JOURNAL OF INTERNATIONAL CRISIS AND RISK COMMUNICATION RESEARCH
ISSN: 2576-0017
2021, VOL 4, NO S4

Building And Scaling Marketing Businesses Across B2B: An AI-Enabled Enterprise Growth Strategy Perspective

Dineth Ratnayake

Independent Researcher

Abstract

The rapid digital transformation of enterprise ecosystems has fundamentally reshaped the architecture of B2B marketing, necessitating scalable, intelligence-driven growth strategies. This study investigates how AI-enabled enterprise systems contribute to building and scaling marketing businesses across B2B environments. Adopting a mixed-method research design, data were collected from 250 medium-to-large B2B enterprises and analyzed using structural equation modeling (SEM) and Random Forest machine learning techniques. The results indicate that AI capability significantly enhances revenue growth both directly and indirectly through enterprise integration maturity. Integration across CRM, ERP, sales, and finance systems emerged as a critical mediating mechanism, while governance and leadership readiness significantly moderated the AI–growth relationship. Machine learning analysis identified predictive analytics usage and CRM–ERP synchronization as the strongest drivers of scalable marketing performance. Distributional and interaction analyses further confirmed that enterprises achieving high AI maturity and strong integration simultaneously experience compounded growth advantages. The findings highlight that sustainable B2B marketing scalability is not driven by technology alone but by the convergence of analytical intelligence, systemic alignment, and governance-supported leadership. The study contributes to enterprise growth theory by conceptualizing AI as a structural growth catalyst embedded within integrated organizational ecosystems and provides actionable insights for firms pursuing data-driven expansion strategies.

Keywords: AI-enabled marketing, B2B scalability, enterprise integration, governance readiness, predictive analytics, revenue growth strategy.

Introduction

The evolving complexity of B2B marketing in digital enterprise ecosystems

Business-to-business (B2B) marketing has undergone a profound transformation over the past decade, driven by digitalization, platform economies, and increasingly data-centric decision-making environments (Tardieu et al., 2020). Unlike business-to-consumer (B2C) markets, B2B ecosystems are characterized by longer sales cycles, multi-layered stakeholder structures, high-value transactions, and complex procurement processes. Enterprise buyers today expect seamless digital experiences, measurable return on investment (ROI), and strategic value alignment rather than transactional engagement (Olayinka, 2021). As organizations scale across industries and geographies, marketing functions must evolve beyond communication-centric roles to become intelligence-driven growth engines. In this context, the challenge is not merely customer acquisition but orchestrating scalable, predictable, and insight-led growth models that integrate marketing, sales, finance, and operations into a unified strategic architecture (Schoemaker & Day, 2021).

The strategic shift from traditional marketing to growth-oriented enterprise systems

Historically, B2B marketing relied heavily on relationship-building, industry networks, and trade-driven visibility. While these elements remain relevant, they are insufficient in hyper-competitive digital markets. Modern enterprises increasingly adopt growth frameworks grounded in analytics, lifecycle management, and revenue attribution modeling (Zhang et al., 2017). Marketing is no longer a cost center; it is a strategic driver of pipeline velocity, customer lifetime value (CLV), and brand equity. This shift requires integration with enterprise resource planning (ERP), customer relationship management (CRM), and advanced analytics platforms (Katuu, 2020). Growth-oriented enterprises prioritize measurable performance indicators such as customer acquisition cost (CAC), marketing-qualified leads (MQL), conversion rates, retention metrics, and revenue per account. Scaling, therefore, demands structured data governance, cross-functional alignment, and automated feedback loops that continuously optimize strategy execution (GAFFAR et al., 2020).

The emergence of AI-enabled marketing intelligence as a competitive differentiator

Artificial intelligence (AI) has become a transformative force in enterprise marketing ecosystems (Wamba-Taguimdje, 2020). Machine learning algorithms enable predictive lead scoring, churn forecasting, dynamic segmentation, and campaign optimization at scale. Natural language processing (NLP) enhances content personalization, while generative AI tools accelerate creative development and customer communication workflows. AI-driven growth systems allow organizations to transition from reactive marketing strategies to predictive and prescriptive decision-making models (Osho et al., 2020). By leveraging real-time behavioral analytics, firms can design adaptive campaigns tailored to specific buyer journeys, improving both engagement quality and revenue predictability. Furthermore, AI facilitates cross-channel orchestration, integrating email, search, and social media, account-based marketing (ABM), and partner ecosystems into cohesive growth engines. As competition intensifies, AI adoption becomes not optional but essential for sustaining enterprise-level scalability (Yao et al., 2015).

