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Research article

The impact of AI-enabled CRM systems on organizational competitive advantage: A mixed-method approach using BERTopic and PLS-SEM

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ABSTRACT

The recent advances in machine learning and deep learning algorithms, along with the advent of generative AI, have led AI to become the "new normal" in organizations. This trend has extended to CRM, resulting in the development of AI-enabled CRM systems, or AI-CRM. Despite the growing adoption of AI as part of competitive strategies, many firms report minimal or no positive effect of AI on performance. This study addresses the research questions: "What are the critical features of AI-CRM systems?" and "How do these features impact organizational competitive advantage?" To explore this, we aim to identify key characteristics of AI-CRM and assess their impact on organizational performance. In Study 1, we utilize BERTopic topic modeling to extract critical features of AI-CRM from user reviews. Study 2 employs PLS-SEM to examine how these features influence organizational competitive advantage. Study 1 reveals four main characteristics of AI-CRM (general, marketing, sales, and service/support), each comprising distinct features. Study 2 shows that these characteristics differentially impact CRM capability, significantly affecting performance and competitive advantage. The findings offer valuable insights for both theory and practice regarding the effective use of AI in organizations.

1. Introduction

Artificial intelligence (AI) is defined as a system which has the ability to accurately interpret vast amount of data, learn from such data, and apply those learnings to achieve specific tasks through flexible adaptation [1]. The term was first introduced in 1955 and evolved rapidly over the years, expanding its usage in numerous fields including text analysis, computer vision, and decision-making [2,3].

The recent advances in machine learning/deep learning algorithms and the advent of generative AI, which refers to computational methods that can create seemingly original and meaningful content, such as text, images, or audio, based on training data, has led AI to become the "new normal" in both manufacturing and service industries [4,5]. Recently, this trend of AI adoption in organizations has extended to the field of customer relationship management (CRM), resulting in the development of a new AI-enabled CRM system, or AI-CRM. Analyzing the increasing volume of customer data using manual techniques is challenging and has led to the necessity of employing AI in the field of CRM [6]. The ability of AI to retrieve, understand, and flexibly adapt to big data is expected to allow AI-CRM to automate routine tasks, segmentate and provide personalized services to customers based on their preference and priority,

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and interact with customers without human intervention by using Natural Language Processing (NLP) technology [1,7]. Furthermore, it is estimated that the adoption of AI-CRM in firms could result in a revenue of $1.1tn [8,9].

While demand for AI-CRM is high in practice, research on the topic is still in its infancy [10]. Additionally, in order for AI to be successfully implemented, it is essential that the employees within an organization, who are responsible for analyzing customer data, effectively utilize AI-CRM to precisely analyze customer preferences, habits, and dislikes [6]. Current studies on AI-CRM focus mostly on understanding the newly emerging trend by building a conceptual framework on the strategic implementation of AI-CRM [11] or conducting an interview or case study-based exploratory analysis [12]. Other studies focus on investigating the early adoption intention of AI-CRM technology by adopting rather outdated technology adoption models, such as the technology acceptance model [13].

Additionally, while there is a growing body of research exploring the applications of AI in various business domains, the specific use of AI in the CRM context remains relatively underexplored. For instance, Chagas et al. [14] highlight that while Machine Learning techniques have been increasingly applied to CRM processes, there is still a significant gap in understanding their practical implications and effectiveness across different CRM dimensions. Similarly, Ledro et al. [10] provide a comprehensive review of AI applications in CRM, identifying key areas for future research, particularly in understanding how AI-CRM impacts long-term customer relationships and organizational performance. These studies indicate a need for further empirical investigation to bridge these gaps and provide clearer insights into the effective integration of AI within CRM systems.

Furthermore, while organizations adopting AI as part of their competitive strategy has increased by 270 % from 2015 to 2019, 70 % of these firms reported minimal or no positive effect of AI on their performance [15]. This indicates that, while the adoption of AI in the workplace is increasing rapidly and new AI enabled software are being introduced, most are "jumping on the bandwagon", thus failing to effectively use the new technology.

Additionally, the current stream of research regarding organizational behavior could be divided into two categories: (1) "behavioral-subjective" research and (2) "quantitative-objective" research [16]. While behavioral-subjective studies are built on well-established theories and primarily use survey based data, they fail to give unanticipated implications and are subject to bias [17]. Quantitative-objective studies, on the other hand, studies use machine learning or other data mining techniques to extract meaningful patterns or information from real-world data. However, they fail to explain complex relations between various constructs and can only identify correlation, not causation [18,19]. Thus, in order to surpass the limitations of prior studies and improve the organizational benefits of AI-CRM adoption, a holistic approach bridging the gap between individual user perception and their implications at the organizational level is needed.

Therefore, this study uses a mixed-method approach to analyze how the use of AI-CRM affects organizational competitive advantage. Specifically, the study is composed of two sections. In Study 1, an exploratory analysis is conducted to identify user perception toward AI-CRM using online reviews and extract the latent variables using BERTopic topic modeling. In Study 2, a confirmatory analysis is conducted at the organizational level, determining the impact of the extracted latent variables from Study 1 on organization performance and competitive advantage using partial least squares structural equation modeling (PLS-SEM). The research framework is presented below in Fig. 1.

2. Study 1

2.1. Literature review

2.1.1. Customer relationship management (CRM)

The concept of CRM emerged in the 1990s and since then, organizations, regardless of size or industry, are investing significant resources to successfully adopt and operate CRM in their strategy [20]. A successful operation of CRM can lead to enhanced customer relations, higher customer loyalty, retention, and eventually profitability [21].

However, a single definition of CRM is not yet established among researchers. For example, early studies on the topic defined CRM as a technology mainly used for customer data warehousing and data mining [22]. Recent studies, on the other hand, define CRM as a

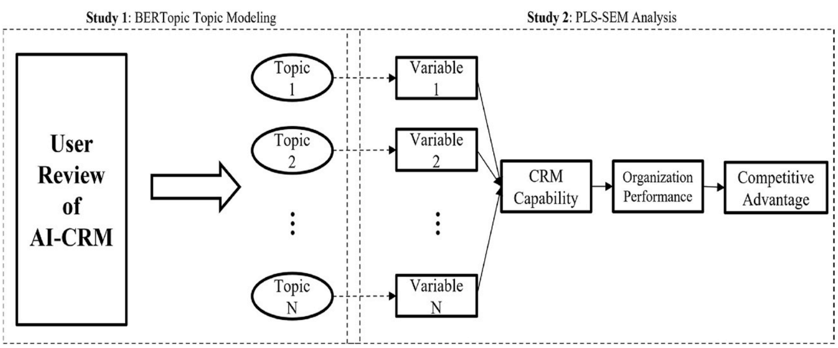

Fig. 1. Research framework.

strategic approach focusing on identifying key customers and managing relations with them, thereby improving shareholder value [23]. This inconsistency in the definition of CRM is mainly due to the fact that CRM is not a single strategy or technology, but a continuous process of initiating, maintaining, and terminating the relation between a firm and the customer [24].

