Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/NA11.20260058
Published: June 9, 2026

From AI Investment to Operational Performance: The Mediating Role of Organizational Capabilities in AI-Enabled CRM Systems

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Abstract

Organizations invest heavily in artificial intelligence (AI) enabled Customer Relationship Management (CRM) systems to improve operational efficiency, customer responsiveness, and revenue growth, yet the empirical evidence on whether such investment produces measurable performance gains remains mixed. Grounded in the Resource Based View, Dynamic Capabilities Theory, and the IT productivity paradox literature, this paper tests a capability mediated model of AI enabled CRM using data from 307 manager level respondents across product oriented (n = 109) and service oriented (n = 198) organizations. The instrument comprised 30 items across nine latent constructs, refined through a three-phase pilot (expert review, informed pilot, blind pilot with exploratory factor analysis). Covariance based structural equation modeling was conducted in R with the lavaan package using the Maximum Likelihood Robust (MLR) estimator. Confirmatory factor analysis supported a nine-factor model (CFI = .913, RMSEA = .068, SRMR = .045) with all standardized loadings exceeding .80 and Cronbach alpha values between .916 and .962. The structural model explained 84.6 percent of variance in business performance. The results reveal an investment paradox: strategic AI investment exerts no significant direct effect on performance (beta = -.02, p = .832) but operates through three significant capability pathways validated by bias corrected accelerated bootstrap (5,000 resamples): innovation capability (indirect = .288, 95 percent CI [.119, .464]), employee expertise (.216 [.093, .352]), and CRM process automation (.171 [.093, .260]). Industry type significantly moderates four predictor performance relationships, with stronger effects in product-oriented firms. The study reframes AI as enabling infrastructure that creates value only through complementary organizational capabilities.

Keywords
Artificial intelligence, AI enabled CRM, organizational capabilities, business performance, structural equation modeling

1. Introduction
Artificial intelligence has emerged as a defining force in digital transformation. Within the Customer Relationship Management (CRM) domain, AI enabled systems are increasingly used to automate workflows, predict customer behavior, analyze sentiment, and support managerial decisions across the sales, service, and marketing functions. Firms adopt these systems with the expectation that better data, better automation, and richer analytics will translate into measurable improvements in operational efficiency, customer sentiment, and revenue growth. The promise has been documented across multiple industries (McKinsey, 2023; Salesforce, 2024; Wamba et al., 2017), yet large scale industry studies continue to report inconsistent adoption outcomes and implementation failures (Gartner, 2022; Deloitte, 2023; Dwivedi et al., 2021).

The disconnect between AI investment and AI outcomes has been described as a contemporary expression of the IT productivity paradox (Brynjolfsson, 1993; Brynjolfsson and Hitt, 2000). Firms acquire advanced tools but fail to convert them into sustained performance gains because technology by itself is insufficient. The Resource Based View (Barney, 1991) and Dynamic Capabilities Theory (Teece et al., 1997) suggest that investment in any technology resource generates value only when it is combined with complementary organizational capabilities — accumulated knowledge, coordinated routines, and adaptive business models — that competitors cannot easily imitate. In the AI enabled CRM context, this means that chatbots, predictive analytics, sentiment analysis, and automation tools may expand analytical potential, but the realization of that potential depends on the firm's ability to absorb, deploy, and refine AI through its people and processes.

1.1 Motivation and Problem Statement

Industry analyses consistently document a gap between AI ambition and AI outcomes. Gartner (2022) reports that high implementation costs and infrastructure constraints prevent many firms from realizing returns on AI investment; Deloitte (2023) cites data quality and integration limitations as primary obstacles; and McKinsey (2023) finds that AI adopters that reorganize work around AI insights capture three times the value of adopters that do not. The pattern is especially visible in CRM, where customer facing value depends on coordinated decisions across data systems, service processes, marketing routines, and managerial oversight. A firm may deploy AI models successfully yet still fail to improve performance if frontline adoption is weak or if model outputs are not integrated into day-to-day operations (Mikalef et al., 2020; Chatterjee et al., 2022).

These observations raise a fundamental empirical question: does strategic AI investment directly improve business performance, or does it primarily operate as enabling infrastructure whose benefits are realized only when organizations have developed the capabilities required to apply AI in practice? The question is not merely theoretical. It determines how managers should allocate scarce digital transformation budgets between software acquisition, infrastructure, workforce capability development, governance, and process redesign (Manimangalam, 2025a, 2025b).

1.2 Research Objectives and Contributions

The paper pursues four objectives derived from the underlying doctoral study (Manimangalam, 2026a). First, it tests whether strategic AI investment exerts a direct effect on perceived business performance. Second, it evaluates whether strategic AI investment strengthens three organizational capabilities — innovation capability, employee expertise, and CRM process automation, that are theoretically necessary to convert AI into value. Third, it tests whether those capabilities mediate the investment performance relationship. Fourth, it examines whether industry type (product oriented versus service oriented) moderates the predictor performance relationships.

