
GLOBAL BUSINESS & FINANCE REVIEW, Volume. 29 Issue. 2 (MARCH 2024), 112-126
pISSN 1088-6931 / eISSN 2384-1648 | Https://doi.org/10.17549/gbfr.2024.29.2.112


**GLOBAL BUSINESS & FINANCE REVIEW**

www.gbfrjournal.org

# The Influence of AI-CRM Adoption and Big Data Analytical Capability on Firm Performance of Large Enterprises in Thailand

Thanatchaporn Jaruwanakul†

*Lecturer, Ph.D. Innovative Technology Management, Graduate School of Business and Advanced Technology Management, Assumption University, Thailand.*

A B S T R A C T

**Purpose:** This research explores the impact of adopting AI-CRM on integration capability, team collaboration, and firm performance. Additionally, it investigates whether big data analytical capability significantly influences integration capability, team collaboration, and competitive advantage. The study delves into whether integration capability is a driver of team collaboration and assesses the influence of competitive advantage on firm performance.
**Design/methodology/approach:** A quantitative approach was employed using a questionnaire as the primary tool. Online Google forms were distributed to 450 middle-high level management professionals across ten large enterprises in Thailand that have implemented AI-CRM and big data analytics. Sampling techniques included judgmental, convenience, and snowball sampling. Data analysis utilized Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) to validate model fit and test hypotheses.
**Findings:** The study revealed that the adoption of AI-CRM significantly impacts integration capability, team collaboration, and firm performance. Big data analytical capability has a significant influence on team collaboration and competitive advantage but lacks a significant effect on integration capability. Furthermore, integration capability is significantly associated with team collaboration. However, the study did not find support for the relationship between competitive advantage and firm performance.
**Research limitations/implications:** Findings are specific to the 450 middle-high level managers in ten large Thai enterprises; caution is needed when applying results to a broader population. Furthermore, the study focused on key factors, but additional variables may influence relationships. Future research could explore a broader range of factors. The study did not deeply investigate potential mediating mechanisms between variables. Further research could explore detailed pathways connecting studied variables.
**Originality/value:** The study provides actionable insights for businesses, particularly those in Thailand, that have implemented AI-CRM and big data analytics. Practical implications may guide strategic decisions to enhance integration, collaboration, and overall performance.

*Keywords: AI-CRM, big data analytical capability, integration capability, competitive advantage, firm performance*

## I. Introduction

The utilization of emerging technologies like big data and artificial intelligence is bringing about substantial transformations in the rapidly evolving

Received: Jan. 9, 2024; Revised: Feb. 5, 2024; Accepted: Feb. 12, 2024
† Corresponding author: Thanatchaporn Jaruwanakul
E-mail: thanatchapornjrw@au.edu

landscape of contemporary business (Baek, 2021). The adoption of Artificial Intelligence in Customer Relationship Management (AI-CRM) and the utilization of big data analytics have emerged as pivotal strategies for organizations seeking competitive advantages (Ledro et al., 2022). As businesses navigate the complexities of integrating these advanced technologies into their operations, questions arise regarding the profound effects on organizational dynamics (Kraus et al., 2022). This research endeavors to shed light on the multifaceted implications of AI-CRM adoption and big data analytical capability by examining their influence on integration capability, team collaboration, and firm performance.

In 2018, the Big Data analytics business in Thailand experienced substantial growth, reaching an estimated value of THB 13.6 billion, marking a 15% increase from the previous year. This surge in value is attributed to heightened spending across various sectors on systems and related services. Looking ahead to 2019, the Big Data market in Thailand is anticipated to further expand, reaching a projected value of THB 15.6 billion. Within this projection, THB 9.2 billion is earmarked for IT and business services, THB 4.7 billion for software, and the remaining THB 1.7 billion for hardware (Frost & Sullivan, 2019).

Simultaneously, the customer relationship management (CRM) software market in Thailand is experiencing significant growth, fueled by the increasing demand for cloud services. In 2018, revenue from CRM software grew by 14.9% year-on-year. Globally, the CRM market is forecasted to reach a value of US$11 billion by 2022, with a compound annual growth rate of 7.9% over five years. Among the top software markets in Thailand, including analytics, artificial intelligence (AI), application platforms, collaborative applications, and security, CRM held the highest market share of 33% in the previous year. This reflects the rising trend of organizations undertaking digital transformation initiatives. Investments in CRM applications are on the rise as organizations prioritize enhancing customer acquisition and retention, omnichannel platforms, and overall customer experience (CX) (Sudechawongsakul, 2019).

Recent literature emphasizes the transformative potential of AI-CRM in enhancing customer interactions and relationship management (Alokla et al., 2019; Verhoef et al., 2021). However, limited research has systematically explored the broader organizational impacts, especially concerning integration capability and team collaboration. Additionally, the role of big data analytics in shaping organizational processes and competitive advantage has been a subject of interest (Chen et al., 2012; McAfee & Brynjolfsson, 2012), yet its specific influence on integration capability and team collaboration remains a relatively uncharted territory.

Integration capability, defined as an organization's ability to seamlessly merge different technological components (Liu et al., 2013), is pivotal in the context of AI-CRM and big data analytics adoption. Understanding how the integration of these technologies affects collaboration among team members is crucial for optimizing their combined benefits. Furthermore, the study seeks to ascertain whether integration capability acts as a catalyst for team collaboration within the organizational framework.

Competitive advantage, a cornerstone of strategic management (Barney, 1991), is undergoing a paradigm shift with the infusion of AI and big data analytics. While prior research acknowledges the role of technology in gaining competitive advantage (Porter, 1985), the specific impact of AI-CRM and big data analytics on competitive advantage and subsequent firm performance requires a nuanced examination.

