ESSAYS ON APPLICATION OF ARTIFICIAL INTELLIGENCE (AI) AND VALUE CREATION IN MARKETING

by

KAUSHIK KRISHNAMURTHY JAYARAM

(Under the Direction of Sundar Bharadwaj)

ABSTRACT

Artificial intelligence (AI) applications are increasingly adopted by marketing practitioners to complement and substitute marketing tasks. However, their financial and non-financial performance implications are not yet clear. This dissertation examines whether and how AI applications used in marketing create value for firms. In Chapter 2, I draw on the customer experience management, customer touchpoint and marketing finance literatures to theorize that AI can be used to deliver personalization and convenience benefits to consumers and thus create financial value for firms. I use a multi-method approach is used to test the mediational process and whether stock market investors value AI-enabled conversational commerce applications (CCAs). I report key findings that the stock market positively values CCA announcement and the financial value for a firm with median market value in the sample increases by $56.9 million (+0.29%). CCA launch strategies and design functionalities explain the heterogeneity in financial market returns. Investors pay attention to CCA announcements. Firms communicate personalization and convenience benefits of CCAs to investors and the benefits mediate the effect of CCA on firm value. Also, customers perceive the personalization and convenience benefits, and it increases their purchase likelihood.

In Chapter 3, I examine whether marketing AI startups utilize textual descriptions of AI applications to inform VCs and whether such textual communication predicts venture capitalist funding beyond other traditional factors (e.g., financial, demographic) commonly used to predict VC funding for startups. In addition, I study which business and marketing strategies communicated by AI startups through text descriptions are more likely to be associated with VC funding. In Chapter 4, I develop a conceptual model to describe how AI applications create value for B2B sellers across buyers' purchase journey. I developed a touchpoint-based framework to theorize how AI applications add efficiency and effectiveness to help buyers achieve goals across different stages of the purchase journey. Insights from this dissertation has implications for both marketing theory and practice. It contributes to knowledge about how AI applications add value to marketing. It also helps marketing practitioners justify their investments in AI applications and provide guidance regarding how to extract better value from AI applications.

INDEX WORDS: Artificial Intelligence (AI), Chatbots, Marketing finance, Investors, Startup funding, B2B AI, Conversational commerce applications (CCA)

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INTRODUCTION AND LITERATURE REVIEW

Artificial intelligence (AI) is rapidly transforming how organizations connect to and interact with customers. According to McKinsey, AI applications will contribute between $1.4 trillion to $2.6 trillion additional value to marketing (Chui, Henke, and Miremadi 2019). Marketing researchers and practitioners alike expect AI applications to influence and improve marketing strategies, sales processes, and customer service, as well as customer behaviors (Davenport, Guha, Grewal and Bressgott 2019). AI applications create value for marketers by automating marketing tasks, providing relevant insights from data, and by engaging customers (Davenport and Ronanki 2018). AI applications that automate tasks, do it with minimal or almost no human intervention. For example, some AI applications can have automated conversations with customers and provide relevant product information and encourage customers to purchase. AI applications that provide relevant insights from data can do so in real-time. For example, some sales AI applications use natural language processing to infer customers' tone and their concerns and provide real-time feedback to the marketer on best next steps. AI applications that engage customers do so by using customers' individual-level data and personalizing their interactions with the firm (Kumar, Rajan, Venkatesan and Lecinski 2019). Thus, AI applications are expected to create significant benefits to marketers and marketing in general.

Despite marketers' and practitioners' positive outcome expectations from using AI applications in marketing, the financial value implications of using these applications is not yet clear. First, it is not clear how customer-facing AI applications would change financial value for firms. For instance, despite increasing firm adoption of and the rising popularity of customer-facing conversational AI applications, there are reasons to believe that these applications will not generate sufficient firm value. This expectation is driven by findings from recent research, which suggests that customers tend to be averse to AI-generated recommendations (Wirtz et al. 2018) and perceive a lack of control. This in turn discourages them from adopting conversational AI applications and decreases future purchases (Buvat et al. 2018; Davenport et al. 2020).

Second, the financial value implications of startups building marketing AI applications is not clear. Typically, marketing AI startups need a lot of financial resources to cover the high cost of cloud computing, required to train complex AI models (Casado and Bornstein 2020). Moreover, they need to store the large amounts of historical and real-time customer data generated, which adds to the high costs. Finally, they need to scale their marketing AI applications, which requires a lot of resources because the underlying AI models have to be re-trained if they need to cater to a marketer's specific usage context. Without understanding the value generating potential of application built by a startup, venture capitalists (VCs) would not be willing to invest in them (Davila, Foster and Gupta 2003). Thus, marketers need to identify how to effectively communicate the value of the applications they build.

Third, the value of AI applications in B2B marketing is not clear. Generally, B2B marketers have positive expectations about the value of AI applications in B2B. However, very few of them have adopted AI applications extensively to all help across the different marketing tasks involved in their customers' purchase journey. B2B marketers state that they lack clear understanding about 'what' marketing activities would generate greater value from AI applications and 'how' to extract value from these applications. A recent survey reported that 32.6% of B2B marketers are not confident about their understanding of AI applications

(Everstring and Heinz 2018). In fact, B2B marketers state that they are not sure how to prioritize use cases for using AI applications in marketing and their current adoption is focused on very limited use cases (Abdulsalam 2020).

In my first essay, I try to understand a firm's financial value implications from using conversational AI applications at the firm-customer interface. To do this, I draw on the customer experience management (e.g., Homburg, Jozić and Kuehn 2017), customer touchpoint addition (e.g., Geyskens, Gielens and Dekimpe 2002) and marketing finance (e.g., Boyd, Kannan and Slotegraaf 2019) literatures to theorize that conversational AI applications can be used to deliver personalization and convenience benefits to consumers and thus create financial value for firms (Berry, Sieders and Grewal 2002; Kalaignanam, Kushwaha and Rajavi 2018). In this essay, I use a multi-method approach to test the underlying mediational process of personalization and convenience, and whether stock market investors value AI-enabled conversational commerce applications (CCAs). I report five key findings from this essay. First, using an event study methodology along with multiple robustness checks, I examine whether CCA launch announcements by a firm significantly changes its market value. I also test the market value change in terms of dollars based on the stock market reactions from the announcement. I find that the stock market positively values CCA launch announcement and the financial value for a firm with median market value in the sample increases by $56.9 million (+0.29%). Second, I use the guided latent Dirichlet allocation (LDA) to identify the contingency factors which help explain variation in the firm's financial value. I find that a firm's CCA launch strategies and the CCA's design functionalities explain the heterogeneity in financial market returns. Third, I understand if investors pay attention to CCA launch announcements. I do this by collecting investor search data from Google Trends and by creating a direct measure for investor attention.

I find that that investors do pay attention to a firm's CCA launch announcements. Fourth, I use a combination of text analysis and difference-in-difference methods to test whether firms communicate personalization and convenience benefits of CCAs to investors. I find that firms do communicate these benefits and it mediates the effect of CCA launch on firm value. Fifth, I conduct two experiments to demonstrate that customers perceive the personalization and convenience benefits and that it increases their purchase likelihood from the firm.

In my second essay, I examine how marketing startups building AI applications can communicate their value to venture capitalists and increase their chances of getting funded. I theorize my hypotheses by using the information asymmetry that exists between VCs and entrepreneurs (Spence 1973; Connelly, Certo, Ireland and Reutzel 2011), and using the signaling theory (Sanders and Boivie 2004). In this essay, I examine whether a marketing AI application's textual description signal the startup's value potential to VCs and whether communicating information through text predicts venture capitalist funding beyond other traditional startup factors (e.g. financial, demographic) commonly used to predict VC funding. In addition, I study what business and marketing strategies communicated by AI startups through text descriptions are more likely to be associated with VC funding. I use machine learning and text-mining approach to examine these research questions.

In the third essay, I explore deeper into the individual components of marketing AI applications and develop a conceptual framework to understand how they create value for B2B marketers across their customers' purchase journey. Using this framework, I further explore how the output generated by marketing AI applications translate into increasing the efficiency, improving effectiveness and increasing the interactions between marketers and end customers across their purchase journey.

The rapid growth and increasing adoption of marketing AI applications urges both marketing researchers and practitioners to link AI adoption to financial value generated. Findings from my three essays not only establish this link, but also provide guidance to marketers about how to effectively use marketing AI applications and how to communicate their value to stakeholders. My findings about CCA launch strategy and its functionalities would help marketers understand what drives financial value in customer-facing AI applications, which would drive their design decisions. By understanding how to communicate about application capabilities, I help AI marketing entrepreneurs to effectively convey their message to relevant stakeholders. Lastly, the conceptual framework I developed would help B2B marketers get a deeper understanding of marketing AI applications and their value creation potential.

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CHAPTER 2

THE FINANCIAL VALUE OF LAUNCHING CONVERSATIONAL COMMERCE APPLICATIONS[1]

[1]Jayaram, K., and S.G.Bharadwaj. Submitted to *Journal of Marketing,* 03/04/2021

ABSTRACT

Conversational Commerce Applications (CCAs) are artificial intelligence enabled automated digital entities that exhibit behavioral realism and interact with customers to assist in searching for product/service information, making purchases, and obtaining customer service. While firms increasingly use CCAs to interact with customers, the returns of this strategic decision are unclear. Using three studies and theorizing that CCAs provide convenience and personalization for customers, I examine the financial value outcomes of launching CCAs. First, an event study in combination with propensity score matching and selection correction to address endogeneity, finds that CCA launch announcements increase the median firm's value (in the sample) by $56.7 million. CCA characteristics such as serving the post-purchase stage (vs. pre-purchase), serving as a partner-owned touchpoint, possessing dual modality (text and audio) and possessing dual functionality (delivering information and performing tasks) enhance the positive stock market returns. However, CCAs launched with authentication functionality lowers the positive stock market returns. Studies 2 and 3 test the underlying mechanisms of personalization and convenience and show that they are indeed communicated to investors and perceived by customers. This essay has important implications for the financial accountability of investment in CCAs, customer benefits, and CCA design.

INTRODUCTION

Use of AI-enabled conversational applications to help customers has risen sharply over the past few years. 80% of firms say they are interested in adopting customer-facing conversational applications, and 89% of executives believe that these applications to be very useful in delivering convenience and personalized customer experiences (Oracle.com 2016; Linthwaite 2019A). These applications recognize customers' intentions and guide them toward touchpoints across their purchase journeys, acting almost like a companion in their decision-making (Hamilton et al. 2021). Guidance from these applications reduces customers' effort and helps them move efficiently along their purchase journey, in turn generating greater revenues for the firm (Hamilton et al. 2021). For example, Starbucks' AI-based conversational application offers personalized options to customers and places orders faster, in turn increasing Starbucks' future cash flows. Recent estimates suggest that by 2023 AI-enabled conversational apps could generate $112 billion from customer transactions[1].

Formally, conversational commerce applications (CCA) are digital entities that exhibit human-like behaviors and are controlled using artificial intelligence to enable two-way interactions with customers (Miao et al. 2021). They converse in natural language and facilitate customer interactions to increase commercial activity for the firm (Eeuwen 2017). CCAs interactions pertain to the product/service offerings that firms' sell. Thus, PayPal's conversational application, which handled over 65% of payment related customer queries during the COVID-19 pandemic, is an example of a CCA. Whereas conversational agents launched by the CDC to provide health (with no commercial intent) information on COVID-19 is not categorized as a CCA.

[1] https://www.retaildive.com/news/chatbots-to-talk-up-11b-in-cost-savings-by-2023/527125/

In their research priorities for 2020-2022, the Marketing Science Institute lists the need to understand how AI applications affect value generated by firms. For shareholders, I expect that launching a CCA can both create and destroy value, making it critical to research. Why? On the one hand, anecdotal evidence indicate that firms gain positive financial returns from launching customer-facing CCAs. For example, Charter Communications' CCA handled 150,000 customer enquiries a month that reduced customer service costs by 44%. Epson received $2 million in additional revenue within just 90 days by launching a CCA. An experiment-based case study offers evidence that CCAs can be up to four times as effective as humans in encouraging customer repurchase (Luo et al. 2019)

On the other hand, there are reasons to believe that CCAs do not generate firm value. First, customers tend to be averse to AI-generated recommendations (Wirtz et al. 2018), and perceive a lack of control, which lowers CCA adoption and decreases additional purchases (Buvat et al. 2018; Davenport et al. 2020). Second, inaccurate prediction of customer intentions by CCA can result in service failure (Brandtzaeg and Asbjorn 2018), which encourages customer switching and lowers purchases (Meuter et al. 2000). Third, multiple CCAs -- including those of Facebook, Inc., and Business Insider – were discontinued within a few years of their launch due to their failure to create value (CBinsights.com 2020). Fourth, investments in firms building CCAs are primarily directed towards early-stage startups, suggesting uncertainty about their success.

Little academic research exists on the financial value consequences of launching CCAs for marketing purposes, though research shows that CCAs can influence customer purchase behavior (e.g., Holzwarth, Janiszewski and Neumann 2006; Köhler et al. 2011; Luo et al. 2019). However, no study has taken a marketing-finance view to examine whether CCAs influence firm value (see Appendix S2.1). Research on the financial impact of CCAs and their characteristics will aid managers as they implement this emerging AI-based customer interaction strategy.

This essay attempts to fill the void in frontline AI applications and marketing-finance literature streams by addressing the following research questions: (1) Does the stock market value CCA launch announcements? (2) What are the moderating effects of a firm's CCA launch strategies, and CCA functionalities on the relationship between the CCA launch and market value reaction? and (3) What are mechanisms through which CCAs create value for firms?

To address these questions, I conduct three complementary studies. I test my hypotheses with an event study on 206 CCA launch announcements by US public firms. In Study 2, I test the proposed mediating mechanisms of personalization and convenience. In a Study 3, I conduct two experiments to test whether customers perceive personalization and convenience, when using CCAs, and whether these mechanisms affect customers' willingness to use CCAs. Together, these studies provide a more complete understanding of how a CCA affects firm value.

I contribute to emerging studies in AI and marketing strategy (e.g., Huang and Rust 2018) with a better understanding of how launching an AI application affects financial accountability. Firms invest nearly half a million dollars to build CCAs; the investment increases when integrating other systems and scales up with firm size (Ismail 2018), making the justification of such investment critical. My finding that CCA launch announcements generate $56.7 million to a median market value firm in the sample, suggests that the initial investments are justified. Second, I contribute to literature on customer experience management by identifying the moderating factors relevant to CCA launch and studying their influence on firm value. For example, I find that CCAs with dual functionality of providing information and doing tasks for customers create value of $125M more than single functionality CCAs and dual modality (voice and text) outperform single modality CCAs by $140M-$280M. Third, by examining the mediating process, my findings are particularly useful for managers considering delivering personalized offerings and enhancing convenience to customers.

RELEVANT LITERATURE REVIEW

As shown in Table 2.1, over the past two decades, research has examined the financial impact of adding new digital touchpoints to a customer interface. While this research identifies underlying mechanisms, it does not empirically model these intermediate relationships. Earlier studies focus on identifying value-creating and value-destroying mechanisms from both the supply side and the demand side (e.g., Geyskens et al. 2002; Homburg et al. 2014). They find that adding new digital touchpoints helps firms engage customers more often and provide services traditionally offered through physical channels. Thus, these touchpoints not only help firms increase demand for their offerings -- they also help lower the cost of providing their offerings. However, as these touchpoints are non-automated and non-AI-enabled, they remain non-interactive. Previous studies also provided insights into the moderating factors that explain the heterogeneity in value created. Among these, Boyd et al. (2019) focus on the characteristics of touchpoints, as well as the moderating effect of design features in a mobile application. Beckers et al. (2017) use the role of industry-related factors and a firm's social media presence to explain heterogeneity. I contribute to this touchpoint-addition literature in marketing-finance by (1) theorizing how adding automated AI-enabled conversational touchpoints enhances and accelerates future cash flows for the firm; (2) identifying strategic CCA choices that help explain the heterogeneity in the value generated; and (3) theorizing and empirically examining the relationships between the AI-enabled CCA and the mediating value-creating mechanisms.

CONCEPTUAL DEVELOPMENT AND HYPOTHESIS

Conversational Commerce Applications

Conversational commerce applications are digital entities that exhibit ‘behavioral realism’ and are controlled using artificial intelligence to enable two-way interactions with customers. Behavioral realism refers to CCA’s ability to have human-like natural interactions with customers (Miao et al. 2021). My conceptualization of CCAs are limited to entities that are designed to increase commercial activity for the firm. Customers could interact with CCAs for the following objectives: obtain information about a firm’s offerings, purchase the offerings and obtain customer service related to their purchase. An insurance company chatbot providing personalized insurance options that customers can purchase would qualify as a CCA. A distinguishing characteristic of CCA is that they do not have to provide social content to customers. Thus, a chatbot built to interact with dementia patients is not categorized as a CCA. A second distinguishing characteristic is that CCAs do not need to exhibit ‘form realism’ i.e. they do not have to appear like a human (Miao et al. 2021). Thus, CCAs differ from other digital entities that exhibit form realism such as avatars and online agents.

Therefore, CCA should have the following five characteristics: (1) is a digital entity, (2) controlled by artificial intelligence technology, (3) exhibits behavioral realism, (4) has commercial focus and (5) has bi-directional interactions with customers. Thus, CCAs are automated firm-customer touchpoints and employees have limited control during customer CCA interactions (Davenport et al. 2020). CCAs could but do not have to possess the following capabilities: (1) providing social content and (2) exhibiting form realism. My conceptualization limits CCAs to AI-customer frontline encounters as described by Robinson et al. (2020). Researchers have used multiple terms such as chatbots, smart speakers, robots, AI agents, virtual avatars, etc. to define these entities. A digital entity is a CCA only if it satisfies the above five characteristics. Last, I do not differentiate CCAs based on intelligence levels defined by Huang and Rust (2018),[2] but rather focus on their characteristics and benefits for customers. Typically, CCAs add value to customers' decision making by substituting (1) for tasks performed by sales agents (Luo et al. 2019); (2) the guidance provided by customers' friends (Hamilton et al.2020); and (3) tasks of customer service agents (Kumar et al. 2019). Overall, CCAs influence customers' purchase experience with a firm by interacting at multiple CCA touchpoints.

The Effect of Launching CCA on Firm Value

In line with the efficient market hypothesis, I expect that a CCA launch announcement would provide new, value-generating information for investors, which would then change the firm's stock price due to the expectation that the CCA will affect the firm's future cash flows (Fama 1970). By launching a CCA, firms personalize interaction and deliver convenience, in turn enhancing the customer engagement and driving additional customer purchases (e.g. Kumar et al. 2019; Grewal et al. 2020). I provide our conceptual model in Appendix S2.3.

"Personalization" refers to the use of customer information and technology to tailor firm interactions for each individual customer (Kalyanaraman and Sundar 2006). Similarly, CCAs use AI technology that draws on customer preference data and interaction history to accurately predict customers' purchase context and purchase intent (Miao et al. 2021), thus generating personalized communications in real time. Longoni et al. (2019) find that personalization increases customers' receptivity to AI recommendations. Moreover, CCA interaction increases customers' uniqueness perceptions of CCA, their engagement with CCA, and their overall purchasing experience with the firm, resulting in additional purchases (Longoni et al. 2019;

[2] While they do not fit my theory of influencing personalization and convenience, I include the types of intelligence of the CCA in the robustness check in Appendix S2.14 as additional moderators.

Kumar et al. 2019). Accordingly, 89% of managers believe that CCAs will help achieve their personalization goals and result in increased customer spending (Linthwaite 2019B). For example, personalized suggestions from L'Oréal's CCA increased customer conversions by 300% and their response rate to marketing emails by 800%[3]. The accuracy of AI-based personalization increases with more data and improves customer experience across all stages of their purchase journey (Venkatesan and Lecinski 2020). Hence, I expect that firms launching CCAs would enhance their future cash flows. Previous studies also find that beyond purchases, digital personalization efforts help firms' buffer from customer switching (Kalaignanam, Kushwaha and Rajavi 2018; Sahni, Wheeler and Chintagunta 2018). Thus, CCAs help firms both enhance future cash flows and reduce their cash flow volatility via improved customer retention. Investors paying attention to these two variables in turn react positively in the stock market (Kalaignanam, Kushwaha and Rajavi 2018). Firms launching CCAs can charge premium prices, due to customer acceptance of personalized communications. Moreover, personalization has been shown to increase customer cross buying (Kalaignanam, et al. 2018; Sahni, Wheeler and Chintagunta 2018). CCAs delivering personalization should therefore increase future cash flows.

"Convenience" refers to the reduced time and effort customers must exert to complete a task, such as buy or use products and services (Anderson and Shugan 1991; Berry et al. 2002). CCAs help customers across each stage of purchase (Hamilton et al. 2020). In so doing, CCAs influence multiple facets of customers' perceived convenience: namely, *decision, benefit, access, transaction* and *post-benefit convenience* (Berry, Seiders and Grewal 2002). CCAs enhance decision convenience by providing customers with relevant product/service information faster and with less effort (than from, say, a website). For instance, retail CCAs could give outfit

[3] https://www.automat.ai/loreal-beauty-gifter-conversational-ai-case-study/

recommendations based on customer purchase intention, something less likely available from a website. CCAs also enhance benefit convenience via easy, quick access to product/service information. Dominos' CCA displays real-time pizza preparation status; later, simple voice commands present delivery tracking. In terms of access convenience, CCAs grant access to numerous services (e.g. music streaming) with simple voice commands, all of which takes less time and effort than other touchpoints. Voice and text commands to a CCA enable automated product and service purchases, enhancing transaction convenience. Lastly, CCAs help firms increase post-benefit convenience by offering follow-up information and fast post-purchase support. On average, CCAs respond to customers within five seconds, compared to a 51-seconds average for human agents[4]. In fact, 35% of customers state that gaining greater convenience drives their use of CCAs (Brown 2019).

Providing convenience, in turn, benefits the firm by increasing customer re-purchase rates, their purchase spends, and the likelihood of recommending the firm to others (Seiders et al. 2005). Grewal et al. (2020) find that AI applications increases firm sales by improving customers' perceived convenience. Perceived convenience also influences purchases indirectly by increasing perceived service quality and customer satisfaction (Berry, Seiders and Grewal 2002). These indirect benefits reduce firms' idiosyncratic risk and increase stock market value (Tuli and Bharadwaj 2009; Bharadwaj, Tuli and Bonfrer 2011). In contrast, lower convenience increases customer frustration, resulting in fewer purchases.

Firms could lower cost of serving customers by replacing tasks performed by human agents (Wirtz et al. 2018). The pandemic period has minimized human interactions and enhanced customers' comfort and experience of interactions through digital interfaces .CCAs will help

[4] https://www.gartner.com/smarterwithgartner/bots-gain-importance-in-gartner-service-technologies-bullseye/

achieve significant economies of scale: due to their virtually limitless memory access and 24/7 availability, a CCA serves a large number of customer requests while lowering the cost for the firm (Wirtz et al. 2018). The lower cost of sales from the CCA also increases the level of positive cash flows.

Launching a CCA is likely to draw investor attention: with it, the firm places a greater emphasis on improving customers' perceived personalization and convenience. Adding AI-automated touchpoints signals to investors that the firm wants to improve its customer purchase experience, which will have direct effects on firm value. A recently published investor views report suggests that delivering personalization and convenience through CCAs would drive firm revenue significantly (Acquisdata 2020). Formally,

H1: CCA launch announcements will generate positive financial market returns.

Contingency Factors' Influencing the Financial Market Reaction to Launching CCAs

Firms leverage several controllable factors related to CCA design and launch that likely explain the potential heterogeneity in the financial market returns to CCA launch announcements. However, given the field's infancy, we have limited literature on the strategic choices managers make to launch customer-facing AI applications. Consequently, I identified these moderating factors using a four-step process. My first step was reviewing the channel addition and customer experience management research to identify firms' strategies for launching customer-facing touchpoints and improving customer experience (e.g., Geyskens, Gielens and Dekimpe 2002; Lemon and Verhoef 2016; Homburg et al. 2017). I then chose moderators relevant to CCA's five characteristics. For instance, as CCAs need to exhibit behavioral realism, having context sensitivity in touchpoints would be a strategic choice for managers. As CCA touchpoints are automated and controlled by AI (vs. human) (Davenport et al. 2020), I did not directly adopt moderators from the channel addition literature. In step 2, I used modality–agency–interactivity model to identify which agent (CCA) related moderators might potentially influence customer perceptions (Sundar 2008; Miao et al. 2021). This helped account for different the customer perceptions arising from interacting with AI versus humans.

In step 3, I used my insights from previous two steps and adopted an empirics first, then theory (EtT) approach proposed for early stage research and used by event studies in marketing (e.g. Bass 1995; Stäbler and Fischer 2020). Here, I follow the practice in event study research and identify firms' strategic choices (obtained from previous steps) that they communicate to investors through the announcement while launching CCAs. (e.g., Homburg et al. 2014; Warren and Sorescu 2017, etc.). I manually read every CCA launch announcement and identified two moderators regarding CCA launch strategy and three moderators that I categorize as CCA design functionalities.

In step 4, I ensure that the moderators chosen were not unduly influenced by researcher bias. Thus, I used a guided latent Dirichlet allocation (LDA) approach (Toubia et al. 2019) to help identify the moderators that are communicated in the launch announcements. I used guided LDA, as it is flexible enough to allow the definition of topics to be informed from my content analysis in previous steps, while allowing topics to emerge freely from the data and to capture other, unrelated constructs. I first conducted a traditional LDA method to identify the number of topics based on its perplexity score (Blei et al. 2003). The perplexity score suggested 25 topics. I read the launch announcements and developed a set of seed words for each strategic choice of the firm (see Table S2.4.1 in Appendix S2.4). The seed words helped in adding supervision to the guided LDA process. Application of the guided LDA approach to the content of CCA launch announcements provided ten common themes across the 25 topics. The topics, the top key words from each topic, the guided LDA methodology and the 4-step process are provided in Appendix S2.4. Last, I identified the dominant topics in each launch announcement and verified that the dominant topics match with the categorization provided by two coders in Study 1 (details in Appendix S2.4). The results strengthened my confidence that CCA launch strategy and CCA functionalities are indeed visible to investors through the launch announcements (see Appendix S2.5 for illustrations).

CCA launch strategy refers to a firm's strategic decisions for improving customer experience across CCA touchpoints. I identify two strategic considerations during launch: (1) the stage of purchase journey the CCA touchpoints will support and (2) whether CCA touchpoints should be brand-owned (on the firm website) or partner-owned (e.g. on Facebook).

Stage of purchase journey. Customers interact with firms at multiple 'touchpoints' that shape their overall experience with a firm (Lemon and Verhoef 2016). The set of customer interaction touchpoints up to the moment of purchase together form the pre-purchase touchpoints (Court et al. 2009). Consistent with this definition, I label the CCAs intended to interact with customers at these touchpoints pre-purchase CCAs. The inclusion of all touchpoints up until the actual purchase helps account for non-linear movement by customers across purchase journeys (cf. Hamilton et al. 2020). In addition, customers may continue to interact with the firm at post-purchase touchpoints regarding their purchase. For example, subscribers of Dish TV, can interact with Dish TV's CCA for show specific information and to operate their Dish device. CCAs focused on these touchpoints are termed post-purchase CCA. I expect pre- vs post-purchase CCAs will generate asymmetric stock market response for two reasons.

At the pre-purchase stage, customers tend to 'browse' and 'explore' different products without clear purchase intent (Bloch et al. 1989; Miles 1998). They use firm touchpoints to find, organize, and evaluate product alternatives (Frambach, Roest and Krishnan 2007) and arrive at a purchase decision. Compared to websites or personal interactions, CCA interfaces have lower capabilities for supporting rich representations of product with multiple attributes, presenting alternatives, or presenting visual product comparisons (Revang 2019; Kannan and Bernoff 2019). Thus, CCAs constrain customers' information access, requiring greater time and effort for purchase decisions. Customers even feel frustrated if they are unable to have open-ended conversations with CCAs (Brandtzaeg and Folstad 2018). Lower pre-purchase decision convenience from CCAs likely discourages customers' use of CCAs, resulting in lower potential cash flow from CCA launch. By contrast, post-purchase CCAs reduce firms' response times for resolving customer issues, thus enhancing benefit and post-benefit convenience (Kannan and Bernoff 2019). Because CCAs are available 24/7 -- and have significant scalability – they can resolve customers' post purchase concerns with limited wait times. 52% of customers indicated convenience as a primary reason to prefer interacting with CCAs (Buvat et al. 2018). As customers have already made a purchase before using post-purchase CCAs, these CCAs do not influence customers' decision or transaction convenience types. The result is an overall positive perception of convenience while using post-purchase CCAs, improving the likelihood of future customer purchases (Berry et al. 2002).

The second reason is that pre-purchase CCAs need to be able to recognize and respond to a greater number of queries from customers than post-purchase CCAs (Kannan and Bernoff 2019). Customer needs, goals, and product preference are likely to be unclear or incomplete in the pre-purchase stage; at times, customers may just muddle through (Park 1982). Consequently, customers' decision-making is complex, and their exact information needs are unknown a priori (Ariely 2000). CCAs often work linearly, use a limited set of information provided by customers and may have a limited understanding of a customer's context (Brandtzaeg and Folstad 2018). A customer frequently changing her information requirements at the pre-purchase stage makes understanding customer requests more difficult and results in less effective personalization from the CCA (Budiu 2018). Inaccurate responses lead to algorithmic aversion (Dietvorst et al. 2015), in turn lowering CCA adoption. Ineffective personalization hurts customer engagement and reduces purchase likelihood (Kumar et al. 2019). Thus, pre-purchase CCAs can falter despite having customer purchase data, as customer requirements for a firm's offerings can vary with every purchase (Kannan and Bernoff 2019). Ineffective pre-purchase CCA personalization would likely discourage customer adoption, again resulting in lower future cash flows.

On the other hand, in the post-purchase stage, customers have much more specific goals, among them renewing service and getting responses to service queries (Frambach, Roest and Krishnan 2007). Per a report by Dixon et al. (2017), 84% of customers need straightforward answers to their requests at firm touchpoints. Because they serve fewer customers, encounter more obvious customer intent, and have ready access to customer transaction data, post-purchase CCAs generate more accurate responses to customer queries and are better able to personalize their responses. Theoretically, this capability will increase customers' use of post-purchase CCAs, lowering the cost of serving customers and once more enhancing cash flows.

A recent case study finds that post-purchase CCAs can be up to four times more effective than humans in generating additional sales (Luo et al. 2019). Thus, due to greater personalization and convenience benefits, I expect that post-purchase CCAs would generate greater future cash flows than pre-purchase CCAs reflecting in the stock market reactions. Formally,

H2: CCA's stage of customer journey focus moderates the positive impact of CCA launch announcement on firm value, such that CCAs launched to assist customers across the post-

purchase (prepurchase) stage of customer journey are likely to accentuate (mitigate) the positive effect.

Brand-owned vs partner-owned. Brand-owned touchpoints refer to customer interactions designed and managed by the firm, whereas partner-owned touchpoints refer to interactions jointly managed by the firm and its partner(s) (Lemon and Verhoef 2016). I expect that the capabilities of partner-owned CCA customer interactions (Kannan and Bernoff 2019) will enhance personalization and convenience benefits delivered by CCAs.

Primarily, customer integration of partner-owned platforms (e.g. Amazon Alexa, Google Home) into their physical environments provides greater access convenience. Such integration means customers develop knowledge about using CCAs with familiar partner touchpoints, which increases their likelihood of better realizing convenience benefits (Eeuwen 2017; Grewal et al. 2020). Improved convenience amplifies customers' future purchase intentions and in turn the firm's cash flows (Seiders et al. 2005). Industry surveys report that convenience drives customers' preference for using partner-owned CCAs (Buvat et al. 2018).

Second, partner-owned CCAs offer better personalization than brand-owned CCAs. Easy access to partner-owned CCAs aids a customer's search and encourages her to buy products bought less often (such as medicines or car rentals) in addition to staples -- groceries, pet supplies, and the like (Buvat et al. 2018). Such purchases provide partners with more information about customers' preferences and intentions. Combined with machine-learning technologies, this information allows for data-driven discoveries of hidden patterns, correlations, and revealing better customer insights. Amazon, to cite one well-known example, captures and stores customer data at its CCA touchpoints in order to improve customer experience (Fowler 2019). This type of rich information helps partners create more dynamic personalized product recommendations for offerings, prices, and promotions. As the Director of Amazon Alexa noted:

"Alexa is always getting smarter, which is only possible by training her with voice recordings to better understand requests, provide more accurate responses, and personalize the customer experience" - (Fowler 2019).

While brand-owned CCAs can capture customer search data, its' difficult for these CCAs to glean more general search related behavior. Partners' access to such general search behavior augments the data, enabling effective personalized recommendations. It is also less expensive for firms launching CCAs to personalize offerings using partners' prediction capabilities than to collect customer data and build all the capabilities in-house (Ismail 2018). Given that partner-owned CCAs can provide greater convenience as well as greater personalization capabilities at a much lower cost than brand-owned CCAs, I expect that,

H3: Launching CCAs as partner-owned (brand-owned) will positively (negatively) moderate the positive impact of CCA launch announcement on firm value.

Functionalities of a technology product refer broadly to its ability to perform a specific action (Goodhue and Thompson 1995). I examine the effect of CCA's functionalities because they can significantly influence customer adoption as well as use (Xiao and Kumar 2019). I identified three key functionalities of CCAs.

Task vs information. Task-oriented CCAs comprehend and respond to customer queries. For example, when Western Union's CCA receives a customer's money transfer request, it verifies the customer's account and begins an automated money transfer. In contrast, information oriented CCAs explain a firm's offerings and support the customer with information throughout the purchase. For example, Briggs and Stratton's CCA provides customers a wide range of mover-related information as the customer transitions through her purchase journey.

If firms use information-oriented CCAs, they have greater control over the information provided at customer touchpoints (Verhoef et al. 2015). Firms can not only personalize the information they provide but also have greater control over customers' purchase experience. Getting personalized and purchase relevant information increases customers' future purchases (Verhoef et al. 2015). Moreover, getting product relevant information reduces customers' time and effort which enhances their decision and benefit convenience. Lastly, informational assistance provided by CCAs after purchase (e.g., how to use a product) enhance customers' post-benefit convenience. These convenience enhancements make future purchases more likely. Thus, using information-oriented CCAs should positively influence stock market reactions.

On the other hand, I expect task-oriented CCAs to lower purchase likelihood. First, task-oriented CCAs execute customers' tasks that require interaction with other systems in their environment. Customer environments can vary significantly, which adds greater complexity to perform tasks effectively. CCAs have limited understanding of the complex inputs in a new environment and have limited ability to recognize situations unique to a customer's environment (Xiao and Kumar 2019), which results in increased malfunctioning (Yang et al. 2017). Second, if CCAs perform tasks incorrectly (e.g., not ordering the customer's preferred brand), they require more time and effort from customers and lower their perceptions of convenience from using CCAs. Third, customers prefer to conduct tasks themselves or similar peers and need to overcome aversion to algorithms performing tasks in order to adopt task-oriented CCAs (Prahl and van Swol 2017; Castelo et al. 2019). Fourth, customers' risk perceptions escalate when they use CCAs to perform consequential tasks, which further reduces CCA adoption (Davenport et al.

2020). Thus, lack of personalization to a customer's environment, lower convenience and customer's aversion to task-oriented CCAs decrease CCA adoption and in turn lowers incremental purchases.

Beyond these two specialized functionality CCAs, firms also launch dual functionality CCAs that provide information as well as perform tasks. Between these CCAs, I expect that information-oriented CCAs will amplify future cash flows and task-oriented CCAs will mitigate future cash flows. Industry surveys indicate that customers are twice as likely to adopt information-oriented vs task-oriented CCAs (Buvat et al. 2018). Further, Boyd et al. (2019) find initial evidence that transaction-oriented (a type of task-oriented) touchpoints reduces firm value. Lastly, I expect that using dual functionality CCAs will both generate positive cash flow from providing information and generate negative cash flow from performing tasks. Thus, I expect investor reaction would be more positive when firms use information-oriented vs dual-functionality CCAs. Moreover, investor reactions would be more negative when firms use task-oriented vs dual-functionality CCAs. Formally,

H4a: CCA's functionality moderates the positive impact of CCA launch announcement on firm value, such that CCAs launched with dual functionalities mitigate the positive effect compared to CCA launched with informational capability alone.

H4b: CCA's functionality moderates the positive impact of CCA launch announcement on firm value, such that CCAs launched with dual functionalities accentuates the positive effect compared to CCA launched with task capability alone.

CCA modality. In order to facilitate human interaction with CCAs, firms build conversational interfaces that either have text or voice capabilities or both (we term this as 'dual interface'). Text-based CCAs and voice-based CCAs influence different types of customers' convenience. Text-based CCAs increase customers' perceived decision convenience. This is because customers need to find, organize, and evaluate alternatives while making decisions at CCA touchpoints. Customers have greater comprehension and improved memory when difficult information is presented text form (Daniel and Woody 2010), which makes text-based CCAs more effective while making decisions. On the other hand, text-based CCAs lower access convenience because customers need to open the CCA and type out their questions, which requires greater effort (Berry et al. 2002). Evidence suggests that presenting information in text format is likely to be less effective at persuading customers than audio (Appiah 2006).

