Artificial Intelligence-Enabled Customer Value Proposition Capability and Market Performance: The Moderating Role of Environmental Heterogeneity

Lixu Li, Yang Tong, Yaoqi Liu, and Shuili Yang

Abstract—**Although artificial intelligence (AI) is becoming increasingly commonplace, many firms are still struggling to develop viable AI initiatives. Drawing on the dynamic capabilities theory, this article proposes a new framework to explore the relationships among AI-enabled customer value proposition capability (AI-CVPC), two customer response capabilities (i.e., response speed and response expertise), environmental heterogeneity, and market performance. The results from 400 Chinese firms across various sectors reveal that response speed and response expertise are two key mediators that link the positive association between AI-CVPC and market performance. More interestingly, environmental heterogeneity enhances the mediating role of response expertise, rather than the mediating role of response speed. This article contributes to the current AI-related business literature by developing a new moderated mediation model that explains the association between AI-CVPC and market performance. These findings also shed fresh light on the areas that firms should prioritize when developing their AI initiatives.**

Index Terms—**Artificial intelligence (AI), customer response capabilities, dynamic capabilities theory (DCT), environmental heterogeneity, market performance.**

I. Introduction

WE LIVE in an era in which artificial intelligence (AI) seems to be everywhere [1]. Many firms have employed AI to manage and automate their technical infrastructure, learn more about their customers, spot and counteract cyber threats, aid in decision-making, and streamline the hiring process [2]. As more and more firms are accelerating their embrace of key AI technologies like machine learning, deep learning, computer vision, and natural language processing, AI has graduated from the "early adopters" phase and entered the "early majority" phase, with the first mover advantage ebbing away [3]. International Data Corporation predicted that over \$97.9 billion would be spent on AI in 2023, 2.5 times more than in 2019 [4]. In an era when AI is rapidly becoming the norm, to keep competitive advantages, AI applicators have a pressing need to distinguish themselves in the marketplace [5].

Given that AI has become an increasingly important asset for firms and that the utilization of an asset is more important than the asset itself [6], many studies are devoted to the topic of AI capabilities [7], [8]. Although studies have discussed AI capabilities in the context of business model innovation [9], service innovation [5], and digitally serviced manufacturing [10], they conceptualize AI capabilities differently. Due to a lack of deep understanding of AI capabilities, particularly at the value proposition co-creation level [11], developing effective AI initiatives remains a challenge for many firms. For example, in 2020, a survey of 116 Chinese firms conducted by Ernst & Young found that 71% of interviewed firms keep AI at the senior management level; only 4% of interviewed firms have integrated AI into multiple processes and can handle advanced transactions [12]. Hence, to better help firms implement AI initiatives, more investigation on AI capabilities at the value proposition co-creation level is needed.

Motived by the work of Abou-Foul et al. [11], this article defines AI-enabled customer value proposition capability (AI-CVPC) as the ability of a firm to use AI to personalize customer experience, set optimal prices in the marketplace, and provide advanced services for customers. Although Abou-Foul et al. [11] have proposed AI-CVPC, their work mainly focuses on the impact of AI-CVPC on servitization. Considering that AI's contribution to the firm's market sales increased from 12% in 2018 to 25% in 2021, and it is expected to reach 36% in 2024 [13], merely investigating the effect of AI-CVPC on servitization is not enough. Moreover, market performance pertains to the degree to which a firm attains success in its current products or markets, as well as in its prospective market positioning [14], [15]. While studies have analyzed the potential of AI in promoting new product development [3] and innovation

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management [16], few studies have directly examined the impact of AI-CVPC on market performance. Because such a gap results in a restricted comprehension of how firms could create and leverage AI-CVPC, further investigation is warranted.

Considering that AI-CVPC requires firms to use deep learning personalization algorithms to better understand customers, which is related to a firm's sensing and seizing capabilities [11], this article primarily clarifies the association between AI-CVPC and market performance from the lens of dynamic capabilities theory (DCT). According to DCT, if a firm wants to achieve sustained competitive advantages in a dynamic environment, such a firm needs not only capabilities related to sensing and seizing but also capabilities associated with resource reconfiguration [17]. To embody reconfiguring capabilities, this article considers customer response capabilities (consisting of response speed and response expertise) because such capabilities reflect how a firm remodifies, rebuilds, and redesigns actions in the form of an enactment, conduct, or praxis in response to customer needs [18]. While past studies have shown that firms with stronger customer response capabilities can provide better customer service [19], little research has discussed the differences in the subdimensions of customer response capabilities, especially in the context of AI applications. More importantly, due to these kinds of knowledge gaps, some firms have noticed the value of AI but are still unsure of which AI projects to prioritize implementation [12]. Hence, the first research question of this article is: *Were response speed and response expertise two mediators in the association between AI-CVPC and market performance?*

The DCT also elaborates on how the modern business environment is characterized by volatility, instability, and high levels of uncertainty [20], implying that firms need to consider their surroundings when making decisions about how to reallocate their resources in response to customer demand. Environmental heterogeneity is a term that describes the variety of customer purchasing patterns and the complexity of market competition [21]. Although the prior work has explored the moderating role of environmental heterogeneity (or similar concepts) in the context of big data-enabled innovation [22], digitalization [23], and low-carbon practices [24], limited effort has been made in the AI application contexts. It may incur a risk of insufficient knowledge on how firms should adjust their AI applications in response to changes in the marketplace. Accordingly, the second research question of this article is: *Does environmental heterogeneity moderate the mediating role of response speed and response expertise in the association between AI-CVPC and market performance?*

