questions, we hope to encourage marketing researchers to study these recent technological advancements in greater depth to uncover their potential and business implications.

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Declaration of Competing Interest

None declared.

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