The paper contributes to the digital transformation and Industrial Engineering and Operations Management (IEOM) literature in three ways. First, it provides empirical evidence for an investment paradox in AI enabled CRM, paralleling the classical IT productivity paradox: strategic AI investment exerts no statistically significant direct effect on business performance but generates substantial indirect effects through capability pathways. Second, it identifies CRM process automation as the strongest single direct predictor of performance among the AI tools tested, while chatbots, predictive analytics, and sentiment analysis do not directly raise performance in the structural model. Third, it documents systematic moderation by industry type: product-oriented firms convert AI tools into performance more strongly than service-oriented firms, consistent with Contingency Theory (Donaldson, 2001) and the Diffusion of Innovations framework (Rogers, 1995).

2. Theoretical Background and Literature Review

The literature review is organized around three themes that map directly onto the conceptual model: AI enabled CRM as decision support infrastructure, organizational capabilities as the conversion mechanism, and industry context as a moderator. This organization avoids a paper-by-paper review and instead synthesizes prior work by category, consistent with IEOM guidance.

2.1 AI Enabled CRM as Decision Support Infrastructure

AI enabled CRM extends traditional CRM by embedding machine learning, automation, and natural language processing in customer related workflows (Manimangalam, 2025c). Four functional categories dominate the literature. Conversational AI in the form of chatbots automates first line customer interactions for inquiries, appointment scheduling, and routine service tasks (Nguyen et al., 2021). Predictive analytics applies statistical and machine learning models to historical customer data to forecast churn, score leads, and prioritize accounts (Wamba et al., 2017). Sentiment analysis interprets customer feedback at scale from reviews, support tickets, and social media to detect dissatisfaction and identify reputational risks (Forrester, 2021). CRM process automation orchestrates workflows across the sales, service, and marketing functions to reduce manual intervention, standardize handoffs, and accelerate cycle times (Salesforce, 2024).

Prior empirical work documents that the four tool categories operate through different mechanisms: chatbots and sentiment analysis tend to influence customer facing perceptions, while predictive analytics and automation influence operational decision quality and throughput. However, much of the literature treats AI enabled CRM as a single composite construct and examines its aggregate effect on firm performance, an approach that obscures whether any specific tool category is doing the work. The paper addresses this limitation by modeling each of the four tools as a separate latent construct (Manimangalam, 2026a).

2.2 Organizational Capabilities, RBV, and the IT Productivity Paradox

The Resource Based View (Barney, 1991) argues that firms achieve sustained advantage when they combine valuable, rare, inimitable, and non-substitutable resources with the routines and managerial processes needed to deploy them. Dynamic Capabilities Theory (Teece et al., 1997) extends this view by emphasizing the sensing, seizing, and reconfiguration capabilities that allow firms to adapt resource bases over time. Both perspectives predict that the value of any technology resource, including AI, is realized only through capability development, not through resource accumulation alone.

This prediction maps directly onto the IT productivity paradox (Brynjolfsson, 1993; Brynjolfsson and Hitt, 1996, 2000; Bharadwaj, 2000). Decades of firm level evidence indicate that information technology spending does not reliably improve performance unless accompanied by complementary investments in skills, organizational redesign, and managerial practice. Brynjolfsson and Hitt (2000) document that the returns to IT investment are several times higher when firms also reorganize work and decision rights around the technology. The logic extends to contemporary AI enabled CRM: investment in models, platforms, and licensing creates value only when employees develop the expertise to interpret model outputs, when firms maintain innovation routines that allow continual model refinement, and when CRM processes are automated to act on AI insights consistently.

The literature identifies three organizational capabilities as particularly salient. Innovation capability captures the firm's ability to generate and absorb new ideas, restructure processes, and learn from experimentation (Calantone et al., 2002; Mikalef et al., 2020). Employee expertise captures the depth of technical and analytical knowledge among the people who interact with AI tools (Gold et al., 2001; Dwivedi et al., 2021). CRM process automation captures the embedding of AI outputs into standardized, repeatable workflows so that insights translate into action without manual rework (Salesforce, 2024). The three capabilities operate together: expertise interprets outputs, innovation refines them, and automation institutionalizes them.

2.3 Industry Context as a Moderator

Contingency Theory (Donaldson, 2001) asserts that no universally optimal organizational strategy exists; effectiveness depends on the alignment between organizational practices and structural context. The Diffusion of Innovations framework (Rogers, 1995) adds that adoption rates and effectiveness vary across industries based on relative advantage, compatibility, complexity, trialability, and observability. Both frameworks predict that identical AI enabled CRM strategies will produce different performance outcomes across industry contexts.