In contrast, customers perceive greater access convenience while using voice-based CCAs because they can initiate conversations using simple voice commands, which lowers their effort and time investments. Moreover, humans process simple auditory information easier than reading text (Liberman 1989). A study by Sun et al. (2020) finds that frequent access to voice-based CCAs increases customer purchase by 23%. However, using audio to compare and evaluate products increases customer effort, which reduces perceived decision convenience. Thus, text-based CCAs and voice-based CCAs increase customers' perception of one type of convenience and reduce it for another. I do not expect that these CCAs would influence customers' other types of convenience and personalization perceptions.

For dual interface CCAs, I expect future cash flows could either decrease or increase. Dual interface CCAs increase future cash flows if customers' convenience needs are congruent with the CCA's modality. For instance, if customers use voice-based CCAs to improve access convenience and text-based CCAs to improve decision convenience. On the other hand, if customers' convenience needs were not congruent with CCA's modality, it would lower customers' convenience perception and purchase experience in turn lowering future cash flows.

Moreover, customers process voice and text information modalities independently in their brain and thus switching between modalities (e.g., while using dual interfaces) requires greater effort (Tavassoli 1998). Customers also find it challenging to integrate information from different modalities. Switching would therefore reduce customers' perceived convenience and lower CCA use. Thus, I expect that the potentially lower convenience perceptions along with challenges of switching between modalities will lower customer adoption of dual interface CCAs compared to single modality interface CCAs. Thus, I expect:

H5a: CCAs modality moderates the positive influence of CCA launch announcement on firm value, such that launching dual interface CCAs lower cash flows more than launching text-based CCAs.

H5b: CCAs modality moderates the positive influence of CCA launch announcement on firm value, such that launching dual interface CCAs lower cash flows more than launching voice-based CCAs.

Authentication. Authentication is a process that helps verify customer identity and allow her to interact with a firm through encrypted touchpoints (Lee et al. 2012). Adding authentication features to a CCA helps a firm limit its usage to authorized customers. Research examining implications of using authentication features finds that adding these features significantly lowers customers' perceived convenience (Weir et al. 2009). Customers appear to value convenience over the risk reduction benefits of authentication (Weir et al. 2009). In fact, customers often disable or stop use of security features that lower their convenience (Lee et al. 2012). Generally, when firms add authentication features to their CCA, customers need to use two-factor authentication to gain access, which requires additional time and effort (Kannan and Bernoff 2019). Customers find the requirements involved in authentication to be complicated and burdensome (Lee et al. 2012). Any additional required time and effort will push pushes customers toward more convenient touchpoints (Odekerken-Schroder and Wetzels 2003). Research finds that customers deem convenience a significant factor in purchase decisions (Anderson and Shugan 1991). Perceived inconvenience and dissatisfaction reduce the perceived value of the technology, with subsequent negative implications for future cash flows (Berry, Seiders, and Grewal 2002; Tuli and Bharadwaj 2009). I therefore expect that launching CCAs with authentication is likely to generate lower financial value than CCAs launched without. Thus:

H6: CCAs authentication functionality moderates the positive impact of CCA launch announcement on firm value, such that CCAs launched with authentication requirement are likely to mitigate the positive effect.

Table S.2.2.1 in Appendix S2.2 summarizes the identifying characteristics of the CCAs launched by firms, the customer requirements CCAs typically recognize, the AI technological capabilities they require to respond to customer queries effectively, and the potential benefits they provide to customers.

EMPIRICAL STRATEGY

I conducted three studies to test the hypotheses and provide supplementary evidence of the process mechanisms. While Study 1 presents tests all of the formal hypotheses, Studies 2 and 3 serve to provide exploratory evidence of the underlying mechanisms.

Study 1. Effect of CCA Launch on Firm Performance

In Study 1, I examine the effect of a CCA's launch announcement on firm's abnormal stock returns by using an event study method, adopted widely in marketing research (Srinivasan and Bharadwaj 2004; Sorescu, Warren and Ertekin 2017).

Sample

Using the Factiva database, which collects data from newswires, press releases, news articles and firm disclosures, I compiled CCA launch announcements made by U.S. public firms between 2003 and June of 2020. To find the announcements, I searched for a combination of terms related to launching CCAs in both headlines and main announcement body. I found very few launch announcements before 2003, and further research showed that the announcements were not related to the launch of automated conversational agents. This generated a sample of 305 announcements across 73 industries (4-digit SIC). From this sample, I first removed 62 announcements pertaining to CCAs aiding firms' internal operations (e.g., HR). From the remaining 243, I followed established practice in event studies by eliminating announcements that had 37 potential confounding event(s), such as stock splits, executive changes, and M&A activity in the event period (Srinivasan and Bharadwaj 2004). This left me with a final sample size of 206 CCA launch announcements. However, recent research does suggest that events accompanied with other confounding events during the event window can be retained in the sample (e.g., Sorescu, Warren and Ertekin 2017). Hence, in the robustness check section, I tested the model on data that included the confounding announcements.

Dependent variable. I use a firm's abnormal stock returns to measure changes in its financial value. I calculated the abnormal stock returns using the market model. I chose this model over the Fama-French-Cahart model because the latter was designed to measure stock market performance over longer windows (Sorescu, Warren and Ertekin 2017). I gathered information on firm and market stock returns from the Center for Research in Security Prices (CRSP). For the estimation, I used daily data on stock market returns for each firm during a 255-trading-day period ending 46 days before the event date.

(1) $$E(R_{it}) = \alpha_i + \beta_i R_{mt} + \varepsilon_{it}$$

where $E(R_{it})$ denotes the expected daily returns for firm i on day t if the event had not taken place, R_{mt} denotes the daily returns of the respective market index in the home market (S&P 500), α_i and β_i are firm-specific parameters, and ε_{it} is the i.i.d. normally distributed error term (Brown and Warner 1985). I then used the estimates to predict the returns for each firm during the event days, AR_{it}:

(2) $$AR_{it} = R_{it} - E(R_{it}) = R_{it} - (\alpha_i + \beta_i R_{mt} + \varepsilon_{it})$$

Here, R_{it} signifies the actual daily returns, and $E(R_{it})$ represents the model estimates. The abnormal returns received by a firm AR_{it} provides an estimate of the future earnings generated by launching CCA.

Next, I identified the most appropriate event window $[t_1, t_2]$ to ensure the availability of information regarding the CCA launch announcement among investors (Srinivasan and Bharadwaj 2004). I calculated abnormal returns for alternative event periods, starting from before the launch announcement t_1 and ending potentially after the launch announcement at t_2. This resulted in the cumulative abnormal return given by:

(3) $$CAR_i[t_1, t_2] = \sum_{t=t_1}^{t_2} AR_{it}.$$

I calculated the cumulative average of abnormal returns for the firms in our sample (N) across multiple event windows (CAAR) and tested the significance of abnormal returns in these event windows using the t-test of Brown and Warner (1985) and the generalized sign z-test. This CAAR is the dependent variable for this research.

(4) $$CAAR[t_1, t_2] = \frac{\sum_{i=1}^{n} CAR_i[t_1, t_2]}{N}.$$

Independent variables. Independent coders categorized all variables that required coding based on the content from CCA launch announcement. The inter-rater reliability for coded variables ranged between 88% and 92%. The coders resolved all conflicts through conversation among themselves. I coded an announcement *pre-purchase* if the CCA's focus was assisting customers before making a purchase (e.g., exploring a food menu) and *post-purchase* if the CCA assisted customers after their purchase (such as getting delivery updates)[5].

I categorized the *task vs information* variable based on whether a CCA responds to customer intents by performing tasks, providing information, or doing both. *CCA Modality*. I coded CCAs that interact with customers only via text as *text-based* and the ones that interact only through voice as *audio-based*. I categorized CCAs with both text and voice capabilities as *dual interface CCAs*. I classified CCAs launched using popular partner CCA platforms, namely Amazon Alexa, Google Assistant, Apple's Siri, Microsoft Cortana, Facebook, and Twitter as *partner-owned*. I categorized other CCAs as *brand-owned*. I classified a CCA as requiring *authentication* if it satisfied two conditions: (1) Requiring customers provide individual authentication information (like a PIN number) to access CCA, and (2) Using this information to generate an individualized response (e.g., showing a checking account balance).

Control Variables. Following established literature, I control for the following firm-related factors: *firm performance*, *firm size*, *market share*, *parent company*, *marketing emphasis*, *technology emphasis* and *information coverage* (e.g., Geyskens, Gielens and Dekimpe 2002; Homburg et al. 2014; Boyd et al. 2019). In addition, I control for industry-related factors that could explain the stock market reaction. Also following previous literature, I control for industry's *market size* (e.g., Homburg et al. 2014) and the *competitive intensity* in the industry and include *industry dummies* to address industry fixed effects. Furthermore, I control for time-related effect by creating a variable called *AI-period*. It accounts for the period when customers

[5] In few cases, CCAs assisted in both pre- and post-purchase. I categorized such CCAs based on the stage at which the CCA recognized greater proportion of customer intentions.

have high awareness of and interest in AI and its related applications. I therefore expect customer attitudes toward CCAs to be different during the AI-period, as CCA functionality, efficacy and availability are likely to be greater (Brandtzaeg and Følstad 2018; Kumar et al. 2019). I include the *order of entry* variable because the opportunity to benefit from market expansion through additional touchpoints declines when the time a firm takes to enter the market increases (Geyskens, Gielens and Dekimpe 2002). Thus, firms launching CCAs later will benefit less from market expansion; launch announcements that come later will generate lower abnormal returns. I provide the independent variables, controls, and their data sources in Table 2.2. Appendix S2.6 provides the correlations and descriptive statistics for the independent and the control variables.

Accounting for Self-Selection

Private information not fully known to investors can lead to voluntary firm actions such as launching CCA (Sorescu, Warren and Ertekin 2017). I need to account for endogeneity and estimate bias for the self-selection resulting from a firm's strategic decision to launch CCA. To do this, I use two methods: (1) Selection on observables through propensity score matching, and (2) Selection on unobservables through a Heckman selection procedure (Heckman 1979).

Propensity score matching. Following earlier research (e.g., Warren and Sorescu 2017), I constructed a counterfactual matched sample of firms that did not launch CCA. The matched set of control firms is similar in observed characteristics to the set of firms that did launch a CCA, and to firms that could ostensibly be inclined to launch a CCA based on these characteristics. I obtained this counterfactual matched sample by matching on covariates used in prior research (e.g., Boyd, Kannan and Slotegraaf 2019). I employed the nearest neighbor matching algorithm (e.g., Warren and Sorescu 2017) to identify the closest one-on-one match within the industry to each firm launching CCAs. To increase quality of my matches, and to ensure that the propensity scores in the control samples are close to treated samples, I limited the absolute distance between the two propensity scores to less than a predetermined caliper (ε), calculated as $\varepsilon = 0.25\sigma_p$, where σ_p is the standard deviation of the propensity score (cf. Warren and Sorescu 2017). I then searched the Factiva database to ensure that the matched firms (control) do not have other confounding announcements and did not launch CCA. Finally, I subtracted each control firm's CAR from the corresponding treatment firm's CAR on the event period of CCA launch announcement. In the "Robustness Checks" subsection, I report results using an alternative Mahalanobis matching method.

In order to ensure that the CAR difference (treatment CAR – control CAR) is due to launching CCA and not due to systematic differences between firms launching (and non-launching firms), I had to test whether the variables used to calculate propensity scores identify firms with a similar likelihood of launching CCA. Oster's (2019) approach allowed us to access potential omitted variable bias in the observables (see Blaseg, Schulze and Skiera (2020) for similar use), by examining two aspects: (1) variation in the estimated coefficient after adding covariates -- for our study, the covariates are the variables used to calculate propensity scores -- and (2) the associated shift in R^2 to assess the sensitivity of our results (see Oster (2019) for a formal derivation). Based on Oster (2019)'s recommendation, we use $\delta = 1$ and $R_{max} = 1.3\tilde{R}$. I presented details of the test and results in Appendix S2.7. My analysis suggests that omitted observable variables are unlikely to be a driver of the differenced CAR and thus the variables used to calculate the propensity score are sufficient.

Furthermore, I conducted the Kolmogorov–Smirnov test used in event studies (cf., Warren and Sorescu 2017) and found that propensity score distributions in the treated and control groups are similar (p-value = 1). I also used the standardized difference in means test (stddiff in STATA) and find that standardized difference percentages between propensity scores of treatment and control groups was 0.005, below Austin (2009)'s recommended cutoff values.

Selection model. In order to account for potential self-selection bias resulting from unobservables, I use the Heckman two-stage self-selection model. In the section equation, I used a probit model, in which the dependent variable is a firm's decision to launch a CCA, to calculate the inverse Mills ratio. I included both firms that launched CCA (coded as '1') and firms that did not launch a CCA (coded as '0'). To facilitate identification in the first stage, I use three exogenous determinants of the decision to launch CCA. The first is a variable named 'cultural individualism.' Research links a firm's ability to sense and respond to technological opportunities based on its cultural individualism scores (Boyd et. al 2019). The second variable is the average number of CCAs in an industry for each year. This variable would be highly correlated with the CCA launch variable and not with unobserved determinants of firm value (error term), thereby providing a strong IV (e.g., Germann, Ebbes, and Grewal 2015). Following Germann et al. (2015), for firms that belong to multiple industries, I calculated the weighted average of CCAs per industry-year using the number of firms within each 2-digit SIC code as the base. Third, I included a cumulative count measure of AI patents granted to a firm until the year of CCA launch. I provide details of the Heckman analysis and results in Appendix S2.8. I control for industry- and time-related factors by controlling for whether the firm serves B2B (or B2C) customers, and whether the CCA launch occurred in the AI-period. Lastly, I control for the firm's market share. I used the inverse mills ratio, λ_i, to correct self-selection in the main model's subsequent analysis.

Results

Main effect. In order to account for potential information leakage, I identified the CAR across multiple event windows (see Appendix S2.10). To determine the most appropriate choice, I followed prior practice and selected the event window with the most statistically significant abnormal return (e.g. Homburg, Vollmayr and Hahn 2014; Boyd et al. 2019). As indicated in Table S2.10.1 (appendix), day 0 has statistically the most significant CAR, at 0.29% (p <.01). This provides support for H1. Based on the market value of the firms in the sample during the day of CCA launch, I find that 0.29% translates into a wealth effect of $56.7 million for a median-sized sample firm.

Effect of moderators on CAR. For an empirical test of the moderating effects of CCA launch strategies and CCA functionalities, I conduct a regression analysis using CAR (0, 0) as the dependent variable.

(5) $$\mathrm{CAR_i}[0,0] = \beta_0 + \beta_1 * \text{Stage of Purchase}_i + \beta_2 * (\text{Partner vs. Brand Owned})_i + \beta_3 * (\text{Dual Functionality vs. Information})_i + \beta_4 * (\text{Dual Functionality vs. Task})_i + \beta_5 * (\text{Dual Modality vs. Text})_i + \beta_6 * (\text{Dual Functionality vs. Audio})_i + \beta_7 * \text{Authentication}_i + \beta_8 * \text{Order of Entry}_i + \beta_{9-15} * \text{Firm Controls}_i + \beta_{16-17} * \text{Industry Controls}_i + \beta_{18} * (\text{AI} - \text{Period})_i + \varepsilon_\mathrm{i}$$

where β_0 is the intercept, β_{1-18} are regression parameters belonging to the independent and control variables, and ε_i is the error term. I also included *industry dummies* (using 1-digit SIC code) not shown in Equation 5.

Table 2.3 presents the estimation results of the second stage equation (main model). Based on the results, I find that the regression model is significant (F-statistic = 2.29, $p < .01$). The variance inflation factors of all our main independent variables are less than 5 indicating multicollinearity is not a concern. The results show that in line with H2, launching post-purchase CCAs has a greater positive effect on abnormal returns relative to launching pre-purchase CCAs

($\beta = .89, p < .01$). I also find that the value generated by launching a CCA as partner-owned is greater than that generated as brand-owned ($\beta = .81, p < .05$). This provides support for H3.

Furthermore, I find that launching dual functionality CCAs generates greater abnormal returns generated than launching information-based ($\beta = .58, p < .05$) or task-based CCAs ($\beta = .82, p < .01$). Thus, I find support for H4b, but surprisingly we find the opposite of what I expected for H4a. Interestingly, I find that launching of dual modality CCAs generate significantly greater abnormal returns compared to solely text-based CCAs ($\beta = 1.63, p < .01$) or voice-based CCAs ($\beta = 1.49, p < .05$). This is the opposite of what I predicted for H5a and H5b. I find, in line with H6 that building an authentication feature has a significant negative effect on firm value($\beta = -.91, p < .01$). A chi-square test of independence ruled out the possibility that the CCAs with authentication features are limited to certain industries (e.g., banks) and thus driving the results.

Additional Analysis: Testing for Investor Attention to CCA Announcement

While the efficient market theory underlying the event, study suggests that investors are valuing the CCA announcement, the measure is still indirect. I follow the literature in finance (e.g., Da, Engelberg, and Gao 2011) and marketing (Xiong and Bharadwaj 2013) and utilize a direct revealed attention measure of investor attention, namely, the aggregate search frequency of firm tickers on Google. Da Engelberg and Gao (2011) document the advantages of this measure. I download the weekly Search Volume Index (SVI) (i.e., the number of searches for the ticker scaled by its time series average) for the treatment and control firms. As model free evidence, I plotted mean SVI for the treatment and control firms (see Figure S.2.11.1 in Appendix S2.11) and the investor attention appears to increase for the treatment firms on the week of the launch. I conducted a regression of CCA launch announcement on investor attention, controlling for past investor attention, selection correction, year and industry dummies (see Appendix S2.11). I find empirical support for our expectation that firms launching CCA receive greater investor attention ($\beta_1 = 2.86, p < .05$).

Robustness Checks

I conducted several robustness checks with alternative firm value measure, inclusion of additional market signaling factors, confounding events, alternative asset pricing model, alternative matching model, industry related controls, Carhart 4-factor model, and using year dummies with AI-period variable. I provide the results of the robustness checks in Table 2.4.

Additional Market Signaling Factors. Investors may react to the signals about a firm, such as how well it performs and it's potential for market growth. Hence, I included return on assets and industry growth to account for firm performance and market growth respectively (e.g. Homburg et al. 2014). The results remain robust (see Table S2.12.1 in the Appendix).

Including Confounding Launch Announcements. To test if excluded confounding observations influence the results, I included CCA launch announcements made by firms with other announcements in the event window (Sorescu, Warren and Ertekin 2017). I replicated the analysis with the new sample of 243 launch announcements. The results remain robust to the inclusion of confounding announcements (see Table S2.12.2 in the Appendix).

Alternative Asset Pricing Model. I re-estimated investors' reactions to CCA launch using the Fama French and the Carhart 4-factor model. The most significant CAR obtained was during the event window (0, 0) with CAR = .34%, ($p < .01$). I replicated the analysis, and the results remain largely robust (Table S2.12.3 and S2.12.4 in the Appendix).

Alternative Matching Technique. To examine robustness of our matching method, I use the Mahalanobis distance to identify the nearest neighbor. I paired each treated observation with a corresponding control identified using the lowest Mahalanobis distance to the treated observation. These results remain largely consistent (see Table S2.12.5 in the Appendix). While directionally consistent, I lose significance for the partner-owned variable. Lastly, I re-ran main model using *B2B vs B2C* dummy (Beckers et al. 2018) as well as *product vs service* dummy identified using SIC code. I replaced AI-period variable with yearly dummies (years starting 2015 coded as '1' and the rest coded '0'). See Appendix Tables S2.12.6 and S2.12.7.

Market value as alternative dependent variable. I used the firm's market value for the year of launch. The model accounts for the firm's industry, AI-period, the firm's return on assets, technology emphasis, size, financial leverage, and slack I find that launching a CCA is positively associated with total q (β=30.44, p<.05). I have added the results of this Appendix S2.13.

Capturing the intelligence level of the CCA. Huang and Rust (2019) propose that AI applications have three types of intelligence, namely, (1) mechanical intelligence that helps perform repetitive tasks (2) thinking intelligence that helps to learn and adapt from data autonomously, and (3) feeling intelligence that interacts empathetically with people. To examine whether a CCA's intelligence capabilities explain the heterogeneity in financial market value, I created a custom dictionary for the three intelligences based on words identified from Huang and Rust (2019). For example, we used words such as 'inspect', 'maintain', 'getting', etc. for mechanical intelligence, 'analyze', 'consult', 'evaluate', etc. for thinking intelligence and 'coach', 'develop', 'motivate', etc. for feeling intelligence. I then used the dictionaries with Linguistic Inquiry and Word Count (LIWC) text-mining method (cf. Berger et al. 2020) to get a measure of the dominant intelligence of a CCA communicated through the launch announcement with the highest percentage of total words in an announcement as the dominant intelligence. I provide results of our estimation in the Appendix S2.14. I find that investors do not value mechanical intelligent CCAs differently from thinking intelligent CCA ($\beta = .29, p > .10$). However, I find that investors value feeling intelligent CCAs more positively than thinking intelligent CCAs ($\beta = .53, p < .05$). Firms could benefit more by signaling the feeling intelligence capabilities of a CCA in the launch announcement.

Study 2. Personalization and Convenience as Investors' Information Cues

Firms typically have more information than investors do about their own strategic decisions, leading to information asymmetry between them (Stiglitz 2000). Unless tipped, this asymmetry is likely to lead to investor uncertainty about the potential cash flow benefits of the strategic investment (e.g., in a CCA), and is likely to prevent investors from making optimal capital allocation decisions. Consequently, firms interested in having their strategic actions and investments valued appropriately will signal their intentions to investors to reduce that uncertainty (Connelly et al. 2011; Devers et al. 2007). Xiong and Bharadwaj (2013) find that information from firms' advertisement of good news attracts investors, in turn increasing stock prices.

In this study, I examine whether firms launching CCA signal the proposed mechanisms of personalization and convenience that mediate the effect of launching CCA on firm performance. I examine the text contained in the 10-K/annual reports, as it offers investors an observable cue of managers' strategic emphasis (Panagopoulos et al. 2018). Strategic intent and mindset-related content on a firm's 10-K help investors evaluate the firm's future prospects (Saboo and Grewal 2013), which is then reflected in firm value. Extant research has used 10-K to understand investors' reactions to firms' strategic focus (e.g., Panagopoulos et al. 2018). Similarly, I use the available 10-K/annual reports to help capture firms' emphasis on personalization and convenience.

Data Source

Using a web crawler, I obtained the text in the Management Discussion and Analysis (MD&A) section of 10-Ks for firms launching CCAs and for their corresponding neighbor firms (identified using the PSM technique described earlier) during the year of the CCA launch. In my sample, approximately 18% of firms did not provide detailed descriptions in their management discussion section. For that 18%, I extracted the firm's letter to shareholders, as it is also a key communication tool for the firm's management and investors (Noble, Sinha, and Kumar 2002).

Personalization and Convenience Measures

I measure a management team's emphasis on personalization and convenience by counting the occurrence of keywords related to these two constructs in the MD&A section (e.g. Berger et al. 2020). First, I created a dictionary based on the words used in previous studies (see Appendix S2.15) pertaining to convenience and personalization constructs (e.g. Berry et al. 2002; Seiders et al. 2007). Second, I processed the full text of the MD&A section using the Linguistic Inquiry and Word Count (LIWC) program (Berger et al. 2020), and our dictionary of terms.

Method

The dependent variables for this study are the count of personalization and convenience words in the MD&A section. The focal independent variable for this study is the launch of a CCA by a firm. The main goal in Study 2 was to assess whether firms launching CCA place a greater emphasis on personalization and convenience. In an experimental sense, I aim to infer the treatment effect, as represented by the incremental emphasis firm launching CCAs place on personalization and convenience. Firms self-select into launching CCAs, and the factors that encourage them to launch are not always clear. To establish a causal link between CCA launch and a firm's emphasis on personalization and convenience, I use three methods: (1) difference-in-differences, (2) difference-in-differences, augmented with selection on observables, and (3) difference-in-differences, augmented with selection on unobservables (e.g. Gill et al. 2017). I assign the year before and 2 years before a launch as the pre-treatment period and the year of launching CCA as the post-treatment period. We provide details about the difference-in-differences procedure in Appendix S2.16.

I tested the mediation of convenience and personalization both separately and together. The dependent variable is a firm's 'total q', a measure of investment opportunities (Peters and Taylor 2017), one year post the year of launch. My expectation is that compared to control firms not launching CCA, firms launching CCA would place greater emphasis on personalization and convenience. Consequently, we expect investors would increase their future cash flow expectations.

I account for endogeneity in the manner described in Study 1. In addition, as I examine the impact on total q accounting for the firm's industry, the *AI-period*, the firms' return on assets, technology emphasis, size, financial leverage, and slack. I provide details about the variables used, along with the results table, in Appendix S2.16.

Results

Based on our model-free evidence, I find that raw mean count of convenience words used in 10-K annual reports in the control and treatment groups were not statistically different in the prelaunch period ($\text{treatment}_{\text{convenience}} = 123.40$, $\text{control}_{\text{convenience}} = 119.77$, $p > .10$). Similarly, count of personalization words used in 10-K annual reports were not different between the control group and treatment group ($\text{treatment}_{\text{personalization}} = 42.18$, $\text{control}_{\text{personalization}} = 43.36$, $p > .10$). However, for firms launching CCAs, the count of convenience and personalization words used in 10-K reports increased in the post-launch period ($\text{treatment}_{\text{convenience}} = 135.30, \text{control}_{\text{convenience}} = 118.30, \text{t} = p < .05$); ($\text{treatment}_{\text{personalization}} = 45.00, \text{control}_{\text{personalization}} = 40.65, p < .10$). The change in the treatment firms' convenience emphasis compared to the control firms' convenience emphasis was significant at was higher (p < .05). Similarly, the change in treatment firm's personalization emphasis compared to the change in control firms' personalization emphasis was also significant at (p < 0.05). I then estimated the difference-in-difference regression model (specified in Appendix S2.16) and find that the treatment effect (launch group x time-period) was significant $\left(\beta_{3-convenience} = 20.87, p < .05; \gamma_{3-personalization} = 9.54, p < .05\right)$.

I examined the effect of CCA on the measure of firm value, total q. I find that the total q for the firms that launched a CCA (treatment firms) increased from a mean of 1.78 to 2.00, while for firms not launching the CCA or the control group, it declined from 1.41 to 1.39 between the prelaunch and post-launch periods. The difference in difference between the two groups on total q is significant (p < .05) suggesting that firms launching CCA were associated with higher firm value. I then estimated our difference-in-difference regression model (specified in Appendix S2.16) and find that the treatment effect (launch group x time-period) was significant on total q ($\delta_3 = 0.28, p < .10$). Together these difference-in-difference analyses suggest that firms launching CCAs communicate the personalization and convenience benefits to investors and enjoy higher firm performance[6].

[6] I report a formal test of mediation in the Appendix S2.17. I examined the direct effect of launching CCA on total q and found this effect significant (η1=1.36,p<.05). Next, firms launching CCAs place greater emphasis on convenience (α_c1=18.45,p<.05), but not on personalization (α_p1=3.16,p>.10). The indirect effect (measured using bootstrap mediation analyses Model 4, Hayes 2013) of CCA launch on total q is significant, through convenience (η_c1=.10,p<.05,[CI_95]=[.01,.46]), while the indirect effect of CCA launch on total q through personalization is insignificant (η_p1=.04,p>.10,[CI_95] = [-.01,1.19]). However, when I include both moderators in the regression, The indirect effect was significant (η_cp1=.09,p<.05,[CI_95] = [.07,1.49]). To a considerable extent, study 2 suggests that firms launching CCAs communicate their convenience and personalization benefits to the investor community and these factors serve as mediators.

Study 3: Customer Perceptions of Convenience and Personalization using CCA

Next, I conduct two experiments to examine whether customers perceive enhanced convenience and personalization when using CCAs. In Study 3a, I assign participants[7] the task of building an order for a pizza both on the company's website and on a CCA. To maintain consistency, I ensure that both of the participants' pizzas include similar options (namely, toppings). In Study 3b, I test whether adding personalization and convenience features to CCAs influences participants' perceptions of these two constructs.

Study 3a: CCA versus Website

One hundred and thirty-nine undergraduate students from a large Southeastern university in the United States (41.25% female; M_{age} = 22.2 years) participated in this study in exchange for course credit. Twenty-nine participants failed the attention check. Thus, I base my analyses on 110 observations. I randomly assigned participants to one of the two conditions (Website vs. CCA) and asked them to imagine that they were hungry and were planning to order pizza from a popular pizza restaurant chain. Next, I provided participants in the CCA condition with a basic description of a CCA and its capabilities using illustrative GIF images. I informed that they would be watching an animation depicting a typical interaction between a human and a CCA. I provided the participants a GIF image, as shown in Appendix S2.18 (Appendix image is in JPEG) and identified for them the interaction texts written by a human and by the CCA. I did not provide information about the CCAs to website participants and asked them to build order using instructions in Appendix S2.18.

The task for participants in each condition was to build a pizza by selecting options from the pizza website (website condition) or through interacting with the CCA via text (CCA

[7] Although these two real-behavioral studies use undergraduate students as participants, the product category and context is familiar to students.

condition). Specifically, I asked them to order a pizza with the three options regarding style, size and toppings. In addition, I asked them to choose "carryout" option to collect the pizza and to pick it up from a store closest to the zip code "AAAAA." Finally, participants responded to survey items measuring their perceptions of personalization and convenience using adapted scales of Sieders et al. (2007) and Kalyanaraman and Sundar (2006). The scale reliability and Cronbach's alpha exceeded .70 for both constructs (scale measures in Appendix S2.18).

Results

I regressed the channel used for building the order (website versus CCA) on participants' convenience and personalization perceptions. This analysis revealed a significant main effect of CCA use on the perception of personalization (b = .42, t= 2.90, p <.05) and on the perception of convenience (b = .26, t = 2.26, p <.05). These results provide initial correlational evidence that using CCA (relative to a website) increases participants' perception of underlying mechanisms.

Study 3b: CCA Personalization and Convenience Evaluation

In Study 3b, I examine the effect of providing convenience and personalization features on customers' perception of the two constructs. I designed a three-one-way, between-subjects design: Personalized CCA vs. Convenient CCA vs. Control CCA (without personalization and/or convenience features). Two hundred eighty-nine undergraduate students from a Southeastern university in the United States (39.13% female; M_{age} = 21.5 years) participated in this study in exchange for course credit. Forty-nine participants failed the attention check. Thus, I base my analyses on 240 observations. I randomly assigned participants to one of the three conditions.

Similar to Study 3a, I provided participants a GIF to show what CCAs are and told them which interaction texts in the interface were written by a human and which by the CCA. I created three CCA interaction images for each of the three CCA conditions (Appendix S2.19). I gave the participants in all three conditions a CCA interaction image corresponding with the condition to which they had been randomly assigned. In the personalization condition, the CCA addresses the customer by their first name (“Andrea”) and provides pizza recommendations based on the customers’ ordering history. In the convenience condition, the CCA gives the customer a button to place a direct order for their pizza, thus making the experience far easier for the customer. In the control condition, the CCA text interaction involves only viewing different pizza deals and then placing the order using natural language text. After viewing the text interactions between the CCA and the customer, participants in our study respond to questions that capture their perceptions of personalization and convenience using a 5-item and 8-item scale respectively and provided in Appendix S2.18.

Results

I first regressed the type of CCA (personalized/convenience CCA vs. control CCA) on participants’ personalization/convenience perceptions. This analysis revealed a significant main effect of using personalized CCAs vs. control CCAs on perception of personalization (b = .26, t = 2.26, p <.05) and a significant main effect of using convenience CCAs vs. control CCAs on perception of convenience (b = .18, t = 2.10, p <.05). I also verified the results using analysis of variance (ANOVA). The results provide support for convenience and personalization specific features in CCA enhancing participants’ perception of convenience and personalization, even while the manipulation is subtle.

Mediation analysis

To test for the proposed effect of providing personalization and convenience on willingness to adopt CCA through customers’ perceived convenience and personalization, I conducted two bootstrap mediation analyses (Model 4, Hayes 2013). I entered the type of CCA as the independent variable (0 = CCA without any personalization and convenience features, 1 = CCA with personalization, 2 = CCA with convenience); customers' perceived convenience and personalization as the mediator; and willingness to adopt as dependent measure. I find an indirect effect of using CCA with personalization features on willingness to adopt (indirect effect = .13; 95% confidence interval $[\mathrm{CI}_{95}]$ = [.02, .26]) through customers' perceived personalization. I also find an indirect effect of using CCA with convenience features on willingness to adopt (indirect effect = .16; 95% confidence interval $[\mathrm{CI}_{95}]$ = [.04, .30]) through customers' perceived convenience.

DISCUSSION AND IMPLICATIONS

In their research priorities for 2020-2022, the Marketing Science Institute lists the need to understand how marketing AI applications affect value generated by firms. Recently, this issue has received academic attention from a conceptual lens (e.g., Hamilton et al. 2020; Miao et al. 2021), as has examining the effect of AI applications on customer purchase behavior (e.g., Sun et al. 2019; Luo et al. 2019). However, there remains a dearth of research regarding the financial value generated from of launching AI applications, even while industry reports indicate that investors and managers give significant importance to value generated from AI applications. Moreover, the unexpected COVID-19 pandemic has forced firms across industries to go contactless in serving customers, forcing many of them to adopt CCAs immediately (Loten 2020).

I find that launching a CCA increases a firm's market value by 0.29%, which translates to $56.7 million for a median firm in the sample. This market value change is closer to the high end of the market value change shown in studies of new digital touchpoints (Geyskens, Gielens and Dekimpe 2002; Beckers, Van Doorn and Verhoef 2018; Boyd, Kannan and Slotegraaf 2019).

I find that firms' CCA launch strategy and their CCA's functionalities help explain variance in the value generated across launch announcements. The finding that CCAs create greater value when used post-purchase extends prior findings that non-transactional touchpoints generate greater financial value in mobile apps (Boyd, Kannan and Slotegraaf 2019). Furthermore, we identify and test the underlying mechanisms potentially driving incremental firm value. I find that firms launching CCAs and placing a greater emphasis on convenience and personalization potentially drive investors' stock market reactions. Similarly, I find that customers perceive CCA's to be more personalized and convenient compared to traditional digital channels, which explains positive future cash flows.

Implications for Marketing Theory

I formally define a CCA that encompasses all AI-based conversational applications used in marketing for generating commerce. By examining the link between CCA launch and firm value, we contribute to two streams of literature. First, I take the growing field of AI applications in marketing beyond their impact on customer purchases (e.g., Sun et al. 2019; Luo et al. 2019), extending them to firm value and stock market reactions. My results suggest that investors expect positive future cash flow from firms launching CCA. Second, I add to the marketing-finance literature by complementing extant research on non-automated, non-AI customer interfaces, by examining AI-based automated and interactive customer touchpoints. Recently, firms such as Bank of America have incorporated automated touchpoints (e.g. CCAs) into non-automated ones (e.g. mobile apps). My study informs the value effects of automated and non-automated conversational touchpoint combinations, and their spillovers. Third, attention is a scarce resource and marketing research has rarely explored the efficient market theory expectation that investors pay attention to marketing strategic actions directly. My test of investor attention finds that the CCA launch does draw investor attention in line with effect market theory in incorporating new information into stock price.

I also contribute to the conceptual customer experience management literature by identifying strategic managerial choices to improve experience from AI-based application. I identify functional design attributes of CCAs that enhance personalization and convenience experiences of customers and thus create firm value. The finding that the effectiveness of AI applications varies across customer purchase stages contributes to the emerging journey research (Hamilton et al. 2020). Adding to the experience management research, I highlight the tradeoff of control vs access in using brand- vs partner-owned CCAs. The finding that dual modality and provision of both information and task enablement CCA more closely reflect behavioral realism is novel. The value premium placed on greater technological capabilities in CCAs suggests that technology endowment is an important asset for firms launching AI applications.

Last, I find that providing authentication features can be detrimental to value creation. This highlights the importance of convenience-privacy tradeoff, in turn providing an empirical validation and richer understanding of customer convenience needs. It also suggests that beyond the personalization-privacy paradox (Grewal et al. 2020), it is also important to account for the convenience-privacy paradox.

I theorize that convenience and personalization serve as mediating mechanisms. I designed a multi-method approach, including text mining, difference-in-difference analysis and experimental studies to formally test the mediating relationships. Examining these relationships in the context of both customers and investors and finding support even in the presence of subtle manipulation in the experiments provides confidence in our theorizing. By extending to autonomous AI agents delivering the dimensions of convenience, my results advance knowledge of customer experience and likewise add to literature on touchpoint convenience (Homburg et al. 2017). Although the literature suggests that investors pay attention to firm launch announcements (Sorescu et al. 2017), I extend this knowledge by demonstrating that firms launching AI applications understand the criticality of conveying to investors the benefits of their customer interface technology.