This article focuses mostly on Chinese firms because China is one of the first major emerging economies to embrace AI as the foundation of a new wave of industrial transformation and strongly urges firms to expedite the deployment of AI scenarios [25]. Survey results from 400 Chinese firms across sectors make significant contributions to the current AI-related business literature in the following aspects. First, although studies have theoretically discussed how AI capabilities help firms improve performance through process efficiency, insight generation, and business process transformation [26], due to the lack of understanding of AI capabilities at the value proposition co-creation level [11], some firms are still overburdened with actual execution. In contrast to prior studies, this article focuses on AI-CVPC and examines its impact on market performance, thus enriching the existing knowledge of AI capabilities.

Second, while studies have used the DCT to understand the phenomenon related to digitalization [23] and AI applications [27], many of them primarily leverage the opinions of DCT, lacking variables explicitly associated with dynamic capabilities. By contrast, this article reifies sensing and seizing capabilities as AI-CVPC and reconfiguring capabilities as customer response capabilities. More importantly, this article novelty reveals the relationships among AI-CVPC, customer response capabilities, and market performance. Consequently, this article broadens the comprehension of the microfoundation of dynamic capabilities by illustrating how various dynamic capabilities can be translated into an AI application context and exploring their new relationships.

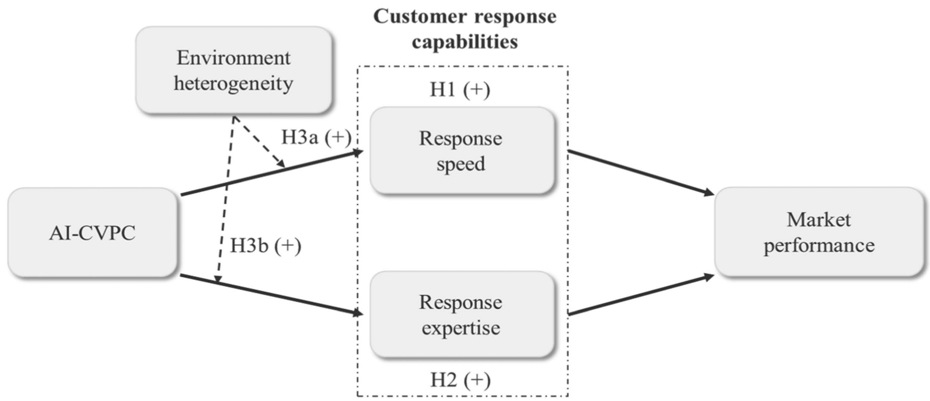
Third, studies have emphasized the importance of customer response capabilities in improving customer loyalty [28], customer satisfaction [29], and customer service performance [18]. However, in the context of AI applications, the understanding of the distinctions in customer response capabilities across various segmentation dimensions and of which aspects businesses should prioritize is not yet comprehensive. By contrast, this article novelty compares the differences in the mediating role of two customer response capabilities (i.e., response speed and response expertise) under varying degrees of environmental heterogeneity, thereby expanding the current understanding of customer response capabilities.

The rest of this article is organized as follows. In Section II, this article introduces dynamic capabilities theory and proposes testable hypotheses. Section III involves data collection, measurements, and bias tests. The estimated results are presented in Section IV. In Section V, this article compares the findings with prior studies and introduces theoretical and practical implications. The conclusion and further research are summarized in Section VI.

II. Theory and Hypotheses

A. Dynamic Capabilities Theory

Capabilities typically refer to the complicated combination of resources (e.g., skills, knowledge, talent, and management) that allow an organization to organize its operations and make use of its assets [30]. To investigate how an organization integrates, constructs, and reconfigures internal and external resources in response to a quickly changing environment, scholars have created the notion of dynamic capabilities [17], [31], [32]. In particular, dynamic capabilities mainly consist of various dimensions: 1) sensing and seizing capabilities that enable an organization to identify and leverage internal and external opportunities [33], and 2) reconfiguring capabilities that permit change, reconstruction, or reallocation of existing resources [34]. Finally, an important claim of the DCT is that firms with stronger dynamic



Note: H1 and H2 predict mediation of the relationship between AI-CVPC and market performance, with response speed and response expertise as the respective mediators. H3a and H3b predict positive moderation of the same mediation relationships by environment heterogeneity.

Fig. 1. Research framework.

capabilities are more likely to succeed than those with lower dynamic capabilities in a dynamic business environment [35].

Because the principal values of AI are related to process automation, cognitive insights, and cognitive engagement [36], which theoretically help firms better sense and seize changes in the business environment, AI-related business research has mainly employed the DCT to analyze the outcomes of AI applications [37]. For example, Mikalef et al. [38] conducted in-depth interviews with three big Norwegian firms and identified the relationships among AI, dynamic capabilities, and B2B marketing operations. Based on the perspective of DCT, Abou-Foul et al. [11] presented how firms in the United States and Europe can use AI to improve their service levels. Collecting data from 317 small and medium-sized enterprises (SMEs) in the United Kingdom, Drydakis [37] found that with the help of AI, SMEs can increase their dynamic capabilities to changing market conditions, thus adapting quickly to changes in demand, improving operational efficiency, and lowering the business risks.