Product oriented industries — manufacturing, logistics, e commerce, financial products, operate with standardized, high-volume processes and structured datasets that are highly amenable to AI automation and data driven optimization (Bughin et al., 2018). Service oriented industries, healthcare, professional services, education, rely more heavily on interpersonal interaction, customized delivery, and regulatory compliance, conditions that slow AI diffusion and diffuse its performance impact across longer timeframes (Kumar et al., 2021; Nguyen et al., 2021). The paper therefore treats industry type as a binary moderator (product oriented versus service oriented) consistent with the underlying study's sampling frame and theoretical specification.

3. Hypotheses Development

Building on the theoretical discussion, the paper advances six hypotheses focused on the capability mediated pathway from strategic AI investment to business performance. The hypotheses are aligned with the larger dissertation framework while focusing on the investment paradox finding (Manimangalam, 2026a).

H1: Strategic AI investment does not exert a statistically significant direct effect on perceived business performance once organizational capabilities are accounted for.

H2: Strategic AI investment positively influences innovation capability.

H3: Strategic AI investment positively influences employee expertise.

H4: Strategic AI investment positively influences CRM process automation.

H5: The effect of strategic AI investment on business performance is fully mediated by innovation capability, employee expertise, and CRM process automation.

H6: Industry type (product oriented versus service oriented) moderates the relationships between AI enabled CRM components and business performance, with stronger effects in product oriented firms.

The hypotheses reflect the view that technology resources generate performance through organizational complements rather than in isolation, and that those complements vary systematically across structural contexts.

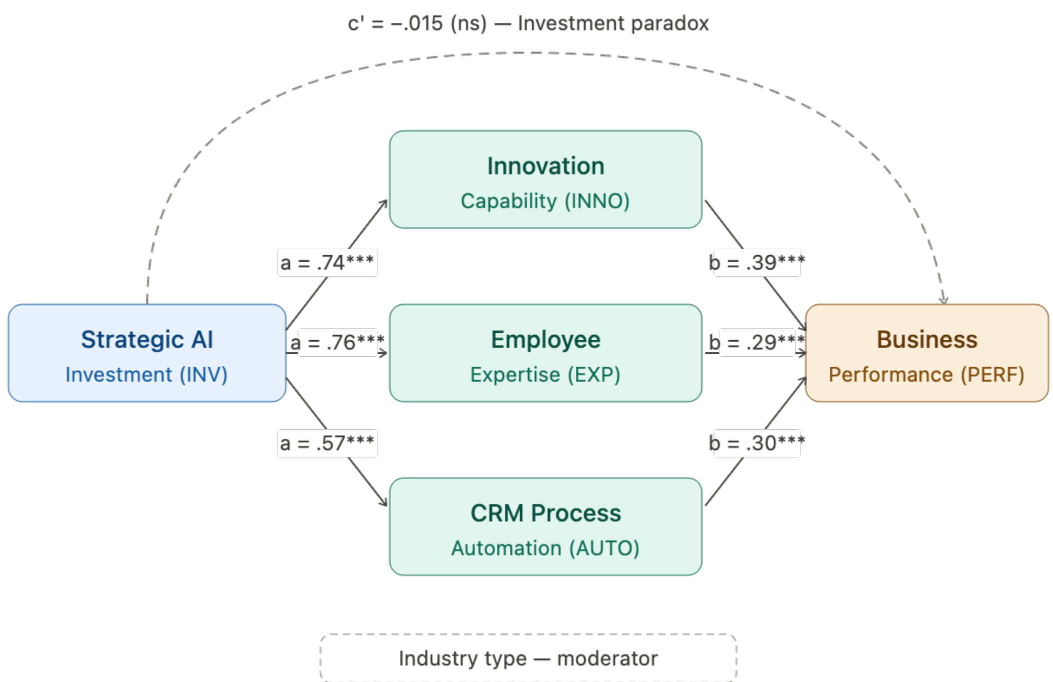

Figure 1. Capability-Mediated SEM Model

Figure 1 shows the standardized path coefficients from the joint multiple-mediator CB-SEM model (lavaan, MLR; N = 307). Dashed line indicates the non-significant direct path from Strategic AI Investment to Business Performance (c′ = −.015, ns) — the "Investment Paradox." All three indirect pathways are significant; full mediation confirmed via BCa bootstrap (5,000 resamples). ***p < .001.

4. Methods

4.1 Sample and Procedure

Data were collected through a structured online survey administered via Qualtrics between October and November 2025. The target population comprised organizations that had adopted or were in the process of adopting AI enhanced CRM technologies. The unit of analysis was the organization, with middle and senior level managers serving as target respondents because they possessed the requisite organizational knowledge to assess AI related initiatives and their impacts on business outcomes (Manimangalam, 2026a). A screening question "Does your organization currently use AI tools in its CRM system?" was placed at the beginning of the survey to ensure construct validity. A stratified purposive sampling approach was employed, stratifying along industry type (product oriented versus service oriented) and company size (small, medium, large).

