INVESTIGATING THE EFFECT OF ARTIFICIAL INTELLIGENCE ON CUSTOMER RELATIONSHIP MANAGEMENT PERFORMANCE IN E-COMMERCE ENTERPRISES

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ABSTRACT

Despite the importance of artificial intelligence (AI) technologies in improving customer relationships, AI usage in enabling customer relationship management (CRM) capabilities and, in turn, enhancing CRM performance has not yet been investigated. This study from the IT-enabled organizational capabilities perspective investigates the impact of AI usage on CRM performance and the mediating effect of CRM capabilities. We tested our core proposition and theory-driven research model using data collected from a sample of 193 e-commerce enterprises in China. The empirical results indicate that AI usage positively impacts CRM performance and that CRM capabilities positively mediate their relationship. Thus, this paper contributes to IS research with an eloquent theoretical explanation and strong empirical evidence on why e-commerce enterprises deploy AI initiatives to improve their CRM capabilities and performance.

Keywords: AI usage; CRM capabilities; CRM performance; E-commerce enterprise

1. Introduction

Stable customer relationships are a vital strategic resource for enterprises in a customer-dominated market (Li et al., 2020; Guerola Navarro et al., 2021). Especially in e-commerce enterprises, due to the wide variety and fungibility of online products, customer loyalty and retention rate is insufficient, leading to low customer relationship management (CRM) performance (Chandra and Kumar, 2018; Komarek et al., 2020; Zhang et al., 2020; Zhao et al., 2021). Strengthening customer relationships and improving CRM performance are significant measures for the competitive advantage of e-commerce enterprises. Artificial intelligence (AI) is an idiosyncratic new digital technology widely used in CRM to provide competitive advantages (Saura et al., 2021). Enterprises utilize AI technologies (such as chatbots, customer feature recognition, and intelligent agent) to manage different marketing

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activities, to acquire, retain, and manage strong customer relationships. AI can manage and analyze a large volume of customer data to generate insights that improve firms' decision-making and timely responses to customer needs (Johnson et al., 2022). AI can also offer personalized recommendations to consumers, reducing the cost of information searches and improving the match between consumers and products (Olan et al., 2022). All in all, AI in marketing applications provides an interactive environment that can swiftly meet customers' demands and create an immense pool of loyal customers for businesses, improving CRM performance.

Although increasingly more managers have recognized the importance of AI technology, knowledge is still limited due to the gap existing in the current literature. Previous studies have presented inconsistent conclusions regarding the impact of AI usage on CRM performance. Some researchers have indicated that AI usage provides customers with rich and reliable information, personalized customization, and accurate problem-solving methods, thus improving customer satisfaction (Li and Mao, 2015; Saura et al., 2021; Johnson et al., 2022; Li and Xu, 2022; Nazir et al., 2023; Rahman et al., 2023), while others argue that AI usage reduces consumer autonomy or causes users to feel that interactions are insincere, thereby reducing favorability and purchase intention (Go and Sundar, 2019; Mikalef and Gupta, 2021; Cao et al., 2023; Jan et al., 2023). From IT-enabled organizational capabilities perspective, this inconsistency can be explained by mediation processes that translate AI usage into CRM performance. CRM capabilities are the ability of enterprises to maintain long-term customer relationships and gain customer-level profits (Guerola Navarro et al., 2021). It can improve customer satisfaction, loyalty, and retention can by retaining key customers, enhancing value customers, and exploring potential customers (Demlehner et al., 2021). Moreover, AI usage can help e-commerce enterprises quickly learn, judge, and make decisions based on large-scale data, gain insight into customer needs, and improve CRM capabilities (Li and Xu, 2022). To wit, CRM capabilities may play a mediating role between AI usage and CRM performance, but empirical evidence of its role as a mediator is scarce. Therefore, we intend to explore it further in this paper.

To address the above research gaps, we draw on the perspective of IT-enabled organizational capabilities to develop a model that explores the impact of AI usage on CRM performance in e-commerce enterprises and the mediating role of CRM capabilities between them. This study makes two key contributions. First, it expands the information systems (IS) research on the business value of IT by providing empirical evidence on how e-commerce enterprises leverage AI to facilitate CRM performance. Second, it provides a novel lens for revealing how AI usage (i.e. Specific IT) positively influences CRM performance in e-commerce enterprises by the mediation role of CRM capabilities (i.e. organizational capabilities).

2. Theoretical Background and Related Research

2.1. IT-enabled Organizational Capabilities Perspective

The IT-enabled organizational capabilities perspective proposes IT resources and capabilities as the enabling factors to develop organizational capabilities, thus affecting firm performance (Benitez et al., 2018a; Turel et al., 2019). This theoretical perspective emphasizes how IT creates business value through the mediating variables (Braojos et al., 2020). Prior IS research consistent with this perspective has found that risk management capabilities(Lin et al., 2022), platform digitization capability (Benitez et al., 2022), knowledge exploration and knowledge exploitation (Castillo et al., 2021), and absorptive capacity (Liu et al., 2013) are organizational capabilities through which IT influences firm performance. In the context of this research, AI usage, as IT usage, reflects the enterprise's IT resources (Ghasemaghaei et al., 2017; Ghasemaghaei and Turel, 2021). CRM capabilities refer to the ability of enterprises to integrate and allocate resources to maintain customer relationships, which is considered as organizational capabilities to efficiently solve the problem of enterprise customer relationship (Wang and Feng, 2012; Guerola-Navarro et al., 2021). E-commerce enterprises develop organizational capabilities (e.g. CRM capabilities) by leveraging IT resources (e.g. AI usage), thus improving CRM performance. Therefore, we draw on this perspective to propose the impact of AI usage on CRM performance through CRM capabilities.

