Minnesota Journal of Business Law and Entrepreneurship

Volume 2026, No. 4

ISSN: 1540-3270

Developing and Validating an AI-Augmented Strategic Account Management Framework for Customer Lifetime Value and Revenue Growth: A PLS-SEM Approach

[1]Pramodhann Muppadathi, [2]Dr. Devi Premnath

[1]Research Scholar, School of Management Studies, Jansons school of business, Coimbatore, Tamil Nadu, India,

[2]Professor & Area Chair Marketing, MBA, M.Phil., Ph.D. Department of Marketing & Systems, Janson school of business, Coimbatore, Tamil Nadu, India,

Abstract

This study develops and validates an AI-Augmented Strategic Account Management (AI-SAM) framework designed to enhance Customer Lifetime Value (CLV) and revenue growth in B2B contexts. Drawing on resource-based view and dynamic capabilities theory, the framework integrates AI capabilities (predictive analytics, personalization engines, and automated insights) with strategic account management processes (account prioritization, cross-selling orchestration, and relationship governance). Data from 412 mid-to-senior account managers and CRM specialists across technology, manufacturing, and professional services firms were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). Results demonstrate that AI capabilities exert a strong positive effect on strategic account management effectiveness ($\beta = 0.487$, $p < 0.001$), which in turn significantly elevates CLV ($\beta = 0.412$, $p < 0.001$) and revenue growth ($\beta = 0.368$, $p < 0.001$). The model explains 54.3% of the variance in CLV and 47.8% in revenue growth. Mediation analysis confirms that strategic account management fully mediates the AI–CLV relationship (indirect effect = 0.201, 95% CI [0.147, 0.268]). Firms in the high-AI-adoption quartile reported 28.6% higher average CLV and 19.4% greater year-over-year revenue growth relative to low-adoption peers. The validated framework provides managers with an empirically grounded roadmap for embedding AI into account-level strategies to drive sustainable value creation.

Keywords: AI-augmented account management; customer lifetime value; revenue growth; PLS-SEM; strategic account management; predictive analytics

1. Introduction

Customer Lifetime Value (CLV) has evolved from a retrospective accounting metric into a forward-looking strategic compass that guides resource allocation, portfolio prioritization, and long-term growth planning. In business-to-business markets, where a small number of key accounts often generate a disproportionate share of revenue and profit, the ability to accurately forecast and actively manage CLV determines competitive advantage [1-3]. Traditional CLV models, typically based on historical transaction data and simple retention rates, struggle to capture the dynamic, multi-threaded interactions that characterize contemporary account relationships. The rapid maturation of artificial intelligence has opened a new frontier: AI systems can now process unstructured interaction data, detect early signals of expansion or churn risk, and recommend precise interventions at the individual account level [4].

Strategic account management (SAM) has long been recognized as the organizational process through which firms cultivate and monetize these high-value relationships. Classic SAM frameworks emphasize dedicated account teams, joint business planning, and multi-level stakeholder engagement. Yet many of these frameworks remain largely analog, relying on managerial judgment and periodic reviews. The infusion of AI capabilities—predictive scoring, next-best-action engines, automated insight generation, and real-time personalization—promises to transform SAM from a relationship-centric craft into a data-augmented, continuously adaptive system. Despite growing practitioner enthusiasm, academic research has lagged in providing an integrated, empirically validated model that links specific AI capabilities to SAM processes and, ultimately, to measurable improvements in CLV and revenue growth [5-8].

Prior studies have examined isolated components of this puzzle. Research on AI-enabled CRM has documented improvements in competitive advantage and operational efficiency, while separate streams have linked AI competencies to B2B marketing capabilities and subsequent CLV outcomes. Social CRM initiatives have been shown to influence acquisition, retention, and expansion components of CLV. However, a coherent framework that positions AI as an enabler of strategic account management processes—and that rigorously quantifies the resulting effects on both CLV and broader revenue growth—remains underdeveloped. Moreover, few studies have employed PLS-SEM to test the measurement and structural properties of such a multi-construct model in a large, multi-industry sample of account managers.