Implications for Firms

My research's primary implication for firms is that financial markets clearly view CCAs as adding value to the firm, encouraging firms to offer AI-based CCAs at customer touchpoints. My findings suggest that CCA applications are valuable even for firms in non-technology industries. In fact, social distancing rules and customers' preference for "contactless" service became necessary in the COVID-19 pandemic and led many non-technology firms to adopt AI-based conversational applications. The pandemic and physical distancing practices have also limited the ability of salespeople-customer interactions. Sales are increasingly digital, and CCAs would clearly serve as a complementary channel as this trend continues. For financially challenged firms and digital firms attempting to sell with a salesforce, CCAs could even substitute for salespeople.

Further, my findings provide guidance to firms in designing CCA launch strategy as well its functionality. As reported in Table 2.5, for firms considering CCA, adopting CCAs for post-purchase touchpoints is more effective in creating value. The results suggests that CCAs post-purchase increase market value by $114.3 million, whereas, using CCAs pre-purchase lowers average value by $58.4 million. These results should make it easier for managers to justify the investment in CCAs.

Data breach incidents (such as Delta Airlines' CCA partner exposing sensitive information) raise concerns about CCAs through partner touchpoints. My finding regarding CCAs launched as partner-owned touchpoints generating greater firm value should help managers evaluate the tradeoffs of access benefits (provided by Facebook, and Alexa) versus the control and privacy benefits of building their own CCA. The research suggests that functionalities that are more human-like, such as dual interface modality, are highly valued. I find that a CCA's with dual modality generates almost 4X the wealth (increase in the firm's stock market value) than for firms using CCAs to provide voice only (Table 2.5). My results caution against firms launching CCAs with limited functionalities, while facing pressure to introduce a CCA.

Firms are often concerned about customer privacy and add authentication features to restrict unauthorized access to appease their concerns. My findings suggest that the tradeoff is loss of convenience. However, with customers and investors value convenience. In fact, European regulators reduced authentication requirements for mobile transactions, reducing the inconvenience of users.

My findings will similarly encourage managers trying to improve customers' convenience or personalization perceptions, as customers notice minor interactional changes in CCA. Managers should consider including personalization capabilities (for example, the CCA addressing customer by name) and convenience features (like a button to place an order directly) during CCA interactions. My findings highlight the importance of communicating to investors how the customer will benefit from an investment in technology.

The findings regarding controls suggest that being early in the industry in launching a CCA may not be a beneficial strategy. I examine our results both across technology and non-technology industries. Thus, even firms that have not invested in AI capabilities would benefit by launching CCA and obtain stock market premiums.

Limitation and Future Research

There are several limitations of this study, which creates opportunities for future research. First, we use a broad categorization, rather than the purchase sub-stages (e.g., need recognition, search, engagement, service request). However, customers have less clarity on the assistance they need from a CCA during the *need recognition* stage, and better articulate their need during search leading to varying effectiveness of CCAs. Second, CCAs could complement or substitute for the sales and service employees. Future research could examine the implication of these alternatives from a customer, firm, and public policy viewpoint. The automation of marketing through CCAs has important implications for future of marketing work and jobs. Research on the (marketing) jobs likely to be replaced or supplemented by AI would be important for universities and governments. CCAs are trained with existing data, and any bias that exists is likely to be embedded in a CCA's algorithms, calling for further research on algorithmic bias. Finally, the combination of automated and non-automated touchpoints can have positive purchase spillover effects needs further examination. I do not examine the product and market characteristics as moderators of firm value. Arguably, a CCA's effectiveness would vary with the mix of new and repeat customers and we lack data to examine this issue. CCA's intelligence grows over time and it might be useful to examine the evolution in terms of ability to deliver personalization and convenience. Further, I do not account for the level of complexity of the tasks performed by a CCA. More complex tasks require greater decisions from a CCA, which could potentially determine its accuracy and in turn influence customer acceptance. Thus, future research can examine the role of task complexity on a CCA's successful adoption.

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Table 2.1 Review of literature on adding Digital Touchpoints and Firm Value

Study	Touchpoint Added Through	Type of Touchpoint	Test Mediators	Functionalities of Touchpoints Tested	Endogeneity Correction Used	Factors used to explain heterogeneity in value	Market Value Change
Geyskens, Gielens, and Dekimpe (2002)	Internet	Non-automated	No	No	No	Firm Characteristics, strategy characteristics and marketplace characteristics	+0.71%
Homburg, Vollmayr and Hahn (2014)	Through external entities	Non-automated	No	No	Yes; Heckman Correction	Firm, industry and channel strategies	+0.46%
Beckers et al. (2017)	Engagement Initiatives	Non-automated	No	No	Yes; Heckman Correction	Firm and industry characteristics	-0.23%
Boyd, Kannan and Slotegraaf (2019)	Mobile applications	Non-automated	No	Yes	Yes; Propensity score matching and Heckman correction	App design features, era and firm characteristics	+0.37%
Tan, Chandukala and Reddy (2021)	Augmented Reality	Non-automated	No	No	Yes; two-stage residual inclusion method	Customer experience with product category, products that are less popular	Significant, coefficient: +0.006
This Study	**Conversational Commerce Applications**	**Automated and AI enabled**	**Yes**	**Yes**	**Yes; Propensity score matching and Heckman correction**	**CCA launch strategies and CCA functionalities**	**+0.29%**

Table 2.2 Variables, Measures, and Data Sources

Variable	Operationalization	Source of Data
Stage of Purchase Journey	Dummy Variable: '0' if CCA assists customers during the pre-purchase stage; '1' if CCA assists customers during the post-purchase stage	CCA Launch Announcement
Partner-owned vs Brand-owned	Dummy Variable: '0' if CCA is launched as brand-owned; '1' if CCA is launched as partner-owned	CCA Launch Announcement
Task vs Information	Dummy Variable: '0' if CCA responses are information-based; '1' if CCA responses are task-based; ‘2’ if CCA both provides information and performs task	CCA Launch Announcement
CCA Modality	Dummy Variable: '0' if CCA is built with a text-based interface; '1' if CCA is built with an audio-based interface; '2' if CCA is built with both a text-based and an audio-based interface	CCA Launch Announcement
Authentication	Dummy Variable: '0' if CCA does not need to be authenticated in order to facilitate interactions; '1' if CCA needs to be authenticated in order to facilitate interactions	CCA Launch Announcement
Firm Performance	Net income over sales of a firm (1-year lagged)	Compustat
Firm Size	Total number of firm employees (1-year lagged) (log-transformed)	Compustat
Market Share	Firm’s sales relative to total industry sales (four-digit SIC code)	Compustat
Parent Company	Dummy Variable: '0' if firm is listed in the stock exchange as the same entity; '1' if the firm is listed under a parent company	Factiva
Marketing Emphasis	Ratio of a firm’s advertising spending over sales in the previous year	Compustat
Technology Emphasis	Ratio of R&D spending by a firm in the year 't-1' divided by the Sales of the firm in the year 't-1'	Compustat
Information Coverage	count of all additional announcements other than the focal CCA announcements	Factiva
Market Size	Total sales volume within the SIC code (four digits)	Compustat
AI-Period	Dummy Variable: '0' if CCA is launched before 2015; '1' if CCA is launched in or after 2015	Compustat
Order of Entry	Entry order of CCA determined relative to all other CCAs launched by firm in the same	CCA Launch

	industry	Announcement
Competitive Intensity	Inverse Herfindahl–Hirschman index for industry concentration within the (four-digit) SIC code	Compustat
Industry Dummies	Dummy variables according to 1-digit SIC code	Compustat

Table 2.3 Moderating Effect of CCA Launch Strategy and CCA Functionalities

Parameter/Independent Variables	**Hypotheses**	**DV: CAR [0, 0]**
CCA Launch Strategy		
Post-Purchase vs Pre-Purchase (Base)	H2	.89 (.32)***
Partner-owned vs Brand-owned (Base)	H3	.81 (.36)**
CCA Functionalities		
Dual Functionality vs Information CCA (Base)	H4a	.58 (.28)**
Dual Functionality vs Task CCA (Base)	H4b	.82 (.30)***
Dual Modality vs Text CCA (Base)	H5a	1.63 (.63)***
Dual Modality vs Voice CCA (Base)	H5b	1.49 (.66)**
Authentication Needed	H6	-.91 (.28)***
Controls		
Technology Emphasis		.02 (1.53)
Order of Entry		.04 (.02)**
Firm Performance		-1.06 (.95)
Firm Size		-.05 (.07)
Market Share		.12 (1.65)
Parent Company		-.03 (.28)
Marketing Emphasis		1.47 (2.02)
Information Coverage		-.00 (.00)
Market Size		-.04 (.08)
Competitive Intensity		-.01 (.01)
AI-period		-.50 (.48)
Industry Dummies		Included
Inverse Mills ratio		-.38 (.39)
Constant		2.00 (1.78)
R^2		.26
N		206
F-Statistic		2.29***

$* p < .10, ** p < .05, *** p < .01$

Table 2.4 Robustness Check Results

Parameter/ Independent Variables	Additional Market Signaling Factors		Including Confounding Announcements		Fama French Model		Mahalanobis Matching		(B2B vs B2C) and (Product vs Service)		Carhart 4-Factor Model		Year Dummy within AI-Period	
CCA Launch Strategy														
Post- vs Pre-Purchase (Base)	.89	(.33)**	.70	(.39)**	.72	(.35)**	1.35	(.36)**	.91	(.29)**	.84	(.44)**	.87	(.32)***
Partner-owned vs Brand-owned (Base)	.79	(.37)**	.76	(.46)*	.75	(.40)**	.26	(.40)	.83	(.36)**	.72	(.49)*	.69	(.37)**
CCA Functionalities														
Dual Functionality vs Information CCA (Base)	.61	(.29)**	.48	(.36)*	.43	(.31)*	.52	(.31)*	.42	(.26)*	.98	(.38)**	.67	(.29)**
Dual Functionality vs Task CCA (Base)	.80	(.31)**	1.00	(.36)***	.58	(.33)**	.57	(.34)*	.83	(.30)**	.38	(.41)	.75	(.31)***
Dual Modality vs	1.63	(.63)**	1.22	(.76)*	1.44	(.69)**	1.26	(.70)**	1.56	(.62)**	1.32	(.92)*	1.65	(.63)***

Text CCA (Base)														
Dual Modality vs	1.48	(.66)**	.97	(.79)	1.31	(.72)**	1.50	(.73)**	1.40	(.65)**	1.72	(.96)**	1.51	(.65)**
Voice CCA (Base)														
Authentication	-.95	(.29)**	-.68	(.36)*	-.57	(.31)**	-1.00	(.31)**	-.77	(.28)**	-.57	(.39)*	-.92	(.28)***
Needed				*										
Controls	Included		Included		Included		Included		Included		Included		Included	
Industry Dummies	Included		Included		Included		Included				Included		Included	
Inverse Mills Ratio	Included		Included		Included		Included		Included		Included		Included	
Constant	2.13	(1.79)	1.68	(2.18)	1.37	(1.95)	-.52	(1.96)	1.44	(1.66)	.04	(1.65)	1.87	(1.79)
R^2	.26		.16		.18		.20		.21		.21		.28	
F-Statistic	2.15***		1.48**		1.33*		1.73**		2.40***		1.64**		2.22***	

$* p < .10, ** p < .05, *** p < .01$

Table 2.5 Average Market value change from CCA Launch Strategies and CCA Functionalities

Variable	Average Change in Market Value ($)	
Post-Purchase vs Pre-Purchase (Base)	$114,366,281.43	($58,462,786.79)
Partner-owned vs. Brand-owned (Base)	$74,872,663.49	$22,336,182.99
Dual Functionality vs Information CCA (Base)	$125,111,584.51	$4,124,772.55
Dual Functionality vs Task CCA (Base)	$125,111,584.51	($48,480,739.00)
Dual Modality vs Text CCA (Base)	$220,900,141.40	($64,510,660.76)
Dual Modality vs Voice CCA (Base)	$220,900,141.40	$62,555,792.26
Authentication Needed - Yes vs. No (Base)	$111,804,997.33	($48,061,838.81)

APPENDIX 2

Appendix S2.1

Table S2.1.1 Review of the Empirical Research on Using CCAs

Study	AI Based Conversational Application	Focus	Type of Agent	Case Study /Multi-firm Study	Across Industries	Across Time	Dependent Variable	Multi-Method
Holzwarth, Janiszewski and Neuman (2006)	No	Customer attitude and purchase intention of avatars	Online Avatar	No	No	No	Purchase intention and product involvement	No
Qiu and Benbasat (2009)	No	Online recommendation system for complex and attribute intensive digital cameras	Anthropomorphic interface agent	No	No	No	Perceived Social Presence	No
Keeling, McGoldrick, and Beatty (2010)	No	Avatar's social orientation and task orientation	Avatar	No	No	No	Customers' trust perception	No
Kohler, Rohm, Ruyter and	No	New customer adjustment and impact	Socialization Agent	No	No	No	Customer Transactions	No

Wetezels (2011)		on transactions						
Nunamaker et al. (2011)	No	Avatar expression and perceptions	Embodied conversational agent	No	No	No	Avatar Perceptions	Yes
Al-Natour, Benbasat, and Cenfetelli (2011)	No	Online shopping for a laptop computer	Automated shopping assistant	No	No	No	Customer enjoyment	No
Chattaraman, Kwon, and Gilbert (2012)	No	Online purchase of apparel by older consumers	Virtual Agent	No	No	No	Patronage intentions	Yes
Verhagen et al. (2014)	Yes	Inquiries about online mobile phone service	Virtual customer service agent	No	No	No	Customer Satisfaction	No
Mimoun and Poncin (2015)	Yes	Customer satisfaction and behavioral intentions through utilitarian and hedonic value.	Embodied conversational agent	No	No	No	Customer Satisfaction	No
Kim, Chen and Zhang (2016)	No	Consumer psychological mechanisms	Digital assistants	No	No	No	Perceived enjoyment	No

Lee and Choi (2017)	Yes	Self-disclosure and reciprocity	Conversational agent	No	No	No	Customer Satisfaction and intention to use	No
Schuetzler et al. (2018)	Yes	Responses to sensitive questions to a person vs. a conversational agent vs. online survey	Conversational agent	No	No	No	Social desirability of response	No
Go and Sundar (2019)	No	Chatbot's message interactivity	Chatbot	No	No	No	Customers' attitude toward the website and return intention	No
Luo et al. (2019)	Yes	Effectiveness of Chatbots	Chatbot	Single firm case study	No	Single Period	Customer Purchases	No
Mende et al. (2019)	No	Consumer response to robots	Robot	No	No	No	Consumer compensatory consumption	No
Castelo et al. (2019)	Yes	Consumer response to AI recommendation	Recommendation Agent	No	No	No	Algorithm acceptance	Yes
Chattaraman et al. (2019)	Yes	Online purchase of by older consumers	Digital Assistant	No	No	No	Behavioral intentions	No
Pizze, Scarpi and Pantano (2020)	Yes	Digital assistants' appearance and	Anthropomorphic digital assistant	Single firm case study	No	Single Period	Choice Satisfaction	No

		activation (automatic vs human-initiated)						
Hildebrand and Bergner (2020)	Yes	Evaluation of Robo-advisors and recommendation acceptance	Robo-Advisors	Single firm case study	No	Single Period	Firm Perception and Recommendation Acceptance	No
Chung, Ko, Joung and Kim (2020)	Yes	Customer perceptions of service encounters	Chatbot	Single firm case study	No	Single Period	Customer Satisfaction	No
Longoni and Cian (2020)	Yes	AI recommenders for Utilitarian vs. Hedonic	AI recommenders	No	No	No	Consumer resistance of AI recommenders	No
This Study	Yes	Impact of launching AI based CCAs on firm value	Conversational Commerce Application	Multi-firm Studies and single firm experiment	Yes	Multiple Years	Firm Value, investor perception and customer perception of mechanisms	Yes; event study, Difference-in-Difference analysis, two customer focused experiments

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Appendix S2.2

Table S2.2.1 CCA and Artificial Intelligence Capabilities

Types of CCA	Role of CCA	Example	Sample Customer Intents	CCA's Key AI/ML Requirements	CCA's Human-Like Capabilities Exhibited	Potential For	
						Personalization	Convenience
Post-Purchase CCA	Helps customers after they purchase product/service.	Bank of America's AI powered Erica helps clients tackle complex tasks and provides personalized guidance to help them stay on top of their finances.	Reset password Upgrade service	1.Domain Specificity of Corpus 2. High Context Awareness	1. Understand user sentiment 2. Understanding customer needs 3. Memory	High	High
Pre-Purchase CCA	Helps customers before they purchase product/service	Taco Bell released AI powered "TacoBot," to allow customers place pickup orders through the bot	Learn product features Obtain product pricing	1. Domain Specificity of Corpus 2. Text Wrangling 3. High Context Awareness 4. Input Clustering	1. Understanding customer needs 2. Ability to switch topics 3. Personality 4. Memory	Medi um	Low

Task CCA	Perform a specific action in customers' environment	OpenTable's Alexa skill helps to make a restaurant reservation and even book preferred tables	Reserve table. Open bank account	1. Domain Specificity of Corpus 2. Text Wrangling 3. High Context Awareness	1. Understanding customer needs 2. Persistence 3. Ability to switch topics	Low	Low
Information CCA	Provides information requested by customers	Express Scripts' Alexa skill allows customers to get prescription order status and notifications of orders being received, processed, and shipped	Get latest news Obtain product features	1. Input Clustering	1. Memory 2. Understanding customer needs 3. Personality	High	High
Voice-Based CCA	Use a human-like voice to interact with customers	Customers can play music from their Pandora accounts by providing voice commands to Amazon Alexa	Play music Get pizza store locations	1. Text Wrangling 2. High Context Awareness	1. Personality 2. Understanding customer needs 3. Persistence	Medium	Medium
Text-Based CCA	Interacts with customers through human understandable text format	MoneyGram allows customers to send money across the globe by messaging their AI-enabled Facebook	Website navigation help View different t-shirts	1. Text Wrangling	1. Memory 2. Understanding customer needs	Medium	Medium

		chatbot					
CCA with Authentication	Validate the identification of the customer	American Express's CCA on Amazon Alexa requires customers to authenticate by providing a 4-digit personal pin	Access bank account Transfer money	1. Text Wrangling 2. Input Clustering	1. Memory 2. Persistence 3. Ability to switch topics	Low	Low

Definition of AI/ML Capabilities: *Domain Specificity of Corpus:* The number of domain (e.g. advertising, retail industry, brand, customer service) specific words a CCA is trained on in comparison to general words it is trained on; *Level of Wrangling*: level of pre-processing of raw text data required in order to train a CCA; *Context Awareness*: this denotes the information available with a CCA regarding an entity's (e.g. customer) situation (e.g. purchase needs, environment); *Clustering*: refers to is a method of discovering hidden structure in unlabeled data; Sentiment analysis: is the interpretation and classification of emotions (positive, negative and neutral) within text data using text analysis techniques.

Appendix S2.3

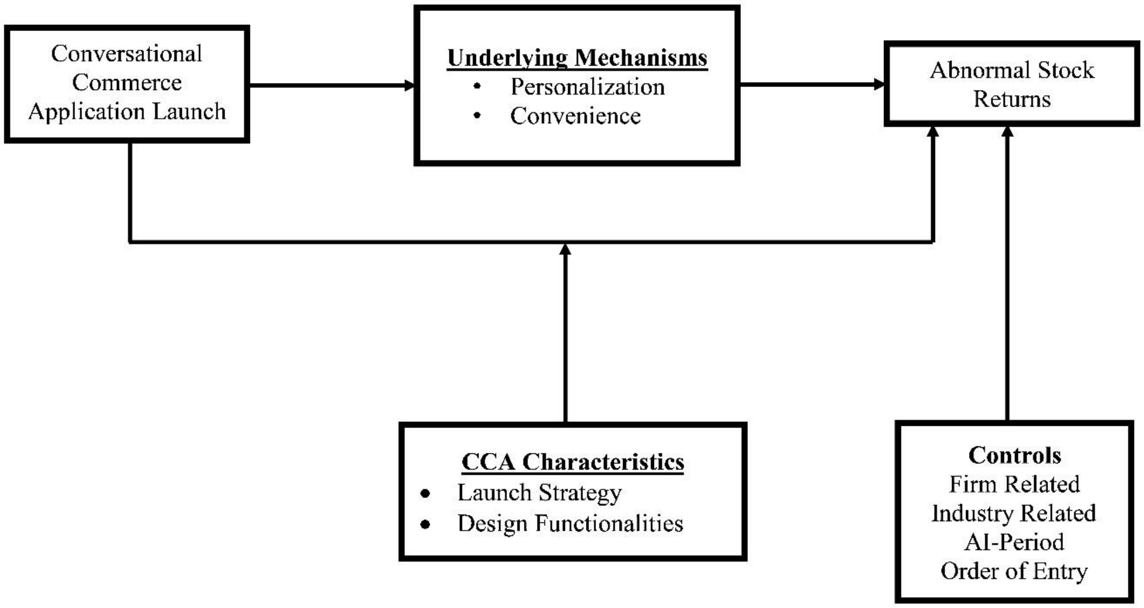


Figure S2.3.1 Conceptual Model

Appendix S2.4 GUIDED LDA and Four-Step APPROACH TO IDENTIFY MODERATORS

The guided LDA approach is flexible enough to allow features to be informed and guided by CCA moderators we identified from in-depth reading of announcements, while allowing other relevant constructs to emerge from the descriptions. The guided LDA approach takes a list of seed words associated with each CCA moderator. My final dictionary of seed words consists of 85 seed words. These seed words reflect a variety of vehicles through which strategic decisions while launching CCA may be featured in the launch announcement. Examples of the set of seed words used for each moderator is provided below in Table S2.4.1.

Table S2.4.1 List of Seed Words

Moderators Seeded	Examples of Seed Words
Task	ordering, tasks, control
Authentication	access, security, control, pin
Voice	voice, speak, interface, music, siri, alexa
Information	information, discover, deliver, questions, insights
Pre-purchase	sales, shopping, orders, discover, help, discovery, requests, search, marketing, purchase
Partner-owned	partnership, technology, amazon, partner, messenger
Post-Purchase	reorder, manage, service, customer service
Brand-owned	account, chatbots, brand, assistants

I first conducted a traditional LDA analysis and increased the number of topics until the change of perplexity for the cross-validation sample flattened out (Zhao et al. 2015). Perplexity is a widely used predictive metric in machine learning based on marginal likelihood. I found that the curve flattened when 25 topics was reached. Next, I used this information to run guided LDA in which each document in the corpus has been tokenized - that is, broken down into individual words or phrases (tokens). Tokens represent the smallest unit of observation in our data (i.e., a document is represented as a collection of tokens). Each token may be thought of as a “slot” in the document that is “filled” with a word. Guided LDA nests traditional LDA by allowing each topic to have two versions: a “regular” version defined as in traditional LDA, which has positive weights on all words in the dictionary (seed and non-seed), and a “seeded” version that has positive weights only on the seed words for the corresponding strategic moderator. The seeded version ensures that topics are guided by seed words, while the regular version allows other relevant dimensions to emerge. I estimate the model using Markov chain Monte Carlo with 10,000 iterations. I found ten themes to emerge. In other words, 10 out of the 25 topics contained words that clearly identified one of the 10 themes and the rest of the topics was a combination of the individual topics. Key themes along with the keywords are shown in Table S2.4.2 below.

Table S2.4.2 Key Topics Themes from Guided LDA

Topics	Examples of Words with High Relevance
Task	control, function, connected
Authentication	security, control, lock
Voice	voice, command, alexa, speaker, hands-free
Information	information, questions, help, available, time, insights
Pre-purchase	deliver, access, channel, sales, shopping, research, understanding
Partner-owned	alexa, partner, echo, device, enabled
Post-Purchase	status, solutions, service, customer service
Brand-owned	chatbot, conversational intelligence, website,

Convenience	convenience, place orders, easily, simply
Personalization	personalized, experience, assistant, real-time

Lastly, to ensure that the topics that emerged from the guided LDA approach is accurate; I identified the dominant topics for each document and compared with the manual coding done by independent coders (Study 1). For example, if the dominant topic of a document was post-purchase, I tested if the CCA launch announcement was indeed coded as having a post-purchase CCA. I identified that the agreement between dominant topics and independent coders ranged between 78% and 95%.

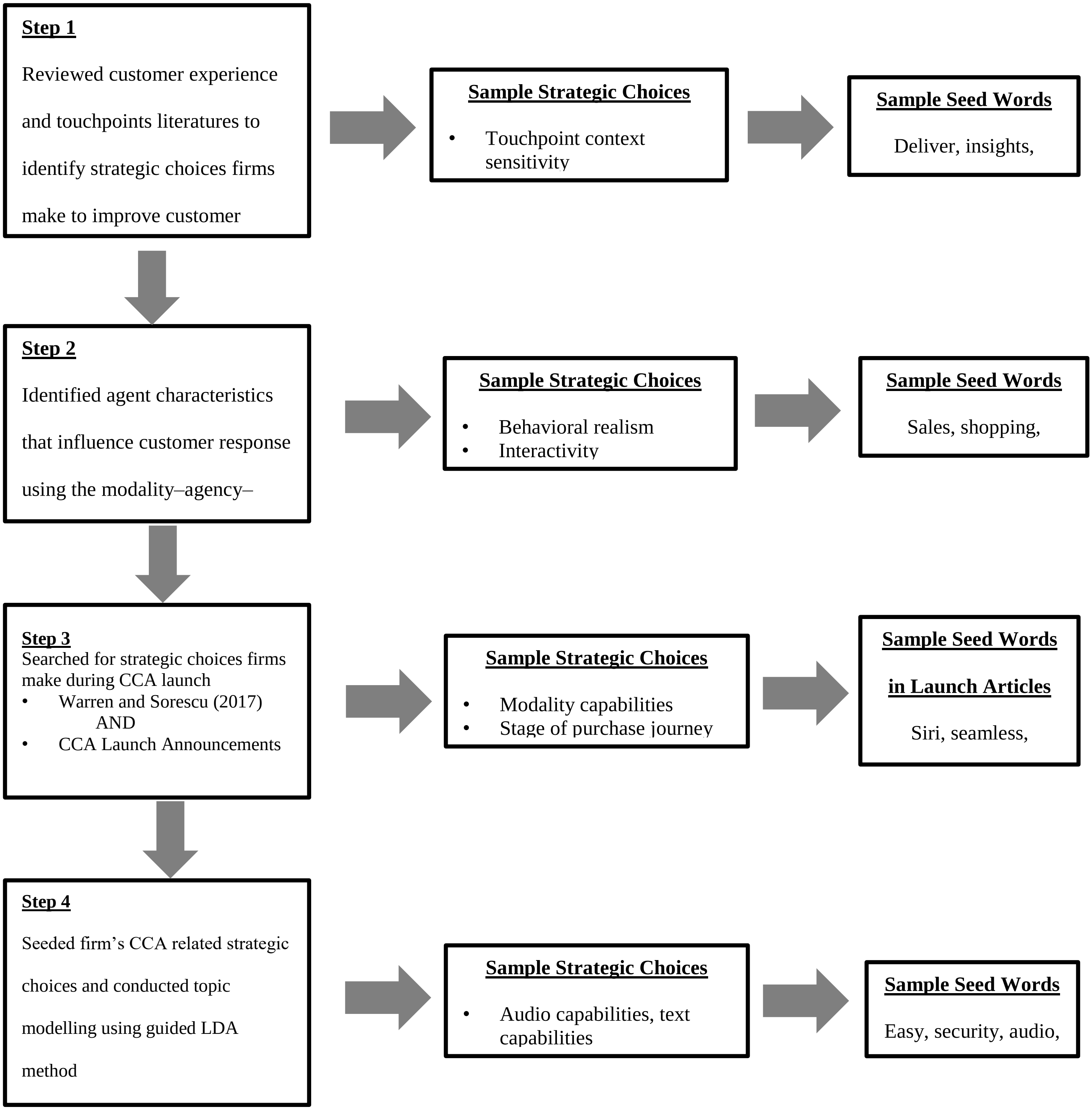


Figure S2.4.1 Four-Step Approach to Identify Moderators

Appendix S2.5

Table S2.5.1 Announcement statement examples

Stage of Purchase Journey	
Pre-purchase Stage	Post-purchase Stage
1. Dunkin' Donuts made on-the-go mobile ordering available through Alexa, Amazon's cloud-based voice service. To start their order, guests need simply say, “Alexa, order from Dunkin’ Donuts.” A more detailed list of steps to follow for placing a Dunkin’ Donuts order. 2. The Yum! Brands-owned (YUM) fast food chain teamed up with Slack to introduce its new “TacoBot,” a service that allows customers to place pickup orders through the messaging app for select menu items. 3. Alaska Airlines and Horizon Air today introduced a virtual assistant named "Jenn" at alaskaair.com. With her own voice and personality, Jenn answers hundreds of common questions and helps customers book travel	1. iRobot is aggressively pursuing opportunities within the connected home to improve our customers' experience with our cleaning robots. User-friendly voice-activated commands work collaboratively and further enable the smart home 2. With this new skill, customers can ask specific questions about flights, such as, "Alexa, ask United what is the status of my flight to San Francisco?" Customers can also learn about amenities on board. he or she will be able to check in for upcoming U.S. domestic flights using voice command 3. Pearson’s free skill for Amazon Alexa gives students easy way to check assignment due dates, and even listen to assigned text via the audio playlist
Brand-owned vs Partner-owned	
Brand-owned	Partner-owned
1. Whether it’s more functionality in our app or more functionality for self-servicing online, we wanted to give our clients the option of solving basic issues through automation. – Director, Citibank 2. Molina Healthcare provides valuable, new self-appraisal feature is available for members looking for current insight, risk factors, live help, and appropriate action to take if covid symptoms are present.	1. You can give a voice command to your smart speaker to order food from the delivery service Grubhub thanks to a new Skill for Alexa, Amazon's voice-activated virtual assistant. Grubhub will share your account information with Amazon. Then, you can ask your Alexa-enabled smart speaker to ask Grubhub to order food. 2. Adding to an already impressive lineup of innovative consumer offerings, Allstate Insurance is releasing a new account specific skill for Alexa. Now, customers with an Alexa device such as Amazon Echo can ask Alexa – the brains behind Echo – for help finding the due date on their next bill or what the minimum amount due might be.
Task vs Information	
Task	Information

<table>
<tr><td>1. Roku® streaming player and Roku TV™ owners in the US can now control their Roku devices using Alexa. “Alexa, pause Roku” or “Alexa, open Hulu on Roku.” Additionally, Roku TV users can turn on the TV, change the volume, mute the TV, switch inputs and change channels.
2. "With OpenTable's Alexa skill, booking a restaurant reservation is as easy as saying 'Alexa, ask OpenTable to make me a reservation' at your favorite restaurant and you'll be set."</td><td>1. Briggs & Stratton Corporation has launched an Alexa Skill that will allow homeowners to simply "Ask Alexa" for information about what type of oil and how much to use and to provide step-by-step instructions on how to perform an oil change on their walk-behind mower.
2. Pearson's new Alexa skill gives students simplified, convenient access to important course content that helps to maximize their learning</td></tr>
<tr><td colspan="2" align="center">CCA Modality</td></tr>
<tr><td align="center">Text</td><td align="center">Dual (Both Voice and Text)</td></tr>
<tr><td>Shake Shack has launched a chatbot that will answer customers’ most burning questions… Using the chatbot, users can type their questions or pick an action from a list to locate their nearest Shake Shack, view the menu and see a list of FAQs. On Messenger, users can also view Shake Shack’s Instagram account or the “Shack Cam,” a live feed of its flagship location</td><td>1. The new digital assistant “Erica” — a play on the bank’s name — will be available inside the bank’s mobile app staring next year. Customers can chat with Erica via voice or text message.</td></tr>
<tr><td colspan="2" align="center">Authentication</td></tr>
<tr><td colspan="2" align="center">1. Discover financial services - Open the Alexa app or go to Alexa.Amazon.com. Tap or select "Skills" and search for Discover. Create a 4-digit voice code. The 4-digit voice code is specific to the skill and separate from any other Discover PINs you may have
2. Voice unlocking is one the newest functions available in the integration between Schlage and Amazon Alexa. The feature was made possible through technological improvements that now requires Alexa to authenticate the user’s identity prior to unlocking the door. The additional step helps to maintain the superior security you expect from Schlage while still enjoying the convenience of voice activation.</td></tr>
</table>

Appendix S2.6

Table S2.6.1 Correlations and Descriptive Statistics

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	Stage of Purchase Journey	1															
2	Brand-owned vs Partner owned	-.06	1														
3	Functionality: Information, Task, Dual	.18**	.14*	1													
4	CCA Modality: Text, Audio, Dual	.14*	.16*	.10	1												
5	Authentication	.04	-.02	-.01	-.10	1											
6	Firm Performance	-.10	-.07	-.04	-.05	.14*	1										
7	Firm Size	-.05	-.13	-.02	-.01	.05	.17*	1									
8	Market Share	.20**	.08	.07	.06	-.01	-.04	.20**	1								
9	Parent Company	.20**	-.08	.01	-.06	.08	-.13*	-.07	-.02	1							
10	Marketing Emphasis	.22**	.14*	-.02	.02	-.08	.12	-.25**	-.04	-.02	1						
11	Technology Emphasis	.10	.03	.02	.04	-.20**	-.18**	-.30**	-.13**	.05	.05	1					
12	Information Coverage	.01	-.11	.01	.03	-.03	.13	.40**	.03	-.10	-.04	.10	1				

13	Market Size	.32**	-.08	.04	-.01	-.03	.02	.02	-.43**	.00	.01	.19**	.08	1			
14	AI-Period	-.01	.35**	.02	-.10	-.12	.03	-.09	.06	19**	.03	.05	-.13	-.14*	1		
15	Order of Entry	-.04	.00	.04	-.08	-.13	.14*	-.09	-.14*	.00	20**	.18**	.16*	.14	.18**	1	
16	Competitive Intensity	.09	-.11	-.11	.00	.36**	.17*	.14*	-.11	.06	-.12	-.13*	-.00	.18**	.06	.10	1
Mean (frequency)		0=29%	0=23%	0=35%	0=20%	0=65%	0=68%	0.10	2.93	0=27%	0.03	0.04	18.41	14.01	0=10%	4.97	7.72
Standard Deviation		1=71%	1=77%	1=23%	1=73%	1=35%	1=32%	0.12	1.94	1=73%	0.06	0.08	37.31	1.78	1=90%	5.91	11.32
				2=42%	2=7%												

$* p < .05, ** p < .01$

Appendix S2.7 Testing bias from omitted variables using Oster (2019) approach

The list of observed firm characteristics that we use to calculate the propensity score of firms to launch CCAs need to account for the differences between firms launching and not launching CCAs and the differences to be small and nonsystematic. In particular, I need to ensure that the firm is not launching a CCA due to its unobservable capabilities. Despite addressing unobserved heterogeneity using Heckman correction, we need to ensure that omitted variables that determine the likelihood to launch CCA does not significantly influence the effect of launching CCA on abnormal returns. I thus investigate the robustness of our variable choice using Oster's (2019) approach. Oster's approach accesses potential omitted variable bias by examining: (1) variation in the estimated coefficient after adding covariates. For my study, the covariates used are the variables used to calculate propensity scores and (2) the associated shift in R^2 to access the sensitivity of our results. The key assumption of the approach is that the selection on observable variables is informative about the selection on unobservable ones.

In Oster's (2019) approach, $\tilde{\beta}$ is the estimated coefficient for the treatment from a model that includes the observed control variables. β^* is a coefficient for the treatment that comes from a hypothetical estimated model that includes controls for both observable and unobservable variables. β^* can be calculated using the following formula:

$$\beta^* \approx \tilde{\beta} - \frac{\delta[\dot{\beta} - \tilde{\beta}](R_{max} - \tilde{R})}{\tilde{R} - \dot{R}}$$

where $\dot{\beta}$ and $\dot{R}$ are the coefficient and R^2, respectively, from a regression with the treatment only, and $\tilde{\beta}$ and $\tilde{R}$ are the coefficient and R^2, respectively, from a regression with the treatment and the observed controls. δ is the coefficient of proportionality and measures the of the correlation between unobservable characteristics and the treatment relative to the observable characteristics. R_{max} is the overall R^2 of the hypothetical model controlling for both observables and unobservables. Based on the recommendation by Oster (2019), we use $\delta = 1$ and $R_{max} = 1.3\tilde{R}$ in order to calculate β^*. The results are provided in the table below:

Variable	No Controls - $\dot{\beta}$, (Std. Error) $[R^2]$	With Controls - $\tilde{\beta}$, (Std. Error) $[R^2]$	R_{max}	Identified Set $[\tilde{\beta}, \beta^*]$	Exclude Zero	Within Conf. Interval	δ for β = 0 and R_{max}
Launching CCA	0.393**, (0.139), [0.022]	0.387**, (0.141), [0.028]	0.036	[0.387, 0.378]	Yes	Yes	7.572

Oster (2019) argues that estimated treatment from the controlled regression can be considered as robust to omitted variable bias if the identified set, $[\tilde{\beta}, \beta^*]$, excludes zero. In addition, if the estimated coefficient does not move towards zero once observed controls are added, Oster (2019) also recommends investigating whether the bounds of the identified set are within the confidence interval of $\tilde{\beta}$. Furthermore, a value of $\delta > 1$ in order to produce zero treatment indicates the result is robust because the identified set are within the confidence interval of $\tilde{\beta}$. Thus the results from the table suggests that unobservable variables do not bias the effect of launching CCA. In other words, the observable variables used to identify matching control firms are sufficient.