Some recent studies emphasize impact of AI-CRM and big data analytics in businesses. The results of the bibliometric analysis facilitated the identification of three primary subfields within the AI literature pertaining to CRM: Big Data integration with CRM as a database, the application of AI and machine learning techniques across various CRM activities, and the strategic management of AI-CRM integrations (Ledro et al., 2022). Hu and Basiglio (2024) emphasize that the integration of CRM technology within automotive firms has led to the establishment of exemplary practices, consequently enhancing business performance and Total Quality Management (TQM) while bolstering their digital culture. Furthermore, the study addresses the challenges associated with the implementation of CRM and Big Data Analytics (BDA) within this context. Chatterjee et al. (2023) underscored the significance and strategies involved in the adoption of AI-integrated Social Customer Relationship Management (CRM) by Multinational Enterprises (MNEs), particularly within the framework of international relationship management amid the social distancing constraints imposed by the Covid-19 pandemic.

This research aims to address these gaps by employing a quantitative approach to analyze the interplay between AI-CRM adoption, big data analytical capability, integration capability, team collaboration, competitive advantage, and firm performance. Through a comprehensive exploration of these relationships, this study contributes to both academic literature and managerial practices, providing insights into the transformative effects of AI-CRM and big data analytics on organizational dynamics.

# II. Literature Review

## A. AI-CRM Adoption

According to Go et al. (2020), artificial intelligence (AI) is one of the innovative technologies in the 4th industrial revolution. AI-CRM is recognized as a transformative technology that can significantly impact an organization's integration capability. Integration capability refers to the ability of an organization to seamlessly merge and utilize different technological components (Chatterjee et al., 2023). Studies have indicated that AI-CRM systems, with their ability to centralize customer data and automate processes, play a crucial role in enhancing integration across various organizational functions (Alokla et al., 2019; Chatterjee et al., 2023; Liu et al., 2013). The integration of AI-CRM tools enables a more cohesive and holistic approach to customer relationship management, contributing to overall organizational efficiency (Ledro et al., 2022).

Effective team collaboration is a cornerstone of organizational success, and AI-CRM adoption has been shown to influence collaborative processes positively (Chen, 2023). AI-CRM tools facilitate real-time data sharing, enhance communication, and provide valuable insights that enable cross-functional teams to work more cohesively (Ledro et al., 2022). The integration of AI-driven analytics into CRM systems allows teams to access relevant information promptly, fostering a collaborative environment that is responsive to customer needs and market trends (Ledro et al., 2022).

The relationship between AI-CRM adoption and firm performance has been a focal point in research, with evidence suggesting a positive correlation (Chatterjee et al., 2023). AI-CRM enhances decision-making processes, streamlines operations, and allows organizations to offer personalized experiences to customers, ultimately contributing to improved financial performance (Alokla et al., 2019). Organizations that strategically leverage AI-CRM technologies experience increased customer satisfaction, retention, and overall profitability (Libai et al., 2020). Building upon this discourse, it leads to below hypotheses:

**Hypothesis 1:** AI-CRM adoption has a significant influence on integration capability.

**Hypothesis 2:** AI-CRM adoption has a significant influence on team collaboration.

**Hypothesis 7:** AI-CRM adoption has a significant influence on firm performance.

## B. Big Data Analytical Capability

Big Data analytical capability refers to an organization's ability to effectively collect, process, analyze, and derive actionable insights from large and diverse datasets (Chen et al., 2012). This capability is integral to leveraging the potential value embedded in massive volumes of data (Mikalef et al., 2020). Chen (2023) indicated a positive relationship between Big Data analytical capability and integration capability within organizations. Big Data analytics provides the tools and methodologies to integrate diverse data sources and types, enabling a more holistic view of organizational operations and enhancing decision-making processes (LaValle et al., 2011).

Big Data analytics fosters team collaboration by providing teams with valuable insights and evidence-based information for decision-making (Anwar et al., 2018). Studies suggest that organizations with advanced Big Data capabilities create a data-driven culture that encourages collaboration among teams, breaking down silos and promoting knowledge sharing (Cai et al., 2016; Davenport et al., 2010; Rezaee & Wang, 2018).

The literature consistently highlights the strategic importance of Big Data analytics in gaining a competitive advantage (Kubina et al., 2015; Prescott, 2014). Organizations that effectively harness Big Data can identify market trends, customer preferences, and operational efficiencies, thereby positioning themselves ahead of competitors (McAfee & Brynjolfsson, 2012). Based on above assumptions, below hypotheses are indicated:

**Hypothesis 3:** Big data analytical capability has a significant influence on integration capability.
**Hypothesis 4:** Big data analytical capability has a significant influence on team collaboration.
**Hypothesis 6:** Big data analytical capability has a significant influence on competitive advantage.

## C. Integration Capability

Integration capability refers to an organization's capacity to harmonize diverse technological elements, systems, and processes into a unified and coherent whole (Chen, 2023). Studies emphasize that integration capability plays a pivotal role in fostering communication and information sharing within organizations (van de Wetering et al., 2021). When different departments and teams have access to integrated data and systems, the barriers to communication are reduced, creating an environment conducive to collaboration (Jha et al., 2020). Technological integration, facilitated by integration capabilities, is identified as a key driver of collaborative processes (Naimi-Sadigh et al., 2021).

Research suggests that organizations with advanced technological integration are more likely to leverage collaborative technologies effectively, leading to improved teamwork and knowledge sharing (Lacity et al., 2009). Enhancing team collaboration within a company is integral to delivering top-notch services to customers and attaining exceptional performance. Integration capability, as defined by Irfan and Wang (2019), pertains to the extent to which a company collaborates with its supply chain partners, encompassing both upstream suppliers and downstream customers. Based on the evidence from previous studies, a following hypothesis is developed:

**Hypothesis 5:** Integration capability has a significant influence on team collaboration.

## D. Competitive Advantage

Competitive advantage refers to the unique strengths and capabilities that enable a firm to outperform its rivals and achieve superior market positioning (Porter, 1985). It is a fundamental concept in strategic management, emphasizing the importance of differentiation and efficiency in gaining a competitive edge (Anwar et al., 2018). According to Pham (2019), Porter's strategies, encompassing differentiation and cost leadership, are commonly recognized as generic competitive strategies and frequently utilized as benchmarks for assessing a firm's competitive advantage (CA). These strategies are acknowledged for their substantial positive impact on the performance of various organizational types, as observed in the significant improvements reported by different entities (Salavou & Sergaki, 2013).