Although prior studies have made substantial contributions to understanding the complex phenomena related to AI from a DCT perspective, many of them mainly use the DCT to explain the theory-building process, lacking variables explicitly associated with dynamic capabilities [23]. Moreover, because dynamic capabilities are the higher order capabilities for a firm [32], it implies that, for many firms, dynamic capabilities may be too theoretical. These two gaps may lead to a limited understanding of the micro-foundation of dynamic capabilities in the context of AI applications and further raise the dilemma of managers not knowing how to develop viable AI initiatives [11]. Given the above reasons, creating more tangible capabilities to aid in the successful execution of AI-related capability development strategies is important for both scholars and practitioners.

To this end, this article considers AI-CVPC and customer response capabilities. The reasons are that first, AI-CVPC requires firms to use algorithms and data science to obtain new insights and business opportunities from their customers [39], involving sensing and seizing capabilities. Second, to adapt rapidly and efficiently to changing customer needs, customer response capabilities require firms to build a flexible resource [28], linking to reconfiguring capabilities. Finally, because the DCT also states the characteristics of the business environment in which the firm operates [40], this article further considers environmental heterogeneity and proposes the research framework in Fig. 1. Next, this article introduces each testable hypothesis.

B. Relationships Among AI-CVPC, Customer Response Capabilities, and Market Performance

From the perspective of the DCT, a firm that wishes to stand out from its peers must first be adept at sensing and seizing changes in customer preferences and market demand [17]. Recall that AI-CVPC may aid business executives in gaining a deeper comprehension of their customers so that they can more effectively target their marketing efforts [11]. In this sense, AI-CVPC embodies the sensing and seizing aspects of dynamic capabilities to a certain extent [11].

Studies have found that by using deep learning personalization algorithms, firms can increase customer satisfaction and market profits by predicting product demand, marketing campaign success, and consumer trends [41], [42]. Furthermore, researchers have suggested that firms with higher levels of AI-CVPC can better promote business model innovation [3] and digital servitization [43], [44], both of which are important prerequisites for helping firms expand their markets. Finally, researchers have found that serendipity, defined as search-leading to unintended discovery [45], is a type of luck that can be used to explain performance differentials between firms [46]. Because serendipity emerges from the application of technology to a new domain [47], the use of AI and machine learning should help firms produce unplanned discoveries [46]. In other words, firms with higher AI-CVPC should lead to more serendipity, thus propelling enhanced market performance. Overall, numerous observations indicate a potential relationship between AI-CVPC and market performance.

This study then discusses the mechanisms behind the above relationship. According to the DCT [17], firms that merely have sensing and seizing capabilities cannot sustain a competitive advantage in the market; firms must also establish restructuring capabilities as a remedy. Considering that customer response capabilities refer to the ability of an organization to quickly and effectively respond to changes in customer preferences and market demand [18], which requires firms to remodify, rebuild, and redesign their resource base, this article focuses on how customer response capabilities influence the association between AI-CVPC and market performance.

Studies have argued that response speed and expertise are two major dimensions of customer response capabilities [28]. Response speed evaluates how quickly a firm responds to customer needs, whereas response expertise describes the effectiveness of a firm's responses [18]. From the perspective of response speed, using natural language processing and algorithmic tools, firms with superior AI-CVPC can better outline and identify potential customer inquiries [26]. Moreover, unlike manual service, which requires intermittent breaks, AI-based automatic chatbots can respond to consumer inquiries 24 h a day, which significantly improves the response speed for firms [48]. Currently, the use of AI-based automatic chatbots to enhance customer response speed has been implemented in a variety of scenarios, such as financial transactions, e-commerce retail, travel, and government services [49].

Furthermore, studies have found that response speed is one of the main core competencies, which may help firms expand their market [28]. In the context of delivery, numerous studies have demonstrated the significance of response speed to successful customer service [29], [50], [51]. Last but not least, although AI-CVPC can help firms better sense and seize changes in customer preferences and market demand, in the digital era, speed has become a major core competency for firms. It implies that to succeed in the market, merely perceiving changes in customers and markets is not enough, firms must turn these perceptions into actual actions, namely improving their response speed. Hence, it follows

H1: Response speed positively mediates the AI-CVPC-market performance association.

From the perspective of response expertise, technical tools like deep learning and neural networks allow AI to achieve self-learning and optimization; more importantly, with the constant gathering and analysis of data in the process of servicing customers, AI can enhance its own intelligence level and coping capacity and further assist firms in improving their response expertise [52]. Kumar et al. [5] have emphasized the importance of AI-enabled customer relationship management in healthcare, which also implies a positive relationship between AI-CVPC and response expertise.

Regarding the relationship between response expertise and market performance, studies have found that response expertise is crucial for market success [51]. An example in the delivery context is that a good customer response not only requires speed but also needs to provide customers with defect-free products or services at the right time and in the right place [53], which cannot be done without the support of responsive expertise.

Finally, even while AI-CVPC may aid firms in sensing and capturing shifts in customer preferences and market needs, adapting to these shifts calls for ongoing updates to the resource portfolio, including enhancements to the response expertise. In other words, to achieve better market performance, relying on AI-CVPC is not enough, and firms must also increase their response expertise. Accordingly, it follows

H2: Response expertise positively mediates the AI-CVPC-market performance association.