2.2. AI Usage

With its full empowerment, AI has become a significant area of research in almost every field, including engineering, medicine, business management, science, law, and marketing (Johnson et al., 2022). Some have defined it as using computers to simulate intelligent human behavior, including human learning, judgment, and decision-making (Shankar, 2018; Spanaki et al., 2021). Others defined it as a system that correctly interprets external data and can achieve specified goals and tasks by gaining insights from data (Libai et al., 2020). In our study, AI is defined as the process of learning and expressing knowledge, and its core is enabling machines to reason and perform related activities, such as decision-making, problem-solving, and learning (Olan et al., 2022). AI usage refers to utilizing AI technology in marketing activities to achieve specific goals and tasks, including improving user experience, optimizing decision-making, and enhancing content marketing (Verma et al., 2021). AI technology can analyze data with high speed, quantity, and diversity, and process complex cognition, relationships, and structures by changing or replacing conventional human tasks (Verma et al., 2021). The effect of AI usage on an enterprise's competitive advantage has long been an academic concern. Prior research suggests that embedded digital technology such as AI, in organizational processes can optimally improve organizational performance (Fosso Wamba, 2022; Olan et al., 2022). Researchers have found that AI usage can create digital options, optimize decisions, enhance productivity, and control costs, improving business performance (Demlehner et al., 2021; Dondapati et al., 2022). Moreover, it can optimize marketing decision-making, improve the consumer experience, help build trust, and positively impact firm performance (Wamba-Taguimdje et al., 2020; Saura et al., 2021; Badawi et al., 2022). However, negative studies have also found that AI programming ignores consumers' uniqueness, and data-driven algorithms bring the risk of information disclosure, thus causing consumer resistance and adverse effects on enterprises' performance (Longoni et al., 2019; Brougham and Haar, 2020). In this sense, we are cognizant that there is no consistent research conclusion on the impact of AI usage on enterprise performance, and the mechanisms are unknown. Therefore, more research on the effects of AI usage on enterprise performance is warranted.

2.3. CRM Capabilities

CRM capabilities refer to the ability of enterprises to build continuous customer relationships by allocating organizational resources to meet different consumer needs, including key customers, value customers, and inactive customers (Hung et al., 2010; Guerola-Navarro et al., 2021). CRM capabilities reflect the enterprise through the resource allocation of various departments to insight consumer demand, and perception response to market opportunities and threats (Foltean et al., 2019). In a data-driven age, the core of CRM capabilities is to provide decision support for enterprises by mining customer data, thus satisfying customer needs and establishing long-term and mutually beneficial relationships (Li et al., 2019). AI can combine big data, the Internet of Things, and deep learning to scientifically analyze large amounts of customer data and provide decisions and solutions in milliseconds (Li and Xu, 2022). AI usage can give technical support for CRM, ensuring that enterprises' activities are closely aligned with customers' needs, thereby facilitating the formation of CRM capabilities. Further, CRM capabilities can improve enterprise performance by improving customer loyalty, shortening the product cycle, and reducing customer development and transaction costs (Dalla Pozza et al., 2018; Foltean et al., 2019). In this way, CRM capabilities mediate between AI usage and enterprise performance, but empirical research is lacking. Consequently, we explore it further in this paper.

According to Wang and Feng (2012), CRM capabilities have three facets: customer interaction management capability, customer relationship upgrading capability, and customer win-back capability. Customer interaction management capability refers to firms' skills to identify, acquire, and retain profitable customers (Guerola-Navarro et al., 2021). Customer relationship upgrading capability refers to the skills that firms use for up-selling (selling more expensive items or upgrades) and cross-selling (selling additional products or services) to existing customers based on scientific customer data analysis (Guerola Navarro et al., 2021). Customer win-back capability is a firm's skills to re-establish relationships with lost or inactive but profitable customers (Wang and Feng, 2012).

2.4. CRM Performance

Enterprise performance is a measure of the degree to which an enterprise achieves its goals and is also the final result of the operation (Fosso et al., 2017; Gupta et al., 2020). This study considers CRM performance from the perspective of customer relationships in e-commerce enterprises. CRM performance refers to the degree to which customers are willing to maintain a long-term relationship with the enterprise and includes customer satisfaction, customer loyalty, and customer retention (Dalla Pozza et al., 2018; Zhang et al., 2020). Superior CRM performance enables enterprises to better understand customer needs, find market opportunities, and gain competitive advantages (Guerola-Navarro et al., 2021). According to scholars, digital technology is a powerful driver of CRM performance. Zhang et al., (2020) indicated that as an enterprise resource, big data analytical intelligence enables enterprises to develop mass customization capability, thus positively impacting CRM performance. Trainor et al., (2014) pointed out that social media technology use and customer-centric management can drive social CRM capabilities that lead to customer satisfaction, loyalty, and retention. Li and Xu (2022) found that AI improves customer retention and satisfaction through human-machine interaction and precise advertising. Although many studies have explored the impact of digital technologies on CRM performance, they mainly focus on enterprises in the general industry, and there are few studies on enterprises in specific sectors (e.g., e-commerce enterprises). In practice, the variety of online products and strong substitutability lead to low customer retention and loyalty for e-commerce enterprises. Using digital technology to help enterprises develop customer relationships and improve CRM performance is vital for e-commerce enterprises (Wang et al., 2022). Therefore, this study develops a theoretical model of AI-driven CRM capabilities to improve CRM performance for e-commerce enterprises.

3. Research Model and Hypotheses

From perspective of the IT-enabled organizational capabilities, this study develops a theoretical model that explores the impact of AI usage on CRM performance in e-commerce enterprises. The research model is shown in Figure 1.