Competitive advantage has recently become a focal point for researchers, with firms successfully implementing these strategies demonstrating enhanced profitability. Notably, competitive advantage not only exerts a considerable influence on a firm's financial performance but also exhibits a robust association with various market performance metrics (Sousa Batista et al., 2016). According to Saeidi et al. (2015), competitive advantage has arisen as the central factor exerting a substantial and elevated influence on firm performance. Accordingly, the investigation leads to a proposed hypothesis:

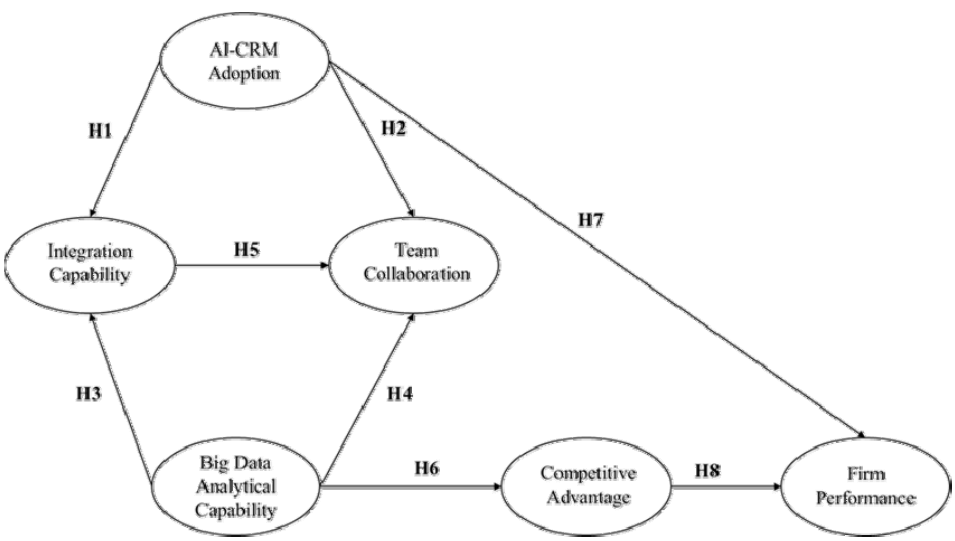
**Hypothesis 8:** Competitive advantage has a significant influence on firm performance.

The conceptual framework is adopted from three previous research. First, Chen (2023) investigated the impact of high-tech firm employees' intention to adopt AI applications and the firm's big data analytical capability on operational performance. Second, Anwar et al. (2018) catered the understanding of the role of Competitive Advantage (CA) as a mediator in this relationship, examining the influence of Big Data Technological Capabilities (BDTC) and Big Data Personal Capabilities (BDPC) on the performance of firms within one of the world's leading emerging economies, specifically China. Third, Chatterjee et al. (2023) conducted empirical research to analyze the impact of the integration of Artificial Intelligence (AI) with Social Customer Relationship Management (SCRM) in Multinational Enterprises (MNEs) concerning international relationship management. This investigation specifically focuses on the challenges posed by social distancing conditions resulting from the COVID-19 pandemic. Figure 1 illustrates the study framework along with the proposed hypotheses.

# III. Methodology

## A. Pre-Test

To ensure content validity, three experts were invited to conduct an Item-Objective Congruence (IOC) index, rating from 0, -1 and 1. A score of 1 signifies that the item effectively measures the objective, whereas a score of -1 indicates the irrelevance of the item to the objective. Meanwhile, a score of 0 suggests that the expert is uncertain about their ability to measure the objective. Consequently, the average Item-Objective Congruence (IOC) index was 0.75, signifying a level of good




Source: Constructed by Author.

**Figure 1.** Conceptual framework

content validity (Turner & Carlson, 2003), leading to the retention of all scale items in the questionnaire. A pilot test involving 40 participants preceded the main data collection, revealing favorable Cronbach's alpha coefficient values that exceeded the acceptable threshold of 0.7, as recommended by Nunnally and Bernstein (1994).

## B. Survey Methods

The questionnaire design was meticulously crafted for accuracy and relevance in data collection. Adopting a quantitative research approach enabled systematic gathering and analysis of numerical data, allowing for statistical analysis to uncover patterns, trends, and relationships. Distribution online from July to September 2023 offered cost-effectiveness, efficiency, and broad sample reach.

Screening questions ensured participant eligibility, focusing on employment status, management level, and familiarity with AI-CRM and big data analytic: "Are you employed in these companies?" "Are you in the middle-high level of management?" and "Do you have information about AI-CRM and big data analytics in your company?"

The survey instrument used a Likert scale to measure items on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). This study included demographic questions for profiling and analysis. This approach allowed for the identification of demographic trends and variations in responses. Overall, the design was tailored to meet study objectives, ensuring the collection of reliable data for comprehensive analysis.

## C. Population and Sample Size

The target population is middle to high-level management professionals within ten prominent enterprises in Thailand that have implemented AI-CRM and big data analytics. The names of these companies remain undisclosed due to the absence of official consent. For the utilization of structural equation modeling—a statistical technique for analyzing intricate relationships—a sample size of at least 200 respondents is recommended for robust and reliable results (Kline, 2011). To ensure a comprehensive dataset, an online survey was distributed to approximately 1,000 participants. Following careful scrutiny, 450 responses were deemed valid, meeting the criteria for proceeding to the subsequent data analysis phase. The online survey conducted for this study was designed with meticulous attention to detail to ensure credibility and reliability in the data collection process. Given the considerations of cost-effectiveness, efficiency, and the aim for a broad sample reach, a participant pool of 450 individuals proves adequate for conducting the structural equation modeling statistical technique, thereby ensuring credibility and reliability in the data collection process.