C. *Moderating Role of Environmental Heterogeneity*

Environmental heterogeneity refers to the diversity of customer purchasing patterns and the complexity of market competition [21]. According to the DCT, maintaining resource allocation flexibility is especially important for firms operating in a turbulent and uncertain business environment [20]. Given that the establishment of response speed and response expertise requires firms to have a flexible resource base [18], some perspectives on the DCT can also be used to explain how environmental heterogeneity may influence the relationships among AI-CVPC, customer response capabilities, and market performance.

Firms with high levels of AI-CVPC can better predict their customer preferences and market changes by using advanced algorithmic tools [11]. Under conditions of high environmental heterogeneity, because customer preferences change rapidly, AI-CVPC may enable firms to display better response speed to customers by quickly introducing new products and services to the market [16], [54]. Using German firm-level data, Rammer et al. [55] have demonstrated that firms that implement AI routinely and have several years of AI experience achieve substantially greater and quicker innovation results. Many examples during the COVID-19 pandemic, such as unmanned vehicle delivery and intelligent chatbots, also illustrate the importance of leveraging AI to improve a firm's response speed in a turbulent environment [48]. Hence, it follows

H3a: Environmental heterogeneity enhances the positive mediation effect of response speed on the AI-CVPC-market performance association.

Moreover, environmental heterogeneity increases market competition and shortens the product update cycle [56]. Because customer service is the key to market success, many firms are focusing their digital efforts on AI-powered customer service to increase their response expertise [57]. More importantly, those firms that fail to implement similar AI initiatives may lose market share in a very brief period of time. An investigation conducted by McKinsey found that firms that use digital technologies to prioritize the customer experience may lead to a 20%–30% bump in customer satisfaction and a corresponding 20%–50% bump in economic returns [57]. In short, facing the rapid changes in customer preferences and market demand, firms need to use digital tools, especially AI, to enhance their response expertise. This is because firms that fail to do so may lose their market share in a short period of time, or worse, be eliminated by the digital revolution. Hence, it follows

H3b: Environmental heterogeneity enhances the positive mediation effect of response expertise on the AI-CVPC-market performance association.

III. Methods

A. Data Collection

China is one of the world's most rapidly expanding economies, especially in the aspect of digital economies [58]. To support the development of AI in China, the Chinese government has established a new generation of AI pilot zones in 15 cities including Beijing, Shanghai, Tianjin, Shenzhen, and Hangzhou since 2021, thus providing a rich sample library for the present research [59]. Despite the progress made in areas like deep learning and other algorithm innovations, technology product implementation, and application scenario promotion in recent years, China's AI firms still have some commercial issues to address, such as business continuity and profitability and low return on deployment investment. To help Chinese firms seize opportunities in the new round of the AI development boom, this article focuses on Chinese firms. Nevertheless, the findings of this article may serve as a point of reference to firms all around the world, not only those in China, by helping their managers better understand and predict where AI will go in the future.

Before the formal survey, the authors designed an English version questionnaire by modifying the tested scale in the IS and business literature. Because this study was conducted in China, to ensure the equivalence of measures, the authors used a back-translation approach by first translating the questionnaire into Chinese and then back-translating it into English. Next, to refine the items and conduct a pretest, the authors also distributed the questionnaire to 50 business managers on an online platform, as well as three operations management scholars.

After that, one of the authors contracted with and hired a third-party web research agency to identify potential Chinese firms. The following criteria made for an ideal surveyed firm:

1) having invested in digital technologies;
2) having deployed AI within the firms;
3) requiring top managers as replies.

The third-party web research agency randomly contacted 857 firms in its sample pool consisting of more than 30 000 firms. By comparing the conditions of the surveyed firms with the set criteria, as well as combining the time to complete the questionnaires, the author finally retained 400 valid questionnaires. The response rate was 46.67%.

The characteristics of the sample are outlined in Table I. Nearly 70% of surveyed firms were privately owned and had been established over 10 years. In addition, SMEs made up about 40% of the total sample. Finally, the surveyed firms were mainly distributed in the three industries of manufacturing (51.50%), information technology (IT) (23.00%), and services (25.50%).

TABLE I
PROFILES OF THE SAMPLE

	Frequency	Percentage
Established years to 2023		
<6 years	10	2.50
6–10 years	105	26.25
11–15 years	108	27.00
16–20 years	97	24.25
>20 years	80	20.00
Number of employees		
<20	7	1.75
20–299	150	37.50
300–999	150	37.50
$\geqslant 1000$	93	23.25
Ownership		
State-owned	59	14.75
Private-owned	282	70.50
Others	59	14.75
Industrial types		
Manufacturing	206	51.50
IT industry	92	23.00
Services	102	25.50

B. Measures

This article used items validated by previous studies to measure the focal constructs. In particular, AI-CVPC, referring to the ability of an organization to use AI to gauge customer demand, provide valuable insights, and set optimal prices in the marketplace, was measured with four items adapted from Abou-Foul et al. [11]. Similar to the work of Jayachandran et al. [28], this article divided customer response capabilities into response speed and response expertise, which describe how quickly a firm responds to customer needs and the effectiveness of a firm's responses, respectively. The seven items for these two constructs were adapted from Setia et al. [18]. Environmental heterogeneity describes the variety of customer purchasing patterns and the complexity of market competition [21], and this article adapted three items from Mikalef et al. [22] to measure it. Market performance was measured by four items adapted from Wang et al. [60], and these items reflect the state of a firm in terms of market share, products, and services.