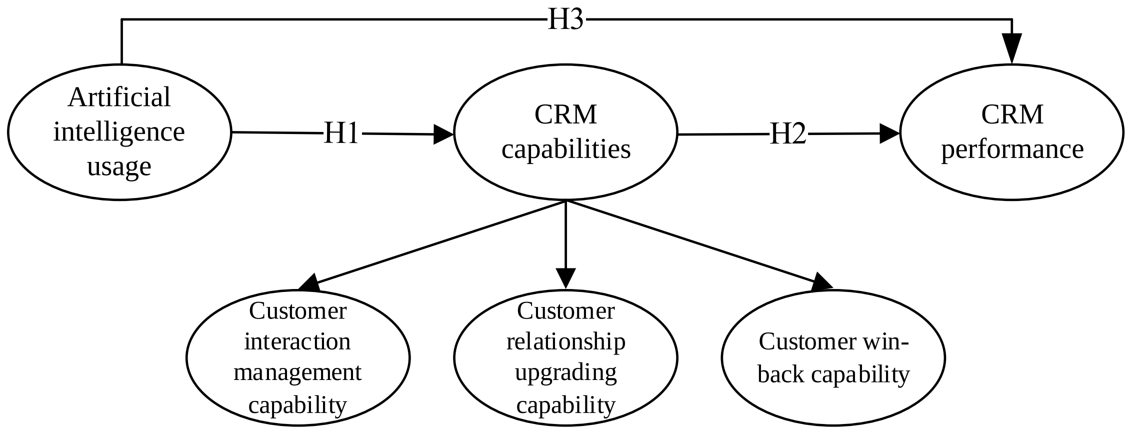

Figure 1: Research Model

3.1. AI usage and CRM Capabilities

AI is based on powerful information integration and efficient coordination to respond quickly to customer needs, enabling collaboration across levels and departments to achieve sustained customer relationships (Di Vaio et al., 2020; Guerola Navarro et al., 2021). This process is a transition from IT technology (e.g., AI usage) to organizational capabilities (e.g., CRM capabilities), reflecting IT- enabled organizational capabilities perspective. In detail, through system algorithms, AI can standardize frequently asked questions and automatically provide satisfactory answers for customers to solve their problems in real-time and improve customer satisfaction (Brougham and Haar, 2020). Second, AI builds a consumption model for a single customer by accurately analyzing customer behavior data, including searches, favorites, likes, comments, forwarding, dropdowns, and swipes (Foltean et al., 2019). Then, through association analysis, e-commerce enterprises can identify the product content consumers may be interested in and push it to them to achieve precision marketing (Johnson et al., 2022). Furthermore, AI can help enterprises analyze customers' historical transaction records and demographic information, identify patterns leading to customer churn, and predict the churn tendency of existing customers before taking corresponding measures to retain them (Li and Xu, 2022). All in all, AI usage enables the development of CRM capabilities across departments, including product development, marketing, and after-sales, to meet dynamic customer needs. Therefore, we hypothesize the following:

H1: AI usage has a positive impact on CRM capabilities in e-commerce enterprises.

3.2. CRM Capabilities and Performance

CRM capabilities enable e-commerce enterprises to configure and reorganize internal and external resources, proactively utilize, analyze and manage customer data and quickly respond to customer needs (Foltean et al., 2019). CRM capabilities can enable e-commerce enterprises to fully grasp customer information, including customer feedback, personalized needs, and consumer preferences, and improve products and services, promoting CRM performance (Dalla Pozza et al., 2018). To be clear, customer interaction management capability can help e-commerce enterprises identify critical customers, form stable partnerships and credit relationships, and improve customer stickiness (Wang et al., 2016). Second, e-commerce enterprises with a high customer relationship upgrading capability can sell high-quality related products and services to customers through cross-selling and additional selling, increasing purchase frequency and improving satisfaction (Guerola Navarro et al., 2021). Third, customer win-back capability can monitor the current situation and the reasons for customer loss and quickly find operational links that need to be improved to re-establish trust with lost customers (Li et al., 2019). In short, the three dimensions of CRM capabilities can respond to customer needs in different aspects of e-commerce enterprises, thereby enhancing CRM performance. Hence, we hypothesize the following:

H2: CRM capabilities have a positive impact on CRM performance in e-commerce enterprises.

3.3. AI Usage and CRM Performance

The development of customer relationships is a dynamic process; AI usage can help e-commerce enterprises to find new customers, retain existing customers, and achieve effective communication with customers (Li and Xu, 2022). Specifically, AI technology can analyze chaotic data from social networks, databases, and search engines to gain insights into individual buying habits and preferences and target customers (Johnson et al., 2022). In the purchase phase, AI provides customers with accurate product information and consulting services and responds to customer doubts, thus promoting the cross-selling and up-selling of products (Demlehner et al., 2021). In the post-sale phase, AI could also standardize frequently asked questions and automatically provide satisfactory answers to solve customers' problems in real-time and improve customer satisfaction (Di Vaio et al., 2020). In addition, e-commerce enterprises can use AI technology to conduct customer satisfaction surveys and identify potential emotions (e.g., happy, sad, calm, or angry) to monitor customer churn and achieve customer care (Chatterjee et al., 2021). In summary, AI usage can support digitization in e-commerce enterprises, optimize decision-making, and help enterprises understand consumer behavior, which is crucial for e-commerce enterprises to stabilize customer relations and improve customer service quality. Accordingly, we hypothesize the following:

H3: AI usage has a positive impact on CRM performance in e-commerce enterprises.

4. Research Design

4.1. Scale Development

This study includes five key variables: AI usage, customer interaction management capability, customer relationship upgrading capability, customer win-back capability, and CRM performance. To ensure content validity, the measurement items were taken from extant literature and modified in the context of e-commerce enterprises to fit the needs of this study (see appendix). AI usage was measured by four items adapted from Libai et al. (2020) and Shankar (2018); customer interaction management capability was measured by five items, customer relationship upgrading capability was measured by four items, customer win-back capability was measured by four items, all of which were adapted from Foltean et al. (2019) and Wang and Feng (2012); CRM performance was measured by five items adapted from Trainor et al. (2014). Moreover, we compared the relevant literature to obtain major control variables that may have potential confounding effects on CRM performance (Li, 2022; Li et al., 2022; Ye et al., 2022). Control variables in the present research included firms' region which was measured as the location of the firm, firm size which was measured as the number of employees, and AI experience which was measured as the number of years the firm has used AI. Since the survey was conducted in China, we followed the forward-backward translation method to develop the Chinese questionnaire. First, the questionnaire was translated into Chinese by a co-author whose native language was Chinese. Second, three other bilingual doctoral students back-translated the Chinese items into English and compared the two versions, modifying the wording differences for the accuracy of the Chinese items. Finally, we pretested the questionnaire with 30 students majoring in artificial intelligence and refined the wording of the scale according to their feedback to form the final questionnaire.

4.2. Data Collection

Agricultural e-commerce is booming in China and has attracted extensive attention from industry and academia. We conducted an online questionnaire on e-commerce enterprises from the database of the Department of Agriculture and Rural Affairs of China and sold agricultural products. Each enterprise selected a key informant, and we sent a questionnaire to the target respondents in May 2021. After three weeks, 211 completed questionnaires were collected. We excluded 18 questionnaires, including those with answer times of less than one minute or more than 30 minutes and those whose enterprises did not use AI, and 193 valid questionnaires were collected. To thank them for their participation, respondents who completed the questionnaire received a red envelope of 10–20 yuan. Table 1 presents the characteristics of the sample. Among the sample surveyed, 83.3% were small- and medium-sized enterprises, and most (76.7%) of the enterprises were located in China's eastern, northern, and southern regions. Moreover, regarding AI usage, 14% within a year. 44.6% for 1-3 years, 21.2% for 4-5 years, and 20.2% for 5 years.

Table 1: Statistical Characteristics of the Sample Enterprises (N = 193)

Attributes	Option	Frequency	Percentage
Firms' region	East China	67	34.7
	South China	46	23.8
	Central China	32	16.6
	North China	35	18.2
	Others	13	6.7
Firm size	<50	18	9.3
	50–200	54	28.0
	201–500	51	26.4
	501–1000	32	16.6
	>1000	38	16.7
AI experience (years)	Never used	0	0.0

	<1	27	14.0
	1–3	86	44.6
	4–5	41	21.2
	>5	39	20.2

5. Empirical Analysis and Results

5.1. Common Method Bias Assessment

We utilized the marker variable technique proposed by Lindell and Whitney (2001) to control for common method bias. In this study, gender was considered to have no relationship with any variable in the model and was used as a marker variable (Ghasemaghaei and Calic, 2020). We then added gender as an exogenous variable to predict each endogenous construct in the research model and compared the models with and without marker variables (Hua et al., 2020). Table 2 shows that there were no significant correlations between the marker variable and each endogenous variable, and the significant paths in the baseline model remained significant after adding the marker variable. Therefore, common method bias was not a problem in this study.