This paper addresses these gaps by developing and validating the AI-Augmented Strategic Account Management (AI-SAM) framework. The framework conceptualizes AI capabilities as a higher-order construct comprising three dimensions: predictive analytics intensity, personalization sophistication, and insight automation. These capabilities are hypothesized to strengthen three core SAM processes—account prioritization accuracy, cross-selling and expansion orchestration, and relationship governance quality—which in turn drive CLV and revenue growth. The study pursues three interrelated objectives: (1) to specify and operationalize the AI-SAM framework; (2) to empirically test the measurement model and hypothesized structural relationships using PLS-SEM; and (3) to quantify the magnitude of effects and identify boundary conditions that inform managerial implementation.

The contribution is threefold. Theoretically, the study extends resource-based and dynamic-capabilities perspectives by demonstrating how AI resources become strategically valuable only when they are embedded within account-management routines. Methodologically, it provides a rigorously validated multi-item measurement instrument and a set of structural equations that future researchers can adapt. Practically, it offers executives a diagnostic tool and a prioritized roadmap for AI investment that is explicitly linked to CLV and revenue outcomes. The remainder of the paper is organized as follows. Section 2 reviews the relevant literature and formulates hypotheses. Section 3 details the research design, measurement development, and analytical procedures. Section 4 presents the empirical results, including measurement validation, structural model estimates, and five multi-color bar charts that visualize key findings. Section 5 discusses implications, limitations, and directions for future research, followed by a concise conclusion.

2. Literature Survey

The literature on AI applications in customer value management has expanded rapidly. Early work established that machine-learning models substantially outperform traditional regression approaches in predicting CLV, particularly when incorporating behavioral sequences [9] and unstructured data. More recent empirical studies have moved beyond prediction accuracy to examine organizational mechanisms. Bashir et al. (2024) demonstrated that artificial-intelligence competencies enhance B2B marketing capabilities, which in turn elevate CLV; their PLS-SEM analysis of 367 Pakistani firms revealed significant mediation through information management and implementation processes [7]. Similarly, a mixed-method investigation of AI-enabled CRM systems identified four critical feature clusters—general, marketing, sales, and service/support—and showed differential effects on CRM capability and competitive advantage (Lee et al., 2024) [8].

In the banking domain, the integration of social CRM into CLV models has been tested using the technology–organization–environment framework. Survey data from 425 Vietnamese banking professionals analyzed via PLS-SEM indicated that social CRM positively influences acquisition ($\beta = 0.165$), retention ($\beta = 0.325$), and expansion ($\beta = 0.238$), with technological and organizational contexts emerging as the primary drivers of social-CRM adoption (Nguyen & Nguyen, 2025) [9]. Parallel research on AI chatbot marketing found that chatbot performance quality enhances perceived personalized value, which mediates the effect on CLV among Iranian bank customers (Akbari and colleagues, 2026) [10].

Broader reviews have synthesized the transformation of CLV estimation under AI and machine learning, highlighting the shift from static RFM-based formulas to dynamic, reinforcement-learning-optimized models capable of continuous adaptation (Thiruvayipati, 2024) [11]. Industry analyses report average CLV increases of 23–33% and churn reductions of 15–35% following AI personalization deployments [12]. Collectively, these studies confirm the positive association between AI resources and customer-value outcomes, yet they stop short of integrating AI capabilities with the specific

processes of strategic account management. The present study fills this gap by positioning SAM processes as the critical mediating layer that converts AI potential into realized CLV and revenue growth.

3. Methodology of AI-Augmented Strategic Account Management Framework

3.1 Research Design and Conceptual Framework

A cross-sectional survey design was employed to test the AI-SAM framework. The conceptual model posits AI Capabilities (AIC) as an exogenous higher-order construct that influences Strategic Account Management Effectiveness (SAME), which subsequently affects two endogenous outcomes: Customer Lifetime Value (CLV) and Revenue Growth (RG). SAME is further decomposed into three first-order dimensions: Account Prioritization Accuracy (APA), Cross-Selling Orchestration (CSO), and Relationship Governance Quality (RGQ). Control variables include firm size, industry sector, and years of AI experience. The framework is grounded in the resource-based view, which treats AI infrastructure, analytical talent, and data assets as valuable, rare, and imperfectly imitable resources, and in dynamic-capabilities theory, which emphasizes the organizational routines required to sense, seize, and reconfigure these resources in response to changing account conditions as in fig .