Appendix S2.8 Selection ON UNOBSERVABLES

I account for potential unobserved factors that could likely influence a firm's decision to launch CCA by the manufacturer by including unobserved factors and then calculating the inverse mills ration (IMR). I calculated the IMR for the firms that launch CCA and do not launch CCA using the expressions in Equations (1) and (2).

(1) $IMR = \frac{\phi(w)}{\Phi(w)}$ for firms that launch CCA and

(2) $IMR = \frac{-\phi(w)}{1-\Phi(w)}$ for firms that do not launch CCA

The selection equation is given by,

(3) $z^* = \gamma_i w + \zeta_i$

CCA launch is equal to 1 if $z^* > 0$ and CCA launch is equal to 0 if $z^* < 0$.

The outcome equation for stage two is given by,

(4) $y_i = \alpha_i + \beta X_i + \varepsilon_i$

If the errors in the selection equation and the errors in the outcome equation are correlated, it suggests that there is an influence of the unobserved factors on the treatment effect. This would result in the treatment effect being biased. One way to overcome biased estimations of the treatment effect is to use parametric assumptions to model the unobserved component and include them along with the other covariates; conditional on the observed covariates and the unobserved component (i.e., selection on unobservables), the treatment effect should be unbiased. Thus, using the Heckman (1979) model, I assess unobserved component by assuming that the errors in the selection model and those in the outcome model are bivariate normally distributed, such that the unobserved component can be obtained as follows:

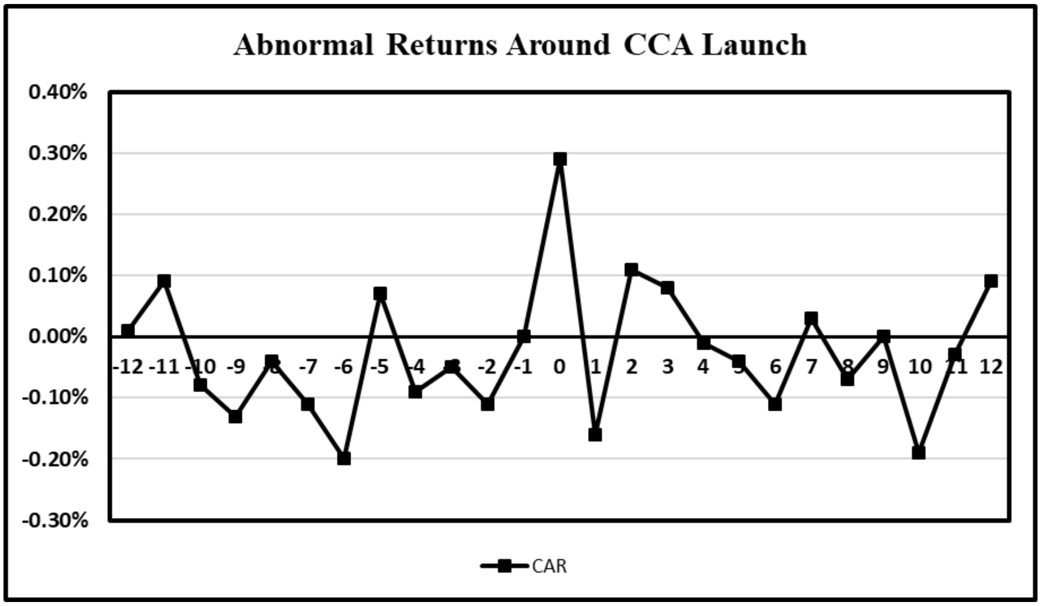
$$IMR_i = (CCA\ Launch_i)\frac{\phi(w)}{\Phi(w)} + (1 - CCA\ Launch_i)\frac{-\phi(w)}{1-\Phi(w)}$$

Table S2.8.1 Selection Based on Unobservables

Matched Sample Analysis	DV – Decision to
Variables	
Weighted Average CCAs in the Industry	9.35 (1.19)***
Cultural Individualism	.00 (.00)***
Cumulative Count of AI Patents	.00 (.00)***
AI-period	.10 (.07)*
Market Share	4.22 (.31)***
B2B vs. B2C (base)	-.01 (.06)
LR chi^2	156.14***
N	13992

$* \, p < .10, *** \, p < .01$

Appendix S2.9



Time (in days before and after the announcement)

Figure S2.9.1 Abnormal Returns over Time

Appendix S2.10

Table S2.10.1 Abnormal Returns from CCA Launch Announcements

Event Window	Average Abnormal Return (%)	*p*-value
(0,0)	0.29	<.01
(-1,0)	0.29	.06
(0,1)	0.12	.20
(-1,1)	0.12	.28
(-2,0)	0.17	.23
(0,2)	0.24	.11

Appendix S2.11 Test of Investor Attention to CCA Announcement

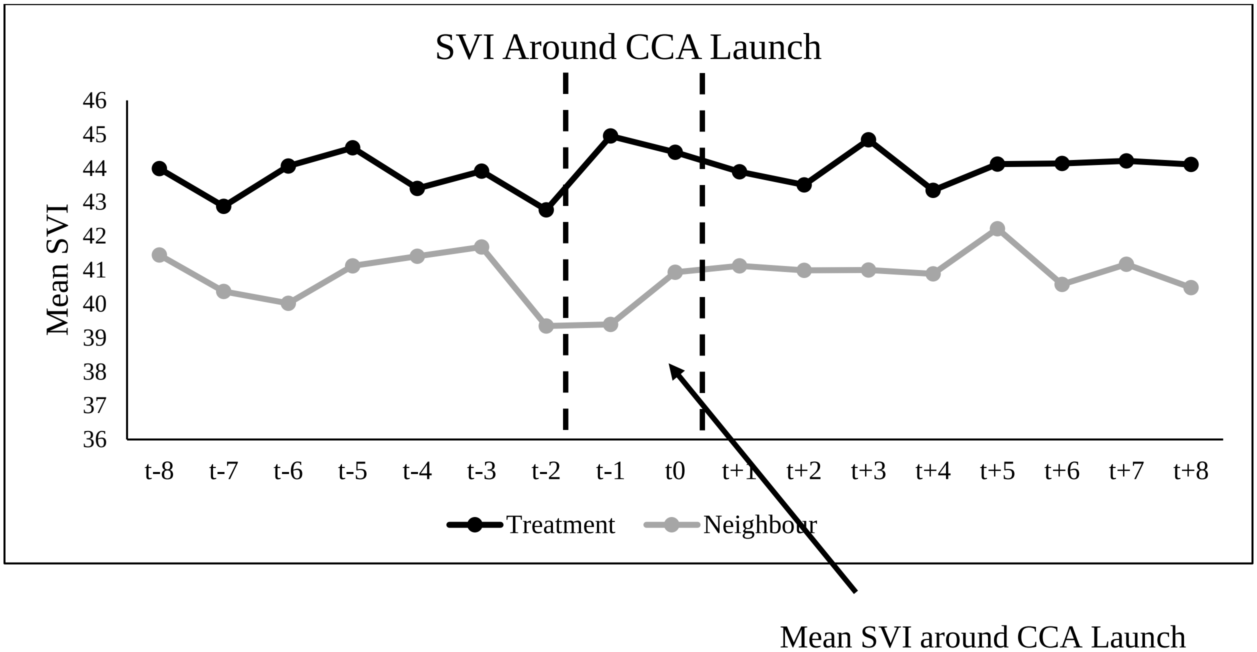


Figure S2.11.1 Mean SVI around CCA Launch for Treatment and Control Firms (Neighbors)

Regression Equation

$$\mathrm{SVI_{it}} = \beta_0 + \beta_1 * \text{CCA Launch} + \beta_2 * \mathrm{SVI_{i(t-4)}} + \beta_3 * \mathrm{IMR} + \beta * \text{Industry Dummies} + \beta * \text{YearDummies} + \varepsilon$$

Table S2.11.1 Influence of Launching CCA on Investor Attention (SVI_t)

	DV: Investor Attention, ($\mathrm{SVI_t}$)
Launching CCA	2.86 (1.36)**
$\mathrm{SVI_{t-4}}$	.86 (.02)***
Inverse Mills ratio	-3.44 (2.74)
Year Dummies	Included
Industry Dummies	Included
R^2 (R^2adj)	0.76 (0.73)
F-value	24.64 ***
N	403

Appendix S2.12 Results of robustness check

Table S2.12.1 Results of Robustness Check – Additional Market Signaling Factors

Parameter/Independent Variables	DV: CAR (Market Model)
CCA Launch Strategy	
Post-Purchase vs Pre-Purchase (Base)	.89 (.33)***
Partner-owned vs Brand-owned (Base)	.79 (.37)**
CCA Functionalities	
Dual Functionality vs Information CCA (Base)	.61 (.29)**
Dual Functionality vs Task CCA (Base)	.80 (.31)***
Dual Modality vs Text CCA (Base)	1.63 (.63)***
Dual Modality vs Voice CCA (Base)	1.48 (.66)**
Authentication Needed	-.95 (.29)***
Controls	
Technology Emphasis	-.10 (1.54)
Order of Entry	.04 (.02)*
Firm Performance	-.63 (1.31)
Firm Size	-.04 (.07)
Market Share	.02 (1.66)
Parent Company	-.00 (.28)
Marketing Emphasis	1.31 (2.03)
Information Coverage	-.00 (.00)*
Market Size	.04 (.08)
Competitive Intensity	-.01 (.01)
Industry Dummies	Included
AI-period	-.55 (.48)
Return on Assets	-1.10 (2.24)
Industry Growth	.48 (.53)
Mills	-.41 (.39)
Constant	2.13 (1.79)
R^2	0.26
N	206
F-Statistic	2.15***

$* \ p < .10, ** \ p < .05, *** \ p < .01$

Table S2.12.2 Results of Robustness Check – Including Confounding Announcements

Parameter/Independent Variables	DV: CAR (Market Model)
CCA Launch Strategy	
Post-Purchase vs Pre-Purchase (Base)	.70 (.39)**
Partner-owned vs Brand-owned (Base)	.76 (.46)*
CCA Functionalities	
Dual Functionality vs Information CCA (Base)	.48 (.36)*
Dual Functionality vs Task CCA (Base)	1.00 (.36)***
Dual Modality vs Text CCA (Base)	1.22 (.76)*
Dual Modality vs Voice CCA (Base)	.97 (.79)
Authentication Needed	-.68 (.36)**
Controls	
Technology Emphasis	-.57 (1.80)
Order of Entry	.03 (.03)
Firm Performance	-.05 (.73)
Firm Size	-.11 (.08)
Market Share	-.05 (1.68)
Parent Company	-.01 (.34)
Marketing Emphasis	1.50 (2.50)
Information Coverage	-.00 (.00)
Market Size	.06 (.09)
Competitive Intensity	-.01 (.01)
Industry Dummies	Included
AI-period	-.62 (.49)*
Mills	-.42 (.47)**
Constant	1.68 (2.16)
R^2	0.16
N	243
F-Statistic	1.48**

$* \, p < .10, ** \, p < .05, *** \, p < .01$

Table S2.12.3 Results of Robustness Check – Different Asset Pricing Model (Fama French)

Parameter/Independent Variables	DV: CAR (Fama French)
CCA Launch Strategy	
Post-Purchase vs Pre-Purchase (Base)	.72 (.35)**
Partner-owned vs Brand-owned (Base)	.75 (.40)**
CCA Functionalities	
Dual Functionality vs Information CCA (Base)	.43 (.31)*
Dual Functionality vs Task CCA (Base)	.58 (.33)**
Dual Modality vs Text CCA (Base)	1.44 (.69)**
Dual Modality vs Voice CCA (Base)	1.31 (.72)**
Authentication Needed	-.57 (.31)**
Firm Characteristics	
Technology Emphasis	.20 (1.68)
Order of Entry	.01 (.02)
Firm Performance	-.08 (1.04)
Firm Size	-.04 (.08)
Market Share	.07 (1.81)
Parent Company	.15 (.31)
Marketing Emphasis	.64 (2.19)
Information Coverage	.00 (.00)
Market Size	.00 (.09)
Competitive Intensity	-.01 (.01)
Industry Dummies	Included
AI-period	-.02 (.52)
Mills	-.27 (.42)
Constant	1.37 (1.95)
R^2	0.18
N	206
F-Statistic	1.33*

$* p < .10, ** p < .05, *** p < .01$

Table S2.12.4 Results of Robustness Check – Carhart Four-Factor Model

Parameter/Independent Variables	DV: CAR (Carhart 4-Factor Model)
CCA Launch Strategy	
Post-Purchase vs Pre-Purchase (Base)	.84 (.44)**
Partner-owned vs Brand-owned (Base)	.72 (.49)*
CCA Functionalities	
Dual Functionality vs Information CCA (Base)	.98 (.38)***
Dual Functionality vs Task CCA (Base)	.38 (.41)
Dual Modality vs Text CCA (Base)	1.32 (.92)*
Dual Modality vs Voice CCA (Base)	1.72 (.96)**
Authentication Needed	-.57 (.39)*
Firm Characteristics	
Technology Emphasis	-4.62 (2.05)**
Order of Entry	.00 (.03)
Firm Performance	-.32 (1.73)
Firm Size	-.14 (.10)*
Market Share	-.11 (2.20)
Parent Company	-.15 (.38)
Marketing Emphasis	-.52 (2.69)
Information Coverage	-.00 (.00)
Market Size	.01 (.11)
Competitive Intensity	-.00 (.01)
Return on Assets	2.75 (2.96)
Industry Growth	-.11 (.69)
Industry Dummies	Included
AI-period	-.53 (.64)
Mills	-.62 (.52)
Constant	5.49 (2.45)
R^2	0.21
N	203
F-Statistic	1.64**

$*\, p < .10, ** \, p < .05, *** \, p < .01$

Table S2.12.5 Results of Robustness Check – Using Mahalanobis Matching

Parameter/Independent Variables	DV: CAR (Market Model)
CCA Launch Strategy	
Post-Purchase vs Pre-Purchase (Base)	1.35 (.36)***
Partner-owned vs Brand-owned (Base)	.26 (.40)
CCA Functionalities	
Dual Functionality vs Information CCA (Base)	.52 (.31)*
Dual Functionality vs Task CCA (Base)	.57 (.34)*
Dual Modality vs Text CCA (Base)	1.26 (.70)**
Dual Modality vs Voice CCA (Base)	1.50 (.73)**
Authentication Needed	-1.00 (.31)***
Controls	
Technology Emphasis	1.75 (1.71)
Order of Entry	.04 (.02)**
Firm Performance	.59 (1.05)
Firm Size	.10 (.08)
Market Share	.65 (1.82)
Parent Company	-.31 (.31)
Marketing Emphasis	2.04 (2.21)
Information Coverage	-.00 (.00)*
Market Size	-.05 (.09)
Competitive Intensity	-.02 (.01)**
Industry Dummies	Included
AI-period	.33 (.52)
Mills	.54 (.43)
Constant	-.52 (1.96)*
R^2	0.20
N	206
F-Statistic	1.73**

$* p < .10, ** p < .05, *** p < .01$

Table S2.12.6 Results of Robustness Check – Using Services (vs Product) and B2B (vs. B2C) Variables

Parameter/Independent Variables	DV: CAR (Market Model)
CCA Launch Strategy	
Post-Purchase vs Pre-Purchase (Base)	.91 (.29)***
Partner-owned vs Brand-owned (Base)	.83 (.36)**
CCA Functionalities	
Dual Functionality vs Information CCA (Base)	.42 (.26)*
Dual Functionality vs Task CCA (Base)	.83 (.30)***
Dual Modality vs Text CCA (Base)	1.56 (.62)***
Dual Modality vs Voice CCA (Base)	1.40 (.65)**
Authentication Needed	-.77 (.28)***
Controls	
Technology Emphasis	-.79 (1.48)
Order of Entry	-.00 (.02)
Firm Performance	-.94 (.95)
Firm Size	-.04 (.07)
Market Share	.48 (1.62)
Parent Company	.17 (.27)
Marketing Emphasis	1.18 (1.97)
Information Coverage	-.00 (.00)
Market Size	.00 (.08)
Services vs Product (Base)	.32 (.34)
B2B vs B2C	.07 (.31)
AI-period	-.34 (.47)
Competitive Intensity	.00 (.01)
Mills	-.21 (.37)
Constant	1.44 (1.66)
R^2	0.21
N	206
F-Statistic	2.40***

$* \, p < .01, ** \, p < .05, *** \, p < .01$

Table S2.12.7 Results of Robustness Check – Coding AI-Period Variable Based on Year of Launch

Parameter/Independent Variables	DV: CAR (Market Model)
CCA Launch Strategy	
Post-Purchase vs Pre-Purchase (Base)	.87 (.32)***
Partner-owned vs Brand-owned (Base)	.69 (.37)**
CCA Functionalities	
Dual Functionality vs Information CCA (Base)	.67 (.29)**
Dual Functionality vs Task CCA (Base)	.75 (.31)***
Dual Modality vs Text CCA (Base)	1.65 (.63)***
Dual Modality vs Voice CCA (Base)	1.51 (.65)**
Authentication Needed	-.92 (.28)***
Controls	
Technology Emphasis	-.38 (1.55)
Order of Entry	.04 (.02)*
Firm Performance	-1.00 (.94)
Firm Size	-.04 (.07)
Market Share	.11 (1.67)
Parent Company	.02 (.28)
Marketing Emphasis	1.75 (2.02)
Information Coverage	-.00 (.00)
Market Size	.05 (.09)
Competitive Intensity	-.01 (.01)*
Industry Dummies	Included
AI-Period with Year Controls	Included
Mills	-.35 (.39)*
Constant	1.87 (1.79)*
R^2	0.28
N	206
F-Statistic	2.22***

$* p < .10, ** p < .05, *** p < .01$

Table S2.12.8 Results of Robustness Check – Using Announcements that Only Mention the Focal Event

Parameter/Independent Variables	DV: CAR (Market Model)
CCA Launch Strategy	
Post-Purchase vs Pre-Purchase (Base)	.95 (.36)***
Partner-owned vs Brand-owned (Base)	.90 (.42)**
CCA Functionalities	
Dual Functionality vs Information CCA (Base)	.56 (.31)**
Dual Functionality vs Task CCA (Base)	.91 (.35)***
Dual Modality vs Text CCA (Base)	1.75 (.67)***
Dual Functionality vs Voice CCA (Base)	1.60 (.70)**
Authentication Needed	-.55 (.32)**
Controls	
Technology Emphasis	-.02 (1.66)
Order of Entry	.02 (.02)
Firm Performance	-1.43 (1.05)*
Firm Size	-.03 (.09)
Market Share	-2.12 (2.05)
Parent Company	.07 (.32)
Marketing Emphasis	2.11 (2.29)
Information Coverage	-.00 (.00)
Market Size	-.02 (.09)
AI-period	-.83 (.56)*
Competitive Intensity	-.00 (.01)
Industry Dummies	
Mills	-.54 (.43)
Constant	3.88 (2.16)
R^2	0.27
N	171
F-Statistic	1.99***

$* p < .01, ** p < .05, *** p < .01$

Appendix S2.13 Direct Effect of Launch on Market Value

I examined the effect of CCA on an alternative measure of firm value, market capitalization. I find that the market value for the firms that launched a CCA (treatment firms) increased from a mean of 66.134 to 82.87 billion dollars, while for firms not launching the CCA or the control group, it declined from 49.73 to 56.61 billion dollars between the prelaunch and post-launch periods. In addition, launching CCA has a significant positive effect on market value. The direct effect and difference in difference results are provided in Table S2.13.1 and Figure S2.13.1 respectively.

Table S2.13.1 Direct Effect of Launching CCA on Market Value

Direct Effect	DV: Market Value	
Launching CCA	30.44	(14.58)**
Return on Assets	313.49	(147.57)**
AI-period	16.68	(27.17)
Technology Emphasis	628.27	(148.20)***
Firm Size	38.96	(4.73)***
Leverage	-44.65	(28.52)*
Financial Slack	182.83	(159.23)**
Mills Ratio	-231.43	(350.37)
Industry Dummies	Included	
Constant	-87.65	(59.14)*

$* p < .01, ** p < .05, *** p < .01$

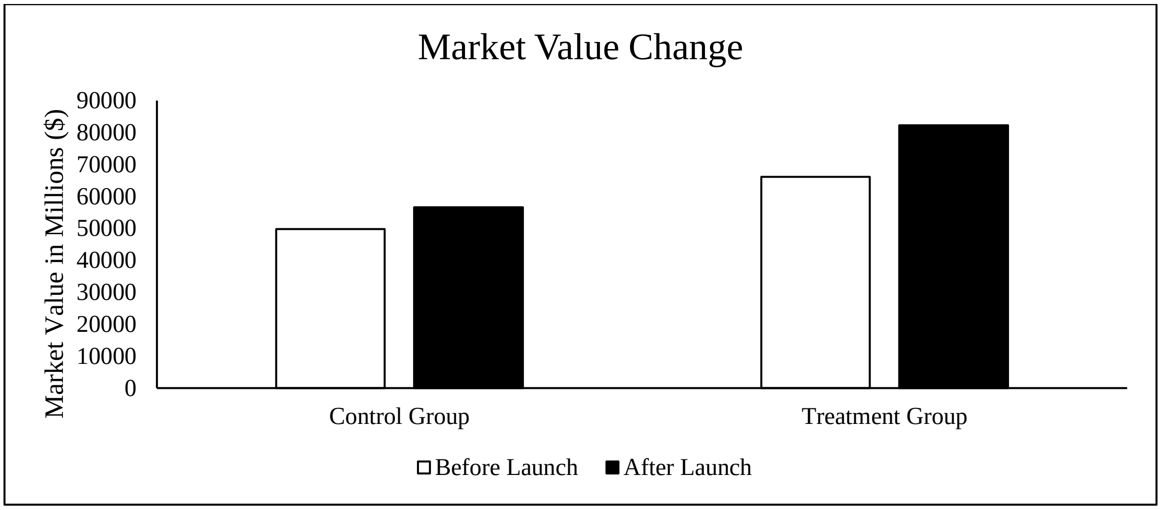


Figure S2.13.1 Difference in Difference between Treatment and Control Groups Before and After Launch

Table S2.13.2 Treatment Effect Estimation Results – Market Value (Difference in Difference)

	Market Value		
	Only Treatment	With Covariates	Heckman Model (with Covariates)
Treatment Effect	8.35 (13.87)	4.16 (11.55)	4.51 (11.57)
Time dummy	-3.09 (13.88)	-.83 (11.46)	-.83 (11.47)
Treatment group dummy	28.06 (19.62)*	24.49 (16.20)*	24.48 (16.21)*
Firm size		36.62 (2.65)***	36.57 (2.65)***
Leverage		-33.14 (15.65)**	-33.41 (15.67)**
Financial Slack		220.38 (52.37)***	218.50 (52.49)***
Technology Emphasis		568.51 (74.63)***	564.46 (74.97)***
AI-Period		13.97 (15.24)	10.75 (16.22)
Inverse Mills Ratio			-9.44 (16.28)
Industry Dummies		Included	Included
Constant	53.04 (9.78)***	-61.56 (34.07)**	-39.59 (50.98)

$* p < .10, ** p < .05, *** p < .01$

Appendix S2.14 Inclusion of CCA Intelligence as Additional Moderators

Table S2.14.1 Results of Robustness Check – Including AI Intelligence (Based on Huang and Rust 2019)

Parameter/Independent Variables	DV: CAR (Market
CCA Launch Strategy	
Post-Purchase vs Pre-Purchase (Base)	.92 (.33)***
Partner-owned vs Brand-owned (Base)	.90 (.37)**
CCA Functionalities	
Dual Functionality vs Information CCA (Base)	.59 (.29)**
Dual Functionality vs Task CCA (Base)	.85 (.31)***
Dual Modality vs Text CCA (Base)	1.63 (.63)***
Dual Modality vs Voice CCA (Base)	1.48 (.66)**
Authentication Needed	-.89 (.28)***
Mechanical AI vs Thinking AI (Base)	.29 (.39)
Feeling AI vs Thinking AI (Base)	.53 (.27)**
Controls	
Technology Emphasis	-.20 (1.54)
Order of Entry	.04 (.02)*
Firm Performance	-1.22 (.96)
Firm Size	-.04 (.07)
Market Share	.01 (1.72)
Parent Company	-.03 (.28)
Marketing Emphasis	1.84 (2.04)
Information Coverage	-.00 (.00)
Market Size	.02 (.08)
Competitive Intensity	-.00 (.01)
Industry Dummies	Included
AI-period	-.65 (.43)*
Mills	-.33 (.39)
Constant	2.27 (1.80)
R^2	0.26
N	205
F-Statistic	2.21***

$* \, p < .10, ** \, p < .05, *** \, p < .01$

Appendix S2.15

Table S2.15.1 Dictionary Words and Agreement

Mechanism	Examples	Words in Category	Alpha
Convenience	accessible, available, convenient, flexible, less effort	36	90%
Personalization	personalized, customized, tailored, preference, relevant	46	92%

Note: Alpha is the percentage agreement of three coders on dictionary words in the category

Appendix 2.16 Difference in Differences Analysis

My goal is to assess if firms launching CCAs place greater emphasis on personalization and convenience compared to control firms that did not launch. In an experimental sense, I aim to infer the treatment effect by the incremental emphasis on personalization and convenience from treatment firms launching CCA. In an ideal setting, I could randomize the treatment and observe personalization and convenience focus of firms that did not launch (L1) and from firms that did (L0). With such a random assignment, the difference in these average focuses on the mediators, L1 - L0, represents the treatment effect - that is, the incremental emphasis firm launching CCA place on the mediators. In my data (as in most observational data settings), firms launching CCA is not random, and I need to account for firms self-selecting into the treatment group. Not all their reasons to launch are observable. Omitted variables that drive firms to launch CCA could correlate with the mediating mechanisms, which would involve an endogeneity bias. Therefore, I consider three potential solutions that vary in the extent to which they correct for selection bias to establish the causal link between app adoption and sales: (1) difference-indifferences, (2) difference-in-differences, augmented with selection on observables, and (3) difference-in-differences, augmented with selection on unobservables.

The difference-in-differences approach compares the personalization and convenience focus differential (post-treatment focus -pretreatment focus) of firms in the treatment group with firms in the control group. Thus,

(5) $$L_{ijt} = \beta_0 + \beta_1 I_j + \beta_2 I_t + \beta_3 I_j \text{ x } I_t + \varepsilon_{ijt}$$

(6) $$M_{ijt} = \gamma_0 + \gamma_1 I_j + \gamma_2 I_t + \gamma_3 I_j \text{ x } I_t + \varepsilon_{ijt}$$

Where L_{ijt} and M_{ijt} is the firm i's emphasis on personalization and convenience from group j in time t, ε_{ijt} is a random error term, clustered across buyers and the two periods. My data set contains two groups j (treatment and control) and two-time periods t (pre- and post launch periods). Then the indicator variable I_j picks up mean differences in the convenience and personalization emphasis between the treatment group and the control group, referred to as group fixed effects and indicated by the coefficients β_1 and γ_1. The indicator variable I_t indicates the mean differences in post launch relative to the prelaunch period personalization and convenience focus, similar to time fixed effects and indicated by the coefficients β_2 *and* γ_2. Finally, β_3 and γ_3 capture the difference in the change in convenience and personalization focus (difference-in-differences) across the treatment and control groups, after controlling for differences across groups and the time shocks common to both groups. Similar to study 2, the dependent variable for the mechanism is the count of personalization and convenience words used by firms in their 10-K/annual reports.

Next, we augmented equation (5) with the observed firm variables (e.g., Angrist and Pischke 2009) as follows:

(7) $$L_{ijt} = \beta_0 + \beta_1 I_j + \beta_2 I_t + \beta_3 I_j \text{ x } I_t + \beta_4 Z_{ij} + \varepsilon_{ijt}$$

where the added vector Z_{ij} captures the set of observables, the effects of which are estimated through the coefficient vector β_4.

Lastly, I modelled a firm's decision to launch CCA as a function of all the observable variables with a probit model, which I use to calculate the IMR for the firms in the treatment and control groups. I then augmented our difference-in-differences model in Equation 5 as follows:

(8) $$L_{ijt} = \beta_0 + \beta_1 I_j + \beta_2 I_t + \beta_3 I_j \text{ x } I_t + \beta_4 Z_{ij} + \beta_5 IMR + \varepsilon_{ijt}$$

Equation for firm i's emphasis on convenience from group j in time t:

(9) $$\text{Convenience}_{ijt} = \beta_0 + \beta_1 I_j + \beta_2 I_t + \beta_3 I_j \text{ x } I_t + \beta_4 Z_{ij} + \beta_5 IMR + \varepsilon_{ijt}$$

Equation for firm i's emphasis on personalization from group j in time t:

(10) $$\text{Personalization}_{ijt} = \gamma_0 + \gamma_1 I_j + \gamma_2 I_t + \gamma_3 I_j \text{ x } I_t + \gamma_4 Z_{ij} + \gamma_5 IMR + \varepsilon_{ijt}$$

Equation for firm i's total q from group j in time t:

(11) $$\text{Total } q_{ijt} = \delta_0 + \delta_1 I_j + \delta_2 I_t + \delta_3 I_j \text{ x } I_t + \delta_4 Z_{ij} + \delta_5 IMR + \varepsilon_{ijt}$$

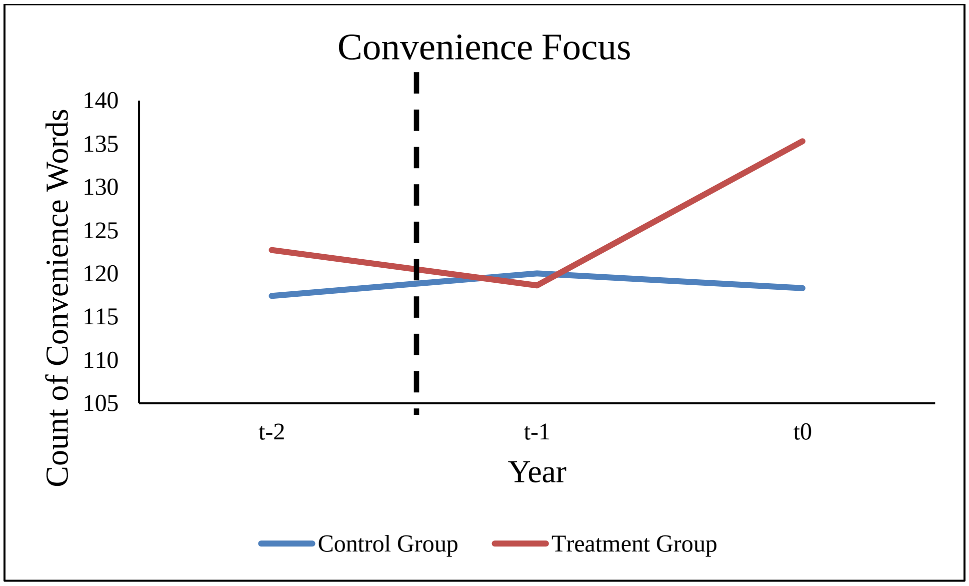


Figure S2.16.1 Convenience Focus from Two Years before To the Year of Launch

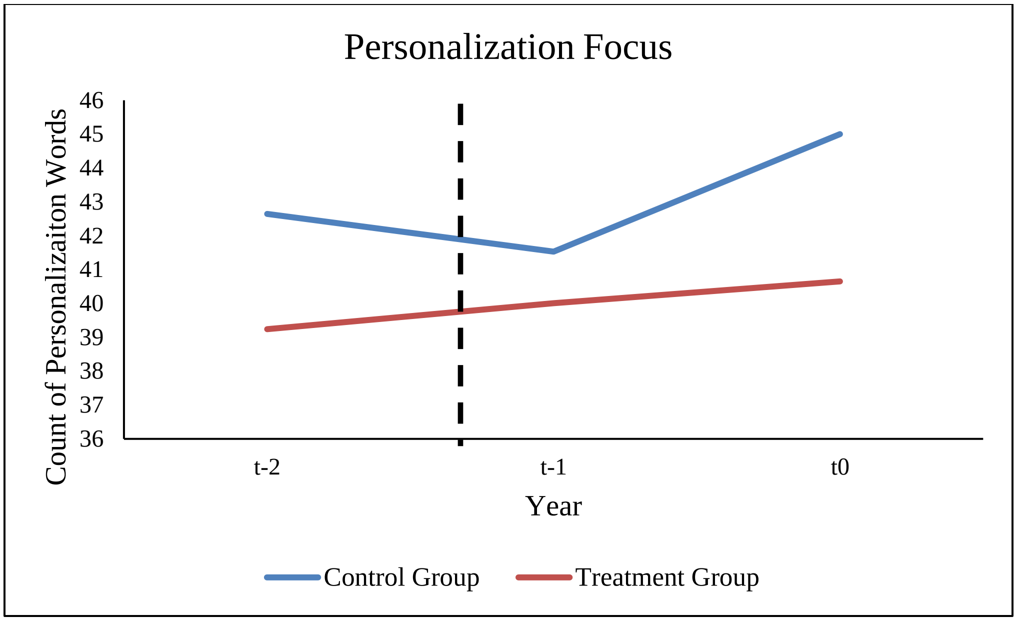


Figure S2.16.2 Personalization Focus from Two Years before To the Year of Launch

Discussion

In this section, I first validate the parallel trends assumption by comparing the treatment group's convenience and personalization focus with that of the control group in the pre-treatment and in the post-treatment period. As we see in the figures, the treatment and control groups convenience and personalization focus are similar in the pre-treatment period and significantly increases during the year of launch. I then followed up with the difference-in-difference analysis as indicated in Appendix tables S2.16.4.