Table 2: Common Method Bias Assessment

	Baseline model (without marker variable)	Adjusted model (with marker variable)
AI usage →CRM capabilities	0.566***	00.564***
CRM capabilities → CRM performance	0.656***	0.628***
AI usage → CRM capabilities	0.167*	0.851**
Maker → CRM capabilities		-0.003
Maker → CRM performance		0.028

5.2. Measurement Model Evaluation

ADANCO is software that is widely adopted for variance based structural equation modeling including abundant statistical techniques, such as partial least squares (PLS) path modeling, ordinary least squares (OLS), consistent PLS, and bootstrapping, providing a bootstrap-based goodness of overall model fit and model diagnostics (Benitez et al., 2020a; Benitez et al., 2020b). In recent years, ADANCO has been consistently used in IS research (Lin et al., 2021; Benitez et al., 2022; Hou et al., 2022).

Variance-based PLS (e.g., ADANCO) is more suitable for our study than covariance-based SEM. First, PLS has advantages in the model estimation of small to medium sample sizes (Yu et al., 2018). In this research, our sample size of 193 is not large, which is sufficient for the use of the PLS technique. Second, PLS does not require identical distribution of residuals (Liu et al., 2018). To examine the coefficients of skewness and kurtosis, we found that our sample data does not fully follow the normal distribution.

In addition, all constructs in this study were considered composite constructs (Benitez et al., 2020a; Benitez et al., 2020b), we used advanced analysis for composites (ADANCO) to estimate the proposed model. Table 3 shows the results of the measurement model assessment. The values of variance inflation factors (VIFs) ranged from 1.085 to 1.383, less than the cutoff score of 10, suggesting that multicollinearity was not a problem. All indicator weights were significant (from 0.145^{***} to 0.566^{***}), and all indicator loadings ranged from 0.482^{**} to 0.860^{***}. Thus, our constructs have good measurement properties.

We also performed a confirmatory composite analysis to evaluate the goodness of fit of our saturated model at first- and second-order levels (Table 4). The results show that standardized root means squared residuals (SRMR) were 0.054 and 0.042, and both values were lower than the threshold of 0.080, and SRMR, d_{ULS}, and d_G were within the 95% and 99% quantiles of bootstrap discrepancies, indicating that the proposed model has good general measurement properties.

Table 3: Measurement Model Assessment

Variables	Item	Loading	Weight	VIF
AI usage	AIU1	0.675***	0.430***	1.136
	AIU2	0.614***	0.287**	1.185
	AIU3	0.641***	0.290**	1.219
	AIU4	0.715***	0.486***	1.124
Customer interaction management capability	CIMC1	0.636***	0.413***	1.130
	CIMC2	0.620***	0.363***	1.135
	CIMC3	0.603***	0.274***	1.261
	CIMC4	0.580***	0.357***	1.085
	CIMC5	0.641***	0.219***	1.383
Customer relationship upgrading capability	CRUC1	0.706***	0.374***	1.229
	CRUC2	0.693***	0.259***	1.473
	CRUC3	0.860***	0.566***	1.341
	CRUC4	0.482**	0.145***	1.251
Customer win-back capability	CWBC1	0.751***	0.466***	1.206
	CWBC2	0.751***	0.365***	1.351
	CWBC3	0.491***	0.208***	1.106
	CWBC4	0.706***	0.389***	1.244
CRM performance	CRMP1	0.614***	0.275***	1.194
	CRMP2	0.705***	0.389***	1.285
	CRMP3	0.627***	0.206**	1.351
	CRMP4	0.641***	0.314***	1.227
	CRMP5	0.611***	0.371***	1.111

Table 4: Confirmatory Composite Analysis

Discrepancy	First-order level			Second-order level		
	Value	HI_{99}	Conclusion	Value	HI_{95}	Conclusion
SRMR	0.054	0.059	Supported	0.042	0.043	Supported
d_{ULS}	0.269	0.318	Supported	0.136	0.147	Supported
d_G	0.097	0.114	Supported	0.063	0.064	Supported

5.3. Structural Model Evaluation

We evaluated the path coefficient (β), significance level, R^2, adjusted R^2, and effect size (f^2) for the structural model. The results showed that all hypotheses were supported. Specifically, AI usage positively affected CRM capabilities ($\beta = 0.566$, $p < 0.001$), supporting H1. CRM capabilities positively affected CRM performance ($\beta = 0.658$, $p < 0.001$), supporting H2. AI usage positively affected CRM performance ($\beta = 0.148$, $p < 0.05$), supporting H3. In addition, we used firms' region, firm size, and AI experience as control variables to test their impact on CRM performance. We found that firms' region ($\beta = -0.010$, ns), firm size ($\beta = -0.019$, ns), and AI experience ($\beta = 0.068$, ns) had no significant effect on CRM performance.

The R^2 values of CRM performance was 0.592, indicating good explanatory power. Furthermore, f^2 values ranged from 0.035 to 0.709, indicating moderate-to-strong effect sizes in our hypothesized significant relationships. We also evaluated the goodness of fit for the structural model. SRMR, d_{ULS}, and d_G were all within the standard range, indicating a good fit between the model and the data. Overall, the results show that our structural model is statistically robust. Table 5 summarizes the results of the final test.

Table 5: Structural Model Assessment

Beta coefficient	Research model	
AI usage → CRM capabilities (H1)	0.566^{***} (9.101) [0.406, 0.726]	
CRM capabilities → CRM performance (H2)	0.658^{***} (11.323) [0.049, 0.421]	
AI usage → CRM performance (H3)	0.148^{*} (2.106) [-0.023, 0.342]	
firms' region → CRM performance (CV)	-0.010 (-0.194) [-0.144, 0.124]	
Firm size → CRM performance (CV)	-0.019 (-0.364) [-0.159, 0.127]	
AI experience → CRM performance (CV)	0.068 (1.208) [-0.083, 0.222]	
Endogenous variable	R^2	Adjusted R^2
CRM capabilities	0.320	0.317
CRM performance	0.592	0.578
Discrepancy	Value	HI_{95}
SRMR	0.044	0.049
d_{ULS}	0.268	0.327
d_G	0.096	0.119
f^2		
AI usage → CRM capabilities (H1)	0.471	
CRM capabilities → CRM performance (H2)	0.709	
AI usage → CRM performance (H3)	0.035	

Note: t-values are presented in parentheses. Confidence intervals are presented in square brackets. $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$. CV=control variable.