Therefore, we adopt a definition that covers the multiple aspects of CRM. We define CRM as "a comprehensive strategy and process of acquiring, retaining, and partnering with selective customers to create superior value for the company and the customer. It involves the integration of marketing, sales, customer service … to achieve greater efficiencies and effectiveness in delivering customer value" [25].

Although we define CRM as a set of multiple strategies, technology has played a crucial role in CRM operation since it allows organizations to quickly adapt to new business environments and identify the constantly changing customer needs [26]. Examples of technology enabled CRM include e-CRM, which utilizes the internet, and m-CRM, which emerged with the adoption of smartphones [27,28]. Furthermore, with the recent advent of social media, firms are utilizing social media platforms to interact with customers [29]. This is referred to as social CRM, or S-CRM and has allowed companies to interact with customers regardless of time or location, and provide personalized experiences based on customer data [30,31].

Several studies focused on these technology enabled CMRs, investigating how user perception toward these systems affect organization performance or system adoption [32,33]. However, the existing literature primarily focuses on conceptual frameworks and exploratory analyses, with a notable lack of comprehensive empirical studies that validate the effectiveness of AI-CRM systems in real-world settings. Chagas et al. [14] conducted a literature review on the application of ML techniques in CRM, identifying the need for more practical and scalable solutions that can be implemented across various industries. Moreover, Ledro et al. [10] emphasize the necessity for future research to explore the strategic implications of AI-CRM, particularly how these systems can be optimized to enhance customer satisfaction, loyalty, and overall competitive advantage. These identified gaps highlight the importance of advancing our understanding through mixed-method approaches that combine qualitative and quantitative analyses to provide a more holistic view of AI-CRM's impact.

2.1.2. Topic modeling and BERTopic

Until now, a majority of studies that analyze user perception towards a certain technology were survey-based and thus, failed to consider the specific characteristics of each technology [34]. Text mining overcomes this limitation by efficiently analyzing user created data, and has been utilized in studies to find meaningful information about newly emerging topics that lack sufficient structured data [35].

Furthermore, these days it is estimated that over 90 % of data are unstructured data, with most of it in text form, such as online reviews, social media posts, and emails. While text data is easy to understand by humans, it is difficult to comprehend and extract meaningful information using computers. Text mining allows researchers and practitioners to extract interesting and non-trivial patterns, thus providing meaningful information [36].

Among different text mining techniques, topic modeling is the most widely used method as it easily extracts latent variables from large datasets [37]. Topic modeling offers advantages over keyword extraction and opinion mining when analyzing online user reviews. Unlike keyword extraction, which identifies frequent terms without context, topic modeling groups similar words into coherent themes, capturing semantic and contextual relationships for a deeper understanding of user feedback [38]. Topic modeling is also effective in identifying patterns through inductive analysis, interpreting these patterns based on prior literature, and subsequently generating or refining new hypotheses, thus making it suitable when conducting a mixed-method analysis [39]. Prior studies have often used topic modeling to extract critical factors affecting customer satisfaction or adoption from user reviews [40,41]. Additionally, Schmiedel et al. [34] states that "Topic modeling offers a broad spectrum of application possibilities in organizational research … organizational research should leverage the potential of various types of texts for gaining insights on organizational phenomena."

Prior studies have utilized topic modeling based on user generated content to gain understanding of newly emerging technologies (Okey et al., 2023). Until now, most studies using topic modeling utilized Latent Dirichlet Allocation (LDA) to perform the analysis. However, major shortcoming of LDA is that it treats text as a bag-of-words and ignores word order and context, thus failing to accurately extract topics [42].

To overcome such limitations, we employ BERTopic, a state-of-the-art topic modeling algorithm based on the BERT. BERTopic is chosen for its ability to accurately extract topics by understanding words and sentences in context rather than treating them as a bag-of-words, which is a limitation of traditional topic modeling methods like LDA. This choice ensures higher accuracy and meaningful extraction of latent variables from user reviews, capturing nuanced user perceptions of AI-CRM features [43,44].

BERT is a transformer-based model specialized for performing natural language processing (NLP) tasks. Unlike traditional deep learning-based models (LSTM, GRU etc.) that process text input one word at a time in a sequential manner, either from left to right or right to left, the BERT model takes in the complete sequence of words simultaneously. Furthermore, unlike other NLP models, BERT uses a large amount of text data to pre-train the model, specifically through masked language modeling (MLM) and next sentence prediction (NSP). This allows BERT to understand words and sentences in context, rather than treating them as a bag-of-words, thus increasing accuracy.

After its first development, different variations of BERT were developed using different training data based on task objective. In the case of BERTopic, which is a BERT-based algorithm specified for topic modeling tasks, the "all-MiniLM-L6-v2" model is utilized to embed each document into a 384-dimensional dense vector space.

BERTopic has been utilized in several contexts, confirming its effectiveness and versatility. For example, Scarpino et al. [45] compared the clustering accuracy between LDA and BERTopic using patient testimonies related to post COVID-19 symptoms. The study concluded that BERTopic outperforms LDA by grouping in the same cluster the 97.26 % of texts, and showing an overall accuracy of 91.97 %. Najmani et al. [46] also concluded that BERTopic was better able to classify MOOC videos based on the topic extracted from the subtitles compared to LDA.

Therefore, this study utilizes the BERTopic to perform topic modeling on user reviews of AI-CRM, thus extracting meaningful latent variables that effectively explain user perception of AI-CRM. The BERTopic algorithm is described in detail in the next section.

2.2. Materials and methods

2.2.1. Data collection and pre-processing

According to the result of the bibliographic literature review by Ngai [21], CRM could be classified into three main functional areas: Marketing, Sales, and Service/Support. Marketing function refers to activities related to attracting and engaging potential customers, sales involves the processes and activities associated with selling products or services to customers, and service/support focuses on handling customer inquiries and resolving issues to ensure customer satisfaction [21].

In the context of AI-CRM, marketing AI-CRMs refer to those that feature AI-based marketing content generator that can create contents and templates for social media marketing, blogs, websites etc. Sales AI-CRMs provide AI-based sales forecasting and customer segmentation functions. Finally, Service/Support AI-CRMs provide AI chatbot-based customer services, as well as automatic email and SMS-based customer support. Thus, to provide a generalizable topic extraction result, we selected two softwares that best represent each of the three CRM categories by analyzing the product introduction and main features. The representative softwares were selected from Getapp. com's "Category Leaders" group. Category leaders are services that have at least 20 unique product revies and meets a certain criteria based on their ease of use, value for money, functionality, customer support, and likelihood. Then, we selected the two softwares that integrated AI into their main service and best fit the CRM field (marketing, sales, service/support) based on their key features. Furthermore, only the reviews that were written after an AI-enabled function was employed based on the review date were scraped.