All the above items were loaded on a seven-point Likert scale, with "1" representing "strongly disagree" and "7" representing "strongly agree". Finally, similar to previous studies [61], [62], this article mainly considered four control variables: firm age (measured by the established years to 2023), firm size (measured by the number of employees), ownership (dummy coding), and industry types (dummy coding).

C. Reliability and Validity

To evaluate the accuracy with which the conceptual model matches the data, this article first performed the confirmatory factor analysis (CFA) in AMOS 21.0. The fit indices, with $\chi^2 = 273.164$, $df = 125$, $\chi^2/\mathrm{df} = 2.185$, comparative fit index (CFI) $= 0.962$, Tucker–Lewis index (TLI) $= 0.954$, relative fit index (RFI) $= 0.918$, incremental fit index (IFI) $= 0.963$, and root mean square error of approximation (RMSEA) $= 0.055$, were acceptable [23].

TABLE II
CORRELATION MATRIX AND DISCRIMINANT VALIDITY

	Mean	Standard deviation	1	2	3	4	5	6
1. AI-CVPC	5.641	0.865	0.774					
2. Response speed	6.007	0.749	0.625**	0.745				
3. Response expertise	5.911	0.752	0.642**	0.652**	0.751			
4. Environmental heterogeneity	5.085	1.126	0.395**	0.308**	0.270**	0.838		
5. Market performance	5.540	0.875	0.640**	0.595**	0.643**	0.426**	0.776	
6. Marker variable	n/a	n/a	0.077	0.025	0.063	–0.013	0.088	n/a

Notes: ** indicates p-values < 0.01; the square roots of AVEs are in the diagonal.

Next, this article calculated the factor loadings, the average variance extracted (AVE), composite reliability (CR), and Cronbach's α (CA) to evaluate the reliability and validity of items and summarized the corresponding results in Fig. 2 in the Appendix. In particular, the factor loadings for different constructs ranged from 0.691 to 0.870, all of which were well above the 0.6 thresholds. In addition, the AVE value for each construct was above 0.5, indicating a good convergent validity [63]. Furthermore, the CR and CA for each construct were over the cutoff of 0.7, thereby providing support for a sufficient level of reliability [64].

Finally, this article listed the square root of the AVE values and the correlations between different constructs in Table II to evaluate the discriminant validity. As expected, evidence for acceptable discriminant validity is provided by the fact that the diagonal values are larger than the correlation coefficients [65].

D. Nonresponse and Common Method Bias

Nonresponse bias and common method bias are two common threats in survey research. To reduce concerns about these two threats, this article conducted some statistical tests. Regarding nonresponse bias, the gathered data were first split into two time intervals: early responses and late responses. Then, a t-test, with a 0.05 level of significance, was used to compare early and late responses on the means of the focal constructs and some control variables (e.g., firm age and firm size). Because the p-values did not indicate a statistically significant difference, nonresponse bias should have a limited effect on this article.

With respect to common method bias, this article first used Harman's single-factor test by loading all items into a single factor in the CFA [66]. The fit indices were unacceptable, with $\chi^2 = 1159.770$, $df = 135$, $\chi^2/\text{df} = 8.591$, CFI = 0.740, TLI = 0.706, RFI = 0.679, IFI = 0.741, and RMSEA = 0.138. These results also indicated that using a common factor to reflect all items was unreasonable. This article also considered the marker variable technique [67]. Marker variables refer to variables that are theoretically irrelevant to the focal constructs in the study, and these variables can be explicit variables or latent variables [68]. Motivated by the work of Lindell and Whitney [67], this article set the shoe size of the respondents as a marker variable. Table II reveals that there is no significant correlation between the marker variable and focal constructs. More importantly, controlling the marker variable did not change the significant correlations between every two focal constructs. Hence, common method bias should also have limited influence on this article.

IV. RESULTS

This section began by calculating the values of variables. Prior studies typically averaged or summed scores of the items to estimate variables [58]. However, these approaches ignored the fact that various items contributed differently to each variable. To overcome such a limitation, this article followed the work of Marzi et al. [69] and used a congeneric latent construct estimator. After that, this article examined the variance inflation factor (VIF) values of the focal variables, as collinearity among the predictors might introduce bias into the estimated coefficients. Typically, the VIF values for the predictors should be lower than the threshold of 10 [70]. Given that the largest VIF value in this article was 2.130, collinearity should not have a serious impact on the estimated coefficients. Finally, to determine whether or not mediation models with indirect effects and moderated mediation models are statistically significant [61], in the following section, this article employed the PROCESS macro in SPSS 23.0 with the hierarchical regression analysis and the bootstrapping analysis [71].

A. Mediation Effects

Table III introduces the relationships among different constructs based on the hierarchical regression analysis. First, the independent variable, AI-CVPC, is positively linked to response speed (model 1: $\beta = 0.541$, $p < 0.001$), response expertise (model 3: $\beta = 0.555$, $p < 0.001$), and market performance (model 5: $\beta = 0.609$, $p < 0.001$). Second, when the independent variable and mediators are included in the estimates, as shown in model 6, AI-CVPC ($\beta = 0.281$, $p < 0.001$), response speed ($\beta = 0.229$, $p < 0.001$), response expertise ($\beta = 0.369$, $p < 0.001$) all show a significant relationship with the dependent variable, market performance. According to the logic of stepwise analysis [71], these results indicate the mediation effects of response speed and response expertise on the association between AI-CVPC and market performance.