5.4. Mediating Effect Testing

Mediating effects were tested by examining whether the indirect effects of independent on dependent variables were significant. The results are shown in Table 6. The indirect and direct effects of the relationship between AI usage and CRM performance were significant, indicating that CRM capabilities were a partial mediator between them.

Table 6: Mediating Effects Assessment

Effect	Indirect effect	Direct effect	Total effect
AI usage → CRM performance	0.372^{***} (6.110) [0.232, 0.545]	0.148^{*} (2.106) [-0.023, 0.342]	0.520 (7.818) [0.359, 0.695]

Note: t-values are presented in parentheses. Confidence intervals are presented in square brackets. $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$.

5.5. Test of Robustness

Three alternative models were estimated to test the robustness of the proposed model. The results are shown in Table 7. In the first alternative model, we assumed that AI usage affected CRM performance through three dimensions of CRM capabilities (mediating variables were customer interaction management capability, customer relationship upgrading capability, and customer win-back capability). The results showed that the SRMR, dULS, and dG were not in the 95% and 99% quantiles of bootstrap discrepancies, indicating that the model fit of alternative model 1 was insufficient. Therefore, the baseline model was better than alternative model 1. In alternative model 2, we considered that CRM capabilities directly affected CRM performance, and AI usage moderated the relationship between them. The empirical results showed that AI usage had no moderating effect. Thus, the baseline model is better than alternative model 2. In alternative model 3, both AI usage and CRM capabilities directly affected CRM performance. The SRMR value of alternative model 3 was greater than the baseline model. Accordingly, the results showed that the baseline model was better. On balance, these alternative models are not statistically better than the proposed research model, so the proposed research model is preferred.

Table 7: Test of Robustness

Beta coefficient	Baseline model		Alternative 1		Alternative 2		Alternative 3	
AI usage → CRM capabilities (H1)	0.566^{***} (9.068)				0.177^{**} (2.789)			
CRM capabilities → CRM performance (H2)	0.656^{***} (11.663)				0.667^{***} (12.299)		0.651^{***} (12.348)	
AI usage → CRM performance (H3)	0.167^{*} (2.367)						0.187^{**} (2.900)	
AI usage → Customer interaction management capability			0.485^{***} (6.548)					
AI usage → Customer relationship upgrading capability			0.489^{***} (7.382)					
AI usage → Customer win-back capability			0.507^{***} (7.593)					
Customer interaction management capability → CRM performance			0.355^{***} (5.016)					
Customer relationship upgrading capability → CRM performance			0.143^{*} (2.381)					
Customer win-back capability → CRM performance			0.399^{***} (5.197)					
AI usage * CRM capabilities → CRM performance					0.017 (0.365)			
Endogenous variable	**R^2**	**Adjusted R^2**	**R^2**	**Adjusted R^2**	**R^2**	**Adjusted R^2**	**R^2**	**Adjusted R^2**
CRM capabilities	0.320	0.316					0.383	0.376
Customer interaction management capability			0.235	0.231			0.423	0.422
Customer relationship upgrading capability			0.239	0.235				
Customer win-back capability			0.257	0.253				
CRM performance	0.582	0.578	0.599	0.592	0.593	0.587		
Discrepancy	**Value**	**HI_{95}**	**Value**	**HI_{99}**	**Value**	**HI_{95}**	**Value**	**HI_{95}**

SRMR	0.042	0.043	0.064	0.063	0.044	0.051	0.045	0.046
d_{ULS}	0.136	0.147	1.020	0.988	0.177	0.238	0.156	0.164
d_G	0.063	0.064	0.365	0.356	0.073	0.086	0.065	0.065

Note: t-values are presented in parentheses; $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$

6. Discussion and Contributions

6.1. Key Findings

First, our findings highlight that AI usage positively affects CRM capabilities in e-commerce enterprises. Previous studies have focused on the impact of information technology use (e.g., social media) on CRM capabilities (Foltean et al., 2019), ignoring the importance of digital technology use (e.g., AI usage). We extend previous research and empirically confirm the positive impact of AI usage on CRM capabilities. This demonstrates that AI usage is a vital foundation for e-commerce enterprises to cultivate CRM capabilities. E-commerce enterprises use AI technology for content sales system recommendations and robot interaction, thus improving enterprise customer interaction management, relationship management, and win-back capability.

Second, we found that CRM capabilities positively affect CRM in e-commerce enterprises. This finding extends the research of Trainor et al. (2014), who found that social media-driven CRM capabilities had a positive association with customer relationship performance. This study examines the impact of AI-driven CRM capabilities on CRM performance in the context of digitization. It shows that e-commerce enterprises can effectively allocate and combine resources and CRM elements to achieve the goal of CRM by building CRM capabilities in a dynamic environment, thus improving customer satisfaction and loyalty.

Third, we discovered that AI usage positively affected CRM performance in e-commerce enterprises. While AI has great potential business value, there has been a rather inconsistent understanding in the literature (Mikalef and Gupta, 2021). We enrich the existing research by examining the effects of AI usage on CRM performance in e-commerce enterprises. This indicates that enterprises' integration of AI technology into marketing can further improve efficiency and boost performance. AI usage enables e-commerce enterprises to automatically integrate and analyze big data on production, processing, distribution, and sales; identify opportunities and threats; and make swift decisions in response to consumer needs, thereby improving CRM performance.

Fourth, the results indicate that CRM capabilities partially mediate the effects of AI usage and CRM performance in e-commerce enterprises. This finding supports the research of Braojos et al. (2020), which postulates that organizations obtain firm performance through the IT-driven knowledge absorptive capacity and knowledge desorptive capacity. From the view of the IT-enabled organizational capabilities, enterprises utilize IT technology to develop organizational capabilities and gain competitive advantages. Consequently, the findings reinforce the view that IT-enabled organizational capabilities lead to enterprise performance.

6.2. Theoretical Contributions

This article contributes to the IS literature in two ways. First, from a theoretical perspective, examining the impact of AI usage on CRM performance has been a critical research topic (Li and Xu, 2022). Yet, there is no consensus on whether AI usage improves or impedes CRM performance. Most prior studies indicate that AI usage has a positive effect on CRM performance (Collins et al., 2021; Li and Xu, 2022), while others have found that AI has delivered minimal to no business impact so far (Mikalef and Gupta, 2021). Scholars argue that AI usage ignores individual uniqueness and initiative, and reduces customer satisfaction and retention (Longoni et al., 2019; Verma et al., 2021). In short, although most previous analyses find that AI usage is generally positive across studies, they also show that AI usage might reduce CRM performance. Thus, there is still a limited understanding of AI usage and how it relates to CRM performance. To fill this gap, this study examined the impact of AI usage on CRM performance. The results show that AI usage not only had a positive effect on CRM performance but also positively affected CRM capabilities and in turn improved CRM performance. This finding enriches IS studies on the value of AI, providing a novel lens for enterprises using AI to improve CRM performance.