The reviews were scraped from Getapp.com, an online CRM software review and recommendation site with over 2.2 million user reviews and 2 million monthly users. The Beautiful Soup Python library was used to scrape the reviews, which is one of the most widely utilized web scraping library to extract specific information from HTML/XML content [47]. After eliminating non-English reviews and inappropriate reviews, a total of 3040 reviews were used for the BERTopic analysis.

Topics were extracted from each software. Then, the topics that were common for all three softwares were classified as "General characteristics". The remaining topics for each software were classified as "Marketing characteristics", "Sales characteristics", and "Service/Support characteristics".

Furthermore, although pre-processing of data is not mandatory for BERTopic, the results of prior studies show that removing stopwords showed higher accuracy and efficiency when compared to using raw data [48]. Thus, the study removed NLTK stopwords and the names of the AI-CRM before performing the BERTopic analysis.

2.2.2. BERTopic algorithm

The BERTopic algorithm is consisted mainly of three stages: 1) Document embedding, 2) Dimension reduction and document clustering, and 3) Topic representation [44].

In the document embedding stage, BERT model "all-MiniLM-L6-v2" is used to embed the text data into a 384-dimensional dense vector space, transforming the text data into numeric data. The model was pre-trained with approximately 1,170,000,000 training tuples using various datasets (e.g., Reddit comments, Yahoo answers etc.) and is targeted for tasks such as clustering of sentences and short paragraphs, making the model suitable for analyzing relatively short documents, such as online reviews [44]. Through the embedding stage, documents with similar semantic meaning are transformed to vectors with similar value.

After the text data has been vectorized into numeric data, the BERTopic algorithm performs dimension reduction and document clustering. As mentioned earlier, the embedding stage transforms the text-based data into a 384-dimensional vector. As the amount of data with high dimension increases, the sparser the data point becomes, making it difficult to find meaningful patterns or information from the dataset. Furthermore, most data mining algorithms are designed to perform with low-dimensional data, thus using a high-dimension data as input leads to lower accuracy. This phenomenon is known as the "curse of dimensionality" [49].

To overcome this problem, the BERTopic algorithm utilizes the UMAP algorithm to perform dimension reduction. UMAP is a non-linear dimensionality reduction technique that excels at preserving both local and global structure in data, making it more suitable for capturing intricate patterns and clusters, making it an effective algorithm for a wide range of applications, especially when dealing with complex, high-dimensional datasets.

In this study, the 384-dimensional vector space was reduced to a 5-dimensional space, using cosine similarity as the distance metric between data points. Furthermore, the nearest neighbor (n_neighbors) parameter was set to 15, indicating that the UMAP algorithm considers the 15 nearest neighbors for each data point.

After the dimension reduction is conducted, the BERTopic algorithm clusters similar data points using HDBSCAN. HDBSCAN is a density-based clustering algorithm that automatically identifies clusters in data with varying densities and shapes. It starts by estimating the density of data points in the feature space and constructs a hierarchical clustering tree. Through a stability analysis, HDBSCAN determines the most stable clusters by assessing how they persist across different minimum cluster size values. It assigns data points to clusters based on their proximity to core points and noise points [50].

After the clustering process is complete, the BERTopic algorithm uses the class-based TF-IDF, or c-TF-IDF, to find the words that accurately represent each cluster. In the original TF-IDF, the importance of a word is calculated by multiplying the term frequency of a word (TF) within a document, which is calculated by dividing the number of times a term appears in a document by the total number of terms in the document, and the inverse document frequency (IDF), which is calculated by taking the logarithm of the total number of documents in the corpus divided by the number of documents containing the term. Therefore, if a certain term appears frequently within a certain document, but rarely appears in the entire dataset, the higher the TF-IDF score, meaning that it should be considered as important [51].

However, TF-IDF calculates the importance of words between each single document, making it inappropriate when attempting to find representative terms for each cluster. Therefore, the c-TF-IDF combines all the documents within the same cluster as a single document, then applies the TF-IDF, resulting in an accurate calculation for extracting representative terms for each cluster [44]. The equation for c-TF-IDF is shown below:

$$W_{x,c} = \|tf_{x,c}\| \times \log\left(1 + \frac{A}{f_x}\right)$$

where, for a term x within class c, $tf_{x,c}$ is the frequency of x in c, f_x is the frequency of x across all classes, and A is the average number of words per class. Furthermore, the equation adds one within the logarithm so that the value remains positive. The resulting score calculated through the equation ($W_{x,c}$) represents the importance of the term within the class [44].

2.3. Results

The BERTopic algorithm was applied separately for the three CRM categories. After performing the topic modeling, overlapping topics were classified as "general characteristics". The remaining topics for each category were each classified as "marketing characteristics", "sales characteristics", and "service/support characteristics". The topics were manually named based on the extracted topic representations, with three experts, all PhDs, participating in this process. These experts reviewed the extracted keywords and selected the most relevant topics, ensuring that the selected topics accurately represented the key themes in the user reviews. The result of the topic modeling is presented in Tables 1–3.

The results of the BERTopic topic modeling show that the three AI-CRMs have 4 topics in common: Data-driven decision making, Customer-centric personalization, User-friendly interface, and Task automation. Thus, these topics were classified as the "general characteristics" of AI-CRM. Next, the remaining topics were each classified as the corresponding AI-CRM. Thus, Creative content generation, Multilingual content support, and Multichannel marketing were classified as "marketing characteristics", Lead nurturing and Sales forecasting were classified as "sales characteristics", and Ticket tracking, Real-time service/support, and Omnichannel service/support were classified as "service/support characteristics".

3. Study 2

3.1. Literature review

3.1.1. Resource-based view (RBV)

The result of Study 1 shows which features are perceived as important by users when utilizing AI-CRM in the workplace. However, how the adoption of AI-CRM in the organizational level is not yet established. Examining how the characteristics of AI-CRM affect an organization's performance and competitive advantage could provide meaningful guidelines for the successful development of new AI-CRM systems and the successful adoption of the technology.

In this sense, the resource-based view (RBV) could provide meaningful implications on how the characteristics of AI-CRM, which were extracted in Study 1, positively impact a firm's CRM capability, performance, and competitive advantage.

The RBV is one of the most widely used and effective framework in the field of management for explaining how a firm gains sustainable competitive advantage over its competitors [52]. According to the RBV, a firm is a collection of resources and it gains competitive advantage by utilizing its valuable, rare, inimitable, and non-substitutable (VRIN) resources [53].

Table 1
Topic modeling result: Marketing.