A total of 309 responses were received. After listwise deletion of two cases with missing values on individual measurement items, the final analysis sample comprised 307 complete responses (99.4 percent completion rate). The sample included 109 product-oriented organizations (35.5 percent) and 198 service-oriented organizations (64.5 percent), with respondents distributed across senior leadership, middle management, and technical specialist roles.

4.2 Measures

All constructs were measured using multiple items, five-point Likert scales (1 = Strongly Disagree to 5 = Strongly Agree) adapted from previously validated sources. The instrument comprised 30 items distributed across nine latent constructs as shown in Table 1. AI enabled CRM was operationalized through four tool categories: chatbot adoption (CHAT, three items), predictive analytics (PRED, three items), sentiment analysis (SENT, three items), and CRM process automation (AUTO, three items). Strategic AI investment (INV) was captured through four items reflecting capital commitment, infrastructure, vendor relationships, and long-term planning. Organizational capabilities were captured through innovation capability (INNO, four items), employee expertise (EXP, three items), and customer centric business model (CCBM, four items). Business performance (PERF) was measured through three items capturing operational efficiency, customer sentiment outcomes, and revenue growth.

The instrument was refined through a three-phase pilot. Phase 1 (June 2025) involved expert content review with a panel of ten domain specialists. Phase 2 (July 2025) was an informed pilot with eight directors and managers used to evaluate usability and item clarity, which led to the splitting of one double barreled item and the simplification of technical terminology. Phase 3 (August to September 2025) was a blind pilot with 51 respondents whose data supported exploratory factor analysis. Eight factors emerged, explaining approximately 86 percent of total variance and supporting the hypothesized nine factor structure. Minor item refinements followed before main data collection.

Table 1. Constructs and Measurement Items (N = 307)

Construct	Code	# Items	Cronbach α
Chatbot adoption	CHAT	3	.934
Predictive analytics	PRED	3	.924
Sentiment analysis	SENT	3	.948
CRM process automation	AUTO	3	.945
Strategic AI investment	INV	4	.949
Innovation capability	INNO	4	.962
Employee expertise	EXP	3	.942
Customer-centric business model	CCBM	4	.916
Business performance	PERF	3	.938

Note. All items measured on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). Reliability values from Confirmatory Factor Analysis output; all exceed the .70 threshold.

4.3 Analytical Procedure

All analyses were conducted in R version 4.4.x using the lavaan package version 0.6-19 (Rosseel, 2012). The Maximum Likelihood Robust (MLR) estimator was applied throughout because Shapiro-Wilk tests confirmed non-normal distributions for all nine construct composites. The analytical protocol comprised five steps: (1) data preparation, descriptive statistics, and reliability assessment; (2) Confirmatory Factor Analysis (CFA) of the nine factor measurement model including assessment of convergent and discriminant validity; (3) Structural Equation Modeling (SEM) to test direct effects on business performance; (4) bootstrap mediation analysis with 5,000 resamples and bias corrected accelerated (BCa) confidence intervals; and (5) interaction based moderation analysis for industry type and supplementary effect size assessment using Cohen's f-squared. Common method bias was assessed through

Harman's single factor test and a CFA based comparison between the nine factor model and a constrained single factor model.

5. Results

5.1 Sample Profile and Descriptive Statistics

Table 2 presents the demographic composition of the final analysis sample. The sample reflects a balanced distribution across organizational levels, with 51.5 percent at the manager level or above and 25.4 percent in technical specialist roles. Service oriented organizations comprised approximately two thirds of respondents (64.5 percent), reflecting broader economic patterns and providing adequate subgroup sizes for moderation analysis. Construct means ranged from 4.02 (employee expertise) to 4.37 (customer centric business model), indicating generally high levels of agreement, with standard deviations between .91 and 1.14.

Table 2. Industry Distribution of the Analysis Sample (N = 307)

Industry type	**n**	**%**
Product-oriented	109	35.5
Service-oriented	198	64.5
Total	307	100.0

Note. Respondents at manager level or above comprised 51.5% of the sample; technical specialists (architect, technical lead, subject matter expert) comprised 25.4%; remaining respondents held junior or associate management roles. Company size was distributed across small (1–499 employees), medium (500–999), and large (1,000–4,999+) categories and was included as a control variable (β = .020, p = .464, not significant). Full demographic tables are available in the underlying dissertation (Manimangalam, 2026a, Tables 5.2.1 and 5.2.3).