Second, scholars believe that using AI to achieve CRM performance is not always simple, and there may be undiscovered mechanisms between them (Foltean et al., 2019; Li and Xu, 2022). However, its internal mechanism has remained unclear. This study adds to the growing body of knowledge in the field of AI-driven CRM by conceptualizing CRM capabilities (customer interaction management capability, customer relationship upgrading capability, and customer win-back capability) to guide enterprises to better maintain positive customer relations. More specifically, customer interaction management capability, customer relationship upgrading capability, and customer win-back capability all add CRM capabilities to enterprises. Enterprises can enhance CRM capabilities by retaining profitable customers, upselling existing customers, and establishing contact with lost and inactive customers, thus improving customer loyalty and satisfaction. This view could explain one possible reason for the conflicting findings about the business value of AI in enterprises. This study provides a possible mechanism for a better understanding of how the presence of AI usage within e-commerce enterprises can improve CRM.

6.3. Practical Implications

This study provides two practical insights. First, the results indicate that to better achieve CRM performance, e-commerce enterprises should make full use of AI technology to accelerate the construction of AI-driven CRM. E-commerce enterprises can employ AI technology to streamline decision-making, make intelligent recommendations, simplify decisions, and improve customer satisfaction and loyalty. In practice, Shenzhen Pagoda Industrial (Group) Corporation is a success story. Pagoda Industrial (Group) Corporation, a leading fruit firm in China, has surpassed 2 billion yuan in online sales since launching its WeChat mini-program in 2018. Through the use of AI recommendation systems and system algorithms, Pagoda's small program provides personalized services and timely interactions for consumers, which has been appreciated by the majority of its consumers. As a result, the total number of users of the small program exceeded 34 million, won the Magic Lamp award for three consecutive years, and was named the best small program of the year. Thus, e-commerce enterprises should develop strategic plans for AI usage, build AI skills training platforms, and promote a digital corporate culture.

Second, since CRM capabilities play a mediating role between AI usage and CRM performance, the development of CRM capabilities cannot be ignored. E-commerce enterprises with a high level of CRM capabilities can customize marketing strategies according to the different needs of existing customers, new customers, and lost customers to meet the personalized needs of consumers and improve customer satisfaction and loyalty. Pagoda Industrial (Group) Corporation has also built a big data platform + AI, making it a retail super brain. First, enterprises form big data platforms by integrating enterprise data from procurement, production, sales, and members. Afterward, they use AI technology for smart ordering, real-time pricing, facial recognition, and sales forecasting to optimize each link, improve CRM capabilities, and ultimately achieve a positive outcome. Thus, e-commerce enterprises should strengthen the construction of an AI-driven CRM platform, improve the platform system, and create a digital culture, thereby facilitating the formation of CRM capabilities.

6.4. Limitations and Future Research

Several inevitable limitations exist in this study. First, although the model explains 58.2% of the variance in CRM performance, other related factors were not fully considered, and need to be studied in the future. Second, AI usage to improve CRM performance is a long-term goal, and it may not be possible to fully comprehend this mechanism based on static models and cross-sectional data, so it is necessary to conduct longitudinal empirical analyses in future studies. Third, enterprise digitization usually adopts a variety of digital technologies, such as big data analysis, blockchain, and the Internet of Things. Therefore, we should explore the impact of AI technology and other digital technologies on CRM performance in the future. Fourth, the CRM relationships and performance of different enterprises using AI may vary by industry. Thus, we should examine the heterogeneity of industries in future studies. Fifth, our study only looks at the impact of the use of AI on CRM from a business perspective but ignores the perspective of the most important group, the consumer. Consequently, we should further explore it from the consumer perspective in future research.

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REFERENCES

Badawi, M. B., Awad, T. H., & El Fahham, I. M. (2022). Application of artificial intelligence for the prediction of plain journal bearings performance. *Alexandria Engineering Journal*, *61*(11), 9011-9029.

Benitez, J., Arenas, A., Castillo, A., & Esteves, J. (2022). Impact of digital leadership capability on innovation performance: The role of platform digitization capability. *Information & Management*, *59*(2), 103590.

Benitez, J., Henseler, J., Castillo, A., & Schuberth, F. (2020b). How to perform and report an impactful analysis using partial least squares: Guidelines for confirmatory and explanatory IS research. *Information & Management*, *57*(2), 103168.

Benitez, J., Llorens, J., & Braojos, J. (2018a). How information technology influences opportunity exploration and exploitation firm's capabilities. *Information & Management*, *55*(4), 508-523.

Benitez, J., Ruiz, L., Castillo, A., & Llorens, J. (2020a). How corporate social responsibility activities influence employer reputation: The role of social media capability. *Decision Support Systems*, *129*, 113223.

Braojos, J., Benitez, J., Llorens, J., & Ruiz, L. (2020). Impact of IT integration on the firm's knowledge absorption and desorption. *Information & Management*, *57*(7), 103290.

Brougham, D., & Haar, J. (2020). Technological disruption and employment: The influence on job insecurity and turnover intentions: A multi-country study. *Technological Forecasting and Social Change*, *161*, 120276.

Cao, L., Chen, C., Dong, X., Wang, M., & Qin, X. (2023). The dark side of AI identity: Investigating when and why AI identity entitles unethical behavior. *Computers in Human Behavior*, *143*, 107669.

Castillo, A., Benitez, J., LIorens, J., & Braojos, J. (2021). Impact of social media on the firm's knowledge exploration and knowledge exploitation: The role of business analytics talent. *Journal of the Association for Information Systems*, *22*(5), 1472-1508.

Chandra, S., & Kumar, K. N. (2018). Exploring factors influencing organizational adoption of augmented reality in e-commerce: Empirical analysis using technology–organization–environment model. *Journal of Electronic Commerce Research*, *19*(3), 237-265.

Chatterjee, S., Chaudhuri, R., Vrontis, D., Thrassou, A., & Ghosh, S. K. (2021). Adoption of artificial intelligence-integrated CRM systems in agile organizations in India. *Technological Forecasting and Social Change*, *168*, 120783.