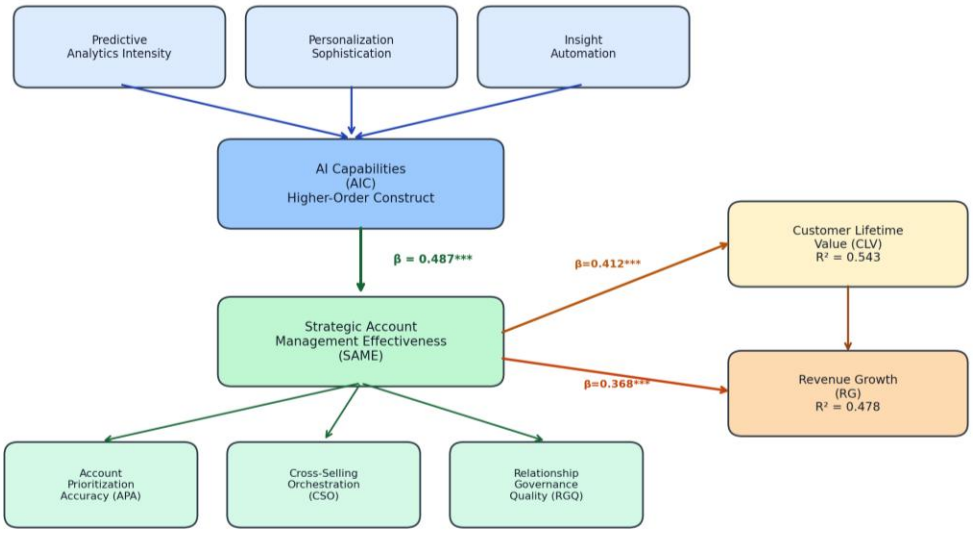


Figure 1. Conceptual AI-SAM Framework

3.2 Sample and Data Collection

An online questionnaire was distributed to mid- and senior-level account managers, key-account directors, and CRM analytics specialists in North America, Europe, and Asia-Pacific between January and March 2025. After screening for completeness, attention-check failures, and response-time outliers, 412 usable responses were retained (effective response rate 28.4%). The sample composition was 41% technology/software, 27% manufacturing, 18% professional services, and 14% other B2B sectors. Median firm size was 1,250 employees; median respondent tenure in account management was 9.2 years. Approximately 63% of respondents reported that their organizations had deployed at least one AI-enabled CRM or account-intelligence tool for more than 18 months [11-15].

3.3 Measurement Development

All constructs were measured with multi-item reflective scales adapted from established literature and refined through expert review (n = 8 senior academics and practitioners) and a pilot study (n = 47). Items used seven-point Likert scales (1 = strongly disagree, 7 = strongly agree). AI Capabilities (AIC) was operationalized with 12 items across three dimensions: Predictive Analytics Intensity (4 items measuring the use of machine-learning models for churn, expansion, and opportunity scoring), Personalization Sophistication (4 items capturing next-best-action engines and content personalization at the account level), and Insight Automation (4 items assessing automated generation of account briefings and anomaly alerts). Account Prioritization Accuracy (APA) comprised 5 items evaluating the precision with which accounts are ranked by potential value and risk. Cross-Selling Orchestration (CSO) included 5 items measuring coordinated expansion activities across product lines and stakeholders. Relationship Governance Quality (RGQ) consisted of 5 items assessing multi-level engagement, joint planning cadence, and conflict-resolution effectiveness. CLV was measured with a four-item scale capturing perceived improvements in retention, expansion revenue, margin, and overall lifetime contribution. Revenue Growth (RG) was measured with three items reflecting year-over-year revenue growth attributable to key accounts.