## D. Sampling Technique

The sampling strategy in this study encompasses judgmental, convenience, and snowball sampling techniques. Initially, high-level management professionals within ten prominent enterprises in Thailand that have implemented AI-CRM and big data analytics were specifically selected by the researcher. Despite the possibility of using employee count for a quota, convenience sampling was chosen. An online survey, distributed through Google Forms, was then utilized to reach voluntary respondents without ensuring proportionate distribution. To broaden the reach, the researcher employed direct communication channels such as emails, LinkedIn, and the Line chat application to engage with the identified group. Additionally, snowball sampling was incorporated, encouraging participants to share the online survey link with their qualified peers and colleagues, thereby expanding the study's scope. This combination of sampling techniques ensures a diverse and representative participant pool for the research investigation.

To mitigate biases associated with judgmental sampling, and snowball sampling, researcher is transparent about the purpose of the study and encourage participation from a diverse range of individuals. Additionally, efforts were to minimize self-selection bias by ensuring anonymity and confidentiality in data collection processes. Furthermore, researcher seeks external validation of findings through replication studies or cross-validation with independent datasets.

### E. Data Analysis

For the data analysis, confirmatory factor analysis (CFA) and structural equation modeling (SEM) were selected as the statistical techniques. These methods were applied to assess the goodness of fit of the proposed model and to test the formulated hypotheses. Various statistical tools were employed throughout this analytical phase to ensure a comprehensive examination of the data.

## IV. Findings

Based on the findings presented in Table 1, the demographic data collected from a sample of 450 participants reveals a diverse representation. In terms of gender, 46.2% are male, while 53.8% are female. Regarding age distribution, the majority falls within the age groups of 31-40 years old (36.9%) and 41-49 years old (29.1%). Those below 30 years old constitute 15.1%, and those aged 50 years and above represent 18.9%. In terms of job roles, the participants encompass a variety of positions, with notable percentages in Sales/Marketing (22.4%), Human Resources (20.2%), and Product Development (14.9%). Other job roles, including C-Level, Finance/Accounting, Administrations, Information Technology, and Others, contribute to the overall diversity of the sample. This comprehensive demographic overview reflects a balanced and varied representation of participants across different gender, age, and job role categories. The demographical data shows that AI CRM software that integrates job functions across Human Resources, Finance/Accounting, and Sales/Marketing typically offer a comprehensive suite of features designed to streamline processes and enhance

**Table 1.** Demographic profile

| Demographic and General Data (N=450) | | Frequency | Percentage |
|---|---|---|---|
| Gender | Male | 208 | 46.2% |
| | Female | 242 | 53.8% |
| | Total | 450 | 100% |
| Age | Below 30 Years Old | 68 | 15.1% |
| | 31-40 Years Old | 166 | 36.9% |
| | 41-49 Years Old | 131 | 29.1% |
| | 50 Years Old and above | 85 | 18.9% |
| | Total | 450 | 100% |
| Job Role | C-Level | 24 | 5.3% |
| | Sales/Marketing | 101 | 22.4% |
| | Finance/Accounting | 60 | 13.3% |
| | Human Resources | 91 | 20.2% |
| | Administrations | 55 | 12.2% |
| | Product Development | 67 | 14.9% |
| | Information Technology | 42 | 9.3% |
| | Others | 10 | 2.2% |
| | Total | 450 | 100% |

Source: Constructed by Author.

collaboration across departments. Some examples of such AI CRM software include Salesforce Einstein, Microsoft Dynamics 365, Oracle CX Cloud Suite etc.

## A. Confirmatory Factor Analysis

Within Confirmatory Factor Analysis (CFA), the data examination involved assessing both convergence validity and discriminant validity. Internal consistency was gauged using Cronbach's Alpha, adhering to the criterion that the value must be 0.70 or higher (Nunnally & Bernstein, 1994), as outlined in Table 2. Acceptability was determined based on criteria such as t-values exceeding 1.98, p-values below 0.5, and factor loadings surpassing 0.5 (Hair et al., 2010).

Additionally, in alignment with the guidance provided by Fornell and Larcker (1981), the Composite Reliability (CR) exceeds the threshold of 0.6, and the Average Variance Extracted (AVE) surpasses the cut-off point of 0.4. These criteria ensured the robustness of the estimates, confirming both convergence validity and discriminant validity within the measurement model.

## B. Discriminant Validity

The assessment of discriminant validity, following Fornell and Larcker's (1981) guidelines, involves computing the square root of the Average Variance Extracted (AVE) for each variable. In the specific context of this study, discriminant validity is confirmed when these calculated values surpass all inter-construct or factor correlations. This outcome signifies that each construct exhibits stronger correlations with its own measures than with measures of other constructs, establishing the distinctiveness of the considered constructs.

Furthermore, the analysis addresses potential multicollinearity concerns by examining correlation coefficients. The results, presented in Table 3, indicate

**Table 2.** Confirmatory factor analysis result, composite reliability (CR) and average variance extracted (AVE)

| Variables | Source of Questionnaire | No. of Items | Cronbach's | Factors Loading | CR | AVE |
|---|---|---|---|---|---|---|
| AI-CRM Adoption (AIA) | Chatterjee et al. (2023) | 3 | 0.884 | 0.826 - 0.875 | 0.885 | 0.719 |
| Integration Capability (IC) | Chen (2023) | 5 | 0.868 | 0.695 - 0.815 | 0.868 | 0.570 |
| Team Collaboration (TC) | Chen (2023) | 9 | 0.877 | 0.604 - 0.708 | 0.878 | 0.445 |
| Big Data Analytical Capability (BDA) | Bhatti et al. (2022) | 6 | 0.855 | 0.664 - 0.736 | 0.856 | 0.498 |
| Competitive Advantage (CA) | Anwar et al. (2018) | 5 | 0.845 | 0.676 - 0.794 | 0.846 | 0.524 |
| Firm Performance (FP) | Chatterjee et al. (2023) | 6 | 0.885 | 0.663 - 0.814 | 0.886 | 0.566 |

Source: Constructed by Author.