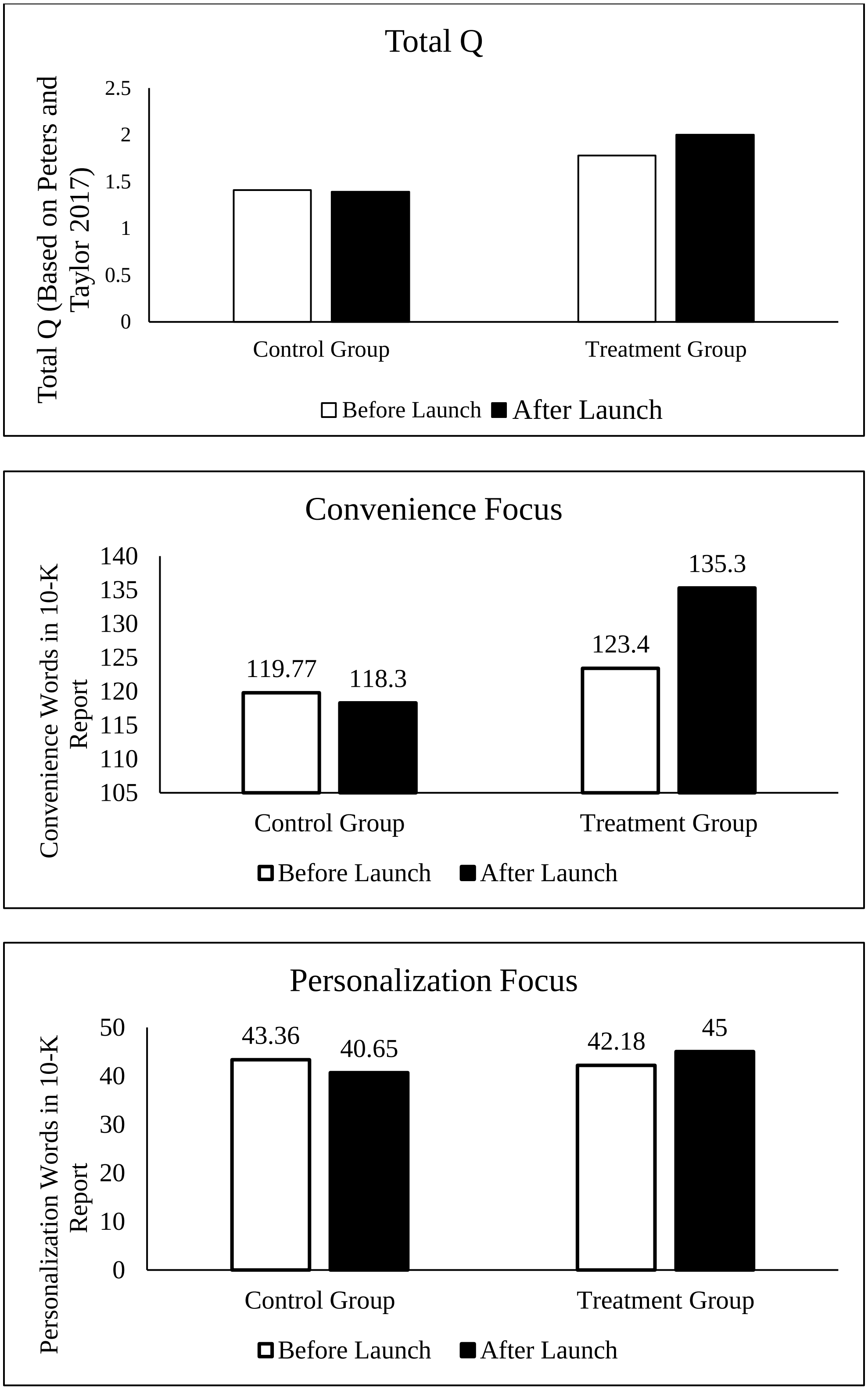


Figure S2.16.3 Model free Evidence

Table S2.16.4 Treatment Effect Estimation Results

Personalization Focus			
	Only Treatment	With Covariates	Heckman Model (with Covariates)
Treatment Effect	10.03 (4.71)**	9.57 (4.62)**	9.54 (4.62)**
Time dummy	-4.95 (3.32)*	-4.84 (3.28)*	-4.81 (3.28)*
Treatment group dummy	-4.05 (2.70)*	-4.99 (2.68)**	-11.13 (8.62)*
Firm size		-4.69 (1.33)***	-4.68 (1.33)***
Revenue		7.02 (1.26)***	7.01 (1.26)***
Competitive Intensity		4.81 (4.61)	4.76 (4.61)
Inverse Mills Ratio			1.47 (1.97)
Constant	43.98 (1.90)***	-7.71 (8.10)	-4.89 (8.93)

$** p < .05, *** p < .01$

Convenience Focus			
	Only Treatment	With Covariates	Heckman Model (with Covariates)
Treatment Effect	23.16 (11.18)**	21.00 (11.11)**	20.87 (11.11)**
Time dummy	-11.65 (.7.89)*	-10.44 (.7.90)*	-10.31 (.7.90)*
Treatment group dummy	1.21 (6.42)	.26 (6.44)	-31.04 (20.72)*
Firm size		-8.33 (3.20)***	-8.25 (3.20)***
Revenue		11.47 (3.07)***	11.45 (3.03)***
Competitive Intensity		-7.47 (11.10)	-7.69 (11.10)
Inverse Mills Ratio			11.53 (4.74)**
Constant	122.58 (4.52)***	49.17 (19.47)***	63.52 (21.47)***

$** p < .05, *** p < .01$

Total Q			
	Only Treatment	With Covariates	Heckman Model (with Covariates)
Treatment Effect (CCA Launch)	1.29 (.69)**	.28 (.21)*	.28 (.21)*
Time dummy	-.59 (.69)	.00 (.15)	.00 (.15)
Treatment group dummy	.42 (.98)	.13 (.15)*	.12 (.15)*
Firm size		-.02 (.03)	-.02 (.03)
Leverage		1.64 (.19)***	1.64 (.19)***
Financial Slack		4.04 (.65)***	4.04 (.65)***

Technology Emphasis		7.98 (.94)***	7.88 (.94)***
AI-Period		-.27 (.19)*	-.30 (.19)*
Inverse Mills Ratio			.07 (.03)**
Industry Dummies		Included	Included
Constant	-.14 (.49)	-.15 (1.48)***	-.11 (1.48)***

$* \ p < .10, ** \ p < .05, *** \ p < .01$

Appendix S2.17

Table S2.17.1 Measures for Study 2

Variable	Operationalization	Source of Data
Personalization Focus	Count of number of personalization related words identified using custom dictionary and Linguistic Inquiry and Word Count (LIWC)	10-K/Annual Reports
Convenience Focus	Count of number of convenience related words identified using custom dictionary and Linguistic Inquiry and Word Count (LIWC)	10-K/Annual Reports
AI Period	Dummy Variable: '0' if CCA is launched before 2015; '1' if CCA is launched in or after 2015	Compustat
Return on Assets	Earnings before extraordinary items in relation to total assets (Homburg et al. 2014)	Compustat
Firm Size	Total number of firm employees (1-year lagged) (log-transformed)	Compustat
Technology Emphasis	Ratio of R&D spending by a firm in the year 't-1' divided by the Sales of the firm in the year 't-1'	Compustat
Financial Leverage	The ratio of long-term book debt to total assets (Luo, Homburg and Wieseke 2010)	Compustat
Slack	Amount of cash available to the firm divided by total firm assets	Compustat
Industry Dummies	Dummy variables according to 1-digit SIC code	Compustat

Model Specification:

Impact on total q

(12) $\text{total } q_i = \eta_0 + \eta_1 * \text{CCA Launch} + \eta_2 * \text{SIC} + \eta_3 * \text{AI} - \text{period} + \eta_4 * \text{ROA} + \eta_5 * \text{Firm Size} + \eta_6 * \text{Technology Emphasis} + \eta_7 * \text{Leverage} + \eta_8 * \text{Financial Slack} + \eta_9 * \text{mills ratio} + \eta * \text{Industry dummies} + \varepsilon_i$

Impact on convenience focus:

(13) $\text{Convenience Focus}_i = \alpha_{c0} + \alpha_{c1} * \text{CCA Launch} + \alpha_{c2} * \text{SIC} + \alpha_{c3} * \text{AI} - \text{period} + \alpha_{c4} * \text{IMR} + \varepsilon_i$

Impact on personalization focus:

(14) $\text{Personalization Focus}_i = \alpha_{p0} + \alpha_{p1} * \text{CCA Launch} + \alpha_{p2} * \text{SIC} + \alpha_{p3} * \text{AI} - \text{period} + \alpha_{p4} * \text{IMR} + \varepsilon_i$

Mediation of total q:

Mediation only through convenience focus:

(15) $\text{total } q_i = \eta_{c0} + \eta_{c1} * \text{Convenience Focus} + \eta_{c2} * \text{CCA Launch} + \eta_{c3} * \text{SIC} + \eta_{c4} * \text{AI} - \text{period} + \eta_{c5} * \text{ROA} + \eta_{c6} * \text{Firm Size} + \eta_{c7} * \text{Technology Emphasis} + \eta_{c8} * \text{Leverage} + \eta_{c9} * \text{Financial Slack} + \varepsilon_i$

Mediation only through personalization focus:

(16) $\text{total } q_i = \eta_{p0} + \eta_{p1} * \text{Personalization Focus} + \eta_{p2} * \text{CCA Launch} + \eta_{p3} * \text{SIC} + \eta_{p4} * \text{AI} - \text{period} + \eta_{p5} * \text{ROA} + \eta_{p6} * \text{Firm Size} + \eta_{p7} * \text{Technology Emphasis} + \eta_{p8} * \text{Leverage} + \eta_{p9} * \text{Financial Slack} + \varepsilon_i$

Mediation through both convenience personalization focus:

(17) $\text{total } q_i = \eta_{cp0} + \eta_{cp1} * \text{Convenience Focus} + \eta_{cp2} * \text{Personalization Focus} + \eta_{cp3} * \text{CCA Launch} + \eta_{cp4} * \text{SIC} + \eta_{cp5} * \text{AI} - \text{period} + \eta_{cp6} * \text{ROA} + \eta_{cp7} * \text{Firm Size} + \eta_{cp8} * \text{Technology Emphasis} + \eta_{cp9} * \text{Leverage} + \eta_{cp10} * \text{Financial Slack} + \varepsilon_i$

Effect on Convenience Focus and Personalization Focus

Table S2.17.2 Direct Effect of Launch on Total Q

Direct Effect	DV: Total Q_{t+1}
Launching CCA	1.36 (.68)**
Return on Assets	-7.66 (5.73)*
AI-period	-.11 (1.27)
Technology Emphasis	3.01 (6.82)
Firm Size	-.32 (.21)*
Leverage	2.19 (1.28)**
Financial Slack	17.38 (7.43)**
Mills Ratio	-.60 (16.52)
Industry Dummies	Included
Constant	1.58 (2.77)

$* p < .01, ** p < .05, *** p < .01$

Table S2.17.3 Mediating (Indirect) Effect of Personalization and Convenience Focus on Total Q

Indirect Effect	Convenience Focus Only DV: Total Q_{t+1}	Personalization Focus Only DV: Total Q_{t+1}	Both Personalization and Convenience Focus DV: Total Q_{t+1}
Convenience Focus	.10 (.05)**		
Personalization Focus		.04 (.04)	
Both Personalization and Convenience Focus			.09 (.06)**
Return on Assets	2.00 (2.46)	1.65 (2.47)	1.89 (2.46)
Technology Emphasis	3.94 (2.47)*	3.46 (2.48)*	3.84 (2.47)*
AI-period	.16 (.45)	.17 (.45)	.17 (.45)
Firm Size	-.33 (.08)***	-.36 (.08)***	-.35 (.08)***
Leverage	1.41 (.48)***	1.45 (.48)***	1.42 (.48)***
Financial Slack	14.35 (2.72)***	15.09 (2.74)***	14.77 (2.73)***
Industry Dummies	Included	Included	Included

$* p < .01, ** p < .05, *** p < .01$

Appendix S2.18

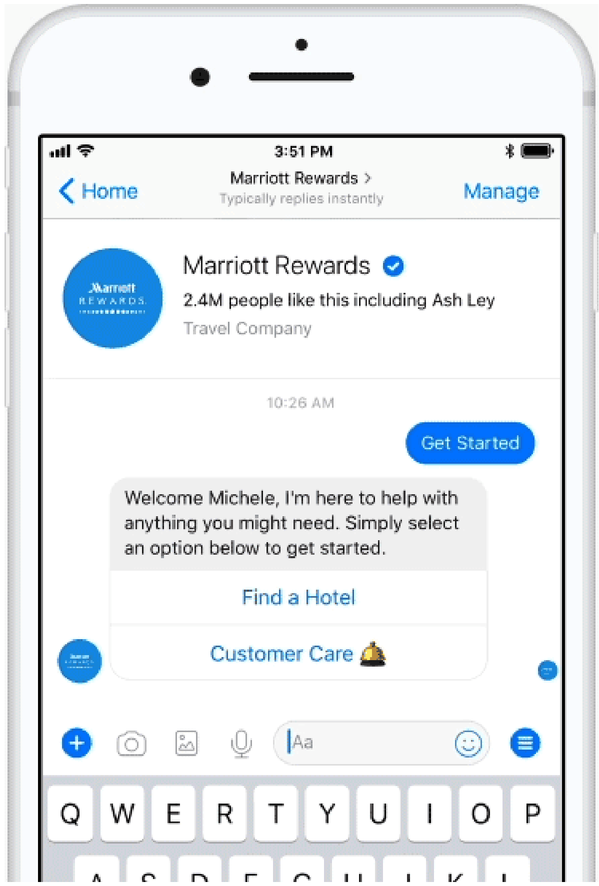


Figure S2.18.1 Image for Study 3a and Scale for Studies 3a and 3b Image showing interaction between CCA and customer. Participants in the CCA condition viewed the GIF image which consisted of the complete conversation.

[Website Condition] For the purposes of this study, imagine that you are hungry and have decided to order a pizza…you will find a set or instructions on how to place an order for a medium pepperoni pizza using the Domino’s Website. Kindly follow the instructions to build your order.

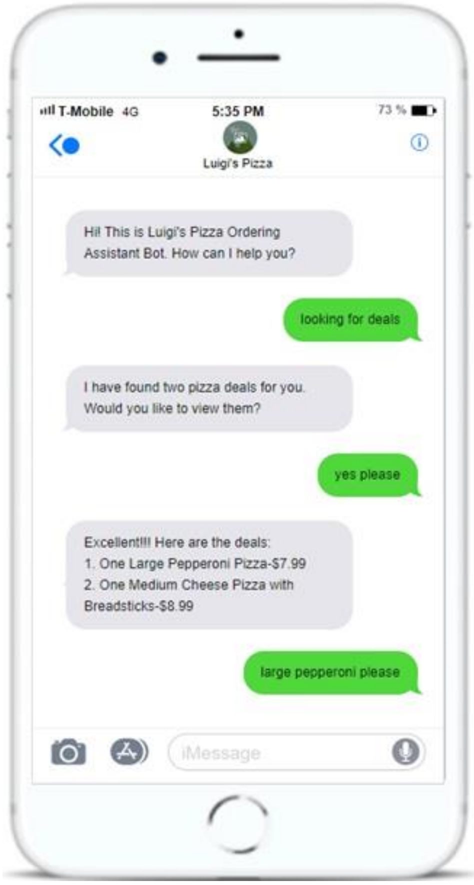
[CCA Condition] For the purposes of this study, imagine that you are hungry and have decided to order a pizza…you will find a set or instructions on how to place an order for a medium pepperoni pizza using the Domino's Chatbot. Kindly follow the instructions to build your order.

Table S2.18.1 Survey Construct Measurements

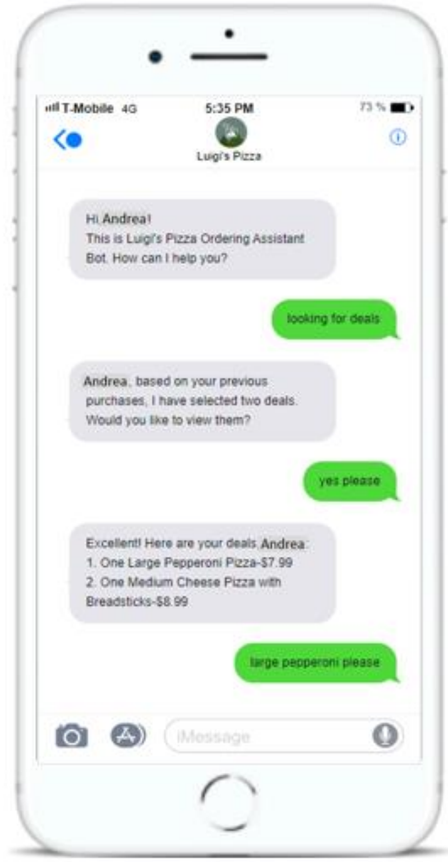
Construct
Convenience
The CCA is accessible during the entire day
I can locate content to build pizza orders on the CCA easily
It is easy to interact with the CCA
It is easy to get the information I need on the CCA to build the order
It takes little time to find information to build my order on the CCA
I am able to place pizza orders on the CCA easily
It takes little time to place orders through the CCA
It takes me minimal amount of effort on my part to place orders through the CCA
Personalization
The CCA provided me with relevant information tailored to my preferences or personal interests
The CCA interaction is easy for me to understand
The CCA interaction is personalized to my needs
Useful options are provided by the CCA
To recommend pizza options on the CCA, my preferences are taken into consideration

Notes: Items are based on five-point Likert scales (1 = “strongly disagree” and 5 = “strongly agree”) unless indicated otherwise. I used the same measures for website as well (i.e. replaced the word chatbot with website).

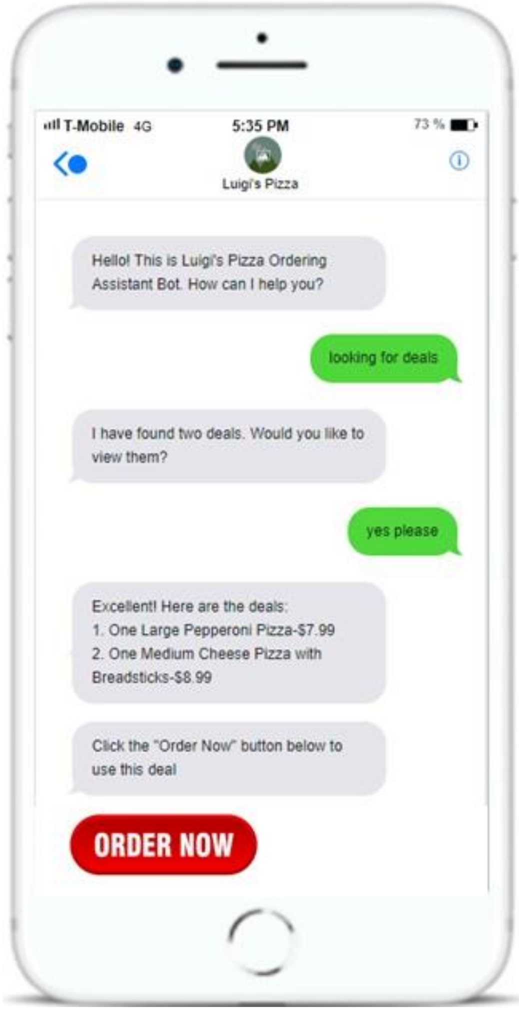
Appendix S2.19



Control CCA Conversation



Personalized CCA Conversation



Convenient CCA Conversation

Figure S2.19.1 Images of CCA Conversations - Study 3b

CHAPTER 3

'MINE' YOUR BUSINESS DESCRIPTION: PREDICTING THE FUNDING OF MARKETING AI START-UPS[1]

[1]Jayaram, K., and Bharadwaj, S.G. To be submitted to *Journal of Marketing Research*

ABSTRACT

Funding for AI startups has been on the rise over the past few years with close to $26.6 billion funded by venture capitalists in the year 2019. Applications built using AI technology are expected to add the greatest financial value to sales and marketing. Even though the value potential from building marketing AI applications is attractive, many startups face high cost of cloud computing due to training complex AI models. Moreover, they face a high costs due to storing large volumes of customer data. Thus, startups building AI applications for marketing need large financial resources to fund the significant costs. The high cost drives marketing AI startups' need and urgency to obtain venture capitalist (VC) funding. Thus, marketing AI startups try to communicate information their application's value potential and try to obtain funding. Typically, marketing AI startups send different signals to investors about their firm, and their product/service offerings. This essay addresses two research questions: (1) Does a marketing AI startup's signaling about its application offerings predict funding beyond other startup factors (e.g. financial, demographic etc.) commonly used to predict VC funding? and (2) What business and marketing strategies communicated through text descriptions are more likely to be associated with VC funding?

To understand the influence of a marketing AI startup's communication efforts on VCs funding, I examine the role of signaling in resolving the information asymmetry that exists between the startup and VCs. I argue and demonstrate that VCs place greater weights on the forward-looking text description of a startup, which mitigates the information asymmetry and increases their likelihood to fund a startup. To address RQ1, I collected data of 1,681 marketing AI startup firms from the CrunchBase database, a database that provides information about new ventures and investor activities. To the data, I applied regularized logistic regression with L1 and

L2 penalization, and applied random forest with best feature selection and extremely randomized trees. I find that the model with textual information adds up to 2.44% in predictive power than model with only the startups' other contingent factors. A back-of-the-envelope calculation reveals that the 2.44% increase in likelihood to fund translates to $242.6 million increase in total VC funding towards marketing AI startups.

To address RQ2, I employed four approaches: naïve Bayes classification, logistic regression with L1 penalization, LDA and LIWC dictionaries. I find that successfully funded startups' textual business descriptions provide information about benefits to customers from using their application offering, such as greater personalization and improving customer experience. Moreover, AI applications that use 'computer vision', 'targeting' right customers, etc. are more likely to be funded. Moreover, we find that funded startups focus on the AI offerings' past success versus future potential. Demonstrating that textual business information used to communicate strategy helps predicts VC funding has important implications for struggling marketing AI startups.

INTRODUCTION

Business applications of Artificial intelligence (AI) seen as a technology that enhances and/or replaces tasks traditionally done by humans is growing in past few decades. Sometimes labelled robotic process automation (RPA), even while these applications have more to do with software programs rather than robots, have been disrupting how companies execute tasks (Davenport 2020). While consulting firm surveys indicate that 20-30% of large enterprises are adopting or experimenting with AI applications, the level of application in marketing tasks of processing, connecting and interacting with customers are significantly higher at about 60%. According to McKinsey, AI will contribute between $1.4 trillion to $2.6 trillion additional value to marketing and sales (Chui, Henke, and Miremadi 2019). AI startups building applications to perform marketing tasks have increased tremendously in number as 90% of organizations state that they would use AI applications to improve marketing (Diorio 2020).

Even though the value potential from building AI applications seems very attractive, building an AI application requires significant investments. First, marketing AI startups require significant financial investment to cover the high cost of cloud computing, required to train complex AI models (Casado and Bornstein 2020). Second, marketing AI startups need to store huge amounts of historical and real-time customer data generated, which adds to the high storage costs. Third, scaling marketing AI applications require lot of resources because the underlying AI models have to be re-trained if they need to cater to a marketer's specific usage context . Fourth, the cost of hiring and retaining high demand employees with computer science training and programing skills adds significantly to the investment requirements of AI marketing startups.

Thus, despite the tremendous enthusiasm among marketing entrepreneurs and venture capitalists (VCs) around the value potential of artificial intelligence (AI) applications in marketing, data suggest that 90% of marketing AI startups fail and only around 1% of them obtain sufficient VC funding (Kotashev 2020). Recent statistics indicate that the funding for AI startups have been declining and firms are finding it increasingly difficult to identify appropriate AI applications to address their business problems (Fabian 2017; Glasner 2019).

Marketing AI startups can try to attract investments by communicating appropriate “signals” that convey their application’s value potential e.g., describing the customer targeting benefits of their application. However, considering the nascence of using AI applications in marketing and the limited research on startups building AI applications for marketing, it is not yet clear what “signals” communicated by marketing AI startups would be more effective. In other words, existing literature does not provide sufficient guidance to marketing AI entrepreneurs on what they should communicate about their marketing AI application to improve chances of getting VC funding.

On the other side, VCs are unaware of the information available with startups and they are unable to view the actions taken by entrepreneurs (Amit, Brander and Zott 1998). Moreover, VCs lack clarity on the intent of the entrepreneurs (Connelly et al. 2011). This creates information asymmetry between the VCs and startups. The asymmetry potentially gives rise to the risk of “adverse selection” in which VCs are unable to distinguish between startups with good and bad potential (Glücksman 2020).

In the case of marketing AI startups, entrepreneurs build applications to help with a wide range of marketing tasks including to conduct market research, to take strategic marketing decisions (e.g. which customers to target) and to take marketing actions such as personalizing content to a customer segment (Huang and Rust 2021). AI startups are not always clear apriori about how their applications will improve a marketer’s current tasks (Minetti 2020). A marketing startup could build an application to generate specific marketing output but marketers can use it to perform completely different marketing tasks. For example, an application can use natural language processing (NLP) to help a marketer to analyze customers' social media content to understand their behaviors (Hartmann et al. 2019). Whereas, a different marketer could use the same NLP application to monitor prospect emails and to get customers interaction recommendations. Thus, in addition to the limited information available about a startup, the lack of clarity about how the marketing application would be used increases the risk of adverse selection for a VC.

In addition to the limited knowledge about a startup and lack of understanding about using a specific marketing AI application, VCs also find it challenging to estimate potential value of the marketing AI application. Traditionally, a VC analyzes startups and decides to fund a startup based on whether it can sufficiently grow in the future (Davila, Foster and Gupta 2003). However, information asymmetries and the long period involved in startups generating revenue makes a VC's value assessment difficult. Assessing a marketing AI startup's potential value is even more challenging for VCs for the following reasons. First, marketing AI applications do not have well-defined performance metrics (Fabian 2017). Traditional metrics such as customer churn and conversion are inappropriate to use because an AI application typically only performs narrowly-defined tasks in a marketing problem e.g., qualifying leads (Paschen, Kietzmann and Kietzmann 2019). Thus, returns from a marketing AI application cannot be directly measured. Second, it is usually not obvious as to what marketing tasks an AI application would complement or replace (Crunchbase 2020). For example, a new application can perform effectively to replace all selling tasks before purchase for a customer, or it could only be valuable to interact with customers during their 'search' stage of purchase (cf. Lemon and Verhoef 2016). The value generated in both these cases could vary significantly. Third, the benefits to frontline employees and customers from using a marketing AI application is often unclear. Considering that AI interacts with humans both on the firm side and on the customer side during frontline interactions (Robinson et al. 2020), understanding who the AI application would benefit more is valuable for VCs to help evaluate the startup. However, VCs lack access to this information.

VCs try to overcome limitations arising from information asymmetry by using startup related information available to them such as the startup's proprietary patent profile, finances, leadership background and the industries served (e.g. Homburg et al. 2014). This helps VCs not only reduce information asymmetry but also helps them draw inferences regarding the startup's value potential. In addition to the traditional signals used by VCs to evaluate startups, Petkova, Rindova and Gupta (2013) find that any additional information communicated by startups about them act as a potential signal and supplements the information used by VCs. Even though information about the startup is useful to reduce the asymmetry, recent reports suggest that AI startups increasingly find it challenging to communicate information about the importance of the problems they solve and how they are solving it (Minetti 2020). Thus, they are not able to communicate sufficient information to VCs, which results in funding shortfalls.

To bridge the gap between startups and VCs, a number of online platforms such as Crunchbase, Dealroom and Pitchbook aggregate textual business descriptions of AI applications and make it available to VCs. These platforms provide VCs with information about different AI applications and allows marketing entrepreneurs to describe the capabilities of their marketing AI applications. By providing an application's description, entrepreneurs can signal their competitiveness, reduce the information asymmetry and convey potential value of their application (Xiong and Bharadwaj 2011; Chase and Murtha 2019).

Accordingly, my main proposition is that the text which marketing AI startups use to describe their applications in online platforms provides additional information about the application's value potential such as the application's capability to perform marketing tasks, the benefits to customers and marketers, the automation capabilities of the application, etc. Business information conveyed through the text descriptions is otherwise not available from information available about the startup e.g., through patents, financials and leadership data. The business text description is analogous to a startup providing an 'elevator pitch' to the VCs or a roadshow by firms prior to IPOs. In line with previous studies that find information about a startup's resources, activities, and growth strategies communicated through media to provide additional valuable information to VCs (Petkova et al. 2013), I expect that the content of a marketing AI startup's text description would help interpret the startup's marketing strategies, the application's marketing capabilities, etc. As information is made available to VCs, I expect that this information is predictive of likelihood of obtaining VC funding beyond all other available information. My hypothesis suggests that the online platforms (a type of "information intermediary") provide information about the marketing AI entrepreneur's intent regarding how to use the application for marketing tasks. I expect that deeper insights about the startup's intent would help reduce information asymmetry that originates from VCs lacking entrepreneur's intent information (Connelly et al. 2011).

To identify which marketing AI startups are more likely to be funded - I apply text-mining and machine learning to a data set of over 1,861 startup descriptions obtained from the startup database, CrunchBase. Using an ensemble stacking approach that includes random forest methods and regularized logistic regressions, I find that the textual descriptions of marketing AI startups significantly improves predictions of VC funding. A simple back-of-an-envelope analysis shows that using textual information to communicate marketing strategies, marketing capabilities of an AI application can increase likelihood of obtaining VC funding over an approach that uses only the startup's financial and demographic information by as much as 2.44%.

To learn which marketing strategies, marketing contexts, customer and marketer benefits conveyed through the text are more likely to be associated with successfully getting VC funding, I further analyzed the data using a multimethod approach including both machine learning and econometric tools. Specifically, I utilized machine learning tools of naïve Bayes and L1 regularization binary logistic model, and used econometric tools such as logistic regression of the topics extracted from a latent Dirichlet allocation (LDA) analysis, and the sub-dictionaries of the Linguistic Inquiry and Word Count dictionary (LIWC; Tausczik and Pennebaker 2010). The results show that successfully funded marketing AI startups are more likely to emphasize customer benefits from using their application (e.g. personalization, engagement), focus more on the past and present success (rather than future potential) of their application, perform marketing tasks that need mechanical intelligence such as automated sales prospecting, generating new content, and have automated conversations on social media. Thus, my results suggest that a marketing AI startup which claims to use customer related data to personalize offerings at scale is more likely to be funded. Whereas, a marketing startup that claims to make a marketer more productive in the future is less likely to be funded. These analyses demonstrate the successful use of machine learning tools in going beyond merely predicting the outcome and into the realm of interpretation by inferring marketing strategies and contexts and customer benefits associated with investors' return expectations.

Applying the LIWC dictionary to the data allows for a deeper exploration into the potential temporal focus of AI entrepreneurs. The results suggest that funded marketing AI startup's descriptions focus more on past success versus their future potential. A marketing AI startup's decision to focus on future possibility versus past success could be a strategic one. This could happen if the startup has not successfully commercialized the application and obtained marketing clients but hopes to use the VC funding to commercialize in the future. In summary, I believe that marketing AI startup's text descriptions informs VCs whether investing in a marketing AI application will generate sufficient returns.

My examination into marketing AI startups' descriptions through text in online platforms contributes to the fast-growing in literature AI and marketing. Researchers in marketing and AI have been investigating how AI applications solve specific marketing problems (Chung et al. 2016), customers reactions to AI (Luo et al. 2019) and effect of AI on marketing jobs (Huang and Rust 2018). My contribution is to the still nascent area of AI and marketing strategy (Huang and Rust 2021). I add to this literature by using archival data and showing how marketing AI startups can communicate their strategies to improve their likelihood of getting funded. In addition, I identify the different marketing strategies, business strategies, the marketing tasks performed communicated through the startup's textual description that increase the likelihood of getting VC funding.

The rest of this essay is organized as follows. In the next section, I draw on signaling theory (Spence 1973, 2002) and discuss how information asymmetry between venture capitalist and AI entrepreneurs leads to an "adverse selection" problem. Specifically, drawing on extant literature I argue that an AI startup's financials and demographics miss important information about their applications' potential that VCs can learn from the startup's text description. I then describe the data, explicate the text-mining and modeling approaches, present the results, and their generalization.

INFORMATION ASYMMETRY BETWEEN ENTREPRENEURS AND VENTURE CAPITALIST

Information asymmetry occurs when one entity in a relationship has more or better information than the other entity (Akerlof 1970). Information asymmetry between VCs and entrepreneurs is one of the primary drivers of financial constraints in small firms (Sahlman 1990; Glücksman 2020). Asymmetry results as entrepreneurs possess information about their startup not known to VCs.

Mitigating Information Asymmetry

A VC's ability to reduce and manage information asymmetry risks helps them distinguish good ventures from the bad ones (Amit et al. 1998). Multiple studies detail the different mechanisms VCs use to mitigate information asymmetry risks (Drover et al. 2017) and overcome the associated adverse selection risks. For example, VCs conduct due diligence with other VCs who bring in complementary evaluation skills which helps to evaluate multiple aspects of a startup (Cumming 2006). VCs also use multi-stage screening process to obtain information about different characteristics of the startup at each stage (Fried and Hisrich 1994). VCs use different mechanisms post funding as well, to overcome "moral hazard" issues arising from information asymmetry. For example, VCs participate in convertible preferred stock so that they can exit the startup deal if they find the entrepreneur to not exert sufficient efforts to the startup (Arcot 2014). To overcome moral hazard issues, VCs place emphasis on monitoring startup activities including focusing even on low-level operational activities (Pruthi, Wright, and Lockett 2003). This ensures that the entrepreneur is acting in the VCs interest. Although VCs use different mechanisms to reduce the risk of adverse selection and moral hazard, they can better evaluate a startup if they have additional information about the startup. For example, Petkova et al. (2013) argue that when evaluating a startup's value potential, VCs are benefited by using a startup's media visibility above and beyond what VCs use for valuation such as the startup's financials and demographics. Media visibility signals that the startup's application might have some popularity and could attract customers' interest.

Venture capitalists face two types of informational asymmetry namely, information about the startup's quality and information about the startup's intent (Connelly et al. 2011). VCs can typically use a variety of information available publically to address their quality concerns (Courtney, Dutta and Li 2017). For example, patents issued to a startup can act as a credible signal of the startup's quality (Hsu and Ziedonis 2013). VCs also need understand the startup's intent, which would help them learn the entrepreneur's future actions (Connelly et al. 2011). Previous research finds that if firms communicate organizational strategic intent and mindset through text, it helps investors evaluate the firm's future prospects (e.g., Saboo and Grewal 2013). In the case of startups, I expect that the textual business information communicated through the online intermediaries (e.g. Crunchbase) would convey the startup's future intent. Typically, startups with low resources gain more from describing their applications on online platforms as they have limited resources in the form of industry contacts, limited finances, and limited talent to attract VC's interest. Even conveying the presence of marketing capabilities in the top management team can signal that the startup can have greater success as they startups with CMOs can better identify customer needs (Homburg et al. 2014). Thus, I expect that the online platforms would help startups provide additional information to VCs and reduce the information asymmetry that VCs face.

On the other side, entrepreneurs try to send different signals about their application to reduce information asymmetries between them and the VCs and to address uncertainties about their startup. In order to convey to VCs the capabilities of their startup, entrepreneurs try to send positive signals about their startup and about their applications' potential. For instance, startups send signals regarding the patents they have, relating the venture to individuals and businesses with higher status, by highlighting educational experience of the management team or by including leaders with functional knowledge in their management team (Connelly et al. 2011; Hsu and Zeidonis 2013; Homburg et al. 2014; Bollazzi, Risalvato, and Venezia 2019). These signals help reduce information asymmetry and helps VCs determine which startups are investment ready (Gregory et al. 2012; Silver, Berggren, and Veghohn 2010).

Information Asymmetry in Marketing AI Startups

I expect that the information asymmetry in marketing AI startups is even higher because beyond VCs' lack information about a startup, there is a lot of uncertainty around how an AI application would be used in a marketing context to effectively generate value (Fabian 2017). For example, if an AI application predicts how likely a lead would convert, it is uncertain whether and how this output would be used by a marketer. Would it automatically interact with a qualified lead to get product requirements or would it send qualified leads to a salesperson? Lead conversions could vary significantly based on which of the two approaches the application takes. Considering the limited knowledge about using AI applications in marketing and the urgency to obtain VC funding, marketing AI entrepreneurs have a stronger reasons to communicate valuable information about their application and try to reduce information asymmetry to attract VC's attention. Thus, I expect that marketing AI startups are more likely to be benefited from using online information intermediaries to describe about their application.

Signaling Theory

The signaling theory, developed by Spence (1973), suggests that sending "signals" is a potential mechanism an entity can use to overcome information asymmetry and communicate about its quality to the other entity. For firms, signaling helps communicate to customers their product's underlying quality (Kirmani and Rao 2000). According to the signaling theory, there are three primary elements– the signaler, the receiver and the signal.

Typically signalers are considered insiders to a firm (e.g., a startup's founders) who have information about the firm's individuals (e.g., Spence, 1973), the firm's products (e.g., Kirmani and Rao, 2000), or the firm (e.g., Ross 1977), which is not available to outsiders. A signal is the positive and negative private information about the firm that is communicated with people outside the organization. A related concept to signal is the signal's observability, which refers to the extent to which a firm's outsiders are able to notice the signal and identify which signals play are valuable. Another related concept to signal is the cost of signaling, which plays a central role in a firm's decisions to signal about its quality. If sending a specific signal turns out to be costly (e.g., obtaining a product certification), the signaler could potentially get discouraged to invest resources to send out that signal (Connelly et al. 2011). Lastly, receivers are outsiders to a firm who lack sufficient information about the firm but are interested to obtain the information.

The signaler (e.g. marketing AI entrepreneur) projects cues to not only reduce VCs' uncertainties about the startup's quality, but also to communicate their intentions. (Devers et al. 2007). These signals sent out by entrepreneurs need to be easily observable to be considered credible by VCs (Connelly et al. 2011). Despite the visibility, the signals sent by a startup may not always be legitimate. As there is information asymmetry, a startup could engage in deceitful behavior and not convey their true future intentions to VCs (Connelly et al. 2011). Thus, VCs (the receiver) look for information from alternate sources so that they can legitimize the startup's activities and in turn reduce the asymmetry (Petkova et al. 2013).

Public firms typically communicate information to investors about their focus areas, their organizational strategic intent and mindset to investors using annual/10-K reports (Saboo and Grewal 2013). Moreover, a firm's top management can communicate the firm's strategy and viability of plans through annual reports. The text information available in these reports help investors evaluate the firm's future prospects and reduce the information asymmetry between them and the firm (Panagopoulos et al. 2018). For example, a CEO's focus towards customers signal her intentions to effectively compete in the market and secure future cash flows, which reduces the information asymmetry between the firm's top management and investors. However, entrepreneurs do not publish publically available reports and hence do not have an opportunity to communicate their strategies or intent. Thus, they look for alternative forums to communicate similar information to VCs.

In the case of new ventures, "information intermediaries" help communicate the startup's information to VCs. These intermediaries could be news media, online platforms that display information about the startup, etc. For example, media presence of a startup can help communicate the startup's narratives and helps VCs obtain information about the startup's available resources, activities, and growth strategies (Lounsbury and Glynn 2001, Martens et al. 2007, Porac et al. 2002). The information intermediaries help reduce the information asymmetry between the entrepreneurs and the stakeholders (e.g., VCs) and also improves their ability to process the information (Zuckerman 1999).

My argument is that, in gauging a new marketing AI startup's value potential, VCs benefit from information publically available about the startup including its marketing strategy, its marketing application intentions, etc. through the information intermediaries (e.g., by using startup information available on the Crunchbase database). Providing description on Crunchbase suggests to VC about the startup's capabilities and help them made funding decisions.