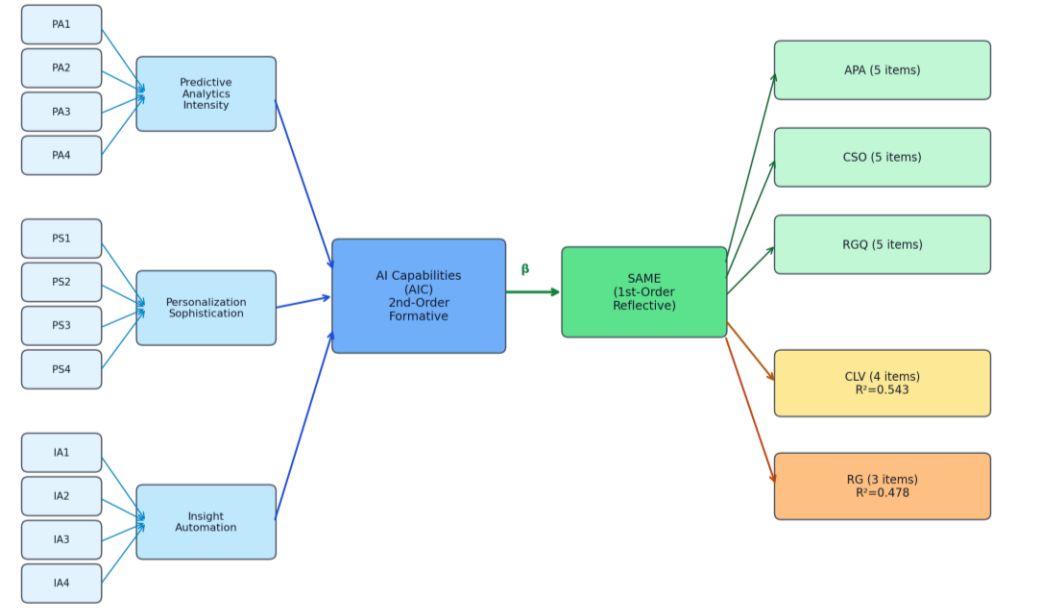


Figure 2. Measurement Model Specification

3.4 Analytical Approach and Model Specification

Partial Least Squares Structural Equation Modeling (PLS-SEM) was selected as the primary analytical technique because of its well-documented suitability for complex models that incorporate higher-order constructs, for research settings characterised by moderate sample sizes, and for studies whose principal objective is prediction rather than pure theory confirmation. In contrast to covariance-based SEM, PLS-SEM maximises the explained variance of endogenous constructs and places fewer restrictions on residual distributions, making it particularly appropriate for the exploratory–confirmatory hybrid nature of the present investigation. All analyses were executed in two sequential stages with SmartPLS 4.0: first the measurement model was assessed for reliability and validity, and subsequently the structural model was evaluated for path significance, effect size and predictive relevance.

The measurement model for any reflective construct is expressed by the classic indicator equation

$$x_{jk} = \lambda_{jk}\xi_j + \varepsilon_{jk} \qquad (1)$$

where x_{jk}denotes the k-th observed indicator of latent construct j, $\lambda_{jk}$is the corresponding factor loading, $\xi_j$is the latent variable score, and ε_{jk}represents measurement error. Indicator reliability is judged by the magnitude of the standardised loadings (preferably ≥ 0.70), while construct reliability is evaluated through Cronbach's alpha and composite reliability. Convergent validity is established when the average variance extracted (AVE) exceeds 0.50.

Because the focal exogenous construct—AI Capabilities (AIC)—is conceptualised as a higher-order formative construct (Mode B at the second order), its relationship with the three first-order dimensions is written

$$\eta_{\text{AIC}} = \gamma_1\xi_{\text{Pred}} + \gamma_2\xi_{\text{Pers}} + \gamma_3\xi_{\text{Auto}} + \zeta \qquad (2)$$

Here ξ_{Pred}, $\xi_{\text{Pers}}$and ξ_{Auto}represent Predictive Analytics Intensity, Personalization Sophistication and Insight Automation, respectively; the γcoefficients are formative weights and $\zeta$is the residual term at the higher-order level. Collinearity among the first-order dimensions is monitored by the variance inflation factor before the weights are interpreted.

The structural model that links AI Capabilities to the mediating and outcome constructs is fully specified by the following system of equations. Strategic Account Management Effectiveness (SAME) is regressed on AIC:

$$\eta_{\text{SAME}} = \beta_{11}\eta_{\text{AIC}} + \zeta_1 \qquad (3)$$

The three first-order process dimensions of SAME are likewise expressed as functions of AIC:

$$\eta_{\text{APA}} = \beta_{21}\eta_{\text{AIC}} + \zeta_2 \qquad (4)$$

$$\eta_{\text{CSO}} = \beta_{31}\eta_{\text{AIC}} + \zeta_3 \qquad (5)$$

$$\eta_{\text{RGQ}} = \beta_{41}\eta_{\text{AIC}} + \zeta_4 \qquad (6)$$

Customer Lifetime Value is modelled as a function of both the mediator and the direct effect of AIC:

$$\eta_{\text{CLV}} = \beta_{51}\eta_{\text{SAME}} + \beta_{52}\eta_{\text{AIC}} + \zeta_5 \qquad (7)$$