Topic #	Topic representation	Topic
1	writers, assistant, create, creative content, original content, writer, helpful, hours, saves, content creation	Creative content generation
2	analytics, operations, features, insights, data analytics, reports, automate, interface, capabilities, business processes	Data-driven decision making
3	template, recipes, templates, automatic template, template suggestions, templates choose, outlines recipe, links, topic ideas, need inspiration	Task automation
4	ads, facebook, facebook twitter, youtube ads, email websites, blogs, youtube tiktok, twitter ads, content facebook, facebook youtube	Multichannel marketing
5	user friendly, options, applications, user interface, features, flexible, five, experience overall, intuitive user	User-friendly interface
6	english, languages, multilingual, spanish language, multiple languages, spanish many, languages also, cannot english, us german, one language	Multilingual content support
7	business, service, clients, experience, understand, payment, personalized, full time, work, found easy	Customer-centric personalization
8	ads, email, customer, google business, step, real time, hire, ads email, products, high converting	

Table 2
Topic modeling result: Sales.

Topic #	Topic representation	Topic
1	lead, track, easy, tracking, keep, software, sale, keep track, management, project	Lead tracking
2	customer, business, feature, sale, management, easy, relationship, track, software, make	Customer-centric personalization
3	automation, marketing, business, sale, software, workflow, easy, marketing automation, user, feature	Task automation
4	analytic, data, easy, dashboard, reporting, report, tracking, management, customer, analysis	Data-driven decision making
5	sale, forecast, accurate, sale forecast, accurate sale, predict, forecast predict, software, sale prediction, prediction	Sales forecasting
6	friendly, software, tracking, intuitive friendly, friendly interface, easy, intuitive, feature plug, plug in	User-friendly interface

Table 3
Topic modeling result: Service/support.

Topic #	Topic representation	Topic
1	customer, chat, customer support, service, platform, feature, message, easy use, customer service, client	Customer-centric marketing
2	live chat, chat, real time, livechat, chatbot, time chat, chat support, customer support, easy use, user experience	Real-time service/support
3	seamless mobile, mobile, omnichannel, mobile omnichannel, omnichannel app, chat, client, application, engagement, app version	Omnichannel service/support
4	customer, data, lot feature, service, feature, easy use, communicate customer, customer support, tool, potential customer	Data-driven decision making
5	use, easy use, interface easy, ux, design, looking user, auto reply, feedback, ui	User-friendly interface, Task automation
6	tracking, ticket tracking, ticket system, feature, track, easy use, reporting, track ticket, campaign drive, tool	Ticket tracking

Furthermore, a firm's resource provide the foundation for its capabilities, which are the skills and accumulated knowledge that firms use to acquire, deploy, and leverage resources to achieve superior performance [54].

Overall, the RBV has been influential in helping firms and researchers understand how an organization could build and sustain a competitive edge by leveraging their internal resources and capabilities [53]. For example, Dubey et al. [55] concluded that a firm's tangible resources, such as data connectivity, and human skills positively affect its big data predictive analytics capability, which consequently led to improved organizational performance. Similarly, Borah et al. [56] found that the social media usage enhances SME's sustainable performance. Furthermore, they concluded that this relation is mediated by the SME's innovation capabilities and moderated by digital leadership.

In the context of CRM, studies have focused on defining a firm's CRM capability and confirming its impact on performance and competitive advantage. According to Wang and Feng [54], a firm's CRM capability is consisted of three constructs: 1) Customer interaction management capability, defined as a firm's ability to identify, acquire, and retain profitable customers, 2) Customer relationship upgrading capability, defined as a firm's ability to up-sell and cross-sell to existing customers based on customer data analysis, and 3) Customer win-back capability, defined as a firm's ability to re-establish the relationship with lost or inactive, but profitable customers. These three constructs of CRM capability have been utilized in prior studies regarding organizational CRM capability and performance based on the RBV framework.

3.2. Research model and hypotheses

Our hypotheses and research model is based on prior studies on AI-CRM, RBV, and the result of Study 1. Specifically, based on the RBV, we assert that the characteristics of AI-CRM significantly affect a firm's CRM capabilities, which then leads to improved performance and competitive advantage.

3.2.1. AI-CRM characteristics and CRM capabilities

According to the topic modeling result of Study 1, there are four AI-CRM characteristics, each consisted of different features that users perceive as important when using AI-CRM. Thus, we define each characteristic as a formative construct consisted of the corresponding features.

3.2.1.1. General characteristics and CRM capabilities. The first characteristic of AI-CRM is the general characteristic, composed of 1) Data-driven decision making, 2) Customer-centric personalization, 3) User-friendly interface, 4) Task automation. Decision making based on data has been found to be a crucial antecedent of a firm's CRM capability in a number of studies. For example, Wells and Hess [57] and Shafiei and Sundaram [58] concluded that the implementation of data warehousing-related decision support systems and a collaborative ERP decision support system significantly benefits a firm's CRM capability.

Similarly, Chatterjee et al. [59] concluded that the personalization feature of big data analytics significantly affect CRM capability, including customer interactivity capability and customer retention capability. Thus, the ability of an AI-CRM to analyze the customer and generate personalized emails or product recommendations could greatly benefit the firm's CRM capability.

In a study regarding organizational adoption of e-CRM, Navimipour and Soltani [60] concluded that user-friendly interface positively affect e-CRM performance. It also contributes to higher customer satisfaction, scalability, and adaptability to change, all of which are essential for effective CRM [61].

Finally, Boujena et al. [62] found that sales force automation showed positive relations with CRM processes, including relationship initiation, maintenance, and termination. Considering that the Automation of repetitive or time-consuming tasks is one of the major advantages of using AI, the task automation could significantly benefit a firm's CRM capability.

Therefore, based on the results of prior studies regarding the four features that compose the general characteristics of AI-CRM and their relation with CRM capability, the following hypotheses are proposed:

H1(a). General characteristics of AI-CRM positively impacts customer management interaction capability

H1(b). General characteristics of AI-CRM positively impacts customer relation upgrading capability

H1(c). General characteristics of AI-CRM positively impacts customer win-back capability

3.2.1.2. Marketing characteristics and CRM capabilities. The marketing characteristics of AI-CRM is composed of 1) Creative content generation, 2) Multilingual content support, 3) Multichannel marketing.

With the recent advances of generative AI, AI-CRM is now able to create original marketing content, helping copywriters create billboard ads, social media posts, and short slogans. Considering that Shahbaz et al. [63] concluded that the use of big data analytics allow the organization to provide more creative services, which positively impacted CRM capabilities, it can be inferred that the use of generative AI, which significantly outperforms traditional analytic methods, would greatly benefit a firm's CRM capability.

Also, With the growth of social media and e-commerce, globalization of firms has become common, creating the need to promote marketing campaigns at a global scale [64]. This trend has led to an increase in demand for employees with multilingual skills [65]. In the CRM context, studies on the relation between multilingual skills and CRM capabilities in the context of the hotel industry concluded that the multilingual features of e-CRM and content management system enhances guest retention [66].