**Table 3.** Discriminant validity

| | TC | AIA | IC | BDA | CA | FP |
|---|---|---|---|---|---|---|
| TC | 0.667 | | | | | |
| AIA | 0.644 | 0.848 | | | | |
| IC | 0.261 | 0.275 | 0.755 | | | |
| BDA | 0.606 | 0.545 | 0.135 | 0.705 | | |
| CA | 0.663 | 0.483 | 0.343 | 0.512 | 0.724 | |
| FP | 0.209 | 0.300 | 0.128 | 0.239 | 0.189 | 0.752 |

Source: Constructed by Author.

no significant issues related to multicollinearity. This determination is made based on the factor correlations not exceeding the commonly recognized threshold of 0.80 (Studenmund, 1992). The absence of high correlations among factors suggests that the variables are relatively independent, contributing to the robustness and reliability of the measurement model in the study.

## C. Structural Equation Model (SEM)

SEM starts with the formulation of a measurement model, specifying the relationships between latent constructs (unobservable variables) and their observed indicators. This aspect involves Confirmatory Factor Analysis (CFA), ensuring that the chosen indicators effectively measure the underlying constructs (Byrne, 2010). Evaluating the goodness of fit is crucial in SEM. The fit indices assess how well the proposed model fits the observed data. The evaluation of the measurement and structural model in Confirmatory Factor Analysis (CFA) involves assessing the goodness of fit. This study utilized various criteria, including CMIN/DF, GFI, AGFI, NFI, CFI, TLI, IFI, and RMSEA, as outlined in Table 4. Notably, all computed values adhered to the established acceptance criteria without necessitating adjustments. Consequently, the convergent and discriminant validities of this study were confirmed, validating and reliability of the measurement model.

## D. Research Hypothesis Testing Result

The results of hypothesis testing, obtained from the regression weights and R2 variances, are displayed in Table 5, and Figure 2. Statistical significance, confirming support for the hypotheses, is determined at a significance level of $p = 0.05$ (Hair et al., 2010).

The study investigated the impact of various factors on organizational performance within the context of AI-CRM adoption, big data analytical capability, integration capability, team collaboration, competitive advantage, and firm performance. The hypotheses were systematically tested, and the results provide valuable insights into the relationships among these key constructs.

The first hypothesis (H1) posited that AI-CRM adoption significantly influences integration capability. The analysis revealed strong support for this hypothesis, with a standardized path coefficient (β) of 0.262 and a significant T-value of 4.887. This suggests that organizations embracing AI-CRM tech-

**Table 4.** Goodness of fit of measurement model & structural model

| Index | Acceptable Values | Measurement Model | Structural Model |
|---|---|---|---|
| | | Statistical Values (No Model Adjustment) | Statistical Values (No Model Adjustment) |
| CMIN/DF | < 3.00 (Hair et al., 2006) | 707.082/512 = 1.381 | 937.339/519 = 1.806 |
| GFI | ≥ 0.85 (Kline, 2011) | 0.915 | 0.893 |
| AGFI | ≥ 0.85 (Kline, 2011) | 0.901 | 0.877 |
| NFI | ≥ 0.85 (Kline, 2011) | 0.908 | 0.878 |
| CFI | ≥ 0.85 (Kline, 2011) | 0.972 | 0.941 |
| TLI | ≥ 0.85 (Kline, 2011) | 0.970 | 0.936 |
| IFI | ≥ 0.85 (Kline, 2011) | 0.973 | 0.941 |
| RMSEA | ≤ 0.08 (Hooper et al., 2008) | 0.029 | 0.042 |
| Model summary | | Acceptable Model Fit | Acceptable Model Fit |

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index, TLI = Tucker-Lewis index, IFI = Incremental Fit Index, and RMSEA = root mean square error of approximation
Source: Constructed by Author.

nologies experience enhanced integration capabilities, aligning with the evolving technological landscape.

Moving to the second hypothesis (H2), which asserts that AI-CRM adoption has a substantial impact on team collaboration, the findings affirm the hypothesis. The path coefficient of 0.454 and a T-value of 7.908 indicate a robust positive relationship. Organizations integrating AI into their customer relationship management processes are likely to witness improved team collaboration, fostering a more cohesive and efficient working environment.

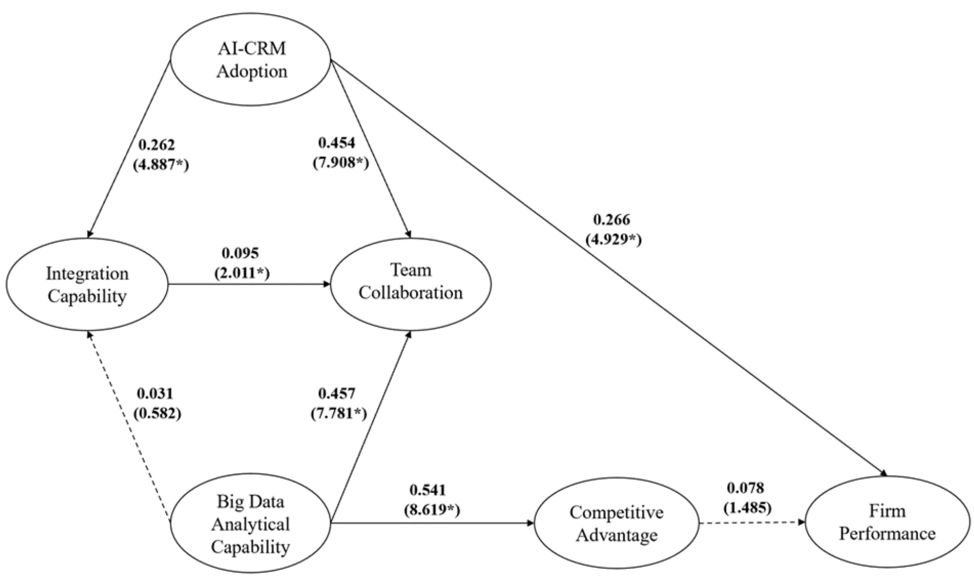
However, the third hypothesis (H3) proposed that big data analytical capability significantly influences integration capability. Contrary to expectations, the results did not support this hypothesis. The low path coefficient (0.031) and the non-significant T-value (0.582) suggest that, in this study, big data analytical capability does not contribute significantly to integration capability.