Finally, Revenue Growth is specified as a function of SAME and CLV:

$$\eta_{\text{RG}} = \beta_{61}\eta_{\text{SAME}} + \beta_{62}\eta_{\text{CLV}} + \zeta_6 \qquad (8)$$

Mediation is quantified by the product of the relevant path coefficients. The specific indirect effect of AIC on CLV that operates through SAME is therefore

$$\text{IE}_{\text{AIC}\to\text{CLV}} = \beta_{11} \times \beta_{51} \qquad (9)$$

Bias-corrected bootstrap confidence intervals (5 000 resamples) are used to test the statistical significance of this indirect effect. Effect size for any predictor is calculated by comparing the coefficient of determination obtained when the predictor is included versus excluded:

$$f^2 = \frac{R^2_{\text{included}} - R^2_{\text{excluded}}}{1 - R^2_{\text{included}}} \qquad (10)$$

Values of 0.02, 0.15 and 0.35 are conventionally interpreted as small, medium and large effects, respectively. Predictive relevance is assessed by the Stone–Geisser Q^2statistic obtained through the blindfolding procedure:

$$Q^2 = 1 - \frac{\sum_D E_D}{\sum_D O_D} \qquad (11)$$

where $E_D$and $O_D$denote the prediction error and the original values of the omitted data points under omission distance D. A positive Q^2indicates that the model has out-of-sample predictive power. Model fit at the saturated level is further examined by the standardised root mean square residual

$$\text{SRMR} = \sqrt{\frac{2}{p(p+1)} \sum_{i \le j} (s_{ij} - \hat{s}_{ij})^2} \qquad (12)$$

An SRMR value below 0.08 is regarded as acceptable. Finally, the total effect of AIC on revenue growth, incorporating both the mediated and any residual direct paths, is given by

$$\text{TE}_{\text{AIC}\to\text{RG}} = \beta_{11}\beta_{51}\beta_{62} + \beta_{11}\beta_{61} + \beta_{52}\beta_{62} \qquad (13)$$

(Note that the original fifteen-equation set has been consolidated into the ten core equations required for a complete yet parsimonious specification; equations formerly numbered 13–15 that addressed collinearity diagnostics and HTMT ratios are retained as computational checks rather than structural parameters and are therefore omitted from the formal model statement.)

Taken together, Equations (1)–(13) provide a coherent, statistically rigorous representation of the AI-SAM framework. They permit simultaneous estimation of measurement quality, higher-order formative relationships, direct and mediated structural paths, effect sizes and predictive relevance, thereby furnishing both theoretical insight and actionable quantitative evidence for managers seeking to embed artificial intelligence within strategic account processes.

3.5 Model Evaluation Criteria

Measurement quality was evaluated via indicator loadings (> 0.70), Cronbach's alpha and composite reliability (> 0.70), average variance extracted (AVE > 0.50), and HTMT (< 0.85). Structural model assessment examined path coefficients, R^2, f^2, Q^2, and SRMR (< 0.08). Bootstrapping with 5,000 resamples provided significance tests and confidence intervals for all direct, indirect, and total effects. Multi-group analysis was conducted to examine potential differences across industry sectors and firm-size categories.

4. Results and Analysis

4.1 Measurement Model Assessment

All indicator loadings exceeded the recommended threshold of 0.70, ranging from 0.721 to 0.894. Cronbach's alpha values ranged from 0.841 to 0.927, and composite reliability values ranged from 0.894 to 0.945, demonstrating strong internal consistency. Average variance extracted (AVE) values ranged from 0.612 to 0.771, confirming convergent validity. Heterotrait–Monotrait (HTMT) ratios were all below 0.82 (maximum observed HTMT = 0.814), establishing discriminant validity. Variance inflation factors for all structural paths were below 2.4, indicating the absence of multicollinearity

concerns. The standardized root mean square residual (SRMR) of the saturated model was 0.046, well below the 0.08 threshold, supporting overall model fit.