Multichannel marketing, which is the use of multiple combination of marketing channels is used by most major firms to reach a larger audience and strengthen the relation with their customers [67]. The use of AI allows marketers to efficiently deploy marketing campaigns over multiple channels thanks to its high compatibility among multiple platforms. Prior studies, including Järvinen and Taiminen [68], concluded that the use of marketing automation technology for cross-channel marketing significantly and positively affected customer satisfaction and CRM capability. Similarly, Foltean et al. [23] explained that a firm's ability to use social media as a marketing channel significantly affects their CRM capabilities.

Therefore, based on the results of prior studies regarding the marketing characteristics of AI-CRM and their relationship with CRM capability, the following hypotheses are proposed:

H2(a). Marketing characteristics of AI-CRM positively impacts customer management interaction capability

H2(b). Marketing characteristics of AI-CRM positively impacts customer relation upgrading capability

H2(c). Marketing characteristics of AI-CRM positively impacts customer win-back capability

3.2.1.3. Sales characteristics and CRM capabilities. The sales characteristics of AI-CRM is composed of 1) Lead nurturing/conversion, 2) Sales forecasting.

Leads refer to any individuals or organizations that have interacted through the firm's marketing channel and has the potential to be a future customer. Therefore, transforming these potential customers into real customers, or lead conversion/nurturing, is a crucial element of CRM [69]. AI, however, is better able to find and identify good leads with higher accuracy compared to probability-based clustering techniques, due to their ability to learn and find patterns from various data sources [1]. Furthermore, AI is able to study and analyze large sets of customer data, thus allowing better customer segmentation and communication with potential customers, which is a crucial antecedent of a firm's CRM capability [70].

Sales forecasting is another crucial antecedent of a firm's CRM capability since accurately forecasting future sales lead to increase in operation efficiency and allows for improvement of the decision-making process along the entire selling process [71]. Integrating AI with CRM tools can amplify the effectiveness of predictive analysis in various aspects of business operations, leading to increased visibility and communication among different operational touchpoints, mitigating forecasting [72,73]. Furthermore, AI has shown superb performance in the context of sales forecasting compared to traditional forecasting methods, such as manual forecasting or statistical methods (e.g., ARIMA) [74].

Therefore, based on the results of prior studies the following hypotheses are proposed:

H3(a). Sales characteristics of AI-CRM positively impacts customer management interaction capability

H3(b). Sales characteristics of AI-CRM positively impacts customer relation upgrading capability

H3(c). Sales characteristics of AI-CRM positively impacts customer win-back capability

3.2.1.4. Service/support characteristics and CRM capabilities. The service/support characteristics of AI-CRM is composed of 1) Ticket tracking, 2) Real-time service/support, 3) Omnichannel service/support.

Tickets are customer queries or complaints about a product or service, and is usually collected through various customer touchpoints, such as emails [75]. The importance of efficiently tracking and accurately allocating the tickets to the correct personnel to enhance CRM performance, particularly customer retention and customer win-back capability, is emphasized in several prior studies [76,77]. AI's ability to analyze large sets of data allows it to significantly increase the efficiency of ticket tracking [78]. Furthermore, it allows employees to focus on solving the problem, rather than interacting with the customer, which is often time consuming.

Customer service/support response timeliness is another crucial determinant of consumer post-recovery perception and behavior [79]. Several studies concluded that a timely response to customer complaints and queries are effective at restoring customer satisfaction positive word-of-mouth and consequently, the firm's customer interaction management capability and win-back capability [80–82]. The use of AI-enabled chatbot as a customer interaction channel allows customers to interact with the firm 24/7, thus improving customer experience while reducing the workload of human employees [83].

As previously mentioned, firms now have multiple touchpoints to interact with customers, implying that customer complaints and queries are collected through multiple channels. While the use of multi-channels help increase customer satisfaction, and consequently repurchase intention, it increases complexity and operational cost from the firm's point of view [84]. AI-CRM, however, is able to collect large amounts of customer queries from various channels and categorize, analyze, and handle them with ease. Also, it is able to analyze and generate optimal response mails or make reservations using text-to-speech technology, thereby increasing customer satisfaction and positively affecting the firm's CRM capability, particularly its customer win-back capability.

Therefore, based on the results of prior studies, the following hypotheses are proposed:

H4(a). Service/Support characteristics of AI-CRM positively impacts customer management interaction capability

H4(b). Service/Support characteristics of AI-CRM positively impacts customer relation upgrading capability

H4(c). Service/Support characteristics of AI-CRM positively impacts customer win-back capability

3.2.2. CRM capabilities, organization performance, and competitive advantage

Ali et al. [85] studied the effect of a firm's CRM capability, which the researchers classified into customer orientation, CRM technology, CRM process, and CRM organization, on organization performance. The study concluded that while not all four dimensions of CRM capability affects performance, there is a significant positive relation between CRM process and CRM organization and organization performance. Similarly, Chang et al. [86] concluded that the use of CRM technology positively affects the firm's marketing capability, which then positively affected its performance. Ardyan and Sugiyarti [87] also found that the adoption of e-CRM and e-CRM capability of SMEs in Indonesia increased its marketing performance.

Furthermore, the use of technology as a resource and its effect on a firm's competitive advantage has been confirmed in several studies utilizing the RBV. Based on a survey data collected from 224 managerial employees, Awamleh and Ertugan [88] concluded that a firm's IT capability, composed of IT infrastructure capability, IT business spanning capability, and IT proactive stance, positively affected organizational intelligence, which affected the firm's competitive advantage, such as exploiting market opportunities and neutralizing threats. Krakowski et al. [89] also concluded that, if used correctly in accordance with human resources, the use of AI could result in a higher performance and consequently provide new sources of competitive advantage.

Therefore, based on the results of prior studies regarding the relation between CRM capability, organization performance, and competitive advantage, the following hypotheses are proposed:

H5(a). Customer management interaction capability positively impacts organization performance

H5(b). Customer relationship upgrading capability positively impacts organization performance

H5(c). Customer win-back capability positively impacts organization performance

H6. Organization performance positively impacts competitive advantage

Thus, based on our hypotheses, our research model is presented in Fig. 2.

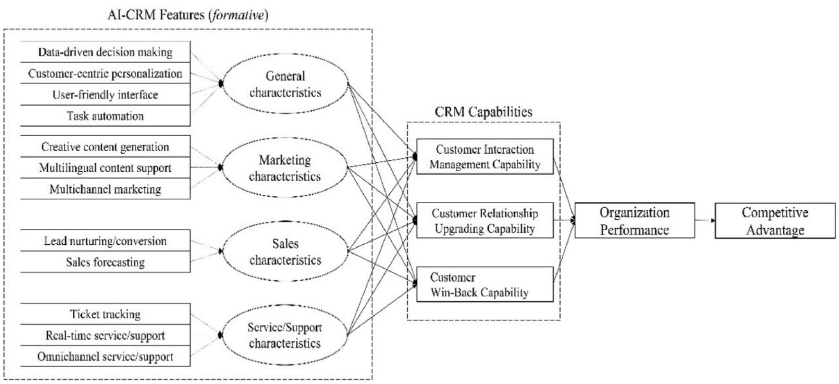

Fig. 2. Proposed research model.