5.2 Measurement Model (CFA)

The nine-factor CFA model demonstrated acceptable to good fit (scaled $\chi^2 = 624.18$, df = 369, $p < .001$; CFI = .913; TLI = .904; RMSEA = .068, 90% CI [.060, .076]; SRMR = .045). All 30 standardized factor loadings exceeded .80 and were statistically significant at $p < .001$, supporting convergent validity. Cronbach alpha values ranged from .916 to .962, exceeding the .70 threshold. Discriminant validity was confirmed through both the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio, with all HTMT values below the .85 strict threshold. Table 3 reports composite reliability (CR) and average variance extracted (AVE) values for all nine constructs. All CR values range from .925 to .963 and all AVE values range from .756 to .896, exceeding the .70 and .50 thresholds respectively (Hair et al., 2019; Fornell and Larcker, 1981) by a substantial margin and providing strong evidence of convergent validity.

Table 3. Composite Reliability and Average Variance Extracted (N = 307)

Construct	**Code**	**CR**	**AVE**	**√AVE**
Chatbot adoption	CHAT	.935	.827	.909
Predictive analytics	PRED	.925	.804	.897
Sentiment analysis	SENT	.949	.861	.928
CRM process automation	AUTO	.944	.850	.922
Strategic AI investment	INV	.949	.824	.908
Innovation capability	INNO	.925	.756	.870
Employee expertise	EXP	.944	.849	.922
Customer-centric business model	CCBM	.927	.759	.871
Business performance	PERF	.963	.896	.946

5.3 Structural Model and Direct Effects

The structural model was fit to the 307-case dataset using MLR estimation. The model explained 84.6 percent of the variance in perceived business performance ($R^2 = .846$), a level that exceeds typical benchmarks in organizational and IS research. The high explanatory power is partially attributable to the restriction of range inherent in sampling only AI adopting organizations, the strong measurement reliability across constructs, and the single source survey design — limitations addressed in Section 8.

Table 4 reports the standardized direct effects of all eight substantive predictors on business performance, controlling for company size (β = .020, p = .464, not significant). The results reveal a striking pattern. Among the AI tool predictors, only CRM process automation exerts a statistically significant direct effect on business performance (β = .431, p < .001) — emerging as the strongest single direct predictor in the model. Chatbot adoption (β = .021, p = .759), predictive analytics (β = .092, p = .338), and sentiment analysis (β = -.144, p = .130) show no significant direct effects, indicating that the operational value of these tools is not realized through technology adoption alone. Among the organizational capabilities, customer-centric business model exerts a significant direct effect (β = .266, p = .024) and innovation capability approaches significance (β = .290, p = .064). Employee expertise, by contrast, shows no significant direct effect in the full structural model (β = .080, p = .691) despite the strongest bivariate correlation with performance of any predictor (r = .830) — a divergence that is the classic empirical signature of mediation and is *examined directly in Section 5.4.*

Table 4. SEM Standardized Direct Effects on Business Performance (N = 307)

Path (→ PERF)	**β**	**p-value**	**Decision**
Chatbot adoption (CHAT)	.021	.759	Not supported
Predictive analytics (PRED)	.092	.338	Not supported
Sentiment analysis (SENT)	-.144	.130	Not supported
CRM process automation (AUTO)	.431	< .001 ***	Supported
Strategic AI investment (INV)	-.020	.832	Supported (H1: no direct effect)
Innovation capability (INNO)	.290	.064 †	Marginal
Employee expertise (EXP)	.080	.691	Not supported
Customer-centric business model (CCBM)	.266	.024 *	Supported
Company size (control)	.020	.464	Non-significant

*Note. Standardized β coefficients from CB-SEM (lavaan, MLR estimator). R^2 for PERF = .846. *** p < .001; ** p < .01; * p < .05; † p < .10.*

5.4 Mediation Analysis: The Investment Paradox

Although strategic AI investment shows no significant direct effect on performance, mediation analysis through bootstrap procedures (5,000 resamples with bias corrected accelerated 95 percent confidence intervals) reveals that its entire effect operates indirectly through three organizational capability pathways. Table 5 reports the indirect effects.

Table 5. Bootstrap Mediation Results — Indirect Effects from Strategic AI Investment to Business Performance

Pathway	**Indirect effect**	**95% BCa CI**	**Mediation type**
INV → INNO → PERF	.288	[.119, .464]	Full
INV → EXP → PERF	.216	[.093, .352]	Full
INV → AUTO → PERF	.171	[.093, .260]	Full
Total indirect	.675	[significant]	—
Direct effect (c′)	-.015	[ns]	—

*Note. Bias-corrected accelerated (BCa) bootstrap with 5,000 resamples. Confidence intervals exclude zero for all three indirect paths, confirming statistical significance. Total effect (c) = **.661**, p < .001; direct effect (c') = **−.015**, ns; total indirect = .675. Internal consistency: c′ + total indirect = −.015 + .675 = .660 ≈ c (.661), confirming joint-mediation coherence.*

The pattern supports H5 and clarifies the substantive meaning of H1. Strategic AI investment significantly strengthens all three capabilities: innovation capability (a = **.74**, p < .001), employee expertise (a = **.76**, p < .001), and CRM process automation (a = **.57**, p < .001). Each capability in turn transmits a significant effect to performance in the joint mediator model (INNO → PERF b = **.39**; EXP → PERF b = **.29**; AUTO → PERF b = **.30**). Once the three capability pathways are controlled for, the unique direct effect of investment on performance is statistically indistinguishable from zero. This is the investment paradox: in this cross-sectional sample, every unit of value created by strategic AI investment is mediated through organizational capability, not through direct resource accumulation. The pattern is theoretically consistent with the predictions of the Resource Based View, Dynamic Capabilities Theory, and the IT productivity paradox literature.