Context Dependent Weighting and VC Funding

The theory of context-dependent-weighting serves to explain how the receiver (the VCs) process the contextual information provided by the marketing AI startups to making their funding decision (e.g., Ariely and Wallsten 1995; Huber, Payne, and Puto 1982; Tversky and Simonson 1993). In the consumer behavior context, consumers evaluate their options by aggregating information regarding different attributes and attach asymmetric weights to the product attributes (Bordalo, Gennaioli, and Shleifer 2013), and the weight or importance of product attributes (i.e., dimensions) can change predictably. Viewing VCs akin to consumers of information on marketing AI startups attributes, I expect that VCs would weigh the available attributes of the startups differently in their funding decision. Huber, Payne, and Puto (1982) assert that an increase in the variability of an attribute draws more attention to that particular attribute, and as such, it becomes more salient (Taylor and Thompson 1982) and receives more weight in consumer decision making (Bonaccio and Reeve 2006; Bordalo, Gennaioli, and Shleifer 2013). Textual business descriptions are more prone to greater variability than firmographic or financial information—which have fairly standard formats of presentation. Thus following context-dependence-weighting theory, this should lead firmographic and financial information aspects to receive less attention and weight (Bonaccio and Reeve 2006; Bordalo, Gennaioli, and Shleifer 2013; Taylor and Thompson 1982; Wedell 1998), and consequently, business description to become more salient and receive more weight. Thus, ceteris paribus, startups with detailed textual business descriptions would be gain importance in the VCs evaluation and thus predictive of VC funding.

SETTINGS AND DATA

I use data from Crunchbase, an online database that provides information about new ventures and investor activities. Data from Crunchbase has been used by multiple marketing studies in the past few years (e.g. Homburg et al. 2014; Blaseg, Schulze and Skiera 2020; Winkler, Rieger and Engelen 2020). In Crunchbase, AI startup firms describe the capabilities of the application they build with information regarding the different types of data the application uses, the AI technologies used underneath and the marketing tasks it helps perform. For example, description of the startup Adtriba states the following:

"Adtriba allows businesses to track, control and optimize their customers journeys, offsite and onsite, through AI and user journey analysis. Adtriba integrates user journey data across all channels - including TV ads and offline marketing campaigns - and applies machine learning to all user journey events. The results are optimization suggestions and actionable insights, allowing for cross-channel optimization of marketing ROI."

I collected descriptions of marketing AI startups founded between year 2000 and 2020, a total of 1,681 startups. I filtered the Crunchbase database to only include startups that are identified with keyword "sales" or "marketing" as well with the keyword "artificial intelligence". Further, I limited my search to startups founded after year 2000. I chose year 2000 as a cutoff point because all the firms launched before 2000 (n = 64) were either acquired, launched an IPO and grew significantly in size such that they do not qualify as a startup.

When a startup creates a profile on the Crunchbase database, the entrepreneur needs to provide information such as the date the startup was founded, website links, social media links, short and long versions of the startup's description, headquarters and founders information. Crunchbase authenticates all the information, including the startup's name, social media data, and employee data and assigns each startup a ranking based on a variety of data such as the number of news articles published by a startup, engagement of the firm in the community, etc. Crunchbase also provides detailed information about funding such as the number of funding rounds a startup participated in, whether it received funding, how much funding it received, etc. Figure 3.1 provides an example of an AI marketing startup's profile available on Crunchbase. As shown in Figure 3.1, each startup has multiple tabs that provide information about different aspects of the startup. A startup can use up to 10,000 characters to describe their company and the applications they build[8]. The description is available in the summary page of a startup. In addition, startups can provide details about their founders, executives, board members and other significant team members.

Once a startup provides the information describing itself, the startup needs to categorize itself into relevant industry categories provided by Crunchbase. Crunchbase organizes firm data into 700+ Industries. Each of these industries are then categorized under 40+ Industry Groups . For example, the industry group "artificial intelligence" contains the following industries "intelligent systems", "machine learning", "natural language processing", etc. Each startup firm is typically associated with three to five industries. Affiliation to an industry helps a firm to appear in the search results. For example, a customer account management marketing AI

[8] https://catalystforbusiness.com/how-to-create-a-crunchbase-company-profile/#:~:text=Full%20Description%20%E2%80%93%20Spend%20some%20time,This%20is%20your%20corporate%20address.

application, “Clari” appears in the search results when we use the terms “artificial intelligence” and “sales and marketing” in the industry groups. As my interest is only in predicting funding for marketing AI startups, I selected only the firms that belong to “artificial intelligence” and “sales and marketing” industry groups, and who have less than 500 employees (Homburg et al. 2014).

I automatically text-mined the raw text in each firm description using the ‘nltk’ package in Python. My textual unit is a marketing AI startup’s description. For each firm description, I first tokenize each word, a process that breaks down each firm’s description into the distinct words it contains. I then use Porter’s stemming algorithm to collapse variations of words into one. For example, “engagement,” “engages,” “engage,” and “engaging” become “engage.” In total, the loan requests in my data set have over 149,000 words, corresponding to 11,772 unique words. I excluded numbers and symbols from our analysis (e.g. Netzer, Lemaire and Herzenstein 2019).

In addition to words/stems, I also examine two-word combinations (an approach often referred to as n-gram, in which for n = 2, I get bigrams). While n-grams with n > 2 (e.g., strings of three or more words) could have been part of my analyses, this would have increased dimensionality and computational difficulty substantially, which ultimately precluded their inclusion. To reduce the dimensionality of the textual data and avoid over-relying on more obscure words, I focus my analyses on the most frequent stemmed words and bigrams that appeared in at least 10 firm descriptions, which left us with 873 bigrams.

Textual, Firm Performance, and Firm Demographic Variables

The dependent variable is whether a marketing AI startup obtained or did not obtain VC funding as reported by Crunchbase (binary: 1 = obtained funding, 0 = did not obtain funding). The data consists of startups that were founded after year 2000. I know whether a firm obtained funding or not by using the 'funding amount' column. If a startup did not receive any VC funding, the funding amount column will missing. If the startup received funding, a dollar value of funding received is provided by Crunchbase. I use a set of independent variables consisting of firm's textual description, firm's financial information, their website traffic, and other demographic variables. I elaborate on each of these.

Textual variables

Overall, I use 873 bigrams from the description of each marketing AI startup. I identify these following the text mining process mentioned previously. Because a startup's textual description differs in length, and words differ in the frequency of appearance in the corpus, I normalize the frequency of a word appearance in the description to its appearance in the corpus and the number of words in the loan request using the term frequency–inverse document frequency (tf-idf) measure commonly used in information retrieval (e.g. Netzer et al. 2019). The term frequency for word m in loan request j is defined by $\mathrm{tf}_{\mathrm{mj}} = \mathrm{X}_{\mathrm{mj}}/\mathrm{N}_{\mathrm{j}}$, where X_{mj} is the number of times word m appears in firm description j and N_{j} is the number of words in firm description j. This component controls for the length of the document. The inverse document frequency is defined by $\mathrm{idf}_{\mathrm{m}} = \log(\frac{\mathrm{D}}{\mathrm{M}_{\mathrm{m}}})$, where D is the number of firm descriptions and M_{m} is the number of startup descriptions in which word m appears. This terms controls for the how often a word appears across documents. The tf-idf is given by $\mathrm{tf} - \mathrm{idf}_{\mathrm{mj}} = \mathrm{tf}_{\mathrm{mj}}$ x $(\mathrm{idf}_{\mathrm{m}} + 1)$. Taken together, the tf-idf statistic provides a measure of how likely a word is to appear in a document beyond chance. *Idf* reflects whether the terms used by a firm is common or rare across all documents in a collection (Manning, Raghavan, and Schütze 2008). This helps a marketing AI startup to differentiate itself from other startups.

Firm's Financial and demographic variables

The second type of variables I consider are a startup's financial information, website traffic information and firmographic information, commonly used in the context of VC funding. These include all information available to VCs on Crunchbase—headquarters location, presence in social media, number of founders, IT spend, revenue generated, number of patents, website traffic growth, Crunchbase ranking, average website visits, etc. I control for the startup's geographical location to account for the different levels of interest among VCs across geographies. I created a variable to indicate whether the startup firm was from United States or China. This helped account for greater interest among VC investors to invest in AI applications within United States and China (Walch 2020).

Finally, to fully account for all the information available about a startup, I extracted information included in the founder's profile, such as their experience in marketing and artificial intelligence and their educational background.

Lastly, I include the popularity of each startup as a predictor in our model. I did this by collecting the number of news events and news articles a marketing AI startup appeared in. A startup appearing in media helps improve its legitimacy and attracts VCs' attention (Petkova et al. 2016). However, given the possibility that Crunchbase's data presentation limitations (having only text descriptions) allows for only few popular startups getting viewed by VCs (thus not fully reflecting a market efficient behavior), my models test whether the text is predictive above and beyond the popularity of startups. Table 3.1 presents summary statistics for the variables in our model.

Predicting Likelihood of Funding

My objective in this section is to evaluate whether the textual business descriptions of marketing AI startups on Crunchbase is predictive of getting venture capitalist funding from the time of establishing the startup. To do so, I need to first build a strong benchmark—a powerful predictive model that includes the financial, website traffic and firmographics information and maximizes the chances of predicting VC funding using these variables. Second, I need to account for the fact that my model may include a very large number of predictors (over 3,000 bigrams). Given the large number of predictors, and the predictive nature of the task at hand, machine learning methods are most appropriate. In the subsequent section, as I aim to understand which marketing strategies and startup descriptions predict VC funding, I combine the machine learning methods with data reductions methods (e.g., topic modeling) and standard econometric tools.

In evaluating a predictive model, it is common to compare alternative predictive models and choose the model that best predicts the desired outcome—VC funding, in my case. From a purely predictive point of view, a better approach, commonly used in machine learning, is to train several predictive models and, rather than choose the best model, create an ensemble or stack the different models. Recent research has demonstrated the superior performance of ensemble models relative to individual models (Lee, Hosanagar, and Nair 2018). An ensemble of models benefits from the strength of each individual model and, at the same time, reduces the variance of the prediction.

The stacking ensemble algorithm includes two steps. In the first step, I train each model on the calibration data. Because of the large number of textual variables in our model, I employ a simultaneous variable selection and model estimation in the first step. In the second step, I build a weighting model to optimally combine the models calibrated in the first step.

I estimate four types of models in the first step. The models vary in terms of the classifier used and the approach to model variable selection. The four models are described next and include two logistic regressions and two versions of tree based methods.

Regularized logistic regressions. I estimate two logistic regressions— L1 and L2 regularization logistic regressions. The penalized logistic regression log-likelihood is:

$$L(Y|\beta,\lambda) = \sum_{j=1}^{n} (y_j \log[p(X_j|\beta)] + (1-y_j) \log[1-p(X_j|\beta)] - \lambda J(\beta)$$

where $Y = \{y_1, \dots, y_n\}$ is the set of binary outcome variables indicating whether a marketing AI startup was funded, $p(X_j|\beta)$ is the probability of getting VC funding based on the logit model, where X_j is a vector of textual, financial, and firmographic predictors for AI startup j, β are a set of predictors' coefficients, λ is a tuning penalization parameter to be estimated using cross-validation on the calibration sample, and $J(\beta)$ is the penalization term. The L1 and L2 models differ with respect to the functional form of the penalization term, $J(\beta)$. In L1, $J(\beta) = \sum_{i=1}^{k} |\beta_i|$, while in L2, $J(\beta) = \sum_{i=1}^{k} \beta_i^2$, where k is the number of predictors. Therefore, L1 is the Lasso regression penalty (shrinks many of the regression parameters to exactly zero), and L2 is the ridge regression penalty (shrinks many parameters to small but nonzero values). Before entering the variables into this regression, I standardize all variables (Tibshirani 1997).

Tree-based methods (random forest and extra trees)

I use two tree-based methods in the ensemble. I estimate one random forest model with best feature selection and extremely randomized trees (extra trees). Both models combine many decision trees; thus, each of these tree-based methods is an ensemble in and of itself. The random forest randomly draws with replacements subsets of the calibration data to fit each tree, and a random subset of features (variables) is used in each tree. In the K-best feature selection, random forest features are selected on the basis of a χ^2 test. That is, I select the K-features with the highest χ^2 score. I use cross-validation (80/20 split) to determine the value of K. The random forest approach mitigates the problem of overfitting in traditional decision trees. The extra trees is an extension of the random forest, in which the cutoff points (the split) for each feature in the tree are also chosen at random (from a uniform distribution) and the best split among them is chosen. Due to the size of the feature space, I first apply the aforementioned K-best feature selection to select the features to be included in the extra trees.

I used the scikit-learn package in Python (http://scikitlearn.org/) to implement the four classifiers on a random sample of 80% of the calibration data. For the logistic regressions, I estimated the λ penalization parameter by grid search using a five-fold cross-validation on the calibration sample. For the tree-based methods, to limit overfitting of the trees, I randomized the parameter optimization (Bergstra and Bengio 2012) using a three-fold cross-validation on the calibration data to determine the structure of the tree (number of leaves, number of splits, depth of the tree, and criteria). I use a randomized parameter optimization rather than an exhaustive search (or a grid search) due to the large number of variables in our model. The parameters are sampled from a distribution (uniform) over all possible parameter values.

Model stacking and predictions

In the second step, I estimate the weights for each model to combine the ensemble of models using the remaining 20% of the calibration data. I use a simple binary logistic model to combine the different predictive models. Though other classifiers may be used, a logistic binary regression meta-classifier helps avoid overfitting and often results in superior performance (Whalen and Gaurav 2013). In the binary logistic regression model, VC funding is the dependent variable and the probabilities of getting VC funding for each marketing AI startup by each of the four models in the ensembles from step one (the two logistic regularization regressions and the two decision tree methods) as predictors. The estimated parameters of the logistic regression provide the weights of each individual model in the ensemble. Specifically, the ensemble VC funding probability for marketing AI startup j can be written as:

$$p(\text{VC Funding}_j) = \frac{\exp(x_j' w)}{[1+\exp(x_j' w)]},$$

where x_j is the vector of VC funding probabilities $p(\text{VC Funding}_j)|\text{model}_s$ for each model s—from step one—and w are the estimated weights of each model in the logistic regression classifier.

I estimated an ensemble of the aforementioned four models and find the following weights for the different model: L1 = .21, L2 = .28, random forest K-best = .29, and extra trees = .22. To test whether the text that startups used to describe their application is predictive of VC funding, I use a tenfold cross-validation. I randomly split the startup descriptions into ten equally sized groups, calibrate the ensemble algorithm on nine groups, and predict the remaining group. To evaluate statistical significance, I repeated the tenfold cross-validation ten times, using different random seeds at each iteration. By cycling through the ten groups and averaging the prediction results across the ten cycles and ten replications, I get a robust measure of 100 predictions. Because there is no obvious cutoff for a probability from which one should consider that a VC would fund a startup, I use the area under the curve (AUC) of the receiver operating characteristic (ROC) curve, a commonly used measure for prediction accuracy of binary outcomes (e.g., Netzer et al. 2019). The AUC is a performance measurement, which provides information on how well the model can distinguish between the funded and not funded startups.

I compare three versions of the ensemble: (1) a model calibrated only on the firm performance and website information, (2) a model that includes just the textual information (i.e., all the variables we created from the freely written text available in startup descriptions) and ignores the performance and firmographic information, and (3) a model that includes performance and website information together with the textual data. Comparing models 1 and 3 provides the incremental predictive power of the textual information over predictors commonly used by venture capitalists to evaluate startups. Comparing models 1 and 2 informs the degree of predictive information contained in the textual information relative to the performance and website information. In addition, I estimated separately the four predictive models that contribute to the ensemble (L1 and L2 regularization logistic regressions, one random forest model, and extra trees model) to assess the value of the textual information in different models.

Prediction Results

Table 3.2 details the average results of the tenfold cross-validation across ten random shuffling of the observations. The results I present constitute clean out-of-sample validation because in each fold we calibrate feature selection, model estimates, and the ensemble weights on 90% of the data and leave the remaining 10% of the data for validation. The results in Table 3.2 are the area under the ROC curve (or AUC). The AUC of the model with textual, performance, and website information is up to 2.44% better than the AUC of the model with only performance and website information, and this difference is statically significant. This translates to $242.6 million increment in the total VC funding received by marketing AI startups. In fact, the model with both textual and financial information has higher AUC in all 100 replications of the cross-validation exercise.

Interestingly, if I were to ignore the performance and website information and use only the startup's textual information, we obtain an AUC of up to 59.67% compared with an AUC of 74.46% for the model with only performance and website information. That is, brief description of a startup using textual information provided by startup with almost no cost is nearly as predictive of getting VC funding as the traditional performance based information of a startup that helps predict VC funding. This result is particularly impressive given the tremendous effort and due diligence VCs conduct to collect a startup's information relative to the simple method used to collect the textual information. This result may also suggest that textual information may be particularly useful in "thin file" situations, where the information available about a startup is limited.

The bottom part of Table 3.2 presents the predictive performance of each of the individual models in the ensemble. I observe that, for each of the models, the textual information significantly improves predictions in the validation sample above and beyond the model with the performance and website information only. I also find that stacking ensemble model further improves predictions over each of the independent models. There are two key takeaways from this comparison. First, the textual information itself, independent of the machine learning model used, significantly contributes in predicting likelihood of VC funding over a startup's performance information (Pollock and Rindova 2003). Second, combining models using an ensemble learning model further helps predict VC funding. The reason for the improvement of the ensemble learning model relative to the individual model is that different models perform better in different aspects of the data.

To quantify the managerial relevance and financial implications of the improvement in predictive ability offered by the textual data, I conducted a back-of-the-envelope calculation. For each of the 1,861 marketing AI startup descriptions I calculated the expected increase in total venture funding received based on the models with and without text. In calculating the expected increase in VC funding, I assume that the VC funding received so far by marketing AI startups is made without considering the textual description.

For each marketing AI startup in the database, I calculate the total funding received so far from VCs since the time the startup was found. That is, if a marketing AI startup received funding more than once, I add the total value of funding received in each of the funding rounds. There were some startups whose funding amounts were not provided in U.S. dollar ($) values. In such cases, I collected the U.S. dollar equivalent amount provided by Crunchbase database. Finally, I added the total funding received by each of the marketing AI startups. I found that so far, marketing AI startups in our database have received $9.93 billion. To this value, I multiplied the improvement in predictions from using textual data i.e. 2.44%. I found that the 2.44% improvement in prediction translates to $242.6 million. In other words, marketing AI startups would have received an additional $242 million dollars to commercialize their startup due to VCs attention paid to text descriptons. Thus, while the improvement in getting VC funding for the model with the textual information might seem modest (nearly 2.5%) even though it is statistically significant, the increase in dollar value of VC funding based on the textual information is substantial and economically meaningful. I do acknowledge that my predictions and financial impact calculations are based on startup firms available through Crunchbase. Thus, I might have not included any firm that was not part of the Crunchbase database. But, considering that Crunchbase comprehensively covers captures all venture related activities, I expect the impact of any such startups to be minimal.

To summarize, what marketing AI startups write in their firm's text descriptions can significantly improve likelihood of getting VC funding above and beyond all other available information available about the startup. I chose the ensemble-based predictive model to maximize predictive ability, but this model provides little to no interpretation of the parameter estimates, the marketing strategies, the business strategies communicated through the textual descriptions. Next, I demonstrate how machine learning approaches combined with econometric models can be used beyond predictions and toward understanding which marketing and business strategies, application's marketing capabilities in marketing AI applications are most likely to be funded by venture capitalists.

MARKETING STRATEGIES AND APPLICATION'S MARKETING CAPABILITIES THAT ARE ASSOCIATED WITH VC FUNDING

The result that text has a predictive ability that is relatively similar to predictive ability of all other information (performance, website) is perhaps surprising, given that marketing AI startups can choose to describe their application on online platforms in their own preferred way. However, this result is consistent with the idea that startups try to communicate information about their firm by sending different "signals" on media describing their startup and attract VCs attention (Petkova et al. 2013). In this section, I describe the four approaches I employed to uncover whether marketing strategies, applications capabilities of some startups that received VC funding differ from the ones that did not receive funding (based on the sample of 1,861 marketing AI startups).

First, I use a naive Bayes classifier to identify the words or bigrams that most distinguish startups that received VC funding and the ones that did not. The advantage of the naive Bayes is in providing intuitive interpretation of the words ("signals") that are most discriminative between startups that received and did not receive funding. However, its disadvantage is that it assumes independence across predictors and thus cannot control for other variables.

Second, to alleviate the concern of independence across predictors, I use a logistic regression with L1 penalization, which reduces the dimensionality of the word space by setting some of the parameters to zero, to uncover the words and bigrams that are associated with VC funding after controlling for the performance and website information.

Third, to look beyond specific bigrams and into the topics discussed in marketing AI startup's description, I use LDA analysis. Fourth, relying on a well-known dictionary, the LIWC (Tausczik and Pennebaker 2010), I identify the temporal focus and sentiments that are most correlated with getting VC funding and not getting it.

Marketing Strategies That Distinguish between Startups That Received and did not Receive Funding

To investigate which words most discriminate between startups that received and did not receive VC funding, I ran a multinomial naive Bayes classifier using the Python scikit-learn 3.0 package on bigrams (all possible words and bigrams) that appeared in at least 10 marketing AI startup's text descriptions (749 bigrams). The classifier uses Bayes rule and the assumption of independence among words to estimate each word's likelihood of appearing in a funded and not funded startup's description. I then calculate the most "informative" bigrams in terms of discriminating between funded and not funded startups by calculating the bigrams with the highest ratio of $\mathrm{P(bigrams|funded)/P(bigrams|not\ funded)}$ and the highest ratio of $\mathrm{P(bigrams|not\ funded)/P(bigrams|funded)}$. Figures 3.2 and 3.3 present word clouds of the naive Bayes analysis of the bigrams. The size of each bigram corresponds to the likelihood that it will be included in a funded marketing AI startups vs a not funded startup (Figures 3.2) or in a not funded marketing AI startups vs a funded startup (Figure 3.3). For example, the word "personalization" in Figure 3.2 is 16 times more likely to appear in a funded marketing AI startups versus a not funded startup, whereas the word "chatbot" in Figure 3.3 is 18 times more likely to appear in the text of a not funded startup versus a funded startup.

I find that relative to not funded marketing AI startups, startups who received funding were more likely to emphasize customers' benefits from using their AI application. First, providing greater emphasis on "personalization" and improving experience for "every customer" seems to be valued positively by VCs. Personalization emphasis by marketing AI startup seem to be valued under different task contexts as well. For example, I find that VC are more likely to fund startups that claim to personalize at scale as well as startups that claim to personalize across channels. My finding acts as a pre-cursor to research study by Sahni, Wheeler and Chintagunta (2018) who find that personalization improves customer email opening rate and also improves sales. VCs potentially value the improved personalization benefits due to the downstream benefits firms obtain from using AI applications. This should benefit the marketing AI startup as the marketers buying the applications are likely are more likely to spend more towards the application. For example, marketing AI startup, Persado, which personalizes customer brand messaging has received close to $66 million in VC funding already[9]. Second, I find that applications that claim to use customers' contextual information to generate output seem more likely to be associated with funding. I find that in the database, startups that were funded seem to use customers' contextual information for different purposes including for providing video advertisements, to send digital communication (e.g. emails), interact with customers based on their context, etc. This finding is in line with recent conceptual work by Hamilton, Ferraro, Haws and Mukhopadhyay (2021) who propose that contextual information used by AI-enabled social companions would help customers move across their purchase journey

[9] https://www.vcnewsdaily.com/Persado/venture-funding.php

and have downstream effects for the firm. Third, I find that marketing AI applications that claim to “improve” or “empower” marketers are more likely to be funded. Interestingly, when I look at the context (sentences) in which these words were used, I found that they are related to improving marketer capabilities to eventually improve customer benefits. For example, Amperity’s (marketing AI startup) text description states that it “*improves* marketing performance, fuels accurate customer insights, and *enables world-class customer experiences*.” Overall, my results from naïve Bayes analysis indicates that marketing AI startups would be benefited by emphasizing end-customers’ benefits.

On the other hand, I find some interesting insights about startups that did not receive VC funding. First, I find that the marketing AI applications that help with “project management” related work are less this to be funded. From the text descriptions, I find startups helping with project management to marketers do not clearly specify the tangible benefits marketers or customers get. Second, I find that marketing AI startups that describe that they build “chatbot” seem to be less likely to be funded. I believe that this is in line with some of the recent chatbot failures in the industry (CBInsights.com 2021). However, the less likelihood to get funded could also be because a greater proportion of marketing AI startups tend to build chatbots and it is harder to gain a competitive advantage. Moreover, recent findings indicate that voice based chatbots built by vendors such as Amazon (e.g. amazon alexa) are adopted increasingly by firms (Sun et al. 2020), which could lower chatbot adoption from marketing AI startups. Third, I find that marketing AI applications that claim to provide “cognitive capabilities” to marketers are less likely to be funded by VCs. It is possible that VCs conceptualize cognitive ability similar to “thinking AI” proposed by Huang and Rust (2018). I believe that this finding is potentially aligned with Huang and Rust (2019)’s finding that thinking tasks are considered to be most important by marketers. I expect that VCs believe that considering the importance of these tasks, firms are less likely to replace thinking tasks with AI and thus would be less likely to fund these applications.

In summary, marketing AI startups getting VC funding are more likely to focus on the tangible benefits that customers receive from the firm that uses the AI application. In other words, venture capitalists want to ensure that the marketing AI application creates tangible improvements for customers, which would potentially increase future sales, and not only benefits marketers perform tasks better. While the naive Bayes analysis is informative with respect to identifying words, marketing strategies and marketing applications that are associated with getting VC funding, VCs may wish to uncover the marketing strategies and "signals" communicated by marketing AI startups' text descriptions that participate in funding rounds.

Relationship between Marketing Strategies, Marketing Tasks and other Signals Associated with Participating in Funding Rounds

It is possible that some marketing AI entrepreneurs are more strategic in text description and the marketing capabilities they "signal" through the text description could be correlated with their decision to participate or not participate in a VC funding round. In other words, it is likely that the marketing AI startups that decide participate in a funding round may provide application text description containing specific marketing capabilities and tasks that they expect to signal greater value to investor and would increase their likelihood to get VC funding. Tian (2011) also find that startups enter a funding round only if they have sufficient information to communicate to VCs and help them overcome their agency problems and reduce risk of adverse selection. To investigate the relationship between marketing strategies associated with the decision to participate in a funding round, I ran a naïve Bayes analysis on the entire set of marketing AI startup database (1,861 startup text descriptions). I assessed the bigrams with the highest ratio of $P(\text{bigrams}|\text{participate})/P(\text{bigrams}|\text{did not participate})$ and the highest ratio of $P(\text{bigrams}|\text{did not participate})/P(\text{bigrams}|\text{participate})$. Here, participate refers participating in a funding round.

I find that the marketing startups that participate in a funding round are more likely to emphasize their previous affiliations with other VCs. They use words related to "ventures" they have connection with. Their emphasis on ventures is 1.33 times more than their emphasis on personalization. As previously, I found that marketing AI startups firms that emphasize personalization are more likely to get VC funding. For each bigram, Figure 3.4 depicts its value on the ratio $P(\text{bigrams}|\text{funded})/P(\text{bigrams}|\text{not funded})$ versus its value on the ratio $P(\text{bigrams}|\text{participate})/P(\text{bigrams}|\text{did not participate})$. A high correlation between the two ratios $P(\text{bigrams}|\text{funded})/P(\text{bigrams}|\text{not funded})$ and $P(\text{bigrams}|\text{participate})/P(\text{bigrams}|\text{did not participate})$ means that marketing AI entrepreneurs are potentially aware that their text descriptions would result in getting VC funding. Results show a fairly strong correlation between the two ratios ($r = .89$, $p < .01$), also suggesting that marketing AI entrepreneurs are at least somewhat rational when writing text to describe their application. Similar to startups not getting funded, I find that startups that do not enter into a funding round are more likely to place greater emphasis on "project management" through their text.

Analyzing the Topics Discussed in Startup's Text Description and Their Relationship to VC Funding

In Figures 3.2 and 3.3, I grouped the bigrams into topics on the basis of my own interpretation and judgment. However, several machine learning methods have been proposed to statistically combine words into topics based on their common co-occurrence in documents. To identify the topics, I use the most commonly applied topic modeling approach in marketing i.e. the LDA analysis. I apply the LDA analysis to the complete data set of marketing AI startups (the 1,861 VC funded and not funded startups).

I use the online variational inference algorithm for the LDA training (Hoffman, Bach, and Blei 2010). This uses a simplified parametric distribution and is empirically shown to be faster than and more accurate than techniques such as MCMC. For the LDA analysis, I used the 621 words that appeared most frequently across the startup's text description of VC funded and not funded startups. By eliminating the infrequent words, I mitigate the risk of rare-words occurrences and co-occurrence confounding the topics. Because the LDA analysis requires the researcher to determine the number of topics to be analyzed, I varied the number of topics between 2 and 30 and used model fit (the perplexity measure) to determine the final number of topics (e.g. Netzer et al. 2019). I did this separately for marketing AI startups that got funding and that did not get funding. I find that the model with 10 topics had the best fit (lowest perplexity) for funded startups. Similarly, the model with 11 topics had the best fit (lowest perplexity) for unfunded startups. I present the list of words with highest relevance to each topic in Table 3.3.

Relative to the "sale automation" and "campaign management" topic, I find that the topics of "improving customer experience," "generating interactive content," and "customer engagement" are more likely to obtain VC funding. These results corroborate the naïve Bayes results that signaling the customer benefits from using the AI application is associated with greater likelihood of getting VC funding. It is possible that a startup's objective performance measures do not fully account the AI applications' value potential. The textual information provides VCs an indirect window into a startup's potential. Consistent with naïve Bayes analysis, I find that the topics that aim to replace ‘thinking’ related tasks for a marketer, for example, applications that claim to develop “marketing strategy” are associated with lower likelihood of obtaining funding. I also find that marketing AI applications that aim to use influencers on social media to interact with customers have a greater likelihood of obtaining VC funding.

Role of Psychological and Social Characteristics Communicated through Text

In this subsection, I rely on one of the more researched and established text analysis tools, the Linguistic Inquiry and Word Count (LIWC). LIWC allows me to use a dictionary based approach to identify different intent and social characteristics communicated through the text descriptions, not made available through naïve Bayes and topic modelling. Academic researchers have extensively used LIWC for getting more insights into human attention and emotions among other things (e.g. Humphreys and Thompson 2014; Netzer et al. 2019). This dictionary groups almost 4,500 words into 64 linguistic and psychologically meaningful categories such as tenses (past, present, and future); forms (I, we, you, she, or he); and social, positive, and negative emotions. The LIWC is composed of sub-dictionaries that can overlap (i.e., the same word can appear in several sub-dictionaries). It provides the proportion of words in a text that belong to a specific sub-dictionary.

In order to apply LIWC dictionaries to the collected data, I first pre-processed the textual description of marketing AI startups using steps suggested by Berger et al. (2020). Specifically, I tokenized, cleaned, removed stop words, and stemmed the text. In addition, I got rid of any numerical data in the text to avoid interference with LIWC’s interpretation of the text.

After preprocessing the text, I calculated the proportion of words in each text description that belong to the 64 dictionaries available in LIWC related to the psychological and social characteristics of text (Tausczik and Pennebaker 2010). I then estimated a binary logit model (startup funded = ‘1’ and startup not funded = ‘0’) to relate the proportions of words in each text description that appear in each dictionary to whether the startups was funded or not. I controlled for the startup’s headquarters, demographic variables and performance related variables. Results are presented in Table 3.4.

I found multiple results, which I expect would provide valuable guidance to marketing AI entrepreneurs regarding what to emphasize in their text descriptions.

- **Popularity of the startup:** In line with findings of Petkova et al. (2013), I find that media presence significantly increases the likelihood of getting VC funding. In fact, I find that likelihood of getting VC funding increases as the number of news articles published about a startup increases. Published news articles about a startup not only provides information about the firm but also helps increase its legitimacy among VCs.
- **Relationship between startup age and signaling**: I find that younger marketing AI startups are more likely to obtain VC funding. A potential reason is that VCs are more likely to fund startups in the early stages and it is in line with recent industry reports, which suggest that investments in marketing chatbot startups is concentrated more towards early-stage startups. Thus, marketing AI startups would be benefited by signaling their application’s benefits during early stages of their startup (e.g., Islam, Fremeth and Marcus 2018).
- **Temporal focus of a startup**: I find that firms that obtain funding contain text descriptions that focus on the past. In contrast, the startups that focus on the future are not associated with funding. If a startup is focused on the future, it potentially suggests that the entrepreneur is trying to get the VCs’ to focus on the future potential of the startup rather than its history. Based on this result, I conclude that it is highly likely that VCs are

more interested to fund marketing AI applications that has shown tangible success in the past to solving marketing problems. The finding that successfully funded marketing AI startups are more likely to focus on the past is in line with research showing that CEOs with greater past focus have a positive influence on the firm's innovation outcomes (Nadkarni and Chen 2014).

- **Length of the text description:** I find that the length of text description does not have an influence on the likelihood of getting VC funding. Marketing entrepreneurs can choose to either summarize their application using a short text or they can describe details of their application using long text in online information intermediary platforms. Knowing that length of text does not affect VC funding would give more freedom to entrepreneurs in describing their application capability. Moreover, previous research finds that longer text descriptions can suggest lack of alignment between what a person writes and what he or she actually believes (Centerbar et al. 2008). Knowing that text length does not influence VC funding, suggests that VCs do not expect longer text to be indicative of misalignment between an entrepreneur's true intentions and their text descriptions.
- **Role of emotions:** I find that marketing AI startups that use positive emotion words in the text description are less likely to obtain VC funding. This result is in line with finding that CEOs' use of greater positive emotions in their narratives are perceived to be more deceptive by shareholders (Larcker and Zakolyukina 2012).
- **Writing text in a cognitively complex language:** I find that using cognitively complex language in a text description is more likely to be associated with getting VC funding. Previous research has demonstrated that online content that requires higher cognitive processing (e.g., insight, reason) receives increased engagement because of its increased

level of cognitive involvement (Stieglitz and Dang-Xuan 2013). Moreover, cognitively complex language tends to include underlying explanations for a phenomenon (Lurie, Ransbotham and Liu 2014). Thus, this result suggests that increased VC engagement when reading cognitively complex language combined with reasoning about how the applications function potentially drives them to fund the marketing AI startup.

- **Providing insights:** I find that text descriptions that are based on a marketing entrepreneur's personal 'insights' are less likely to be funded. Insights are conceptualized as moments of ideas generated by a person and not based on actual benefits from the application or past experience of the person (Miceli, Scopelliti and Raimondo 2020). Text descriptions that convey insightful thinking typically consist of words such as "think", "know", etc. This is in line with the finding that VCs are less likely to fund startups that have a future focus because future focus suggests benefits in the future based on the entrepreneur's expectation versus tangible success. In other words, if the VC does not have reasons to believe how the marketing entrepreneur's insight would translate to actual performance, they are less likely to fund the startup.
- **Describing concrete achievements:** I find that marketing AI startups that describe their achievements are more likely to get funded by VCs. Communicating a firm's achievements is found to increase engagement among its stakeholders (Leek, Houghton and Canning 2019), suggesting that VCs are more likely to get more interested in the startup when they emphasize their achievements. This is also in line with my finding that showing concrete success from the past (vs. future potential) helps increase VCs funding likelihood.

- ***Describing the rewards of using the application*****:** Similar to the results obtained from naïve Bayes, I find that marketing AI startups that describe the rewards that a marketer gets (using words such as “benefit”, “get”) from using the application is less likely to be funded by VCs.
- **Discrepancy in the text:** I find that marketing AI startups’ description that have discrepancy related words (e.g., “could”, “should”) are less likely to be funded. This is not surprising considering that VCs would have less motivation to fund startups that merely predicts that application might add value. Marketing entrepreneurs would be benefited if they instead described how exactly the application would create value for marketers.

Taken together, I find that several of the LIWC sub-dictionaries previously used by researchers and that were found to be associated with helping interpret human intentions through text, are also associated with startups getting VC funding. However, it is not clear how many entrepreneurs are strategic while writing textual descriptions. Entrepreneurs can use these results to improve their chances of getting VC funding. For instance, if a marketing AI startup already has marketing clients who experienced improved performance from using their AI application, they can highlight concrete past client achievements from using their applications in their descriptions. On the other hand, if a startup has not had past success in commercializing their application, it becomes more challenging to describe concrete past achievements. In such cases, the entrepreneur can increase her chances of getting funding by avoiding using overly optimistic language (positive emotions) and by focusing more on the work done to build the application versus their expectations from the application based on personal insights. Overall, using LIWC sub-dictionaries provided me with insights that not only supported findings from naïve Bayes analysis, but also gave me deeper insights into the intents of marketing entrepreneurs who successfully received VC funding.

DISCUSSION

In this essay, I show that text has the ability to help VCs evaluate a marketing AI startup's future potential which in turn gets reflected in their funding decisions. Using data from Crunchbase, an online database that collects information about AI startups, I show that incorporating a marketing AI startup's textual description into the models that predict VC funding on the basis of the startup's financial performance and demographic information significantly and substantially increases their predictive ability. Using machine learning methods, I uncover the marketing strategies, business strategies and application benefits that marketing AI entrepreneurs often include in their text description and the ones that lead to funding. I find that, startups that received funding emphasized the tangible benefits that customers get from using the application. Moreover, I find that applications claim to not only improve marketers' tasks but also the ones that claim to automate marketers' thinking capabilities are less likely to be funded by VCs. Building on research methods used in marketing and using the commonly applied LIWC sub-dictionaries, I infer that firms positively evaluated by VCs tend to describe their firm's past success than the future potential. Simply put, I show that marketing AI entrepreneurs tend to signal their underlying intentions, their application's marketing capabilities, and their marketing strategies through the text they provide through online information intermediaries such as Crunchbase.