To further confirm such mediation effects, Table IV presents the results based on the bootstrapping analysis. When neither of the 95% confidence intervals (i.e., the upper and lower) derived from bootstrapping contain 0, the mediation effect of such a path is statistically significant. As expected, the 95% confidence intervals of response speed [0.055, 0.199] and response expertise

TABLE III
HIERARCHICAL REGRESSION ESTIMATES

	Response speed		Response expertise		Market performance	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	2.789***	4.017***	2.664***	4.514***	1.845***	0.222
Control variables						
Firm age	0.049	0.054	0.085**	0.085***	0.020	–0.022
Firm size	–0.016	–0.019	–0.031	–0.029	0.047	0.062
State-owned	0.036	0.026	–0.034	–0.041	0.161	0.166
Privately owned	0.093	0.098	–0.045	–0.043	–0.102	–0.106
Manufacturing	–0.054	–0.061	–0.023	–0.028	0.126	0.147
IT industry	0.019	0.035	–0.121	–0.105	0.180	0.220*
Independent variables						
AI-CVPC	0.541***	0.275*	0.555***	0.215	0.609***	0.281***
Environmental heterogeneity (EH)		–0.239		–0.392*		
AI-CVPC × EH		0.051		0.071**		
Response speed						0.229***
Response expertise						0.369***
Degrees of Freedom	7, 392	9, 390	7, 392	9, 390	7, 392	9, 390
R^2	0.397	0.409	0.430	0.441	0.433	0.544
F-value	36.916***	29.975***	42.268***	34.216***	42.719***	51.680***

Notes: ***, **, and * represent significance at 0.001, 0.01, and 0.05 levels, respectively.

TABLE IV
INDIRECT EFFECTS OF AI-CVPC ON MARKET PERFORMANCE

Paths	Effect	BootSE	BootLLCI	BootULCI
Total	0.329	0.045	0.246	0.423
AI-CVPC → RS → MP	0.124	0.037	0.055	0.199
AI-CVPC → RE → MP	0.205	0.042	0.124	0.290

Note : RS, RE, and MP are the abbreviations of response speed, response expertise, and market performance, respectively.

TABLE V
CONDITIONAL INDIRECT EFFECT TEST

Paths	Values of EH	Effect	BootSE	BootLLCI	BootULCI
AI-CVPC → RS → MP	4.000	0.110	0.036	0.047	0.189
	5.030	0.122	0.035	0.057	0.191
	6.340	0.137	0.038	0.064	0.212
AI-CVPC → RE → MP	4.000	0.184	0.041	0.109	0.268
	5.030	0.211	0.041	0.130	0.290
	6.340	0.245	0.047	0.152	0.339

Note: RS, RE, EH, and MP are the abbreviations of response speed, response expertise, environmental heterogeneity, and market performance, respectively.
EH values in conditional tables are the 16th, 50th, and 84th percentiles.

[0.124, 0.290] do not include 0. These results again verify the mediation effects of response speed and response expertise on the association between AI-CVPC and market performance, thus supporting H1 and H2.

B. Moderated Mediation Effects

Models 2 and 4 in Table III reveal the moderating effect of environmental heterogeneity in the relationship between AI-CVPC and two customer response capabilities. In particular, the interaction between AI-CVPC and environmental heterogeneity has a significantly positive relationship with response expertise ($\beta = 0.071$, $p < 0.01$) and a nonsignificant relationship with response speed ($\beta = 0.051$, $p > 0.05$). These results, thereby, illustrate the positive moderating role of environmental heterogeneity in the relationship between AI-CVPC and response expertise. However, a significant moderating effect does not necessarily mean that the moderated mediation effect is also significant. To this end, this paper conducted a conditional indirect effect test and presented the results in Table V. More importantly, the 95% confidence intervals of the indexes of moderated mediation for response speed and response expertise are [–0.015, 0.030] and [0.001, 0.051], respectively. These results only confirm the significant moderated mediation effect of response expertise on the association between AI-CVPC and market performance, thus supporting H3b but rejecting H3a.

V. DISCUSSION

This article sought to examine the paths of leveraging AI for market success. For this purpose, a moderated mediation model based on the DCT was developed [17]. After performing an analysis of the survey responses from 400 Chinese firms operating in a variety of sectors, the following are some significant discoveries.

First, similar to previous studies that suggest the positive effect of AI on innovation [25], servitization [11], and B2B marketing [38], this article finds a positive association between AI-CVPC and market performance. From a DCT perspective, such a positive effect can be attributed to the fact that firms with higher levels of AI-CVPC are better able to seize and seize opportunities derived from changes in customer preferences and market demand. In the context of digitalization, Torres et al. [72] interviewed 171 business professionals and found that business intelligence and analytics can help firms develop dynamic capabilities related to sensing and seizing, which eventually contribute to the improvement of firm performance. Surveying 165 Chinese manufacturing firms, Li et al. [34] revealed that digitalization capabilities, that is, the ability of a firm to leverage digital technologies to integrate data and processes, can enhance firm performance by enabling firms to better sense and seize unexpected trends. These two studies indirectly support the findings of the presented research.