5.5 Moderation Analysis: Industry Effects

Industry type significantly moderated four predictor-performance relationships, supporting H6 in part. CRM process automation showed the strongest moderation ($p < .001$), with the simple slope substantially larger in product-oriented firms than in service-oriented firms. Predictive analytics ($p = .001$), employee expertise ($p = .003$), and chatbot adoption ($p = .024$) likewise showed significantly stronger effects in product-oriented firms. Sentiment analysis, innovation capability, and customer centric business model did not exhibit significant industry moderation, indicating that their effects are relatively invariant across industry contexts. Strategic AI investment did not significantly moderate any technology-performance relationship in supplementary tests (all $p > .10$), reinforcing the mediation finding: investment generates performance value through capability development rather than by amplifying the direct effects of individual AI tools (Table 6).

Table 6. Industry Type Moderation Results (Product-oriented vs. Service-oriented)

Path moderated by Industry	p (interaction)	Δ R²	Significant?
CRM process automation × Industry	< .001	.019	Yes ***
Predictive analytics × Industry	.001	.020	Yes **
Employee expertise × Industry	.003	.009	Yes **
Chatbot adoption × Industry	.024	.008	Yes *
Sentiment analysis × Industry	.051	.007	No
Innovation capability × Industry	> .10	—	No
Customer-centric BM × Industry	> .10	—	No

Note. Interaction tested via hierarchical regression with mean-centered predictors. Significant paths show stronger predictor → performance effects in product-oriented firms.

5.6 Common Method Bias and Robustness Checks

Three checks were performed to assess whether common method variance (CMV) or outlier influence could account for the observed relationships. First, Harman's single-factor test was conducted on the 30 measurement items. The first unrotated factor explained 62.7 percent of total variance, which exceeds the conventional 50 percent threshold and warrants further scrutiny. However, the scholarly criticism of Harman's test runs in the direction of the test being too lenient rather than too conservative (Podsakoff et al., 2003; Fuller et al., 2016), and the test is therefore reported here as a baseline rather than as a decisive criterion. Second, the hypothesized nine-factor CFA model was compared against two constrained alternatives: a single-factor model in which all 30 items load on one common latent factor, and a four-factor model in which the four AI tools were collapsed into one AI-technology factor and the three capabilities collapsed into one organizational-capability factor. The nine-factor model fit substantially better than both alternatives — against the single-factor model, $\Delta\chi^2$ scaled = 1,795.92, $p < .001$, $\Delta CFI = .295$; against the four-factor model, $\Delta\chi^2$ scaled = 976.05, $p < .001$, $\Delta CFI = .158$ — confirming that the construct structure is empirically distinguishable and is not an artifact of common method variance. The CFA model comparison constitutes a substantially more rigorous test than Harman's alone and provides the primary evidence against common method bias as the explanation for the observed relationships.

Third, procedural remedies were implemented during data collection to further reduce CMV risk: respondent anonymity, separation of independent and dependent variables across survey pages, variation in Likert scale anchor wording across sections, and conceptually distinct item phrasing across constructs. A sensitivity analysis comparing path estimates with and without multivariate outliers identified via Mahalanobis distance produced no substantive change in the pattern of significant and non-significant paths. The investment paradox finding — strategic AI investment having no significant direct effect on performance while operating through three significant capability pathways — held under both specifications.

5.7 Effect Sizes and Hierarchical Variance Decomposition

To complement the standardized path coefficients, Cohen's f^2 effect sizes were computed for each predictor by comparing the full structural model to a reduced model with that predictor removed. CRM process automation showed the largest effect size ($f^2 = .131$, medium), consistent with its role as the strongest direct predictor. Customer-centric business model ($f^2 = .089$) and innovation capability ($f^2 = .078$) showed small-to-medium effects, employee expertise showed a small effect ($f^2 = .022$) consistent with its largely mediated contribution, and the three non-significant AI tool predictors (sentiment analysis $f^2 = .011$, chatbot adoption $f^2 = .010$, predictive analytics $f^2 = .010$) along with strategic AI investment ($f^2 = .001$) all showed negligible effects, confirming that their performance contribution operates indirectly rather than directly.