Theoretical Contribution

My essay contributes to four streams of literature. First, I contribute to the nascent yet growing area of AI applications and marketing. So far, the academic literature in marketing has focused on identifying how to solve marketing problems using AI applications (e.g. Chung et al. 2016), understanding customer response to firms' using AI applications (e.g. Luo et al. 2019) and understanding the effect of AI applications on marketing jobs (e.g. Huang and Rust 2018). However, limited attention has been given to understanding effective strategies for using AI applications for marketing (Huang and Rust 2021). Even though both academics and practitioners generally agree that AI would add value to marketing tasks, we do not know how they would add value. By identifying what marketing capabilities and strategies communicated by marketing AI startups are valued by VCs, I partly help understand the 'how' link between using marketing AI application and generating value.

Second, findings from my essay contribute to the recent yet growing marketing literature on uncovering insights using the text that firms communicate to investors (e.g. Panagapoulos et al. 2018). I demonstrate the text descriptions that marketing AI startups provide on information intermediary channels not only signal information about their firm, but also gives insights into the entrepreneurs' underlying intents. As VCs face significant information asymmetry due to lack of knowledge about the quality of a startup and the entrepreneur's intent (Connelly et al. 2011), firm written text description helps reduce the information asymmetry and provides signals to VCs even though the text written by the may not be immediately verifiable. Typically, marketing AI startups are free to describe their application's capabilities however they wish on the online information intermediary platforms. Despite this freedom available with startups, the text entrepreneurs write are still predictive of VC funding. This finding implies that whether it is intentional and conscious or not, a marketing AI startup's description can disclose its value generating potential to VCs. This is analogous to public firms using annual/10-K reports to signal their value generating potential to investors (Saboo and Grewal 2013).

Third, findings from my essay contribute to the limited yet important marketing and entrepreneurship literature. Marketing researchers have examined the role of CMO presence in the top management team, examined the characteristics of CMOs, and the effects of data regulations on getting VC funding and on the startup's performance (Homburg et al. 2014; Winkler, Rieger and Engelen 2020; Jia, Jin and Wagman 2021). Although the effect of startup's past performance on their valuation has been studied previously (Xiong and Bharadwaj 2011), researchers have not explored how marketing startups' description of themselves helps VCs value the startup and leads to obtaining funding. Marketing studies examining the role of firm-generated textual content on investors' valuation of them were conducted in the context of public firms and has not been examined in the context of marketing startups yet. My results show that marketing AI entrepreneurs would not only be benefited by providing descriptions of their startup through information intermediaries, but my findings also provides guidance on how to increase the effectiveness of their textual descriptions. Further research can examine the role of text on VC funding across non-AI marketing startups as well. In addition, research can be done to identify the impact of the descriptions on other factors such as the monetary value of funding received, customer engagement with the startup's website, etc.

Fourth, my essay contributes to the marketing-finance literature. Xiong and Bharadwaj (2011, p. 101) state that "insights into marketing strategy and financial performance of start-up firms, have rarely been studied in the extant marketing-finance literature". Prior research in the startup context have focused on investor reactions to stock market–listed start-ups or IPOs (e.g., Luo 2008; Rao, Chandy, and Prabhu 2008). Marketing literature has not placed much emphasis on understanding VC funding behaviors due to marketing actions, with the notable exception of Homburg et al. (2014). Drawing on theory on information asymmetry and the signaling theory, my findings suggest that signaling a startup's marketing actions will help reduce the information asymmetry and likely lead to getting financial investment.

Contribution to Practice

Venture capitalists face significant information asymmetry when evaluating startups because the startups possess hidden information and they perform hidden actions, which reduces VCs' visibility into the startup's quality and the entrepreneur's intent (Amit et al. 1998; Connelly et al. 2011). Information asymmetry can lead to adverse selection and moral hazard problems for VCs (Glücksman 2020). The risk of adverse selection increases in the case of investing in marketing AI startups because these startups are typically not aware apriori about how their application's capabilities will be used by marketing clients (Minetti 2020). Thus, VCs have a very high need to reduce information asymmetry when evaluating the potential of marketing AI startups.

Typically, VCs use different mechanisms to reduce information asymmetry such as conducting due diligence about the startup to better understand their capabilities, screen potential startups, etc. (Cumming 2006; Gompers and Lerner 2004). However, using these mechanisms potentially require significant resource investments from VCs (e.g. hiring AI experts to understand the technology used in an application). In fact, the cost of acquiring information plays a very important role in VCs' ability to reduce information asymmetry (Connetlly et al. 2011). Results from my study suggest that using text information is an effective way to supplement the objective data that VCs have collected about a marketing AI startup. The text description is a good alternative source of information for VCs if a marketing AI startup does not have sufficient objective data to help VCs evaluate their value potential. A survey conducted by Kisseleva and Lorenz (2017) revealed the different sources of information gaps between VCs and entrepreneurs and also found that many startups do not have the necessary information to helps VCs evaluate the firm. Thus, to overcome the limitations of missing objective data, VCs try to find other sources of information to fill the gap and help them evaluate a startup. Communicating marketing strategies, business strategies and a marketing entrepreneur's intent through text descriptions helps mitigate information asymmetry and more accurately value the startup's potential.

For marketing entrepreneurs, findings from my study will help them recognize that there is value in using online information intermediaries to communicate information about their AI startup. My approach to predicting funding behavior relies on an automatic algorithm that mines individual words, including those without much meaning (e.g., articles, fillers), in the entire textual corpora. Human coders are prone to human mistakes and is not scalable, which limits its predictive ability and practical use. Entrepreneurs can use these methods to replicate potentially these insights in a different context or to obtain additional insights for specific research questions that they have. More importantly, entrepreneurs can use insights from my study and adapt their textual descriptions to improve their chances of gaining funding. For instance, if a startup's description is focused more on its application's future potential, the startup would be benefited by re-writing the text to provide emphasis on its past achievements.

Lastly, my results provide evidence to AI startups that the methods of automatically analyzing free text is an effective way of supplementing a startup's traditional objective data. Textual information, such as the marketing AI startup's text descriptions I analyze, not only sheds light on the application's potential but also offers information about the future that are not available through current objective information available about the startup. These marketing AI applications can be narrow (e.g., perform only a specific task) or can be designed to automate a set of a marketer's job tasks (e.g., automating prospecting). Capabilities provided by marketing AI applications affect VC funding decisions. A back-of-the envelope calculation revealed that the 2.44% increase in prediction capability translates to $242 million increase in total VC funding for marketing AI startups. Thus, marketing AI entrepreneurs would be more encouraged to use online intermediaries to describe their applications.

Avenues for Future Research

My research takes the first step in automatically analyzing text to predict venture capitalist funding and therefore initiates multiple research opportunities for the future. First, I focus on predicting VC funding in the context of marketing AI startups because these startup firms have an urgent need to obtain funding and commercialize their application. Theoretically, many aspects of a VC's decision to provide funding to AI startups would be based on their expectation of the startup's performance and the entrepreneur's intent. There are more opportunities for future researchers to further explore data in the text to get additional insights about not only marketing AI startups but marketing startups in general. In this essay, I analyze data from only one platform, Crunchbase. Future research can use data from multiple online platforms to obtain insights about a startup. Researchers can examine the consistency of intent communicated by the startup across different information intermediaries.

Second, results from my study can also be extended to other type of media through which startup signal's information to investors. For instance, many marketing AI entrepreneurs communicate information through social media channels, through blog posts, and on media. These startups are free to describe their applications as they prefer in different information intermediaries. Using these alternate sources of information can provide complementary information for VCs to evaluate the startup.

Third, I identify what different marketing strategies, entrepreneur intent, temporal focus, etc. influence venture capitalist funding likelihood. In line with literature on information asymmetry and signaling theory, if VCs find a different way to obtain the information communicated through a startup's textual description (e.g. by attending elevator pitches), my results about the value of text could change. It would be valuable for researchers to use discover-oriented, theories-in-use approach to identify the mental models to understand what factors do entrepreneurs try to communicate through text description. On the other side, it would be valuable to interview VCs to learn what pieces of information they try to obtain from firm descriptions. I want to emphasize here that the objective of my study is to explore and uncover the entrepreneur's intent and other application related information in the text that are associated with getting VC funding. This objective is descriptive rather than prescriptive.

Fourth, considering the incidence of the COVID-19 pandemic recently, funding for AI startups declined in the year 2020[10]. In fact, the funding for AI startups went down by more than 40% compared to year 2019. It would be valuable to see if the results of my essay continue to hold under such uncertain situations. Alternatively, researchers can investigate if VCs look for a new set of information from marketing AI startups when the market environment is uncertain.

Fifth, while I am studying the predictive ability of text provided by a marketing AI startup about their application potential, my approach can be easily extended to other types of AI application and also to other marketing startups. For example, many AI startups that serve the finance teams, HR teams tend to focus more on improving their internal operation efficiencies. These AI startups might be benefited by highlighting the benefits provided to their internal teams

[10] https://www.cbinsights.com/research/report/ai-in-numbers-q2-2020/

than to the external stakeholders. Similarly, it would be useful to know which results from my essay would apply to non-AI marketing startups and which results would differ.

Sixth, I do not account for characteristics of the venture capitalists. Venture capitalists might have varying interest in technology-based marketing startups, which could potentially influence their decisions to invest in a marketing AI startup. Lastly, I have not accounted for the marketing AI entrepreneur’s background. Entrepreneurs with previous experience in marketing and AI applications would potentially know about the benefits of a marketing AI application and thus would communicate the benefits more effectively to VCs.

To conclude, marketing AI startups communicate valuable signals through textual description of their startup and helps predict the likelihood of getting VC funding. My research adds to the literature using text mining in firm communication (Panagopoulos et al. 2018), and especially in the realm of marketing-finance in startups (Homburg et al. 2014).

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TABLES

Table 3.1 Summary Statistics of Marketing AI Startups

Variable	Min	Max	Mean	SD	Freq.
Number of News Articles	0	650.0	9.7	37.5	
Number of Investors	0	37.0	2.0	3.6	
Number of Patents	0	50.0	0.4	2.5	
Average Monthly Website Visitors	0	20979748.0	60421.1	766662.2	
Average Duration Spent on Website (in secs)	0	12713.0	175.1	600.0	
Average Pages Views Each Visit	0	49.6	1.1	2.7	
Number of Employees	6	375.0	39.9	63.9	
Total Funding ($)	0	393848044.0	5855735.7	23725505.0	
Years Since Founded	1	21.0	6.8	3.9	
Word Count	2	584.0	56.8	42.6	
Percentage of Positive Emotion Words	0	50.0	6.0	4.6	
Percentage of Cognitively Complex Words	0	50.0	12.9	6.6	
Percentage of Past Focused Words	0	16.7	1.0	1.7	
Received Funding					0.43
Firm in US or China					0.44
Has Generated Revenue					0.54

Table 3.2 AUC for Models with Text Only, Performance and Website Information Only, and a Combination of Both

	Model 1 Performance and Website Only	Model 2 Text Only	Model 3 Text, Performance, and Website
AUC of the Underlying Models of the Ensemble	74.23%	57.89%	76.19%
Logistic L1	73.42%	56.71%	75.78%
Logistic L2	73.71%	55.70%	74.68%
Random forest (best features selection)	74.46%	59.67%	76.90%
Extremely randomized trees (extra trees)	75.37%	58.91%	77.43%

Table 3.3 Lists of Words with the Highest Relevance Measure for Each LDA Topic

Topics of Funded Marketing AI Startups	Words in the Topic	Topics of Not Funded Marketing AI Startups	Words in the Topic
Improving Customer Experience	customer, experience, platform, interactions, engage, marketing, use, analytics	***Shopper Technology***	product, video, intelligence, develop, shopper, technology, engage, artificial,
Segmentation and revenue prediction	market, data, custom, team, sale, audience, revenue, predict, analytics, companies	***Campaign management***	market, company, ad, custom, digit, develop, service, partner, design
Generating Interactive Content	content, video, use, new, intelligence, brand, learn, time, technology, artificial	***Sale Automation***	custom, sale, use, automate, market, intelligence, business, data, manage, lead
Customer Engagement	company, venture, person, platform, mobile, psychology, customer, sale, engage	***Market Strategy***	market, data, platform, intelligence, strategy, power, offer, provide, company
Social media marketing campaigns	influence, platform, help shift, market, leanplum, message, social, curate	***Selling Conversation***	business, sale, help, custom, company, chatbot, chat, time, conversation, crm
Mobile advertising	brand, data, product, advertisement, mobile, proprietary, shopifi, weft, platform, company	***Lead Generation***	brand, data, market, consumer, custom, technology, reach, team, help, predict
Social Media conversation	local, market, lytic, fan, platform, center, social, manage, application	***Sales Funnel***	video, user, platform, funnel, content, license, glymt, recommend, machine
Event Intelligence	event, intelligence, system, ecosystem, use, create, data, pushspr, revalu	***Automated Agents***	agent, seo, influence, persona, competitor, real, politics, audience, ai
Voice Interactions	platform, music, physic, consumer, voice, ad, linkedin, bloom reach,	***Healthcare AI***	custom, data, program, organ, tool, voic, clout, platform, confid, help
Pipeline Management	sale, stack la, simple, market, pipeline, leadspace, cien, data hug, rep	***Customer Networks***	Offers hub, network, api, persist, understood, playbook, gamma, prevent, ai
		B2B Pipeline Management	instantloc, floor, travel, salesifi, b2bsignal, canspam, ai, pipeline

Table 3.4 Binary Regression using data from LIWC

DV: VC Funding	Coefficient
Length of Text	-.00 (.00)
Popularity of Startup	.01 (.00)***
Cognitively Complexity of Language	.08 (.03)**
Providing Personal Insights	-.06 (.03)**
Describing Concrete Achievements	.03 (.02)*
Describing Rewards	-.04 (.02)**
Discrepancy in the Text	-.09 (.06)*
Focus on Present	.02 (.01)*
Focus on Future	-.01 (.03)
Focus on Past	.10 (.03)***
Positive Sentiment	-.02 (.01)**
Negative Sentiment	-.05 (.05)
Analytical Text	.02 (.01)
News Articles Published	.02 (.00)***
log(Employee Count)	.21 (.05)***
Years Since Founded	-.03 (.01)**
Controls	Included
Intercept	-2.35 (1.36)*

$* p < .10, ** p < .05, *** p < .01$

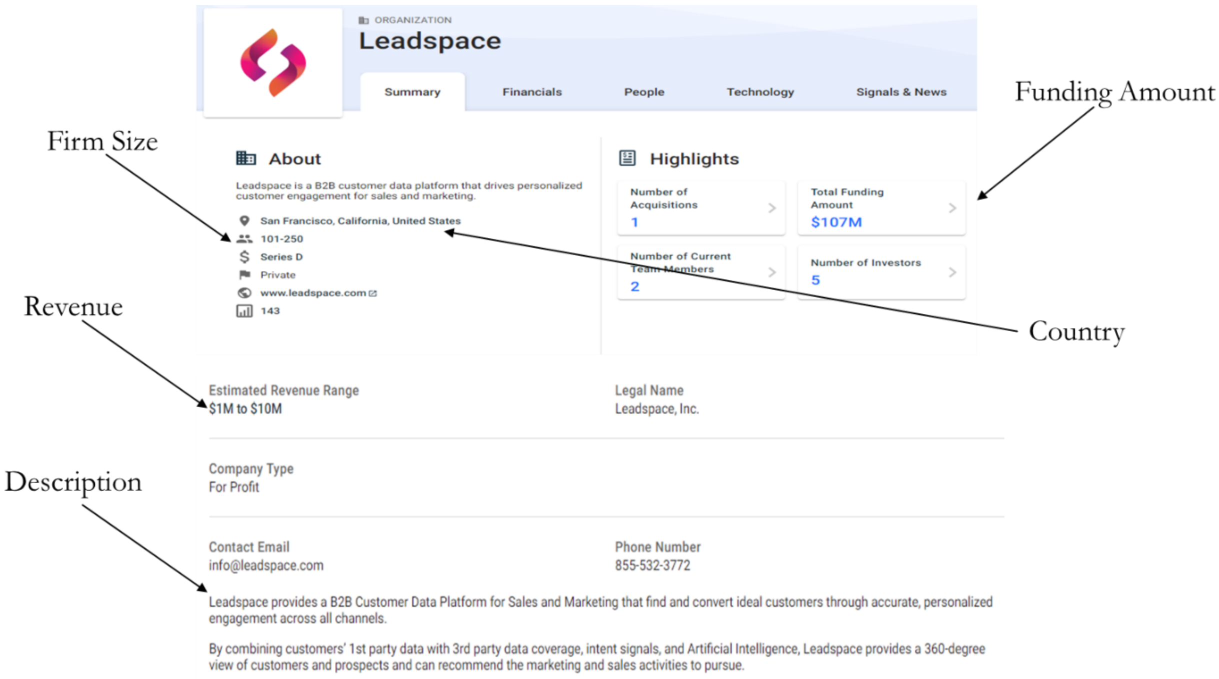

Figure 3.1 Company Profile Example on Crunchbase

Figure 3.2 Marketing strategies likely to be funded by VCs

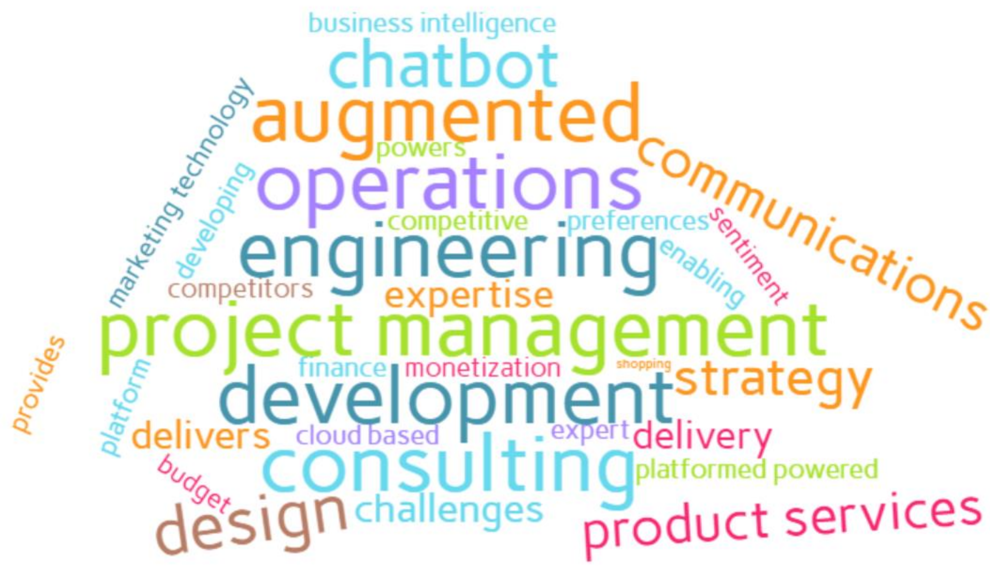

Figure 3.3 Marketing strategies not likely to be funded by VCs

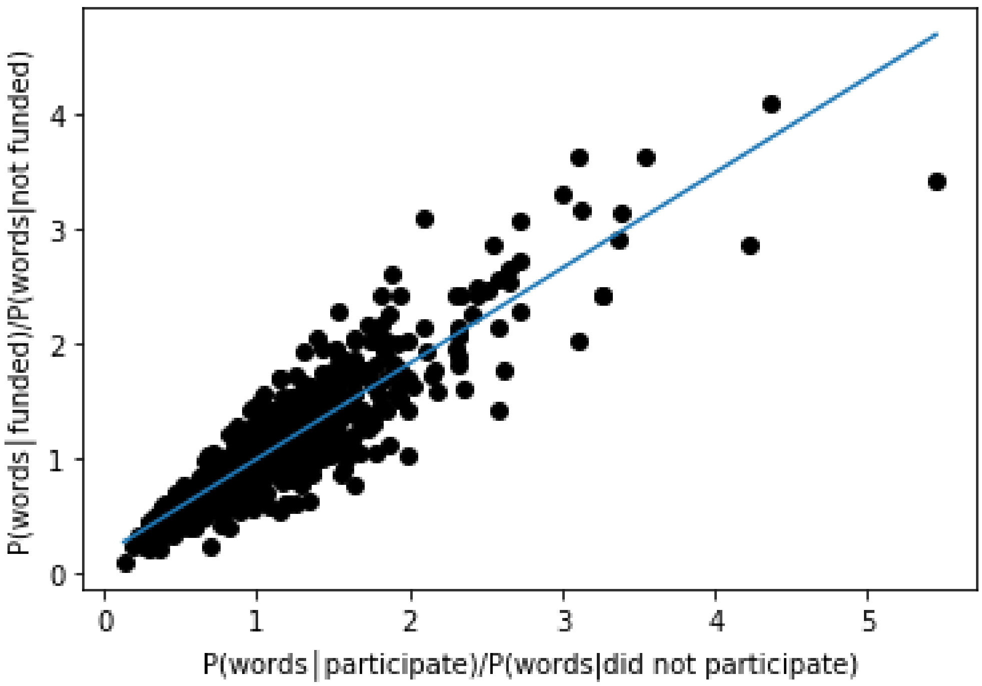

Figure 3.4 Naive Bayes analysis for funding round participation and getting VC funding

CHAPTER 4

DELINEATING THE VALUE B2B ARTIFICIAL INTELLIGENCE APPLICATIONS: A CUSTOMER-TOUCHPOINT PERSPECTIVE[1]

[1]Jayaram, K., and Bharadwaj, S.G. To be submitted to *Journal of Marketing*

ABSTRACT

In this essay, I develop a four-component B2B marketing AI framework to help B2B marketers help understand how to derive value from marketing AI applications. The framework consists of the following components: the marketing context, data planning, AI strategy and feedback generation. This framework is generalizable for B2B marketers using AI applications to help across different stages of their customer purchase journey. To identify the marketing context, marketers need to clearly define their goals, identify nuances of customer purchase stage and identify the output required. For data planning, marketers need to identify the types of data needed, how to label the data and how to automate the data collection process. Forming an AI strategy requires marketers to decide between the learning method and whether the AI application would be narrow or broad. Further, I examine how marketers' use of marketing AI applications with the sub-components improve efficiency, increase effectiveness and increase their opportunities to interact with customers. Lastly, I apply the B2B marketing AI framework across the different stages of the customer purchase journey. My framework will provide valuable guidance to B2B marketers.

INTRODUCTION

The use of Artificial Intelligence (called henceforth as AI) applications to help tasks performed by B2B marketers has increased tremendously over the past few years. According to McKinsey, AI applications are expected to contribute between $1.4 trillion to $2.6 trillion additional value to marketing and sales (Chui, Henke, and Miremadi 2019), with some reports indicating that as many as 30% of B2B companies are already employing some form of AI in their frontline processes (Selling Power 2020).

There are multiple reasons to believe that AI applications will add significant value to B2B marketers. First, expectations about the value potential of AI applications is high not only among B2B marketers who have already adopted these applications, but is also high among marketers who are yet to adopt them (Demandbase.com 2019). Marketers expect positive outcome from these applications not just in terms of improvements in their productivity, but more than 90% of B2B marketers surveyed said they expect AI applications will improve sales performance downstream (Insidesales.com 2018). Second, beyond just having expectations, marketers are actually increasingly adopting AI applications to improve customers' experience across their purchase journey. For example, a recent survey indicated that 40% of B2B marketers are already using AI applications to help them with different tasks including qualifying leads, engaging customers, increasing conversions, etc. (Perng 2018). B2B marketing leaders state that adopting AI applications is one of their top three priorities (Insidesales.com 2018). Third, venture capitalists' (VCs) investments towards B2B marketing AI startups rising rapidly. In fact, venture capitalists invested more towards marketing startups building B2B applications versus the ones building B2C applications after the COVID-19 pandemic hit (Wilhelm 2020). A case in point of a marketing AI startup, Megvii, received funding of more than $750 million in only one round of funding at a valuation of more than $4 billion (Pymnts.com 2019). Such high investments suggest the increasing confidence VCs have towards B2B marketing AI startups' potential. Lastly, B2B marketers from numerous firms already started getting positive financial returns from adopting AI applications. A case in point is that of CenturyLink, Inc. who used lead scoring algorithms and AI assistants to identify and reach highly interested customers and in turn engage them, resulting in a return of 2000% on every dollar spent. The website www.aimultiple.com provides more than 100 successful use cases of B2B marketers using AI applications across their customers' purchase journeys[11]. Thus, there are various reasons to expect AI applications will add value to B2B marketers.

Despite the overall positive outlook towards the value generating potential of AI applications in marketing, very few B2B marketers have adopted AI applications extensively to help with a wide range of marketing tasks across the different stages of the customer purchase journey. For example, a study by Boston Consulting Group found that only 5% of marketers have extensively incorporated AI in their offerings and processes across the customer purchase journey (Ransbotham et al. 2017). Moreover, only the marketers who work in technology industries have adopted AI applications extensively (Harrison 2019). A deeper exploration of the lack of extensive adoption points towards three primary underlying factors. First, B2B marketers state that even though they expect AI applications would add value, they lack clear understanding on 'how' to extract value from these applications. A recent survey reported that 32.6% of B2B marketers are not confident about their understanding of AI applications (Everstring and Heinz 2018). B2B marketers further state that they are unsure about how to choose use cases for using AI applications in marketing and their current adoption is focused on

[11] https://research.aimultiple.com/ai-usecases/

very limited use cases (Abdulsalam 2020). Second, B2B marketers state that they expect high value potential from using AI applications during the early stages of the customer purchase journey for activities such as managing pipeline, qualifying leads and prospecting (Insidesales.com 2018). However, they lack understanding about how AI applications can improve efficiency and effectiveness of marketing tasks across the entire customer purchase journey. Third, B2B marketers face issues communicating the value generated from using marketing AI applications to senior leadership and in turn get their buy in to increase firm investments in marketing AI applications (Chui and Malhotra 2018). In fact, a 2017 Deloitte survey found that the number one obstacle to the successful deployment of AI was that it was "difficult to integrate cognitive projects with existing processes and systems" (Davenport, Loucks and Schatsky 2017).

Against this backdrop, the main goal of this essay is to develop a comprehensive framework to identify the different components of a marketing AI application and to identify how marketing AI applications create value for B2B marketers. To achieve this, I use the framework provided in Figure 4.1. In the sections that follow, I explore deeper into each of the blocks 1, 2 and 3 provided in Figure 4.1. I do the following in the next sections: (1) Develop a B2B marketing AI framework to identify the different components of marketing AI applications used by B2B marketers i.e. explore deeper into block 1 in Figure 4.1, (2) Identify how marketers' use of marketing AI applications with the sub-components described within block 1 improve efficiency, increase effectiveness and increase their opportunities to interact with customers (see block 2 in Figure 4.1), and (3) Apply the B2B marketing AI framework across the different stages of the customer purchase journey i.e. explore deeper into block 3 provided in Figure 4.1.

B2B MARKETING AI FRAMEWORK

I identify four main components required in a B2B marketing AI application to enable marketers to use them and to improve performance of their marketing tasks. Figure 4.2 provides the main components of this B2B marketing AI framework. As indicated in Figure 4.2, the ‘marketing context’ component drives the decisions made in the ‘data planning’ and the ‘AI strategy’ components. All the three components together drive the output a B2B marketer obtains from the marketing AI application. In addition to the three components, the fourth component i.e. ‘feedback generated’, uses the output generated using the other three components, compares with the marketer’s expected output and then updates the inputs provided into the three components. The feedback component adds value by improving the output generated by the three components and in turn improves the marketer’s performance.

A few recent studies in marketing have developed framework to partly understand value co-creation from AI applications in B2B marketing (e.g. Paschen et al. 2019; Huang and Rust 2021b). However, these studies focus on the benefits B2B marketers get from using different levels of intelligences provided by AI applications. Current marketing frameworks fail to provide in-depth guidance to B2B marketing practitioners regarding the different decisions they need to take in order to successfully adopt a marketing AI application across the purchase journey. Moreover, they fail to explain the role of feedback and how it helps to increase the changes of successfully adopting a marketing AI application. I explain the role of each component in my framework below.

Understanding the Marketing Context

B2B marketers incorporating marketing AI applications for marketing tasks can use it for a variety of purposes including for marketing research, marketing strategy and marketing action

(Huang and Rust 2021a). In order to understand the marketing contexts that drive marketers' choice of using marketing AI applications, I identified three sub-components based on my review of the limited marketing literature and practitioner insights available on using AI applications in B2B marketing.

B2B marketers' goals for using the AI application. B2B marketers' choose to use marketing AI applications in order to augment their capabilities. For instance, B2B marketers need to augment capabilities to influence customer decisions across their purchase journey. By, providing a marketing AI application access to a wide rich variety of individualized customer data and to high computational power, B2B marketers can generate suggestions from these applications in real-time, collaborate with it and eventually adapt their interactions with customers. AI applications help marketers understand customers' changing needs not identified by a human and thus helps them persuade customers effectively across interactions in their purchase journey (Hamilton et al. 2021). Typically, B2B marketers adopt marketing AI applications in order to achieve one or more of the following goals: (1) to reduce their repetitive tasks, (2) to enhance their decision making capabilities, and (3) to increase opportunities to influence customers.

First, B2B marketers are capable of understanding customer contexts better than AI applications, and thus want to expend more resources towards understanding customer specific problems and offering solutions (Huang and Rust 2021b). Thus, they prefer to reduce tasks that are repetitive in nature, such as qualifying leads and reaching out to prospects (Terry 2015). These marketers try to use marketing AI applications that provide consistent or standard output based on the input parameters they provide (Huang and Rust 2021a). For example, B2B marketers look for non-linear classification capabilities in marketing AI applications to qualify leads using customer interaction data and predict if a website visitor a potential lead. Specifically, marketers look for applications that can use high-dimensionality data to make predictions that reduce repetitive thinking work. In addition to reducing time investments, marketers also to reduce their resource investments required, e.g., to present prototypes of their offerings to customers. Thus, they look for AI applications that provide augmented or virtual reality capabilities and allow them for rapid prototyping. Overall, marketers' first goal is to reducing time and resource investments towards tasks that are non-contextual, repetitive and potentially that they do not desirable to perform (Huang and Rust 2021b)

Second, B2B marketers want to adopt AI applications increase their marketing decision making capabilities. Marketers want to get a deeper and better understanding of customer preferences beyond their intuition based thinking, which will help them to provide personalized offerings to customers. Thus, they look for marketing AI applications that provide analytical capabilities to marketers, which complements their intuitive thinking and improves outcomes from the customer interactions (Fugener et al. 2020). A case in point is a marketing AI application developed by the firm MarketChorus, which generates creative content based on customers' previous content viewing patterns and browsing behavior. By generating content that requires creative skills, these applications help marketers influence customer purchases more effectively. In fact, predictions from AI applications can also help marketers justify decisions by providing payoff functions and decision counterfactuals (Kleinberg et al. 2018). Thus marketers' second goal is to look for marketing AI applications that complement their human intuition-based thinking capabilities with machine-generated analytical capabilities.

Lastly, B2B marketers use marketing AI applications to increase their opportunities to influence customer behavior. They want the opportunity to provide immediate responses to customer queries that can be difficult or expensive to achieve through direct interactions. Thus, B2B marketers typically try to increase their interactions by adopting AI-enabled ‘avatars’. Using AI-enabled avatar applications such as automated conversational agents, physical robots and virtual reality devices provide opportunities to have two-way interactions with customers that influence their behaviors (Miao et al. 2021). Overall, marketers want to provide customers opportunities to have conversations in which customers feel they are in ‘control’ of the conversations but the marketer is also able to influence their decisions during interactions (Hamilton et al. 2021).

Customer purchase stage: As B2B marketers choose marketing AI applications, they focus more on certain goals based on characteristics of the firm-customer interactions specific to each stage of the purchase journey. For purposes of this framework, I adopt a broad categorization of customer purchase journey stages provided by Lemon and Verhoef (2016) and categorize them in to pre-purchase, purchase and post-purchase stages.

During *pre-purchase stage*, marketers typically have minimal influence at the customer-firm touchpoints. Marketers have lower influence at this stage because customers typically prefer to do product/service research by themselves without having interactions with human agents from a firm (Grewal et al. 2015; Paschen et al. 2020). B2B marketers want to use marketing AI applications to tackle their lack of influence during the pre-purchase stage. Typically, marketers at this stage look to use conversational AI applications to respond to frequently asked customer questions or to engage customers by having two-way interactions, thus getting a better understanding of their needs in the pre-purchase stage. For example, a B2B AI firm, Hubspot, uses an AI chatbot to generate leads and to engage its website visitors. The chatbot asks questions to the visitors and qualifies them as either only visitors or as customers, which in turn helps capture leads and provides visitors personalized product information based on their needs. Thus, marketers at the pre-purchase stage want to use marketing AI applications to actively influence customer behaviors instead of playing a passive role.

The *purchase stage* is temporally the most compressed of the three stages and provides the least number of touchpoints for customers to interact (Lemon and Verhoef 2016). B2B marketers have very few opportunities to influence customers' experience at this stage and thus marketers need to make sure that every customer interaction creates value. Thus, marketers try to adopt marketing AI applications that help maximize the value from their interactions. For example, a marketing AI application by Cognizant creates value for marketers by analyzing customer sentiment in real-time during their firm-interactions and offers conversation tips to marketers based on the direction of the conversation between the marketer and customer (Antonio 2018). As the B2B purchase stage requires greater personal involvement from marketers, marketing AI applications in this stage will play a vital role in augmenting the analytical capabilities available to a marketer during the interactions.

The *post-purchase stage* provide opportunity for marketers to actively monitor customer usage behaviors and understand their underlying intent to uncover any new needs existing customers would have (Lemon and Verhoef 2016). B2B marketers want to use this information to identify which customers to more actively engage, which customers' service requests to handle pro-actively and in turn identify new opportunities to cross-sell and up-sell (Paschen, Wilson and Ferreira 2020). Hence, marketers look for marketing AI applications at this stage that can automate customer monitoring and identify opportunities to engage them, which would also discourage customers them from churning. Furthermore, engaging customers using marketing AI applications also leads to increased purchases, referrals, and valuable feedback (Kumar et al.

2019). Thus, B2B marketers look to adopt marketing AI applications that increase customer engagement at this stage and create indirect value benefits for them (Pansari and Kumar 2017). Examples of marketing AI applications that marketers use to engage are chatbots, smart speakers, etc. A case in point is that of Hyatt Hotels who use machine learning based AI applications to improve cross- and up-selling by engaging B2B customers who book rooms, which resulted in a 60% increase in average incremental room revenue (Diaz 2017). By identifying patterns based on customer history and past behaviors and comparing these to guests with similar profiles, Hyatt is able to identify customers that are likely to upgrade their room or may be interested in the hotels' amenities.

Output Requirement. To get returns from investments in marketing AI applications, marketers need to clearly identify the output they need from the application. Further, they need to design their process such that output from the marketing AI application can be successfully used with other marketing tasks. In other words, marketers need to identify how output from a marketing AI application will inform decision making of marketers or become inputs into other systems that are internal or external environment of the firm's business (Paschen et al. 2019; Huang and Rust 2021b). In order to be effectively deployed in large organizations, marketing AI applications need to be integrated with existing systems and processes (Davenport 2021). For example, if a marketer adopts a lead scoring marketing AI application, she need to identify whether she would to use the scores to reach out to potential customers or whether she would build an AI agent to send automated emails to potentials. The output decisions (i.e. what output and how it would be used) will be related to the other two sub-components described in the marketing context. I discuss about the 'data planning' component of the framework in the next section.

Data Planning

Data Planning is valuable to marketers for multiple reasons. First, data, considered to be the 'fuel' allows marketers to perform analytics and enables them to use marketing AI applications (Wedel and Kannan 2016). Second, lack of good quality data and no data planning are among the top challenges that marketers face when using AI applications (Brenner 2019). To generate required output from a marketing AI application, marketers have plan on how to provide the required input data necessary for the application. To do so, first, marketers identify the types of data necessary for the application to generate the output. Next, they need to plan how to label the data economically and then how to automate the data collection.

Third, by providing large volumes of input and/or output data from past customer interactions and training a marketing AI application, marketers can get accurate predictions of customer needs and are able to personalize their interactions at customer touchpoints (Chui et al. 2018). Fourth, if past customer interaction data cannot help generate accurate predictions of customer behavior during unexpected situations such as the during COVID-19 pandemic, marketers need to identify alternate sources of data that can generate accurate predictions using the same marketing AI applications (Wallaert and Karimi 2020).

In the following sub-sections, I provide an overview on the types of data that marketers use, about data labelling and how to automate data collection.