Collins, C., Dennehy, D., Conboy, K., & Mikalef, P. (2021). Artificial intelligence in information systems research: A systematic literature review and research agenda. *International Journal of Information Management*, *60*, 102383.

Dalla Pozza, I., Goetz, O., & Sahut, J. M. (2018). Implementation effects in the relationship between CRM and its performance. *Journal of Business Research*, *89*, 391-403.

Demlehner, Q., Schoemer, D., & Laumer, S. (2021). How can artificial intelligence enhance car manufacturing? A Delphi study-based identification and assessment of general use cases. *International Journal of Information Management*, *58*, 102317.

Di Vaio, A., Palladino, R., Hassan, R., & Escobar, O. (2020). Artificial intelligence and business models in the sustainable development goals perspective: A systematic literature review. *Journal of Business Research*, *121*, 283-314.

Dondapati, A., Sheoliha, N., Panduro-Ramirez, J., Bakhare, R., Sreejith, P. M., & Devi Prasad Kotni, V. V. (2022). An integrated artificial intelligence framework for knowledge production and B2B marketing rational analysis for enhancing business performance. *Materials Today: Proceedings*, *56*, 2232-2235.

Foltean, F. S., Trif, S. M., & Tuleu, D. L. (2019). Customer relationship management capabilities and social media technology use: Consequences on firm performance. *Journal of Business Research*, *104*, 563-575.

Fosso, S., Gunasekaran, A., Akter, S., Ren, S. J. f., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research*, *70*, 356-365.

Fosso Wamba, S. (2022). Impact of artificial intelligence assimilation on firm performance: The mediating effects of organizational agility and customer agility. *International Journal of Information Management*, *67*, 102544.

Ghasemaghaei, M., & Calic, G. (2020). Assessing the impact of big data on firm innovation performance: Big data is not always better data. *Journal of Business Research*, *108*, 147-162.

Ghasemaghaei, M., Hassanein, K., & Turel, O. (2017). Increasing firm agility through the use of data analytics: The role of fit. *Decision Support Systems*, *101*, 95-105.

Ghasemaghaei, M., & Turel, O. (2021). Possible negative effects of big data on decision quality in firms: The role of knowledge hiding behaviours. *Information Systems Journal*, *31*(2), 268-293.

Go, E., & Sundar, S. S. (2019). Humanizing chatbots: The effects of visual, identity and conversational cues on humanness perceptions. *Computers in Human Behavior*, *97*, 304-316.

Guerola-Navarro, V., Gil-Gomez, H., Oltra-Badenes, R., & Sendra-García, J. (2021). Customer relationship management and its impact on innovation: A literature review. *Journal of Business Research*, *129*, 83-87.

Guerola Navarro, V., Oltra Badenes, R., Gil Gomez, H., & Iturricha Fernández, A. (2021). Customer relationship management (CRM) and innovation: A qualitative comparative analysis (QCA) in the search for improvements on the firm performance in winery sector. *Technological Forecasting and Social Change*, *169*, 120838.

Gupta, S., Drave, V. A., Dwivedi, Y. K., Baabdullah, A. M., & Ismagilova, E. (2020). Achieving superior organizational performance via big data predictive analytics: A dynamic capability view. *Industrial Marketing Management*, *90*, 581-592.

Hou, T., Luo, X., Ke, D., & Cheng, X. (2022). Exploring different appraisals in deviant sharing behaviors: A mixed-methods study. *Journal of Business Research*, *139*, 496-509.

Hua, Y., Cheng, X., Hou, T., & Luo, R. (2020). Monetary rewards, intrinsic motivators, and work engagement in the IT-enabled sharing economy: A mixed-methods investigation of internet taxi drivers. *Decision Sciences*, *51*(3), 755-785.

Hung, S. Y., Hung, W. H., Tsai, C. A., & Jiang, S. C. (2010). Critical factors of hospital adoption on CRM system: Organizational and information system perspectives. *Decision Support Systems*, *48*(4), 592-603.

Jan, Z., Ahamed, F., Mayer, W., Patel, N., Grossmann, G., Stumptner, M., & Kuusk, A. (2023). Artificial intelligence for industry 4.0: Systematic review of applications, challenges, and opportunities. *Expert Systems with Applications*, *216*, 119456.

Johnson, P. C., Laurell, C., Ots, M., & Sandström, C. (2022). Digital innovation and the effects of artificial intelligence on firms' research and development – Automation or augmentation, exploration or exploitation? *Technological Forecasting and Social Change*, *179*, 121636.

Komarek, A. M., De Pinto, A., & Smith, V. H. (2020). A review of types of risks in agriculture: What we know and what we need to know. *Agricultural Systems*, *178*, 102738.

Li, F., & Xu, G. (2022). AI-driven customer relationship management for sustainable enterprise performance. *Sustainable Energy Technologies and Assessments*, *52*, 102103.

Li, L. (2022). Digital transformation and sustainable performance: The moderating role of market turbulence. *Industrial Marketing Management*, *104*, 28-37.

Li, L., Lin, J., Ouyang, Y., & Luo, X. (2022). Evaluating the impact of big data analytics usage on the decision-making quality of organizations. *Technological Forecasting and Social Change*, *175*, 121355.

Li, M., & Mao, J. (2015). Hedonic or utilitarian? Exploring the impact of communication style alignment on user's perception of virtual health advisory services. *International Journal of Information Management*, *35*(2), 229-243.

Li, X., Liao, Q., Luo, X. R., & Wang, Y. (2020). Juxtaposing impacts of social media interaction experiences on e-commerce reputation. *Journal of Electronic Commerce Research*, *21*(2), 75-95.

Li, Y., Huang, J., & Song, T. (2019). Examining business value of customer relationship management systems: IT usage and two-stage model perspectives. *Information & Management*, *56*(3), 392-402.

Libai, B., Bart, Y., Gensler, S., Hofacker, C. F., Kaplan, A., Kötterheinrich, K., & Kroll, E. B. (2020). Brave new world? On AI and the management of customer relationships. *Journal of Interactive Marketing*, *51*, 44-56.

Lin, J., Luo, Z., Benitez, J., Luo, X., & Popovič, A. (2021). Why do organizations leverage social media to create business value? An external factor-centric empirical investigation. *Decision Support Systems*, 113628.

Lin, S., Lin, J., Han, F., & Luo, X. (2022). How big data analytics enables the alliance relationship stability of contract farming in the age of digital transformation. *Information & Management*, *59*(6), 103680.

Lindell, M. K., & Whitney, D. J. (2001). Accounting for common method variance in cross sectional research designs. *Journal of Applied Psychology*, *86*(1), 114-121.