Second, this article shows that two customer response capabilities, that is, response speed and expertise [28], are two key mediators that link the association between AI-CVPC and market performance. From a DCT perspective, the reason for such significant mediation effects is that firms need more than sensing and seizing capabilities if they want to maintain their advantage in the market; they also need to develop restructuring capabilities. In this sense, customer response capabilities in relation to firms re-modifying, rebuilding, and redesigning their actions are quite important for linking the association between AI-CVPC and market performance. Similar to the findings of this study, Kumar et al. [5] adopted a mixed-method approach in healthcare and found that customer service flexibility is a key mediator that explains how AI-enabled customer relationship management capability influences service innovation. In the context of a big disaster, Li et al. [73] also proved that reactive capability is an important factor that enables firms that deploy big data to achieve superior supply chain performance.

Third, although studies have shown that environmental factors are important moderators that determine the outcome of digitalization [22], [24], [74], in the context of AI applications, this article further reveals that environmental heterogeneity primarily enhances the mediation effect of response expertise, rather than the mediation effect of response speed. One possible reason is that increased environmental heterogeneity leads to longer processing times for AI. Nevertheless, owing to the ongoing advancements in AI processing capabilities, the disparity in processing times between low and high environmental heterogeneity is tiny. This characteristic poses a challenge for customers to discern little variations in processing time, leading to the insignificance of the moderating role of environmental heterogeneity in response speed.

Another reason is that more and more firms are utilizing AI chatbots to improve their customer service [48], allowing a great improvement in response speed. However, this also means that simply relying on response speed cannot allow customers to obtain a differentiated service experience. Many studies have confirmed that differentiated service experience is the key to successful customer relationship management [75]. Some statistics also show that while the majority of online customers demand a response time of fewer than five minutes, just 30% of customers find AI chatbots extremely helpful in solving problems [57], and 86% of consumers prefer humans to chatbots [76]. Hence, facing high environmental heterogeneity, firms may pay more attention to the improvement of response expertise than response speed.

A. Theoretical Implications

Several theoretical contributions are made in this article. First, the present operationalization and conceptualization of AI capabilities are predominantly concentrated in a few contexts, such as business model innovation [9], organizational creativity [8], and service innovation [5]. While these studies contribute to understanding the role of AI in business, they cannot adequately answer questions such as how firms should prioritize their AI deployments and how to leverage AI to reshape their value propositions. Wessel et al. [77] have argued that one of the primary distinctions between digital transformation and IT-enabled organizational transformation is that the former aims to use digital technologies to (re)define the value proposition, whereas the latter is to use digital technologies to support the value proposition. Because AI is a crucial catalyst for digital transformation [78], understanding how firms develop AI capabilities related to value propositions is important [11]. Compared with previous studies, this paper contributes to the existing literature on the comprehension of AI capabilities by elaborating on the business outcome of AI-CVPC.

Second, because the modern business environment is characterized by volatility, instability, and high levels of uncertainty [20], many studies have used the DCT to understand the phenomenon related to digitalization [23], big data analytics [79], and AI applications [27]. Although these studies help to understand how digitalization and digital technology usage provide firms with business value [26], [80], some of them primarily leverage the opinions of DCT and lack variables explicitly associated with dynamic capabilities. Dynamic capabilities are the higher order capabilities for a firm [32], which implies that, for many firms, dynamic capabilities may be too theoretical, calling for the creation of more tangible capabilities to aid in the successful execution of related capability development strategies. This article reifies dynamic capabilities in the AI application context as AI-CVPC, response speed, and response expertise and reveals their corresponding relationships, deepening the current understanding of the microfoundation of dynamic capabilities.

Third, in service research, customer response capabilities are regarded as important drivers that lead to service success [28]. Even in some broader contexts, such as supply chain disruptions [51], [73], supply chain collaboration [50], and supply chain visibility [81], customer response capabilities have also been shown to be critical for achieving sustainable performance. Although past studies have made great contributions, they typically operationalize customer response capabilities as a whole and do not distinguish various segmentation dimensions. Such a gap may lead to a limited understanding regarding which components of customer response capabilities should be prioritized. Motivated by the work of Setia et al. [18], this article divides customer response capabilities into two dimensions: response speed and response expertise. More importantly, this article has confirmed their unique mediation role in the association between AI-CVPC and market performance under different degrees of environmental heterogeneity, thereby expanding the current understanding of customer response capabilities.

B. Managerial Implications

This article finds that firms that actively participate in AI activities often perform better than those that do not, indicating that embracing should be a major trend for global firms. Nevertheless, many firms are still confused about how to conduct effective AI-related activities. To address such confusion, some practical implications derived from the present findings are as follows.

First, this article illustrates that AI-CVPC plays a significant role in the market success of firms; hence, developing such a capability may be a viable direction for those firms that have not yet chosen the priority of AI deployment. In particular, firms should consider developing efficient and friendly service chatbots [11]. This is because customers have come to expect speedy and pleasant service from every firm they interact with; AI chatbots may help firms meet this expectation by offering consistent, high-quality support [41], [42]. In addition, to further strengthen relationships with customers and provide new goods or services that enhance sales, firms should explore using AI to deliver accurate, individualized advice to customers. To do this, firms must apply text analytics based on deep learning personalization algorithms to consumer feedback and evaluations in order to better comprehend customers and obtain valuable insights about their purchasing preferences [16].