Types of Data. Marketing AI applications typically use two types of data to generate predictions namely, *structured data* and *unstructured data* (Wedel and Kannan 2016; Paschen et al. 2020). Structured data are data that are standardized and organized according to predefined schema. Examples of structured data used by B2B marketers include customer demographics, customer web browsing data or customer transaction data. Typically, structured data are captured internally and are available within the marketer's firm. Beyond internally available data, marketing AI applications can use data from external sources such customers' social media activities, engagement levels in blogs, etc. Providing both internally and externally available structured customer data to AI applications helps marketer generate more accurate predictions of customer behavior and intent. Using structured data is beneficial to marketers when used in AI applications that generate output in real-time because AI applications can process structured data much faster than unstructured data (Paschen et al. 2020).

On the other hand, unstructured data are data that are not standardized or organized according to a pre-defined schema. Marketing AI applications' ability to use unstructured data to make predictions is a primary distinguishing factor between marketing AI applications and non-AI based marketing applications (e.g. CRM software). Unstructured data can be in the form of blogs, reviews, and tweets and offer opportunity to obtain deep insights about customer behavior. For example, a marketing AI application, resonance.ai, captures multiple formats of unstructured data from different sources including TV series, advertisements, news, movies and user-generated social media content to generate content that resonates with customers and uses it to effectively engage them.

Based on the marketing context, marketers need to make decisions on whether they would only use structured data and/or use unstructured data to train the marketing AI applications they adopt. If marketers decide to use unstructured data to train their applications, they need to decide which dimensions of the unstructured data they would capture, e.g. whether they would collect syntax of a text, whether they would use semantics of a text (Balducci and Marinova 2018). These concurrent representation provide marketers the ability to generate richer insights. However, they need to be aware of the efficiency and speed limitations that arise from using unstructured data.

Data Labeling: Depending on the marketing AI application's 'learning' requirements identified using the marketing context, marketers need to determine how to label the data. If the marketing AI application uses supervised learning techniques, marketers need to provide labeled data of the inputs as well as the outputs to train the applications and generate the required output (Syam and Sharma 2018). Professors Jordan and Mitchell state

"*Many developers of AI systems now recognize that, for many applications, itcan be far easier to train a system by showing it examples of desired input-output behavior than to program it manually by anticipating the desired response for all possible inputs*." – Davenport (2021).

Depending on the number of input data points required to generate the output for a marketing task, a B2B marketer might have to extensively label the data. For example, if a marketers uses a marketing AI application that automatically predicts customer satisfaction based on their email response, the marketer needs to manually label a large number of features from previous customer emails and map the inputs to the output of customer satisfaction. This process can be laborious, expensive, which could hinder marketers from adopting these marketing AI applications. Moreover, manual labelling would be required even after deploying an AI application if the marketer wants to use additional features in marketing AI application to generate the output. Investor reports indicate that, firms that the manual labelling cost requirements for a firm building marketing AI applications can be up to 15% of their generated revenue (Casado and Bornstein 2019). Thus, it is not surprising that B2B marketers use tend to adopt 3rd party AI applications to label the data e.g. the applications built by Labelbox and Scale.

The value benefits to B2B marketers from these labeling applications is indicated by the high positively value that venture capitalists place towards these applications (Kahn 2020).

On the other hand, if a marketing AI application learns through unsupervised machine algorithms, it does not require extensive data labeling as these applications are typically used determine the structure or patterns in the data (Syam and Sharma 2018). In these applications, any labelling required by marketers would only be for the input and the output is not labelled. This reduces the labeling efforts of B2B marketers. Unsupervised learning is useful for applications such as segmentation, classification, etc. (Sanchez-Hernandez et al. 2013).

Automating Data Collection: Once B2B marketers determine their data needs based on their marketing context, they need to consider is how to automate their data collection for their marketing AI application. Automation might require extensive planning as some marketing AI applications might use data from a variety of sources such as the market, the environment, the firm, the competitors, and the customers. Huang and Rust (2020a) show that routine and repetitive tasks such as sensing, tracking, and collection have can be easily automated by marketing AI applications.

B2B marketers can choose to automate data collection across all stages of the purchase journey. For example, in the pre-purchase stage, retailers can adopt marketing AI applications that use customer heat maps, use video surveillance, and use data from beacons to automate customer profiling (Kirkpatrick 2020). During the post-purchase stage, marketers can automate product usage tracking, customer experience visualization to help make understand right customers to engage. Automating data collection will reduce the need for human intervention during data collection, which I believe would encourage more marketers to adopt marketing AI applications for their tasks. For example, publishers use a marketing AI application named

'Yuktamedia' to automate cross-channel customer data collection including customer product usage, campaign responses, etc. which helps publishers with media planning and revenue management.

AI Strategy

Typically, a marketing AI application uses information in the data to estimate the underlying parameters and learns how to accurately generate the required output based on the inputs. Depending on the marketing context, marketers need to identify how the application should learn from the data and whether it would solve a narrowly-defined task or a broad-task.

Learning Method: After identifying the marketing output required, B2B marketers can adopt a marketing AI application with a wide variety of learning capabilities to generate output necessary for the marketing task. Marketer can choose from marketing AI applications that are capable of learning in four ways. First, they can use AI applications that use *supervised learning* in which the application learns the mappings given a labeled dataset of input-output pairs and predicts the marketing relevant outcome. For example, Crisply, a marketing AI application, collected salesperson-customer interaction data along with customer response to make recommendations to the salesperson on how to maximize their selling efforts. Second, startups can use *unsupervised learning* in which the training dataset contains only the input variables, while the output variables are either undefined or unknown, which helps generate new knowledge for marketers. For example, Comprendi is a marketing AI application that customer generated text data on social media to find customer segments that are most likely to buy a marketers' offerings and helps her build more effective and hyper targeted advertising campaigns.

Third, if the output is known only for a subset of the available data, marketers can use marketing AI applications built with *semi-supervised learning*. As the output is not observed for part of the training set, marketers can use methods such as 'label propagation' to increase the sample size of available output data. For instance, Personafier is a marketing AI application that collects social media data about target customers and identifies other customers with similar social media personas, which helps increase size of training data available with marketers. Fourth, if marketers want to measure feedback to their actions, they can use marketing AI applications with *reinforcement learning* that continuously interacts with the environment (e.g. with customers) to optimize a certain objective function, in turn generating feedback (Sutton and Burto 2018). Over the past few years, reinforcement learning has been gaining popularity in business applications (Davenport 2021). For example, ImpressTV monitors customer responses to personalized advertisements and improves the personalized recommendations based on customer response to it.

Narrow versus broad AI. Once the marketing context is identified and marketers know whether they want to generate output for a narrowly-defined task or a broad set of tasks, they can choose marketing AI applications with narrow or broad capabilities (Davidson 2019; Paschen, Kietzmann and Kietzmann 2020). Narrow marketing AI applications are built to generate output for a specific task. They are tailored to a specific problem or task and cannot perform other tasks without being re-trained and/or modified. For example, LeadRebel is an application that identifies leads by capturing information about website visitors. This application would not be of much value during prospecting because the way this application is trained is to improve focused on lead generation.

On the other hand, 'broad' marketing AI applications are not tailored to a specific problem or task and can be used to perform a variety of marketing tasks. For example, Loc8te in an application that helps firms to push messages to customers at the right time. Messages can be pushed and any time in the customer purchase journey including during the need recognition stage to help customers identify needs or to engage during the post purchase stage. Thus, the application's capability to push messages to customers across their journey in real-time complements the other tasks that marketers perform at different purchase stages. To develop a broad AI application, marketers can combine multiple narrow AI applications integrate them. Combining provides these applications the ability to perform a variety of tasks across the purchase journey and almost provides capabilities that can replace a marketer's cognitive capabilities (Davenport 2021).

Feedback

For a marketing AI application to learn changing customer needs, marketer requirement and to update the output generated, marketer need to compare the application's predictions with the expected output, which provides guidance on how model estimates need to be updated (Fletcher 2019). For a marketing AI application, the output generated from the applications provides guidance to marketers on how to update all the three components of the B2B marketing AI framework i.e. the marketing context, their data planning and their AI strategy.

Feedback about the marketing context. As stated previously, to develop marketing context-based goals when adopting marketing AI application, marketers need identify their augmentation capabilities they need from using the application, learn the nuances involved across the three customer purchase stages and have to identify the output they want from the application. B2B marketers adopt marketing AI application to typically try and maximize value both for them and for their customers during firm-customer interactions. The analytical capabilities that marketing AI applications provide complement marketers' relationship building qualities such as displaying interpersonal empathy, providing encouragement, adapting conversations based to customer interaction, etc., thus improving customer's experience with the firm (Brynjolfsson and Mitchell 2017; Davenport and Ronanki 2018; Deming 2017). Even though marketers collaborate with marketing AI applications to perform marketing tasks (Paschen et al. 2020), it is not always clear apriori how effective the AI application's output will work with human collaboration in the frontline (Robinson et al. 2020). Thus, performance feedback obtained from using AI application will guide marketers about the effectiveness of the collaborated output and will help them take decisions on how to update the sub-components of the marketing context. Even industry articles report that many B2B marketing AI applications fail to perform initially due to unrealistic expectations from the application and feedback is very helpful to collaborate and perform marketing tasks[12]. For example, only getting lead conversion probabilities will not be of much value of to a B2B marketer. She needs to identify how to use the information to perform her marketing tasks and thus increase the value from this information. The feedback loop will help find the right balance between a marketer and AI working collaboratively.

Feedback about data planning. AI applications with their hard data computation skills provide a distinctive strength in processing big data and learning the latent patterns hidden in the structured and unstructured data (Davenport and Ronanki 2018; Luo et al. 2019; Puntoni et al. 2021). Marketing AI applications will be typically used for marketing tasks that require heavy processing and insights from large amounts of complex data. Thus, marketers need to be aware

[12] https://www.leadspace.com/ai-sales-marketing-hype/

of the data collection efforts required in the future. They need to monitor the returns from the application after accounting for the cost of collecting and labeling the required data. Recent industry observations suggest that not accounting for cost of data collection and the cost of human efforts needed to label data significantly affects profitability of marketing AI firms (Casado and Bornstein 2019). Thus, marketers need to monitor cost of data collection and need to identify ways to automate the data collection and to reduce labelling efforts, where possible. This feedback will help marketers keep a check on the overall cost of using the application and enable them to scale the application.

Feedback about AI strategy. Marketers need to use output from the marketing AI applications to identify how to improve the applications' learning, how to re-define the output generated based on the task, in turn, marketers re-define their AI strategies. If a marketing AI application does not provide the necessary output to help perform the marketing task at hand, marketers will need to identify what algorithms, learning methods, etc. they could use to improve the performance of the application (De Bruyn et al. 2020). Typically, AI applications are trained with a moderate amount of data initially and then through human intervention and re-training the application with new data, the accuracy of predictions increase (Davenport 2021).

Marketers can also adapt output generated by applications with unsupervised learning to their specific requirements. For instance, if marketers use unsupervised learning algorithms to identify customer segments, some clusters identified by the application may not be meaningful and hence would be challenging for the marketers to target these segments with personalized messaging. In order to discontinue using uninterpretable segments, the marketer can decide to pick a subset of customer segments from unsupervised learning and then label customer data with based on the segments identified. This labeled data with a sub-set of cluster information can be used with supervised learning to enable the AI applications to learn the estimate and predict the customer segment for each customer.

TRANSLATING MARKETING AI APPLICATION OUTPUT TO INCREMENTAL VALUE AT FIRM-CUSTOMER TOUCHPOINTS

Use of marketing AI applications improve interactions at the firm-customer touchpoints and provide incremental value to marketers using these application. The incremental value comes from after marketers have defined their three application usage goals described in the previous section. In this section, I describe how marketers get incremental value from marketing AI application output at each of the three customer purchase stages due to:

- Increase in the number of interaction touchpoints
- Higher effectiveness of interaction at these touchpoints
- Higher efficiency of interaction at these touchpoints

Pre-purchase

As stated previously, marketers have minimal influence across their customers' pre-purchase journey. At this stage, customers prefer doing research themselves instead of directly interacting with a marketer (Think with Google 2013). Many customers also rely extensively on social media and online communities during this stage (Grewal et al. 2015). For example, 'Oil and Gas IQ' is an online community helping customers with useful information about digital technologies used in the oil and gas industry, provides alternate sustainable solutions available, etc. The wealth of information and connections in such communities leads to customers having ready access to ample amount of valuable information. Customers do not have to interact with human marketing agents and instead get can information themselves from brand-owned (e.g. website), partner-owned (e.g. Facebook) and social touchpoints (e.g. industry connections). Even industrial surveys point to the fact that B2B customers do not talk to marketers till they conduct their own research using different digital touchpoints[13].

Having less influence over customers' pre-purchase journey necessitates marketers to find better ways to provide new perspectives, market their products and offer customized solutions. Hence, in response marketers have adopt big data strategies, use social platforms to demo their products/solutions and participate in online communities to respond to customers (Grewal et al. 2015). For example, YouTube has become a popular social channel to provide information about product/solutions and generate customer interest. B2B marketers need to develop strategies for influencing customers not only through the brand-owned touchpoints but also in these partner-owned touchpoints such as YouTube. AI applications provide marketers the ability to influence customers even more effectively and extract greater value from customers. In addition to improving effectiveness, AI also increases efficiency of marketers' activities and creates new opportunities to engage customers.

Incremental Value from AI

As stated previously, AI applications increase marketers' influence and it creates incremental value for them via three mechanisms. First, AI applications create additional touchpoints for customers and marketers to engage at the pre-purchase journey. These touchpoints can be in the form of automated conversational agents, physical robots, virtual reality devices prototyping products/solution, etc. Marketers use these additional touchpoints to interact with customers without customers to interact with a human agent. At these additional touchpoints, conversational agents have automated interactions with customers to help them get product/service information in natural language form. Having higher control over such AI

[13] https://www.demandgenreport.com/industry-topics/industry-news/1786-demand-gen-report-unveils-third-annual-b2b-buying-survey-showing-preferences-built-prior-to-sales-engagement.html%23.VM-HKGfwvIW

applications encourages customers to interact with the firm more often (Hoffman and Novak 2018). Marketers, on the other hand, are able to provide information regarding their products/services using rich media content. Marketer interactions at these additional touchpoints are found generate up to four times the value as generated from human-based touchpoints (Luo et al. 2019). Recent research also indicates that use of augmented reality based marketing applications have downstream consequences and helps increase sales (Tan et al. 2021). Marketers can also personalize interactions with customers at these touchpoints using a wide variety of data specific to customers (Kumar et al. 2019). Thus, adding new interaction touchpoints benefits B2B marketers and helps influence customers across purchase decisions (e.g., Hamilton et al. 2021).

Second, AI applications increase the effectiveness of marketer communications at the pre-purchase touchpoints. This occurs due to customers being more receptive to marketer-generated information that is augmented with analytical capabilities from AI applications. Marketers utilize regression trees, neural networks, hidden Markov models, support vector machines, etc. along with structured and unstructured data from a variety of sources to learn customer preferences and to identify the ones that likely generate highest value (Syam and Sharma 2018). Customers' preference is used to generate relevant and effective content. For example, AI application by the firm MarketChorus generates content based on customers' previous content viewing patterns and browsing behavior. Features such as customer intent, information from their visits and data from non-brand owned touchpoints are used to identify the right time to reach out to customers. A use case is that of a firm named 6sense that developed an AI application using predictive analytics techniques to identify customer buying signals and help marketer identify the optimal time to contact a buyer[14]. They used this information to personalize content for customers resulting in increasing profits generated from leads by more than 35%[15]. Increased customers' receptivity to marketers' messages resulting from effective content delivery and engaging them at the right time motivates them to try new products/solutions (Paschen, Kietzmann and Kietzmann 2019), and purchase faster creating incremental value back to marketers.

Third, AI applications increase the efficiency of marketer activities performed at the pre-purchase touchpoints. Huge gains in efficiency at the pre-purchase stage comes from AI applications' capability to automate the lead qualification tasks. Marketers spend around 80 percent of their time qualifying leads and only 20 percent in closing (Terry 2015). Researchers have demonstrated that marketers can use customer information with machine learning algorithms such as support vector machines, artificial neural networks, discriminant analysis, and k-nearest neighbor to identify a customer's propensity to buy and to generate quality leads (Syam and Sharma 2018). Carbonneau et al. (2008), Ghose et al. (2012) use a combination of support vector machines and neural networks to forecast demand and show that these methods are superior the traditional forecasting methods such as trend, moving average and linear regression. AI applications also increase efficiency of other pre-purchase tasks as well. For example, Jaipuria and Mahapatra (2014) used artificial neural network to develop an integrated approach for improving demand forecasting for industrial marketers. Applications such as chatbots reduce human workload by automating pre-purchase interactions and facilitating marketer or customer-initiated communications. AI applications that have automated interactions are a good potential replacement for human interactions because accuracy of speech recognition in some AI

[14] https://6sense.com/platform/
[15] http://growthintelligence.com/case-studies/

applications is nearly 97 percent (Davenport 2021). Applications such as augmented and virtual reality allow for rapid prototyping, allowing customers to evaluate multiple designs without marketers having to manufacture them. Industry experts believe that AI applications will bring about 50 to 60 percent reduction in cost which would create value for marketers (Mckinsey.com 2018).

Purchase**:** This stage of the customer journey provides the least opportunity for marketers to improve customer experience. This is due to the purchase stage being temporally the most compressed of the three stages and consisting of lowest number of touchpoints (Lemon and Verhoef 2016). Product/service evaluation by customers is completed before this stage and the purchase stage usually consists of building the final order and paying for it. Marketers have even fewer opportunities to improve experience for routinized customers and transactional customers at this stage compared to for organic customers (Grewal et al. 2015). Despite fewer opportunities available to influence customer experience, marketers have adopted technology to improve the experience so far. For example, marketers provide capabilities such as automated re-ordering based on inventory, auto-creation of purchase orders, accepting online payments and auto-updating ERP systems. Marketers have also started exploiting AI applications to create additional ways to improve the customer experience.

Incremental Value from AI: AI applications add value at this stage by increasing the effectiveness and efficiency of purchase touchpoints. Effectiveness increases due to the AI application generated suggestions being readily available to sales reps in real-time. Suggestions are generated using natural language processing technologies and using past data from marketer-customer interactions and from deal closing. This generates interaction suggestions effective for closing deals. More than 50% of marketers say that AI applications increase the effectiveness of their conversations (Schultz 2019). AI applications like chatbots reduce sales rep's time spent on brand touchpoints helping close deals by interacting with customers and helping overcome any concerns they have. Touchpoints can be more automated for routinized and transactional customers such that customers can automatically order based on current inventory. A case in point of increasing efficiency is CitiBank who demonstrate how payment touchpoints can be made more efficient with AI. They use an AI application capable of automatically processing customer payments by using a wide variety of customer related data points such as discounts provided to each customer, currency used to pay and purchase size. Such applications make the payment process more efficient and marketers can focus on improving their interactions with the customer.

***Post-purchase*:** The post-purchase stage touchpoints provides opportunity for marketers to monitor and influence the customer experience after they purchase the product/service. Specifically, these touchpoints provide opportunity for marketers to monitor customers' product/service usage, engage them and handle their service requests (Lemon and Verhoef 2016). By monitoring customer usage, marketers are able to better understand when and how to engage customers and discourage them from churning. For example, Gainsight, a company that offers software to manage sales and customer service, automatically alerts salespeople if customers do not utilize the purchased product/service and provides a list of at-risk buyers. Marketers use these insights to engage at-risk customers more often and proactively resolve their concerns. Engaging customers provides value to marketers not only in the form of more purchases but also through referrals, influencing other customers, and providing feedback (Kumar et al. 2010). Marketers can engage customers both on an individual level and at the organizational level (Reinartz and Berkmann 2018). Using AI technologies, marketers are able to improve the customer experience even further reducing the possibility of customer churn and generating opportunities to upsell and cross-sell.

Incremental Value from AI: Similar to pre-purchase, AI creates additional value in the post-purchase stage through the same mechanisms. First, AI applications improve the effectiveness of marketer activities. Bloemer, Brijs, Vanhoof and Swinnen (2003) use classification and regression trees to determine which specific customer segments are more likely to churn. They use a partial classification technique of customers and compare its superiority over complete classification technique. Lemmens and Croux (2006) use bagging and boosting techniques with classification trees and find that it improves the forecasting of at-risk customers. Using such techniques help marketers to spend more time in engaging customers who are at-risk resulting in higher effectiveness of their efforts. Second, AI applications improve the efficiency of marketer activities. For example, Schwartz, Bradlow and Fader (2014) developed a decision tree for model selection, which can be used by managers to save time in searching for best fit models based on post-purchase customer data. Ascarza (2018) uses random forest algorithms to estimate which customers respond favorably to marketer interventions. This helps in optimizing firm communications and saving time identifying right customers to engage with. Third, customers have more number of AI-application touchpoints to create service requests in the form of chatbots, smart speakers, etc. This provides marketers with additional touchpoints to resolve post-purchase customer issues and in turn increasing the indirect engagement behaviors. These factors result in increasing the value for the marketers.

APPLYING THE B2B MARKETING AI FRAMEWORK ACROSS DIFFERENT STAGES OF THE PURCHASE JOURNEY

In the previous section, I provided a summary of the different components in a marketing AI application and how it creates value for marketers. In this section, I examine how these different components combine to generate value across the different purchase stages. My main proposition is that the decisions marketers take for each component help generate the output they need to perform the marketing task. Specifically, in Table 4.1, I provide different customer goals at each of the three purchase stages, the tasks performed by marketing AI applications at this stage and the incremental value from these applications.

Further, in Figure 4.3, I provide examples of for the different components of the marketing AI application. For instance, I describe a use case in which marketing AI applications with unsupervised learning capabilities generates customer clusters and thus helps B2B marketers during the need recognition stage. Further, I provide examples of different marketing AI startups that build applications to help in specific sub-stage of purchase. For instance, Carrotbox is a marketing AI startup whose application is used to engage customers post-purchase in order to improve customer retention.

FUTURE RESEARCH TOPICS

As marketers are increasingly adopting marketing AI applications, they need to better understand how to define their goals for using the application, how to capture data, how to adapt learning strategies, etc. so that they adopt AI applications successfully in the marketer process and are able to extract greater value from their customer across the B2B purchase journey. Future marketing studies should focus on the following topics:

1. Role of AI applications in personalizing touchpoints its impact on value generated to marketers

2. The skillsets required by B2B sales and service teams in balancing technologically-enabled service efficiency and relationally-oriented service effectiveness

3. Understanding heterogeneity in the effectiveness of AI applications across different sub-stages of customer purchase journey

4. How to effectively use marketing AI applications to reduce cost of serving customers at the post-purchase customer touchpoints

KEY CONTRIBUTIONS

I make five contributions to theory and to practice. First, I contribute to the emerging literature on AI applications in marketing (e.g. Luo et al. 2019) and examine what decisions marketers need to make successfully adopt marketing AI applications and extract value from them. Second, I develop a framework using the B2B marketing AI framework to examine how AI applications create value across the different customer purchase stages. Third, I provide B2B marketers with a better understanding of the components of AI applications and provide information about how marketing AI applications adopted across the different customer purchase stages to create value. As I identify in my essay, it is challenging to identify the right marketing AI application considering the sub-stages (e.g. information search, usage) in the customer journey having various that have different data and AI technology requirements, and one-size-fits-all applications are not possible. Fourth, I provide three mechanisms by which AI applications create value. Instead of marketers adopting marketing AI applications to perform multiple tasks, they can adopt applications that generate output for narrowly defined problems, which could deliver value sooner and in turn justify their investments in AI applications. By understanding how value is created, marketers will be able to learn if the high cost of developing AI applications for their specific needs are justified.

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TABLE

Table 4.1. AI Applications across the Buyer Purchase Journey

Customer Stage	Customer Sub-Stages	Customers Goals	Papers Applying AI Technologies Across The Customer Journey	AI Algorithms Used	Marketing Tasks Performed by AI Application	Improvement in Customer Experience	Incremental Value for Marketers
Pre-purchase	Need recognition, information search, evaluation	• Identifying if there is need • Increase breadth of information available • Clarify firm goals • Reduce interactions • Reduce risk perceptions • Get customized solutions • Learn product and seller capabilities	Ben-Hur et al. (2001); Huang et al. (2007); Florez-Lopez et al. (2009); Carbonneau, Laframboise, and Vahidov (2008); Kim et al. (2005);	Support vector clustering, k-means clustering, decision trees, artificial neural network, propensity modelling	• Lead generation • Sales contact analytics • Sales content personalization • Retargeting • Recommendation engine • Social media monitoring and analytics • Content generation	• Better omni-channel experience • Better mobile application usage experience • 24/7 seller availability through bots	• Decreased acquisition cost • More cross-platform users • Richer data about buyers • Reduced time to reach buyers • More deals closing • Learn effectively engaging content

		• Learn relational orientation of supplier			• Website personalization • Chatbot		
Purchase	Ordering and payment	• Product/service providing value • Fulfillment of end-user goals	N/A	N/A	• Purchasing through chatbots • Sales rep action suggestion • Meeting setup • Prescriptive sales	• Faster negotiation and payments	• Identify customers to close
Post-purchase	Usage, engagement and service request	• Reduce risk of using product • Evaluate a product/service • Provide acceptable quality of service • Good service quality at the moments of truth	Bloemer et al. (2003); Lemmens and Croux (2006); Liu et al. (2016); Zhang and Godes (2018); Timoshenko and Hauser (2019)	Natural language processing Text classification and machine learning (ML) ML with PCA and LDA	• Customer service call analytics • Customer contact analytics • Social listening and analytics • Customer service chabot	• Lower wait time for service • Getting appropriate responses • Faster resolution of problems	• Higher renewal rate • Improved productivity of service agents • Lower cost of training

	• Reliability of service Frequent interactions	Convolutional neural networks	• Call intent discovery • Contextual mobile marketing

FIGURES

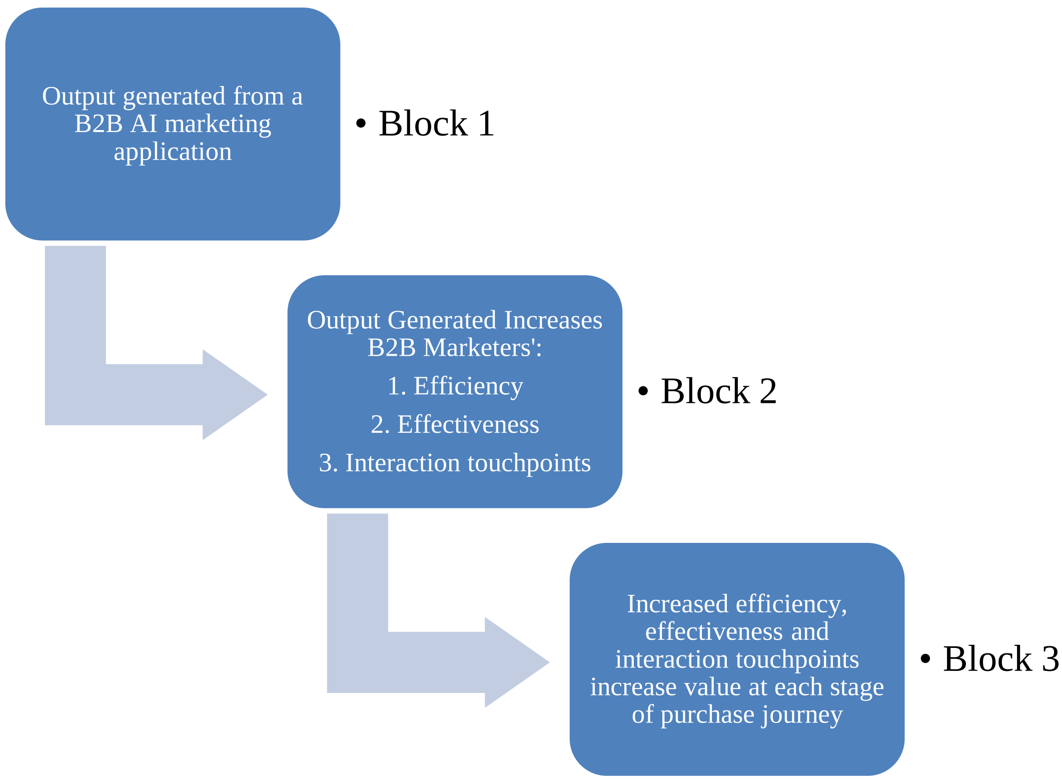

Figure 4.1. Article Framework

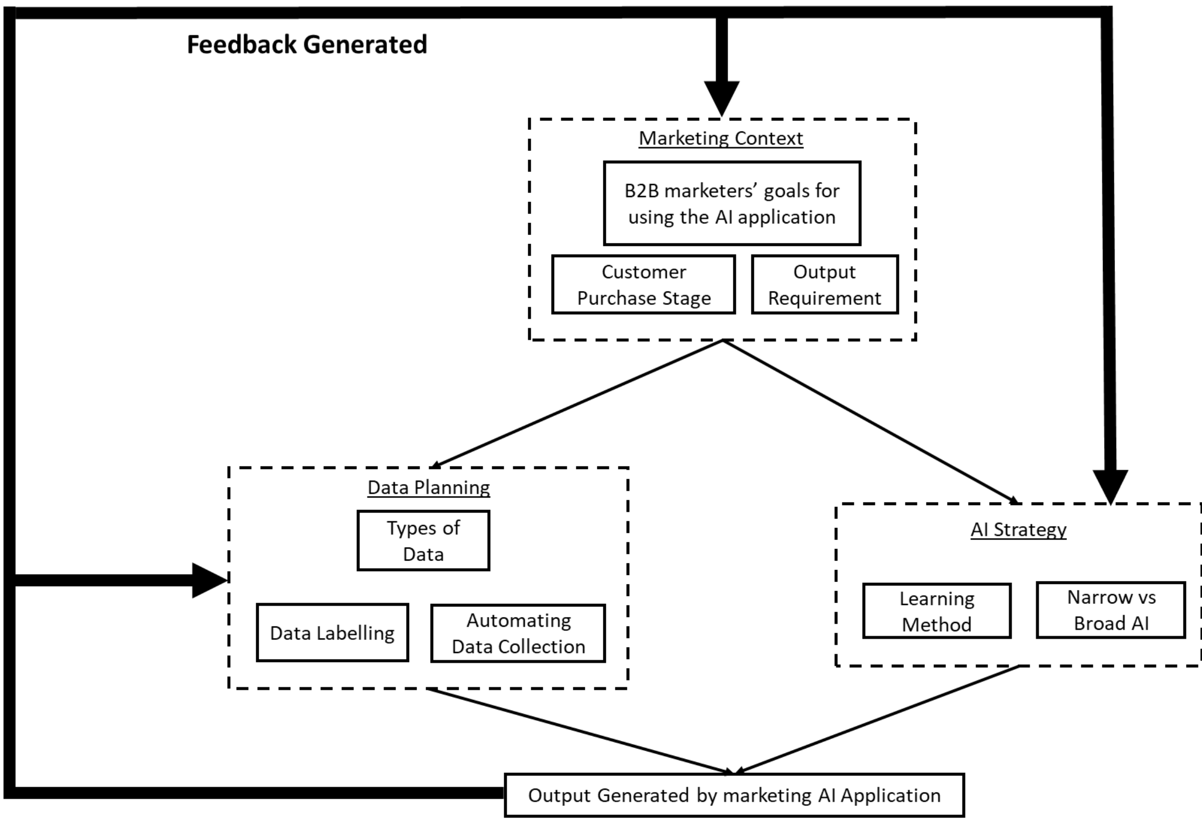

Figure 4.2. B2B Marketing AI Framework

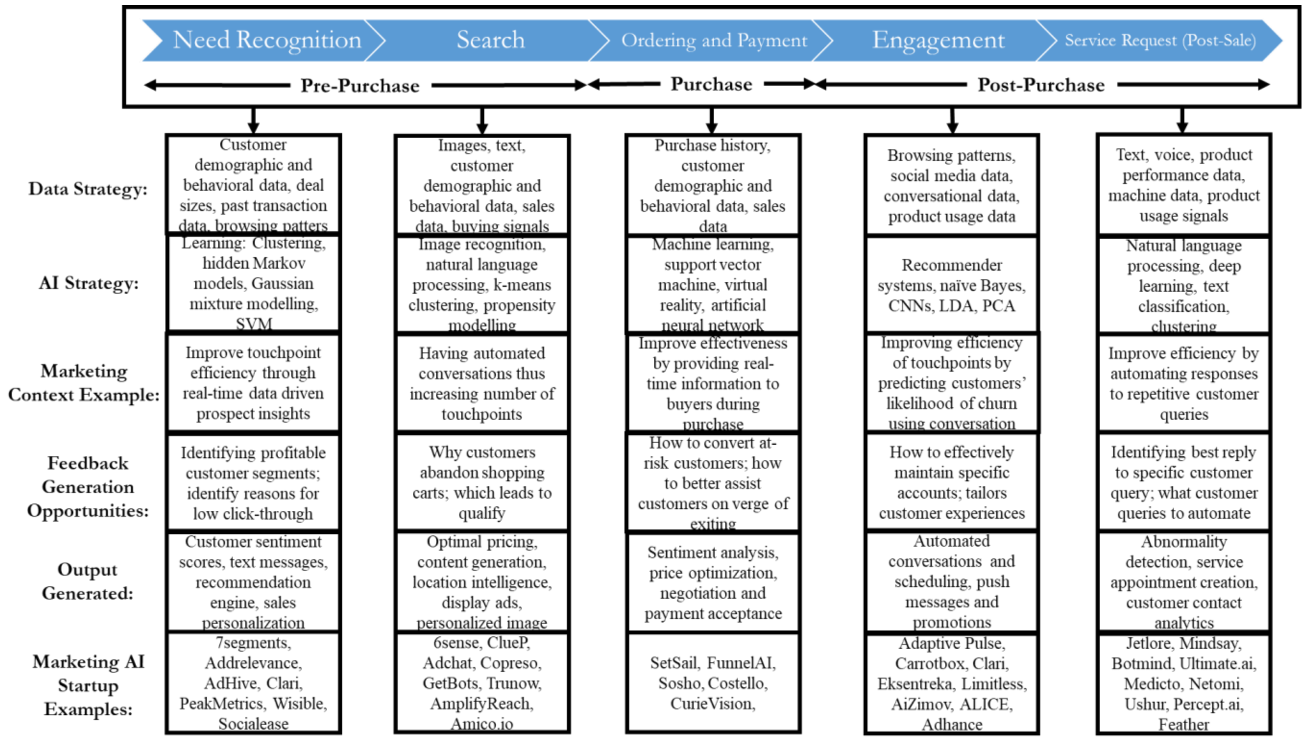

Figure 4.3. Examples for Each Component of B2B Marketing AI Framework at Each Stage of Purchase

CHAPTER 5

CONCLUSION

Overall, in this dissertation, I attempt to uncover and empirically examine how AI applications create value in marketing under different contexts. In my first essay, I find that launching an AI-enabled CCA increases a firm's market value by 0.29%, which translates to $56.7 million for a median firm in the sample. This market value change is closer to the high end of the market value change shown in studies of new digital touchpoints. I find that launching post-purchase CCAs create greater value for the firm than launching them to help during the pre-purchase stages of the customer purchase journey. I find that launching CCAs as partner-owned touchpoints create greater firm value. Moreover, I find that the stock market values CCA that have greater functionalities i.e. the ones which have both information and task capabilities and the ones that have dual modality functionalities. I find that providing authentication features is detrimental to firm value and firms need to consider about the convenience-privacy paradox. Furthermore, I identify and test the underlying mechanisms potentially driving incremental firm value. I find that firms launching CCAs and placing a greater emphasis on convenience and personalization potentially drive investors' stock market reactions. Similarly, I find that customers perceive CCA's to be more personalized and convenient.

In my second essay, I show that text has the ability to help VCs evaluate a marketing AI startup's future potential which in turn gets reflected in their funding decisions. Using data from Crunchbase, an online database that collects information about AI startups, I show that incorporating a marketing AI startup's textual description into the models that predict VC funding on the basis of the startup's financial performance and demographic information significantly and substantially increases their predictive ability. Using machine learning methods, I uncover the marketing strategies, business strategies and application benefits that marketing AI entrepreneurs often include in their text description and the ones that lead to funding. I find that, startups that received funding emphasized the tangible benefits that customers get from using the application. Moreover, I find that applications claim to not only improve marketers' tasks but also the ones that claim to automate marketers' thinking capabilities are less likely to be funded by VCs. Building on research methods used in marketing and using the commonly applied LIWC sub-dictionaries, I infer that firms positively evaluated by VCs tend to describe their firm's past success than the future potential.

In my third essay, I develop a comprehensive framework to identify the different components of a marketing AI application and to identify how marketing AI applications create value for B2B marketers. Specifically, I develop a B2B marketing AI framework to identify the different components of marketing AI applications used by B2B marketers, I identify how marketers' use of marketing AI applications with the sub-components improve efficiency, increase effectiveness and increase their opportunities to interact with customers, and I apply the B2B marketing AI framework across the different stages of the customer purchase journey.

In summary, my dissertation presents some novel findings regarding artificial intelligence applications create value for marketers and for firms in general.