Liu, H., Ke, W., Wei, K. K., & Hua, Z. (2013). The impact of IT capabilities on firm performance: The mediating roles of absorptive capacity and supply chain agility. *Decision Support Systems*, *54*(3), 1452-1462.

Liu, Y. Y., Tseng, F. M., & Tseng, Y. H. (2018). Big data analytics for forecasting tourism destination arrivals with the applied vector autoregression model. *Technological Forecasting and Social Change*, *130*, 123-134.

Longoni, C., Bonezzi, A., & Morewedge, C. K. (2019). Resistance to medical artificial intelligence. *Journal of Consumer Research*, *46*(4), 629-650.

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management*, *58*(3), 103434.

Nazir, S., Khadim, S., Ali Asadullah, M., & Syed, N. (2023). Exploring the influence of artificial intelligence technology on consumer repurchase intention: The mediation and moderation approach. *Technology in Society*, *72*, 102190.

Olan, F., Ogiemwonyi Arakpogun, E., Suklan, J., Nakpodia, F., Damij, N., & Jayawickrama, U. (2022). Artificial intelligence and knowledge sharing: Contributing factors to organizational performance. *Journal of Business Research*, *145*, 605-615.

Rahman, M. S., Bag, S., Gupta, S., & Sivarajah, U. (2023). Technology readiness of B2B firms and AI-based customer relationship management capability for enhancing social sustainability performance. *Journal of Business Research*, *156*, 113525.

Saura, J. R., Ribeiro-Soriano, D., & Palacios-Marqués, D. (2021). Setting B2B digital marketing in artificial intelligence-based CRMs: A review and directions for future research. *Industrial Marketing Management*, *98*, 161-178.

Shankar, V. (2018). How artificial intelligence (AI) is reshaping retailing. *Journal of Retailing*, *94*(4), 6-11.

Spanaki, K., Karafili, E., & Despoudi, S. (2021). AI applications of data sharing in agriculture 4.0: A framework for role-based data access control. *International Journal of Information Management*, *59*, 102350.

Trainor, K. J., Andzulis, J., Rapp, A., & Agnihotri, R. (2014). Social media technology usage and customer relationship performance: A capabilities-based examination of social CRM. *Journal of Business Research*, *67*(6), 1201-1208.
Turel, O., Liu, P., & Bart, C. (2019). Is board IT governance a silver bullet? A capability complementarity and shaping view. *International Journal of Accounting Information Systems*, *33:* , 32-46.
Verma, S., Sharma, R., Deb, S., & Maitra, D. (2021). Artificial intelligence in marketing: Systematic review and future research direction. *International Journal of Information Management Data Insights*, *1*(1), 100002.
Wamba-Taguimdje, S. L., Fosso Wamba, S., Kala Kamdjoug, J. R., & Tchatchouang Wanko, C. E. (2020). Influence of artificial intelligence (AI) on firm performance: The business value of AI-based transformation projects. *Business Process Management Journal*, *26*(7), 1893-1924.
Wang, D., Luo, X., Hua, Y., & Benitez, J. (2022). Big arena, small potatoes: A mixed-methods investigation of atmospheric cues in live-streaming e-commerce. *Decision Support Systems*, 113801.
Wang, S., Cavusoglu, H., & Deng, Z. (2016). Early mover advantage in e-commerce platforms with low entry barriers: The role of customer relationship management capabilities. *Information & Management*, *53*(2), 197-206.
Wang, Y., & Feng, H. (2012). Customer relationship management capabilities: Measurement, antecedents and consequences. *Management Decision*, *50*(1), 115-129.
Ye, Y., Yu, Q., Zheng, Y., & Zheng, Y. (2022). Investigating the effect of social media application on firm capabilities and performance: The perspective of dynamic capability view. *Journal of Business Research*, *139*, 510-519.
Yu, Y., Li, M., Li, X., Zhao, J. L., & Zhao, D. (2018). Effects of entrepreneurship and IT fashion on SMEs' transformation toward cloud service through mediation of trust. *Information & Management*, *55*(2), 245-257.
Zhang, C., Wang, X., Cui, A. P., & Han, S. (2020). Linking big data analytical intelligence to customer relationship management performance. *Industrial Marketing Management*, *91*, 483-494.
Zhao, X., Pan, C., Cai, J., & Luo, X. R. (2021). Driving e-commerce brand attachment through green packaging: An empirical investigation. *Journal of Electronic Commerce Research*, *22*(3), 178-198.

Appendix. Measurement Scales of the Key Constructs

Code	Indicator	Source
AI usage (AIU)		Shankar (2018) and Libai et al. (2020)
AIU1	Our enterprise uses AI to build personalized recommendation systems to improve user experience.	
AIU2	Our enterprise uses AI to simplify the decision-making process.	
AIU3	Our enterprise uses AI to enhance effective content marketing.	
AIU4	Our enterprise uses AI to communicate with customers at any time.	
Customer interaction management capability (CIMC)		Wang and Feng (2012) and Foltean et al. (2019)
CIMC1	Our enterprise regularly meets customers by learning their current and potential needs for new products.	
CIMC2	Our enterprise is good at creating relationships with key customers.	
CIMC3	Our enterprise maintains interactive two-way communication with our customers.	
CIMC4	Our enterprise has a continual dialogue with each customer and uses well-developed methods to improve our relationships.	
CIMC5	Our enterprise is good at maintaining relationships with key customers.	
Customer relationship upgrading capability (CRUC)		
CRUC1	Our enterprise measures customer satisfaction systematically and frequently.	
CRUC2	Our enterprise has formalized procedures for up-selling to valuable customers.	
CRUC3	Our enterprise has formalized procedures for cross-selling to valuable customers.	
CRUC4	Our enterprise tries to systematically extend our "share of customers" with high-value customers.	
Customer win-back capability (CWBC)		
CWBC1	Our enterprise apologizes or compensates in time for the inconvenience or loss that we bring to customers.	
CWBC2	Our enterprise has a systematic process/approach to re-establish relationships with valued lost customers and inactive customers.	
CWBC3	When our enterprise finds that customers are unhappy with the appropriateness of our product or service, it takes corrective action immediately.	
CWBC4	Our enterprise maintains positive relationships with migrating or unattractive customers.	
CRM performance (CRMP)		Trainor et al. (2014)
CRMP1	Compared with competitors, our customers have worked with our enterprise for a long time.	
CRMP2	Compared with competitors, once we get new customers, they tend to stay with our enterprise.	

CRMP3	Compared with competitors, our customers are very loyal to our enterprise.	
CRMP4	Compared with competitors, our customers are satisfied with our enterprise.	
CRMP5	Compared with competitors, customer retention is very important to our enterprise.	