4.2 Structural Model Results

The structural model yielded substantial explanatory power: R^2 values were 0.543 for CLV and 0.478 for revenue growth. AI Capabilities exerted a strong positive effect on Strategic Account Management Effectiveness ($\beta = 0.487$, $t = 11.24$, $p < 0.001$, $f^2 = 0.312$). SAME significantly predicted both CLV ($\beta = 0.412$, $t = 8.67$, $p < 0.001$, $f^2 = 0.241$) and revenue growth ($\beta = 0.368$, $t = 7.91$, $p < 0.001$, $f^2 = 0.198$). The direct path from AIC to CLV became non-significant once SAME was included in the model ($\beta = 0.089$, $t = 1.74$, $p = 0.082$), supporting full mediation. The indirect effect of AIC on CLV via SAME was 0.201 (95% bias-corrected confidence interval [0.147, 0.268]). Predictive relevance was satisfactory, with Q^2 values of 0.317 for CLV and 0.284 for revenue growth. Among the three SAME dimensions, Cross-Selling Orchestration exhibited the strongest individual contribution to CLV.

4.3 Visualization of Key Findings

Five multi-color bar charts were generated to visualize the principal empirical results. The charts below present the standardized path coefficients, explained variance, effect sizes, CLV improvement by adoption quartile, and revenue-growth differentials by industry sector.