Moving to the fourth hypothesis (H4), which

**Table 5.** Hypothesis result of the structural model

| Hypotheses | Paths | Standardized Path Coefficients (β) | S.E. | T-Value | Tests Result |
|---|---|---|---|---|---|
| H1 | IC<---AIA | 0.262 | 0.047 | 4.887* | Supported |
| H2 | TC<---AIA | 0.454 | 0.039 | 7.908* | Supported |
| H3 | IC<---BDA | 0.031 | 0.055 | 0.582 | Not Supported |
| H4 | TC<---BDA | 0.457 | 0.048 | 7.781* | Supported |
| H5 | TC<---IC | 0.095 | 0.037 | 2.011* | Supported |
| H6 | CA<---BDA | 0.541 | 0.057 | 8.619* | Supported |
| H7 | FP<---AIA | 0.266 | 0.043 | 4.929* | Supported |
| H8 | FP<---CA | 0.078 | 0.055 | 1.485 | Not Supported |

Note: *p<0.05
Source: Constructed by Author.




Remark: Dashed lines, not significant; solid lines, significant. *p<0.05
Source: Constructed by Author.

**Figure 2.** The results of structural model

suggests that big data analytical capability has a significant influence on team collaboration, the findings align with the hypothesis. The strong path coefficient (0.457) and a significant T-value of 7.781 indicate that organizations with advanced big data analytical capabilities are more likely to experience enhanced team collaboration.

The fifth hypothesis (H5) posited that integration capability significantly influences team collaboration. The results support this hypothesis, with a path coefficient of 0.095 and a significant T-value of 2.011. This indicates that organizations with strong integration capabilities are likely to foster improved team collaboration.

The sixth hypothesis (H6) proposed that big data analytical capability significantly influences competitive advantage. The results strongly support this hypothesis, with a high path coefficient (0.541) and a significant T-value of 8.619. Organizations with advanced big data capabilities are positioned to gain a competitive edge, emphasizing the strategic importance of data analytics.

Turning to the seventh hypothesis (H7), which suggests that AI-CRM adoption significantly influences firm performance, the findings provide strong support. The path coefficient of 0.266 and a significant T-value of 4.929 indicate that organizations embracing AI-CRM technologies are likely to experience enhanced overall firm performance.

Finally, the eighth hypothesis (H8) proposed that competitive advantage significantly influences firm performance. However, the results do not support this hypothesis. The low path coefficient (0.078) and the non-significant T-value (1.485) suggest that, in this study, competitive advantage does not exert a significant influence on firm performance.

In conclusion, the study's findings shed light on the intricate relationships among AI-CRM adoption, big data analytical capability, integration capability, team collaboration, competitive advantage, and firm performance. While some hypotheses received strong support, others revealed nuanced relationships, emphasizing the complexity of organizational dynamics in the context of emerging technologies. These results offer practical implications for organizations aiming to leverage AI and big data capabilities to enhance collaboration, integration, and overall performance. The study also suggests potential avenues for further research to deepen our understanding of the interplay between technology adoption and organizational outcomes.

# V. Discussion

The study delved into the complex interrelationships among AI-CRM adoption, big data analytical capability, integration capability, team collaboration, competitive advantage, and firm performance. The results offer valuable insights into the impact of these factors on organizational dynamics, providing a nuanced understanding of their roles in shaping modern business environments.

The study unequivocally supports the positive influence of AI-CRM adoption on integration capability (H1), team collaboration (H2), and firm performance (H7). Organizations embracing AI technologies in their customer relationship management processes are better equipped to integrate diverse functions, enhance collaboration among teams, and ultimately achieve superior overall performance (Ledro et al., 2022). This aligns with the broader trend of technology-driven transformations in the business landscape (Alokla et al., 2019; Chatterjee et al., 2023; Liu et al., 2013).

While big data analytical capability significantly influences team collaboration (H4) and competitive advantage (H6), the study brings to light a nuanced picture regarding its impact on integration capability (H3). The non-significant relationship between big data analytical capability and integration capability suggests that, in this context, the analytical prowess offered by big data may not inherently contribute to improved integration across organizational functions (McAfee & Brynjolfsson, 2012).

The study supports the idea that integration capability positively influences team collaboration (H5). This underscores the importance of streamlined internal processes and the ability to connect various facets of an organization to foster effective collaboration among teams (Chen, 2023). As supported by Irfan and Wang (2019), organizations that prioritize integration are more likely to witness collaborative efforts that span across departments and functions.

The findings reveal that, in this study, competitive advantage does not significantly influence firm performance (H8). This unexpected result prompts further exploration into the factors contributing to organizational success. It suggests that while gaining a competitive edge through strategies like big data analytics (H6) is crucial, this advantage might not always translate directly into enhanced overall firm performance (Kubina et al., 2015; Prescott, 2014).

In discussing the potential reasons for unsupported hypotheses, one potential explanation for the lack of significant influence of big data analytical capability on integration capability may stem from the organization's pre-existing technological infrastructure. Further investigations could employ qualitative or mixed-methods approaches to delve into the intricate dynamics between big data analytical capability and integration capability.

Furthermore, consideration of a mature industry, where competitors share similar levels of product differentiation, pricing strategies, and market share, sheds light on the challenges of attaining sustainable competitive advantage. In such contexts, competitors can swiftly replicate or counteract any implemented competitive strategies, rendering the achievement of sustained advantage difficult. Future research endeavors could focus on exploring mediating or moderating factors that impact the relationship between competitive advantage and firm performance.

## A. Theoretical Contributions

The theoretical implications of this study are multifaceted and significant in advancing our understanding of organizational dynamics in the digital era.