A hierarchical regression was conducted to assess the incremental explanatory power of organizational factors beyond AI technology tools. Step 1 included only the control variable (company size, $R^2 = .004$, $F(1,305) = 1.27$, $p = .261$, ns). Step 2 added the four AI tool predictors (CHAT, PRED, SENT, AUTO), producing a substantial significant increment ($\Delta R^2 = .688$, $F(4,301) = 168.02$, $p < .001$). Step 3 added the four organizational factors (INV, INNO, EXP, CCBM), producing a further significant increment ($\Delta R^2 = .107$, $F(4,297) = 39.71$, $p < .001$). The pattern reinforces the central claim: organizational capabilities explain meaningful additional variance in business performance beyond what AI technology adoption alone can account for. The cumulative regression model explained 79.9 percent of variance in business performance; the parallel SEM model explained 84.6 percent ($R^2 = .846$), with the difference attributable to SEM's correction for measurement error that attenuates OLS estimates (Hair et al., 2019). The majority of explained variance is attributable to the capability-related predictors and their mediation of the AI-investment-to-performance pathway.

6. Discussion

6.1 The Investment Paradox

The headline finding reframes the managerial problem of AI enabled CRM. In the present sample, strategic AI investment did not directly raise business performance; instead, its full effect operated indirectly through three organizational capability pathways. This empirical pattern is theoretically consistent with the prediction that information technology spending creates value through complementary organizational assets rather than through direct resource deployment (Brynjolfsson and Hitt, 2000; Bharadwaj, 2000). It also extends the IT productivity paradox to the contemporary AI enabled CRM setting and clarifies the conversion mechanism: investment builds capability, capability creates performance.

The interpretation is consistent with the broader finding that among the AI tool predictors, only CRM process automation exerts a significant direct effect on business performance. Chatbots, predictive analytics, and sentiment analysis, while important sub dimensions of AI enabled CRM, do not appear to convert directly into performance in the structural model. The likely explanation is that those tools require additional layers of integration — automated workflows, expert interpretation, and innovation routines — before their outputs translate into operational outcomes. CRM process automation captures precisely that integration layer, which may explain why it emerges as the strongest single direct predictor.

6.2 Industry Specific Mechanisms

The moderation pattern indicates that the AI-to-performance conversion is not equally efficient across industry contexts. Product oriented firms benefit more from automation, predictive analytics, employee expertise, and chatbot adoption than service-oriented firms. Several mechanisms support this pattern. First, product-oriented firms typically operate with more standardized, high-volume processes and richer structured data, conditions that favor automation and predictive modeling (Bughin et al., 2018). Second, the regulatory and interpersonal complexity of service industries lengthens AI adoption cycles and diffuses performance impact across longer time horizons (Donaldson, 2001; Nguyen et al., 2021). Third, the decision cycles in product-oriented industries are typically shorter, allowing AI insights to feed back into operations faster and produce measurable performance gains within the cross-sectional window observed here.

The non significance of moderation for innovation capability, customer centric business model, and sentiment analysis suggests that the value of these constructs is relatively context independent. Innovation capability appears to operate as a general-purpose lever for AI value creation, regardless of whether the firm produces tangible goods or delivers services. Customer centric business model adaptability and sentiment analysis likewise appear to influence performance in similar ways across industry contexts.

6.3 Positioning Relative to Prior Empirical Work

The investment paradox finding extends rather than contradicts prior empirical work on AI capabilities and firm performance. Mikalef et al. (2020) found that big data analytics capabilities positively influenced innovation through dynamic capabilities mediation, with environmental dynamism as a moderator. The present results parallel this mediation logic but generalize it to the AI-enabled CRM domain, identify three specific capability mediators rather than a single composite, and document an industry-based rather than environment-based moderation pattern. Wamba et al. (2017) reported direct effects of big data analytics on firm performance through process-oriented dynamic capabilities; the present finding that strategic AI investment exerts no significant direct effect once capability mediators are included refines that result by clarifying that the conversion to performance is fully indirect for investment specifically, while operational AI tools such as CRM process automation can exert direct effects when integrated into workflows. Chatterjee et al. (2022) demonstrated that customer information transparency moderates AI-CRM integration outcomes; the present industry-type moderation finding is consistent with this broader pattern of context-dependent AI returns.

The R^2 of .846 is higher than the .40 to .65 range typically reported in CRM-performance SEM studies (e.g., Mikalef et al., 2020; Wamba et al., 2017). Three factors likely contribute: the restriction of range from sampling only AI-adopting firms, the strong measurement reliability across all nine constructs (α = .916 to .962), and the inclusion of both technology and capability predictors in a single integrated model. The finding should therefore be interpreted as the upper-bound explanatory power achievable when AI tools and complementary capabilities are jointly specified within an AI-adopting population, rather than as a population-level estimate.