Second, this article suggests that response speed is an important factor that links the association between AI-CVPC and market performance. Hence, to ensure the positive effect of AI-CVPC on market performance, firms should improve their response speed. A feasible way for firms is to utilize AI to develop 24/7 support. This is because modern customers are digitally connected, purchasing online around the clock and seeking support outside of business hours [48]. Facing such a purchasing habit, firms need to provide service and support outside of normal business hours to retain these customers. However, it is virtually impossible for most firms to maintain their staff working outside business hours while remaining within budget. Hence, firms must utilize AI to develop 24/7 support, enabling customers to change their order, book an appointment, or get a question answered in a timely manner.

Third, to enhance the positive association between AI-CVPC and market performance, firms cannot ignore the role of response expertise, especially in a business environment with high environmental heterogeneity. To improve response expertise, firms need to make use of AI to improve the processing of unstructured data such as sales records, logs, weekly reports, and monthly reports. This will enable firms to gain insight into the effectiveness of work performed in the process of serving or following up with customers, which will, in turn, improve the expertise experience of customer service [5]. Moreover, firms should use AI to empower their employees [82]. This requires firms to use machine learning and other technologies to identify and recommend relevant knowledge to the necessary employees and to use AI knowledge management systems to help employees share knowledge, thereby making knowledge sharing smoother and more efficient [83].

VI. Conclusion

AI is an important driving force for a new round of technological revolution and industrial transformation. To help firms better implement their AI initiatives, this article draws on the DCT to investigate the relationships among AI-CVPC, two customer response capabilities (i.e., response speed and response expertise), environmental heterogeneity, and market performance. Analyzing the sample of 400 Chinese firms across various sectors, this article finds a positive association between AI-CVPC and market performance, and two essential mediators related to this association are response speed and response expertise. More importantly, environmental heterogeneity reveals a significant moderating effect on the association between AI-CVPC and market performance. These findings contribute to the growing body of business literature on AI by shedding light on how firms might more successfully integrate AI into their operations.

Although this article has produced several novel and intriguing findings, it is also important to acknowledge its limits and provide inspiration for future research. First, this article mainly focuses on AI capabilities related to the customer value proposition. However, AI may be utilized to increase consumer value propositions, optimize crucial resources and processes, and even contribute to the societal good [11]. Future research, therefore, can explore the relationship between AI capabilities and market performance from a broader capability perspective. Second, given the increasing emphasis on environmental issues, stakeholders are not only concerned with the market success of firms but also with the extent to which firms contribute to environmental sustainability. It implies that future research could examine the relationship between AI capabilities and environmental performance. Third, this article explains how firms could maintain and expand the positive effect of AI-CVPC on market performance. However, AI is not always beneficial. Therefore, it would be interesting to further investigate how to mitigate the negative impacts of AI on employees and operations.

Appendix

See Fig. 2.

Construct	Measurement items
Artificial intelligence-enabled customer value proposition capability, AI-CVPC, adapted from Abou-Foul et al. (2023) (CR = 0.856; AVE = 0.599; Cronbach's α = 0.856)	• Our firm is collecting after-sales insights and uses AI to personalize the customer experience and ensure our customers' success. (FL = 0.806) • Our specialized data science team uses tools to calculate our customer's optimal warranty cost and duration. (FL = 0.748) • Our firm is using machine learning models in pricing and quoting optimization. (FL = 0.766) • Our firm collects and analyses embedded sensor data to provide our customers with predictive maintenance, and operation optimization services. (FL = 0.774)
Response speed, RS, adapted from Setia et al. (2013) (CR = 0.833; AVE = 0.555; Cronbach's α = 0.830)	• When we identify a new customer need, we are quick to respond to it. (FL = 0.797) • When we find that customers are unhappy with the appropriateness of our product/service, we take corrective action immediately. (FL = 0.691) • We believe in being proactive to shape market demand than being reactive. (FL = 0.705) • When we discover that customers want to modify the product/service, various departments make related efforts. (FL = 0.782)
Response expertise, RE, adapted from Setia et al. (2013) (CR = 0.795; AVE = 0.564; Cronbach's α = 0.793)	• We can easily satisfy the new needs of customers. (FL = 0.696) • We can satisfy the needs of customers than other peers. (FL = 0.776) • We have a solid reputation for effectively meeting customer needs. (FL = 0.779)
Environment heterogeneity, EH, adapted from Mikalef et al. (2019) (CR = 0.876; AVE = 0.702; Cronbach's α = 0.875)	• Our customer buying habits are changing rapidly. (FL = 0.847) • The competitive attributes of our firm's products/services change rapidly. (FL = 0.794) • Our firm's product line changes rapidly. (FL = 0.870)
Market performance, MP, adapted from Wang et al. (2012) (CR = 0.858; AVE = 0.602; Cronbach's α = 0.858)	*Over the past three years...* • ...we have entered new markets more quickly than our competitors. (FL = 0.802) • ...we have introduced new products or services to the market faster than our competitors. (FL = 0.785) • ...our success rate of new products or services has been higher than that of our competitors. (FL = 0.739) • ...our market share has exceeded that of our competitors. (FL = 0.777)

Note: FL is the abbreviation of factor loadings; the content in the right box is the measurement items of the corresponding construct.

Fig. 2. Measurement of constructs.

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