3.3. Materials and methods

3.3.1. Research method

The research was conducted using PLS-SEM via the SmartPLS 4 software. According to Hair et al. [90], PLS-SEM has advantages over CB-SEM when a model involves one or more formatively measured constructs. Furthermore, PLS-SEM allows for the assessment of measurement error and can effectively analyze the complex causal relationship between several latent variables. Finally, PLS-SEM has higher robustness when data are non-normal, which is the case for most survey-based data. CB-SEM, on the other hand, could present abnormal results when the data set size is limited [90].

3.3.2. Survey items and data collection

We adopted survey items from studies related to AI-CRM, CRM capability, and the RBV and modified them to fit our research context. The items for measuring the four characteristics of AI-CRM were adopted from Chatterjee et al. [13] and Chatterjee et al. [59]. Additionally, each characteristic had an additional item that captures the essence of the characteristic for the redundancy analysis, which is required when measuring formatively measured constructs [91]. The three dimensions of CRM capabilities were measured using items from Wang and Feng [54]. Finally, both organization performance and competitive advantage were measured using items adopted from Chatterjee et al. [15]. All items were measured based on a 5-point Likert scale, ranging from 1 for “strongly disagree” to 5 for “strongly agree.”

An online survey was distributed and collected via Amazon MTurk. Only respondents whose job function is Marketing, Sales, and Business Development and has experience using AI-CRM participated in the survey to ensure that the respondents had adequate knowledge on CRM and AI-CRM. Each participant was rewarded $0.50 for participating in the survey. After eliminating 20 responses with no experience of using AI-CRM or with insincere or incomplete responses, a total of 252 samples were used for the analysis. The demographic characteristics of the respondents are presented in Table 4.

3.4. Results

Evaluating the result of PLS-SEM is consisted of mainly two steps: measurement model testing and structural model testing. Furthermore, the validity criteria for examining the measurement model differ for reflective and formative constructs. Thus, in the following sections, the PLS-SEM analysis is conducted following the guidelines presented by Hair et al. [90].

3.5. Measurement model testing

According to Hair et al. [90], different metrics must be applied based on whether the construct is reflectively measured or formatively measured.

The validity criteria for reflective measurement constructs are as follows: (1) the factor loadings of the survey items exceed 0.6 (indicator loading), (2) the average variance extracted (AVE) of the constructs exceed 0.5 (internal consistency reliability), (3) the composite reliability (CR) and Cronbach’s α exceed 0.7 (convergent validity), and (4) the heterotrait-monotrait ratio of the correlations

Table 4
Demographic characteristics.

Characteristic		Frequency (N = 252)	Percentage (%)
Gender	Male	159	63.1
	Female	93	36.9
Work experience	<3 yrs.	22	8.7
	3–5 yrs.	134	53.2
	5–10 yrs.	59	23.4
	10–15 yrs.	26	10.3
	>15 yrs.	11	4.4
Job position	Junior manager	36	14.3
	Mid-level manager	144	57.1
	Senior manager	67	26.6
	Other	5	2.0
Firm size	Self-employed	17	6.7
	2-10 employees	20	7.9
	11-50 employees	36	14.3
	51-100 employees	71	28.2
	101-500 employees	72	28.6
	501-1000 employees	26	10.3
	Over 1000 employees	10	4.0
AI-CRM use experience	<6 months	26	10.3
	6–12 months	129	51.2
	1–2 yrs.	82	32.5
	>2 yrs.	15	6.0
Industry type	Service firm	147	58.3
	Manufacturing firm	105	41.7

(HTMT) is lower than 0.9 (discriminant validity) [90]. The results of the measurement model testing for reflective constructs presented in Tables 5 and 6 confirm the validity of the constructs.

In the case of formative constructs, (1) the correlation between the formative construct and a single-item construct measuring the same concept should exceed 0.7 (redundancy analysis), (2) VIF lower than 3 is ideal while VIF > 3–5 is acceptable, and (3) the statistical significance of weights must be significant at the p-value <0.05 level [90]. As presented below in Table 7, all the validity criteria were met, thus confirming the validity of our measurement model.

3.6. Structural model and hypotheses testing

According to Hair et al. [90], structural model assessment must meet the following three criteria: (1) VIF is ideally lower than 3, while VIF > 3–5 is acceptable, VIF higher than 5 indicate collinearity issues, (2) R^2 value of 0.75, 0.50, 0.25 depict substantial, moderate, and weak explanatory power, and (3) $Q^2_{predict}$ value higher than 0, 0.25, 0.50 depict small, medium, and large predictive accuracy.

As presented below in Table 8, the VIF for all variables met the required criteria, indicating that collinearity is not an issue. Furthermore, the R^2 value of Customer interaction management capability, Customer relationship upgrading capability, Customer win-back capability, Organization performance, and Competitive advantage were 0.639, 0.623, 0.489, 0.580, and 0.358 respectively, indicating that all the variables show moderate explanatory power. Also, the $Q^2_{predict}$ value of these constructs were 0.612, 0.596, 0.453, 0.607, and 0.306 respectively, implying medium to large predictive accuracy.

After the validity of the structural model was confirmed, the hypotheses testing, using a bootstrap resampling procedure to test path significance, was conducted. The result of the hypotheses testing is presented below in Table 9.

The results confirm the significant effect of the general characteristics ($\beta = 0.476$, $p = 0.000$; $\beta = 0.303$, $p = 0.000$; $\beta = 0.368$, $p = 0.000$) and service/support characteristics ($\beta = 0.210$, $p = 0.028$; $\beta = 0.285$, $p = 0.000$; $\beta = 0.208$, $p = 0.035$) of AI-CRM on CRM capability. Thus, H1 and H4 are supported. However, marketing characteristics only significantly affected customer relationship upgrading capability ($\beta = 0.200$, $p = 0.001$), but had no significant effect on customer interaction management capability and customer win-back capability. Thus, only H2(b) is supported. The sales characteristics of AI-CRM had a positive significant effect on both customer interaction management capability ($\beta = 0.225$, p = 0.004) and customer win-back capability ($\beta = 0.154$, $p = 0.046$), but its effect on customer relationship upgrading capability was insignificant. Thus, H3(a) and H3(c) are supported, while H3(b) is rejected.