Firstly, by affirming the transformative impact of AI-CRM adoption on integration capability and team collaboration, this study enriches existing theories in technology adoption and organizational structure. It contributes to the body of knowledge by demonstrating how the integration of AI technologies into CRM systems can lead to enhanced integration across departments and improved collaboration among teams. This aligns with theories of technology adoption, which posit that the successful implementation of new technologies can reshape organizational structures and processes.

Secondly, the findings provide nuanced insights into the role of big data analytics. By supporting its positive influence on team collaboration and competitive advantage, the study highlights the strategic importance of leveraging big data for organizational success. However, the revelation of a non-significant relationship between big data analytics and integration capability challenges prevailing expectations and underscores the need for further exploration of the complexities surrounding data integration processes within organizations.

Moreover, the study challenges conventional wisdom by indicating that competitive advantage may not significantly influence overall firm performance in the context examined. This finding prompts a reevaluation of traditional perspectives on the relationship between competitive advantage and organizational outcomes, suggesting that other factors may play a more prominent role in driving firm performance in the digital era.

Overall, this holistic examination of interconnected constructs contributes to a more comprehensive theoretical understanding of organizational dynamics in the digital era. It emphasizes the importance of considering the intricate interplay between technology adoption, organizational structure, and competitive dynamics in shaping organizational outcomes. The study calls for further exploration of contextual factors that influence these complex relationships, paving the way for future research to delve deeper into the evolving landscape of digital transformation and its implications for organizational theory and practice.

### B. Practical Implications

The study's findings highlight the significant positive impact of AI-CRM adoption on integration capability, team collaboration, and firm performance. This underscores the strategic importance for organizations to incorporate AI technologies into their customer relationship management strategies. By leveraging AI-CRM systems, organizations can streamline processes, personalize customer interactions, and gain valuable insights into customer behavior and preferences. This not only enhances operational efficiency but also strengthens customer relationships, leading to improved business performance and competitive advantage.

The study also emphasizes the importance of big data analytics in fostering team collaboration and gaining a competitive advantage. Organizations that invest in data-driven capabilities can harness the power of big data to extract actionable insights, identify market trends, and make informed business decisions. By leveraging advanced analytics techniques, organizations can optimize resource allocation, anticipate customer needs, and adapt quickly to changing market conditions. This enables them to stay ahead of the competition and drive sustainable growth in today's dynamic business environment.

In summary, the study's outcomes underscore the transformative potential of technology, particularly AI-CRM adoption and big data analytics, in driving organizational performance and competitiveness. By recognizing the strategic importance of incorporating AI technologies into CRM strategies and investing in data-driven capabilities, organizations can position themselves for success in an increasingly digital and data-driven marketplace.

## VI. Conclusion

In conclusion, this study contributes valuable insights into the intricate web of relationships within modern organizations leveraging AI-CRM and big data analytics. It highlights the multifaceted impacts of these technologies on integration, collaboration, competitive advantage, and overall firm performance. The findings offer practical guidance for organizations seeking to navigate the evolving technological landscape and underscore the need for nuanced strategies that consider the specific dynamics of each organizational facet.

## VII. Limitation and Further Study

It is essential to acknowledge the study's limitations. The non-significant relationship between big data analytical capability and integration capability raises questions about the specific contextual factors influencing this dynamic. Future research could delve into industry-specific nuances or organizational characteristics that may shape the relationship between big data analytics and integration.

Additionally, the unexpected result regarding the limited influence of competitive advantage on firm performance warrants further exploration. Future studies may investigate other potential mediators or moderators that could elucidate the complex relationship between gaining a competitive advantage and achieving superior overall organizational performance.

## References

Alokla, M., Alkhateeb, M., Abbad, M., & Jaber, F. (2019). Customer relationship management: A review and classification. *Transnational Marketing Journal, 7*(2), 187-210. doi:10.33182/tmj.v7i2.734

Anwar, M., Khan, S., & Shah, S. (2018). Big data capabilities and firm's performance: A mediating role of competitive advantage. *Journal of Information & Knowledge Management, 17*(2), 1-28. doi:10.1142/S0219649218500454

Baek, C. (2021). A study on consumer strategy of artificial intelligence service using importance-satisfaction analysis. *Global Business & Finance Review, 26*(2), 110-120. doi:10.17549/gbfr.2021.26.2.110

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management, 17*(1), 99-120. doi:10.1177/014920639101700108

Bhatti, S., Ahmed, A., Ferraris, A., Hussain, W., & Fosso Wamba, S. (2022). Big data analytics capabilities and MSME innovation and performance: A double mediation model of digital platform and network capabilities, *Annals of Operations Research*, 1-24. doi:10.1007/s10479-022-05002-w

Byrne, B. M. (2010). *Structural equation modeling with AMOS: Basic concepts, applications, and programming*. Routledge.

Cai, Z., Huang, Q., Liu, H., & Liang, L. (2016). The moderating role of information technology capability in the relationship between supply chain collaboration and organizational responsiveness: Evidence from China. *International Journal of Operations & Production Management, 36*(10), 1247-1271. doi:10.1108/IJOPM-08-2014-0406

Chatterjee, S., Chaudhuri, R., Thrassou, A., & Vrontis, D. (2023). International relationship management during social distancing: The role of AI-integrated social CRM by MNEs during the Covid-19 pandemic. *International Marketing Review. Advance Online Publication*. doi:10.1108/IMR-12-2021-0372

Chen, C. (2023). Influence of employees' intention to adopt AI applications and big data analytical capability on operational performance in the high-tech firms. *Journal of the Knowledge Economy. Advance Online Publication*. doi:10.1007/s13132-023-01293-x

Chen, H., Chiang, R. H., & Storey, V. C. (2012). Business intelligence and analytics: From big data to big impact. *MIS Quarterly, 36*(4), 1165-1188.