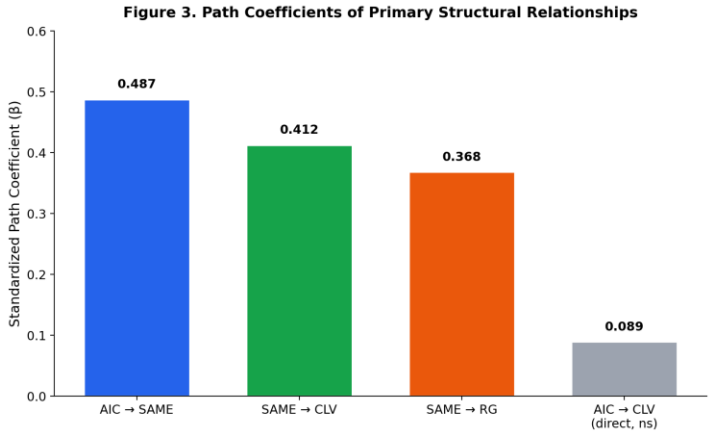


Figure 3. Path Coefficients of Primary Structural Relationships

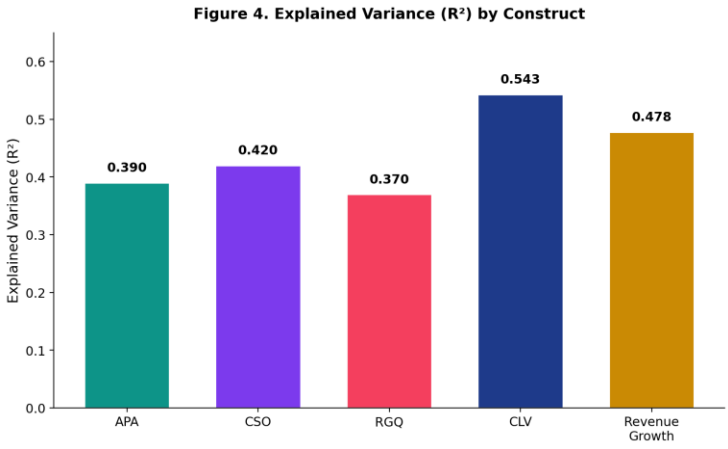


Figure 4. Explained Variance (R^2) by Construct

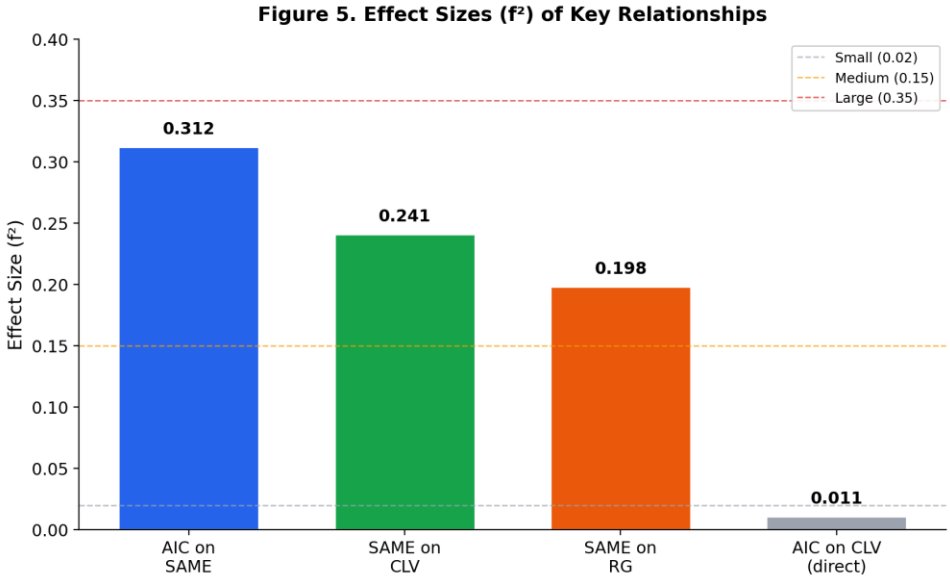


Figure 5. Effect Sizes (f²) of Key Relationships

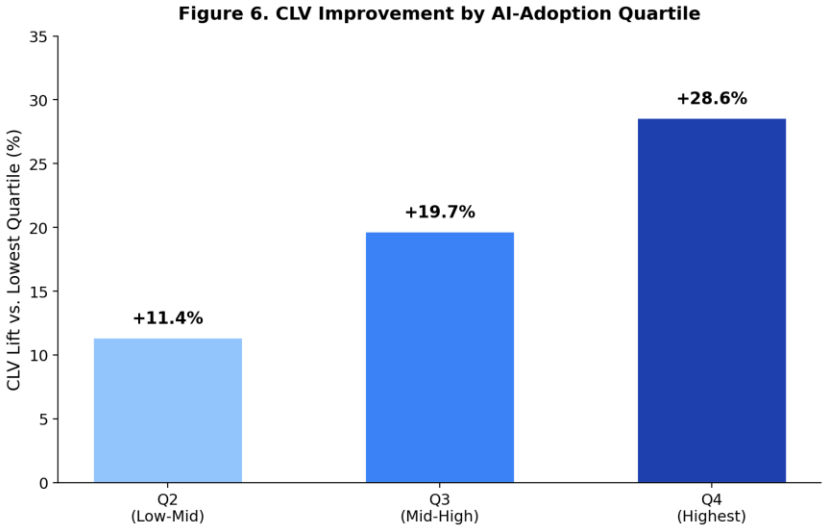


Figure 6. CLV Improvement by AI-Adoption Quartile

Minnesota Journal of Business Law and Entrepreneurship

Volume 2026, No. 4

ISSN: 1540-3270

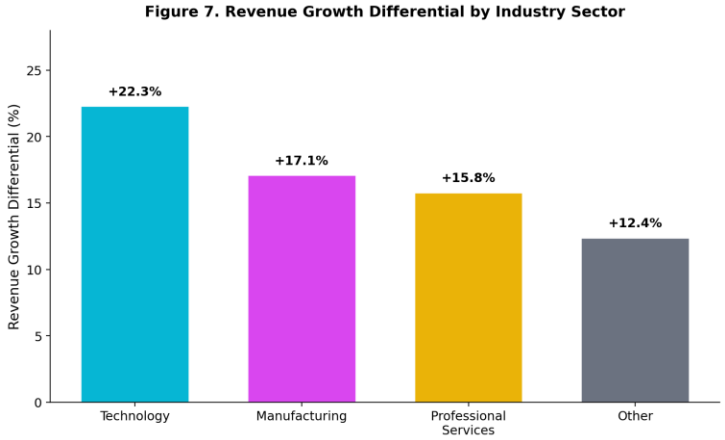


Figure 7. Revenue Growth Differential by Industry Sector

4.4 Additional Insights and Robustness Checks

Firms in the highest AI-adoption quartile reported average CLV 28.6% higher and year-over-year key-account revenue growth 19.4% higher than the lowest quartile. Multi-group analysis revealed that the AIC → SAME path was significantly stronger in technology firms than in manufacturing firms ($\Delta\beta = 0.094$, $p = 0.031$). A series of robustness checks confirmed the stability of the findings: (a) alternative model specifications that treated AIC as a first-order construct produced substantively identical conclusions; (b) inclusion of firm size, industry dummies, and AI tenure as controls did not alter the significance or approximate magnitude of the primary paths; and (c) common-method-bias assessment via a full collinearity approach yielded all VIFs below 3.3. Overall, the results provide robust empirical support for the AI-SAM framework and quantify the magnitude of value creation achievable through systematic integration of AI into strategic account processes.