For the relation between CRM capabilities and organization performance, all three dimensions of CRM capability significantly affected organization performance ($\beta = 0.324$, $p = 0.002$; $\beta = 0.297$, $p = 0.010$; $\beta = 0.190$, $p = 0.010$). Thus, H5 is supported. Finally, organization performance had a significant effect on competitive advantage ($\beta = 0.599$, $p = 0.000$) and thus, H6 is supported.

Additionally, we examined the Cohen's f^2, which explains the effect size of the independent variable on the dependent variable. According to Cohen (2013), $f^2 \geq 0.02$, 0.15, 0.35 each imply small, medium, and large effect size. Thus, based on Cohen's criteria, most paths showed small effect size ($f^2 \geq 0.02$), while H1(a) showed medium effect size ($f^2 \geq 0.15$) and H6 showed large effect size ($f^2 \geq 0.35$). Furthermore, while H3(c) was statistically significant, it did not meet Cohen's criteria for effect size.

3.7. PLSpredict analysis

The predictive performance of PLS-SEM has often been criticized, due to the fact that the analysis only has measures for assessing statistical significance, while lacking predictive performance assessment for out-of-sample data [92]. Recently, the PLSpredict technique, developed by Shmueli et al. [93], is utilized to conduct out-of-sample predictive analysis, thereby facilitating the evaluation of the predictive performance when analyzing new data.

According to Hair et al. [90], the first step of PLSpredict is selecting the key endogenous construct, which in this study are organization performance and competitive advantage. Next, the $Q^2_{predict}$ statistic must be assessed. A positive $Q^2_{predict}$ implies that the PLS-SEM prediction outperform the naïve benchmark. As mentioned above, the $Q^2_{predict}$ value was positive for all items in the chosen constructs. Finally, the PLS-SEM Root Mean Squared Error (RMSE) and naïve LM benchmark RMSE value must be compared. If the PLS-SEM shows higher RMSE for all indicators, it implies that the model lacks predictive power. If the majority of indicators show higher RMSE in the PLS-SEM analysis, it implies that the model has low predictive power. If the minority of indicators show higher RMSE in the PLS-SEM analysis compared to the naïve LM benchmark, it indicates medium predictive power. Finally, if none of the indicators in the PLS-SEM analysis has higher RMSE compared to the naïve LM benchmark, it indicates high predictive power of the

Table 5
Validity results of reflective constructs.

Variable	Factor loadings	AVE	CR	Cronbach's α
Customer interaction management capability	0.680, 0.780, 0.725, 0.785, 0.756	0.557	0.808	0.801
Customer relationship upgrading capability	0.769, 0.773, 0.801, 0.776	0.608	0.786	0.785
Customer win-back capability	0.761, 0.753, 0.750, 0.723	0.558	0.740	0.737
Organization performance	0.722, 0.783, 0.731, 0.779	0.569	0.752	0.748
Competitive advantage	0.835, 0.776, 0.784	0.638	0.726	0.719

Table 6
Discriminant validity results (HTMT).

	CIMC	CRUC	CWBC	OP	CA
CIMC					
CRUC	0.899				
CWBC	0.882	0.891			
OP	0.853	0.857	0.812		
CA	0.737	0.745	0.741	0.793	

Note: CIMC: Customer interaction management capability, CRUC: Customer relationship upgrading capability, CWBC: Customer win-back capability, OP: Organization performance, CA: Competitive advantage.

Table 7
Validity results of formative constructs.

Variable	Item	VIF	Item weights (*p*-value)	Redundancy analysis
General characteristics	GC1	1.375	0.198 (0.001)	0.885
	GC2	1.504	0.483 (0.000)	
	GC3	1.280	0.422 (0.000)	
	GC4	1.589	0.275 (0.000)	
Marketing characteristics	MC1	1.427	0.412 (0.000)	0.925
	MC2	1.187	0.576 (0.006)	
	MC3	1.476	0.298 (0.000)	
Sales characteristics	SC1	1.045	0.574 (0.000)	0.939
	SC2	1.045	0.708 (0.000)	
Service/Support characteristics	SS1	1.827	0.427 (0.000)	0.721
	SS2	1.218	0.463 (0.000)	
	SS3	1.699	0.362 (0.000)	

Table 8
Validity results of collinearity test (VIF).

	CIMC	CRUC	CWBC	OP	CA
GC	3.081	3.081	3.081		
MC	1.990	1.990	1.990		
SC	2.611	2.661	2.611		
SS	3.432	3.432	3.432		
CIMC				2.451	
CRUC				2.427	
CWBC				2.176	
OP					1.000

Note: GC: General characteristics, MC: Marketing characteristics, SC: Sales characteristics, SS: Service/Support characteristics, CIMC: Customer interaction management capability, CRUC: Customer relationship upgrading capability, CWBC: Customer win-back capability, OP: Organization performance, CA: Competitive advantage.

Table 9
Results of hypotheses testing.

Hypotheses	Path coefficient (β)	t-value	Results	f^2
H1(a)	0.476	4.565	Supported	0.203
H1(b)	0.303	4.824	Supported	0.079
H1(c)	0.368	4.106	Supported	0.086
H2(a)	−0.058	0.787	Rejected	–
H2(b)	0.200	3.243	Supported	0.054
H2(c)	0.039	0.519	Rejected	–
H3(a)	0.225	2.853	Supported	0.054
H3(b)	0.098	1.171	Rejected	–
H3(c)	0.154	1.998	Supported	0.018
H4(a)	0.210	2.195	Supported	0.036
H4(b)	0.285	3.502	Supported	0.063
H4(c)	0.208	2.113	Supported	0.025
H5(a)	0.324	3.084	Supported	0.091
H5(b)	0.297	2.570	Supported	0.077
H5(c)	0.190	2.570	Supported	0.035
H6	0.599	7.500	Supported	0.559

research model [90]. As shown below in Table 10, a majority of the indicator showed higher PLS-SEM RMSE compared to the naïve LM benchmark, indicating low, but significant predictive power.

4. Discussion

The results of the PLS-SEM analysis are as follows: first, while all four characteristics significantly affected CRM capability to some degree, not all the characteristics affected all three dimensions of CRM capability. Specifically, while the general characteristics and service/support characteristics of AI-CRM significantly affected all three dimensions, marketing characteristics significantly affected only customer relationship upgrading capability. Also, sales characteristics significantly affected customer interaction management capability and customer win-back capability, but did not significantly affect customer relationship upgrading capability.

The positive effect of AI-CRM general characteristics and service/support characteristics on CRM capability is confirmed in prior studies that analyzed the effect of newly emerging technologies [31,94]. Thus, the AI-CRM's ability to extract meaningful information from large datasets and solve various tasks, along with the recent advance of NLP technology, could significantly help a firm improve their over CRM capability.