Davenport, T. H., Harris, J., & Shapiro, J. (2010). Competing on talent analytics. *Harvard Business Review, 88*(10), 52-58.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39-50. doi:10.2307/3151312

Frost & Sullivan. (2019). Thailand digital technology foresight 2035. Depa. https://www.depa.or.th/storage/app/media/file/Second%20Deliverable%20RevVer%20EN%20V12%20140819%20FIN.pdf

Go, J. E., Moon, J., & Kim, J. (2020). Analysis of the current and future of the artificial intelligence in financial industry with big data techniques, *Global Business & Finance Review, 25*(1), 102-117. doi:10.17549/gbfr.2020.25.1.102

Hair, J., Black, W., Babin, B., Anderson, R., & Tatham, R. (2006). *Multivariate data analysis* (6th ed.). Pearson Prentice Hall.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis* (7th ed.). Pearson.

Hooper, D., Coughlan, J., & Mullen, M. R. (2008). Structural equation modelling: Guidelines for determining model fit. *The Electronic Journal of Business Research Methods, 6*, 53-60.

Hu, L., & Basiglio, A. (2024). A multiple-case study on the adoption of customer relationship management and big data analytics in the automotive industry. *The TQM Journal, 36*(9), 1-21. doi:10.1108/TQM-05-2023-0137

Irfan, M., & Wang, M. (2019). Data-driven capabilities, supply chain integration and competitive performance: Evidence from the food and beverages industry in Pakistan. *British Food Journal, 121*, 2708-2729. doi:10.1108/BFJ-02-2019-0131

Jha, A. K., Agi, M. A. N., & Ngai, E. W. T. (2020). A note on big data analytics capability development in supply chain. *Decision Support Systems, 138*, 113382. doi:10.1016/j.dss. 2020.113382

Kline, R. B. (2011). *Principles and practice of structural equation modeling* (3rd ed.). Guilford Press.

Kraus, S., Durst, S., Ferreira, J. J., Veiga, P., Kailer, N., & Weinmann, A. (2022). Digital transformation in business and management research: An overview of the current status quo. *International Journal of Information Management, 63*, 102466. doi:10.1016/j.ijinfomgt.2021.102466.

Kubina, M., Varmus, M., & Kubinova, I. (2015). Use of big data for competitive advantage of company. *Procedia Economics and Finance, 26*, 561-565

Lacity, M. C., Khan, S. A., & Willcocks, L. P. (2009). A review of the IT outsourcing literature: Insights for practice. *The Journal of Strategic Information Systems, 18*(3), 130-146. doi:10.1016/j.jsis.2009.06.002.

LaValle, S., Lesser, E., Shockley, R., Hopkins, M. S., & Kruschwitz, N. (2011). Big data, analytics and the path from insights to value. *MIT Sloan Management Review, 52*(2), 21-32.

Ledro, C., Nosella, A., & Vinelli, A. (2022). Artificial intelligence in customer relationship management: Literature review and future research directions. *Journal of Business & Industrial Marketing, 37*(13), 48-63. doi:10.1108/JBIM-07-2021-0332

Libai, B., Bart, Y., Gensler, S., Hofacker, C. F., Kaplan, A., K€otterheinrich, K., & Kroll, E. B. (2020). Brave new world? On AI and the management of customer relationships. *Journal of Interactive Marketing, 51*(2), 44-56.

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. doi:10.1016/j.dss.2012.12.016.

McAfee, A., & Brynjolfsson, E. (2012). Big data: The management revolution. *Harvard Business Review, 90*(10), 61-67.

Mikalef, P., Krogstie, J., Pappas, I. O., & Pavlou, P. (2020). Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities. *Information & Management, 57*(2), 103169. doi:10.1016/j.im.2019.05.004

Naimi-Sadigh, A., Asgari, T., & Rabiei, M. (2021). Digital transformation in the value chain disruption of banking services. *Journal of the Knowledge Economy, 13*, 1212-1242. doi:10.1007/ s13132-021-00759-0

Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.). McGraw-Hill.

Pham, C. H. (2019). Factors affecting the competitive advantage of supermarkets: Evidence from Vietnam. *Global Business & Finance Review, 24*(1), 59-70. doi:10.17549/gbfr.2019.24.1.59

Porter, M. E. (1985). *Competitive advantage: Creating and sustaining superior performance*. Free Press.

Prescott, M. (2014). Big data and competitive advantage at Nielsen. *Management Decision, 52*(3), 573-601.

Rezaee, Z., & Wang, J. (2018). Relevance of big data to forensic accounting practice and education. *Managerial Auditing Journal, 34*(3), 268-288. doi:10.1108/MAJ-08-2017-1633

Saeidi, S. P., Sofian, S., Saeidi, P., Saeidi, S. P., & Saaeidi, S. A. (2015). How does corporate social responsibility contribute to firm financial performance? The mediating role of competitive advantage, reputation, and customer satisfaction. *Journal of Business Research, 68*(2), 341-350.

Salavou, H. E., & Sergaki, P. (2013). Generic business strategies in Greece: Private food firms versus agricultural cooperatives. *Journal of Rural Cooperation, 41*(1), 44-59.

Sousa Batista, P. C., de Oliveira Lisboa, J. V., & Augusto, M. G., & de Almeida, F. E. B. (2016). E®ectiveness of business strategies in Brazilian textile industry. *Revista de Administracao, 51*(2), 225-239.

Studenmund, A. H. (1992). *Using econometrics: A practical guide* (2nd ed.). HarperCollins.

Sudechawongsakul, A. (2019). The omnichannel customer experience. Bangkok Post. https://www.bangkokpost.com/business/general/1727267/the-omnichannel-customer-experience

Turner, R. C., & Carlson, L. (2003). Indexes of item-objective congruence for multidimensional items. *International Journal of Testing, 3*(2), 163-171. doi:10.1207/S15327574IJT0302_5

van de Wetering, R., Kurnia, S., & Kotusev, S. (2021). The role of enterprise architecture for digital transformations. *Sustainability, 13*(4), 1-4. doi:10.3390/su13042237

Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Dong, J. Q., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research, 122*, 889-901. doi:10.1016/j.jbusres.2019.09.022