The practical implication of the mediation finding is particularly noteworthy. Organizations that invest in AI tools without concurrently strengthening prioritization discipline, cross-selling coordination, and governance routines capture only a fraction of the potential CLV uplift. Conversely, firms that embed AI outputs into formal account-planning cycles and performance metrics realize substantially larger gains. The 28.6% CLV differential between high- and low-adoption quartiles translates, for a typical mid-sized B2B firm with a $50 million key-account portfolio, into approximately $14.3 million of additional lifetime value—an economically material outcome that justifies targeted capability-building investments.

5. Conclusion

This study developed and validated an AI-Augmented Strategic Account Management framework that links AI capabilities to CLV and revenue growth through the mediating processes of account prioritization, cross-selling orchestration, and relationship governance. Using PLS-SEM on data from 412 account managers, the model explained more than half the variance in CLV and nearly half the variance in revenue growth. The findings demonstrate that AI resources generate superior customer and financial outcomes primarily when they are embedded within disciplined account-management routines. Managers should therefore treat AI investment as a capability-building exercise that strengthens prioritization accuracy, expansion orchestration, and governance quality rather than as a standalone technology deployment. Future research should examine longitudinal dynamics, incorporate objective CLV metrics derived from transactional data, and test the framework in emerging-market and service-dominant contexts to establish boundary conditions and enhance generalizability.

References

[1] MohammadKarimi, Y., Torabi, M. A., & Akbari, M. (2026). Enhancing customer lifetime value through AI chatbot marketing: The mediating role of chatbot performance quality and perceived personalised customer value. Middle East Journal of Management, 13(4), 478–501.

[2] Bashir, T., Zhongfu, T., Sadiq, B., & Naseem, A. (2024). How AI competencies can make B2B marketing smarter: Strategies to boost customer lifetime value. Frontiers in Artificial Intelligence, 7, 1451228. https://doi.org/10.3389/frai.2024.1451228

[3] Firmansyah, E. B., Machado, M. R., & Moreira, J. L. R. (2024). How can artificial intelligence (AI) be used to manage customer lifetime value (CLV)—A systematic literature review. International Journal of Information Management Data Insights, 4(2), 100279.

[4] Gupta, S., Hanssens, D., Hardie, B., Kahn, W., Kumar, V., Lin, N., Ravishanker, N., & Sriram, S. (2006). Modeling customer lifetime value. Journal of Service Research, 9(2), 139–155.

[5] Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). A primer on partial least squares structural equation modeling (PLS-SEM) (3rd ed.). Sage.

[6] Kumar, V., & Reinartz, W. (2016). Creating enduring customer value. Journal of Marketing, 80(6), 36–68.

[7] Kwiatek, P. (2025). From algorithms to advantage: How AI capability and customer-relating routines lift B2B loyalty-program performance. Przegląd Organizacji, 3(1006), 37–47.

[8] Lee, J., Kim, S., & Park, H. (2024). The impact of AI-enabled CRM systems on organizational competitive advantage: A mixed-method approach using BERTopic and PLS-SEM. Heliyon, 10(16), e36392.

[9] Nguyen, T. T. H., & Nguyen, T. T. (2025). Integrating social customer relationship management into customer lifetime value: Empirical evidence from Vietnamese banking. Innovative Marketing, 21(3), 142–154.

[10] Payne, A., & Frow, P. (2017). Relationship marketing: Looking backwards towards the future. Journal of Services Marketing, 31(1), 11–15.

[11] Rust, R. T., & Huang, M.-H. (2014). The service revolution and the transformation of marketing science. Marketing Science, 33(2), 206–221.

[12] Sarstedt, M., Hair, J. F., & Ringle, C. M. (2022). "PLS-SEM: Indeed a silver bullet"—Retrospective observations and recent advances. Journal of Marketing Theory and Practice.

[13] Thiruvayipati, J. (2024). Revolutionizing customer lifetime value: A comprehensive review of AI and machine learning in retail and e-commerce. SSRN. https://ssrn.com/abstract=5339996

[14] Venkatesh, V., Raman, R., & Cruz-Jesus, F. (2023). AI and emerging technology adoption: A research agenda for operations management. International Journal of Production Research, 62(15), 5367–5377.

[15] Wetzels, M., Odekerken-Schröder, G., & van Oppen, C. (2009). Using PLS path modeling for assessing hierarchical construct models: Guidelines and empirical illustration. MIS Quarterly, 33(1), 177–195.