Furthermore, the significant effect of the marketing characteristics of AI-CRM on customer relationship upgrading capability is confirmed in real-world cases. By adopting machine learning to their marketing campaign, the Hyatt Hotels Group was able to significantly increase room upgrades (up-selling) and hotel amenity sales (cross-selling), resulting in a 60 % increase of average incremental room revenue [95].

Additionally, the positive impact of sales characteristics of AI-CRM on customer interaction management capability is consistent with the result of Becker et al. [96], who concluded that the use of IT as a technology to track leads affects CRM performance, particularly customer relation initiation. Also, the impact of the sales characteristics on customer win-back capability is confirmed by Chang et al. [97], who asserted that sales forecasting and understanding sales trends is crucial for customer retention.

For the relation between CRM capability, organization performance, and competitive advantage, all three dimensions of a firm's CRM capability significantly affected organization performance, which then affected its firm's competitive advantage. This result confirms the validity of RBV in the AI-CRM context.

Finally, the result of the PLSpredict analysis confirms the predictive power of the research model, thereby, supporting the generalizability of our result.

5. Research implications

The results of our study provide a comprehensive view of the major topics related to AI-CRM and their effects on organizational performance. These findings offer valuable insights for both theory and practice, which are discussed in the following sections.

5.1. Theoretical implications

Our study adopts a holistic approach, combining both quantitative and qualitative analyses of the emerging AI-CRM technology from individual and organizational perspectives. This mixed-method approach addresses the limitations of previous studies that often relied solely on either qualitative or quantitative methods.

First, this study is pioneering in integrating the technological aspects of AI-CRM with organizational context. By using BERTopic for topic modeling, we extracted latent variables from a substantial dataset of online user reviews, providing a more accurate and up-to-date topic extraction compared to traditional qualitative studies, which often rely on small-scale interviews. This methodological advancement enhances our understanding of user perceptions and the critical features of AI-CRM.

Furthermore, Study 2 is among the first to apply the RBV framework to AI-CRM, using PLS-SEM to analyze survey data from users with actual AI-CRM experience. This approach moves beyond the typical focus on adoption intentions, providing a deeper insight into the relationship between AI-CRM features and CRM capabilities, and their subsequent impact on organizational performance. By examining these dynamics, our study contributes to the RBV literature by illustrating how AI-CRM can serve as a valuable, rare, inimitable, and non-substitutable (VRIN) resource that enhances CRM capabilities.

Also, the combination of BERTopic and PLS-SEM bridges the gap between behavioral and technological perspectives. This convergence allows us to capture the complex interactions between user perceptions of AI-CRM features and their impact on organizational outcomes, offering a more nuanced understanding of how these systems drive competitive advantage.

5.2. Practical implications

The practical implications of our study are crucial for AI-CRM developers and firm managers aiming to leverage AI for competitive advantage.

First, our study highlights the necessity for a strategic approach to AI-CRM development and adoption. AI-CRM developers should focus on implementing and upgrading features identified as critical by users. These features vary across different CRM functions (marketing, sales, service/support), suggesting that developers should tailor their software to meet specific user needs within these domains. A user-centric design approach will enhance the relevance and effectiveness of AI-CRM systems.

Also, for firms, the successful adoption of AI-CRM requires a strategic assessment of their CRM capabilities. Firms should evaluate their strengths and weaknesses across the three dimensions of CRM capability—customer interaction management, customer

Table 10
PLSpredict result.

Construct	Indicators	PLS RMSE	LM RMSE	PLS-LM
Organization Performance	OP1	0.583	0.584	**−0.001**
	OP2	0.705	0.704	0.001
	OP3	0.673	0.650	0.023
	OP4	0.725	0.729	**−0.004**
Competitive Advantage	CA1	0.693	0.675	0.018
	CA2	0.740	0.725	0.015
	CA3	0.729	0.740	**−0.011**

relationship upgrading, and customer win-back capability. By identifying specific areas for improvement, firms can select AI-CRM solutions that best address their needs and monitor performance post-implementation to make necessary adjustments.

Furthermore, the automation of routine tasks and customer interactions through AI-CRM can significantly enhance CRM capabilities. Consequently, firms may need to reallocate human resources to more complex and strategic tasks, thereby increasing operational efficiency. This shift can help maximize the benefits of AI-CRM, ensuring that human employees are utilized where they add the most value.

Overall, the study's findings indicate that AI-CRM systems not only improve CRM capabilities but also enhance overall organizational performance and competitive advantage. Firms that strategically implement AI-CRM can expect improvements in customer satisfaction, loyalty, and retention, leading to sustained competitive advantage.

6. Conclusion

The implementation of AI has brought substantial changes to the workplace, and CRM is also expected to be affected significantly. However, adopting AI without planning ahead has failed to provide positive outcomes in terms of organizational performance and may lead to employee resistance. Therefore, in the inevitable trend of AI adoption, it is crucial to provide a strategic guideline on the implementation of AI-CRM, considering both user perception and organizational performance.

To understand user perception toward AI-CRM, key features of AI-CRM were extracted using BERTopic. The result showed that different features were considered as important by the users based on its main function. Overall, user felt that the AI's ability to learn customer data and perform various task automatically was the main advantage of adopting AI-CRM. Furthermore, different characteristics of AI-CRM had different effects on CRM capability.

The results of the analysis provide meaningful implications for researchers and managers. By building a strategic guideline based on the results of our study, it is expected that an effective implementation of AI-CRM will be possible.

However, the study is not without its limitations. Potential biases in user reviews could include self-selection bias, recency bias, and a non-representative sample, which could skew the results. Future research could mitigate these biases by incorporating multiple data sources and using sentiment analysis to balance perspectives. The generalizability of findings across different industries is also a concern. Industries relying on quantitative data (e.g., manufacturing) may experience different impacts from AI-CRM compared to those dependent on qualitative interactions (e.g., service). Future studies should investigate the performance of AI-CRM features across various sectors to enhance generalizability. Additionally, the sample size in this study may not be large enough to capture the full variability in responses, affecting predictive power. Increasing the sample size and incorporating longitudinal data could provide a more comprehensive view. The study also does not address potential employee resistance to AI-CRM adoption, which can significantly impact implementation success. Future research should explore the relationship between employee acceptance and the effectiveness of AI-CRM technologies.

Furthermore, to further explore causal relationships between AI-CRM features and organizational performance, future studies could conduct experimental and longitudinal studies to establish causality and understand long-term effects, thereby overcoming the limitations of a survey-based analysis. Also, exploring the role of organizational culture and leadership in AI-CRM adoption can offer valuable guidance for managers. Finally, to confirm the specific effects of AI-CRM on organizational performance, future studies could perform a difference-in-differences analysis using real-world financial data.

Data availability statement

Data is available upon request.

CRediT authorship contribution statement

Joon Woo Yoo: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Junsung Park:** Writing – review & editing, Validation, Methodology, Data curation. **Heejun Park:** Writing – review & editing, Supervision, Software, Resources, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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