7. Managerial Implications

The findings translate into four practical implications. First, AI investment budgets should be balanced between technology acquisition and capability building. Allocating funds exclusively to software, infrastructure, and vendor licensing without parallel investment in workforce expertise, innovation routines, and process automation is unlikely to produce measurable performance gains. Second, among the four AI tool categories tested, CRM process automation is the highest leverage direct investment. Firms that have already invested in chatbots, predictive analytics, or sentiment analysis but have not embedded those outputs into automated workflows are likely leaving substantial value on the table.

Third, governance practices for AI enabled CRM should preserve human oversight, particularly where AI outputs influence customer facing or strategically sensitive decisions. The data indicate that employee expertise is one of the three significant capability mediators between investment and performance, suggesting that AI is most productive when employees can interpret, validate, and override model outputs rather than operating as passive recipients. Fourth, implementation approaches should differ by industry context. Product oriented firms can rapidly capture value through automation and analytics; service-oriented firms should expect longer realization cycles and may benefit from front loading investments in innovation capability and business model adaptability, both of which were found to influence performance in ways that are relatively invariant across industry contexts (Manimangalam, 2025b, 2026b).

8. Limitations

Three limitations should be considered. First, the cross-sectional design cannot rule out reverse causation or common cause confounding; high performing firms may invest more in AI and may also develop stronger capabilities, generating the observed mediation pattern without strict causality. Longitudinal designs would clarify the direction and stability of these relationships. Second, the sample is restricted to organizations that already use AI in CRM, producing a degree of restriction of range that may inflate variance explained. Third, the analysis relies on single source self-report data, which raises the possibility of common method variance. The risk was mitigated through procedural remedies (anonymity, separated independent and dependent variables, varied scale anchors) and statistical assessment (Harman's single factor test and CFA model comparison), but cannot be eliminated entirely. Future research should triangulate across data sources, including administrative performance records and longitudinal capability measures.

9. Conclusion

Regarding Objective 1, strategic AI investment did not exert a statistically significant direct effect on perceived business performance, supporting the central claim of the investment paradox in the AI enabled CRM context. Regarding Objective 2, strategic AI investment significantly strengthened all three theorized capabilities — innovation capability, employee expertise, and CRM process automation. Regarding Objective 3, all three capabilities transmitted the effect of strategic AI investment to business performance through statistically significant indirect pathways with bootstrap confidence intervals excluding zero; the structural model explained 84.6 percent of variance in business performance. Regarding Objective 4, industry type significantly moderated four predictor-performance relationships, with stronger effects in product-oriented firms than in service-oriented firms.

The study contributes to the digital transformation and IEOM literatures by reframing AI enabled CRM as enabling infrastructure whose value is realized through organizational capabilities rather than through direct resource deployment. The findings extend the classical IT productivity paradox to the contemporary AI enabled CRM context and clarify the specific capability pathways through which conversion occurs. For practitioners, the implication is that AI investment without capability investment is unlikely to produce measurable performance gains. Future research should examine the stability of these relationships across time, geography, and AI maturity stages, including emerging generative and agentic AI applications (Manimangalam, 2026b, 2026c).

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Biography

Praveen Manimangalam is a Doctor of Business Administration (DBA) candidate at Florida International University and an enterprise systems practitioner with eighteen years of digital transformation experience across healthcare, energy, and technology sectors, including engagements with Cigna, Vizient, Prime Therapeutics, and Energy Exemplar. His research develops capability-mediated structural models of AI-enabled enterprise systems, grounded in the Resource-Based View, Dynamic Capabilities Theory, and the IT productivity paradox literature. Recent peer-reviewed publications appear in IEEE Xplore (SoutheastCon 2026), AAAI Press (2026 Spring Symposium), the INFORMS ICSS 2026 Springer Proceedings track, the IEOM 2026 Proceedings, and the Kennesaw State University CognoCon Proceedings, with additional book-chapter work in progress for Edward Elgar Publishing and journal manuscripts under development for international business and innovation management outlets. He holds two U.S. provisional patent applications — the Drone Tree Network for autonomous UAV logistics and ASICRM-Pro for self-configuring agentic CRM — and has introduced the Intent-to-Schema Automation framework for enterprise AI deployment. He serves as a peer reviewer for the Academy of Management (STR and TIM divisions) and ACM SIGCHI, is a founding participant in ASTM International Committee F50 on AI in Manufacturing Systems and has contributed research-informed recommendations to the U.S. Office of Science and Technology Policy. He is a 2026 EURAM Doctoral Colloquium scholarship recipient (selected from 183 international applicants), an elected member of Sigma Xi, and an invited speaker at the Commercial UAV Expo 2026. His current work extends the capability-mediation framework toward agentic CRM architectures, multinational AI governance, and high-assurance autonomous logistics.