Integrating marketing scalability with enterprise-wide digital transformation

Building and scaling marketing businesses across B2B domains requires alignment with broader digital transformation initiatives (Papadas et al., 2017). Cloud-native infrastructures, microservices architectures, and data lake environments enable scalable analytics frameworks capable of handling large volumes of structured and unstructured data. Enterprise growth strategies increasingly rely on real-time dashboards, automated reporting, and performance optimization models embedded within decision-making workflows (John, 2020). Strategic alignment between marketing and finance ensures that growth investments are supported by accurate forecasting and risk modeling. Additionally, supply chain transparency and operational agility influence brand credibility in B2B contexts, reinforcing the need for integrated enterprise systems. A scalable marketing enterprise, therefore, is not a standalone function but a digitally interconnected ecosystem that aligns technology, talent, and governance structures (Valdez-De-Leon, 2019).

Addressing organizational capability, leadership, and governance in AI-driven growth models

While technology enables scalability, organizational readiness determines sustainability (Olszak et al., 2018). Effective AI-enabled marketing systems require skilled data scientists, growth strategists, marketing technologists, and cross-functional leaders capable of translating analytics into actionable strategies. Governance frameworks must address ethical AI deployment, data privacy compliance, algorithmic bias, and transparency in automated decision-making (Felzmann et al., 2020). Leadership plays a critical role in fostering a culture of experimentation, iterative learning, and performance accountability (Alluri et al., 2020). Enterprises that successfully scale marketing across B2B markets adopt agile experimentation models, continuous A/B testing frameworks, and machine learning-supported optimization processes.

Positioning AI-enabled enterprise growth strategies as the future of B2B marketing scalability

This research article examines how AI-enabled enterprise systems redefine the architecture of B2B marketing scalability. By integrating predictive analytics, digital transformation frameworks, and governance-driven innovation models, organizations can transition from fragmented marketing efforts to cohesive growth platforms. The study positions AI not merely as a technological tool but as a strategic enabler that reshapes customer engagement, revenue forecasting, and competitive positioning. Ultimately, building and scaling marketing businesses across B2B ecosystems demands a convergence of technological intelligence, operational alignment, and leadership-driven strategic vision.

Methodology

The research design and philosophical positioning of the study

This study adopts a mixed-method, explanatory sequential research design to investigate how AI-enabled enterprise systems influence the building and scaling of B2B marketing businesses. The research is grounded in a positivist paradigm for quantitative model testing, complemented by a pragmatic orientation for integrating qualitative managerial insights. The design combines cross-sectional survey data, secondary enterprise performance metrics, and structured executive interviews to capture both measurable growth outcomes and strategic implementation dynamics. The primary objective is to model the relationships among AI adoption intensity, marketing capability maturity, enterprise integration depth, and scalable growth performance in B2B contexts.

The sampling framework and data collection procedures

The study targets medium to large B2B enterprises operating across technology, manufacturing, consulting, and enterprise services sectors. A stratified purposive sampling approach is employed to ensure representation across industry verticals and organizational scales. The quantitative dataset consists of 250 firms, with responses collected from Chief Marketing Officers (CMOs), Growth Heads, Marketing Operations Leaders, and Enterprise Strategy Managers. Structured questionnaires are distributed electronically, supplemented by validated archival data such as annual revenue growth rates, customer acquisition costs (CAC), customer lifetime value (CLV), and marketing-attributed revenue. Additionally, 20 semi-structured interviews are conducted to contextualize AI implementation depth, governance mechanisms, and cross-functional integration challenges.

The operationalization of core constructs and measurement variables

The independent variable, AI-enabled marketing capability, is operationalized through a composite index comprising predictive analytics usage, automated lead scoring adoption, generative AI content deployment, cross-channel orchestration systems, and real-time personalization engines. Each indicator is measured on a five-point Likert scale assessing implementation maturity and integration depth.

The mediating construct, enterprise integration maturity, captures the extent of alignment between marketing, sales, finance, and operations systems. Indicators include CRM–ERP synchronization, shared performance dashboards, unified data architecture, and automated revenue attribution modeling.

The dependent variable, B2B marketing scalability performance, is measured using both perceptual and objective metrics: revenue growth rate, pipeline velocity, conversion ratio, CLV/CAC ratio, marketing ROI, and expansion revenue from key accounts.

Control variables include firm size (employee count), industry sector, digital transformation budget, years of AI adoption, and market competitiveness index. Governance and leadership readiness are included as moderating variables, measured via organizational agility, experimentation culture, and AI governance policy robustness.

The instrument validation and reliability assessment procedures

Content validity is ensured through expert panel review involving academic researchers and enterprise marketing leaders. Construct validity is assessed using exploratory factor analysis (EFA) followed by confirmatory factor analysis (CFA). Factor loadings above 0.70 are considered acceptable. Reliability is evaluated through Cronbach's alpha and composite reliability (CR), with thresholds set at 0.70 and above. Convergent validity is examined using average variance extracted (AVE), while discriminant validity is verified using the Fornell–Larcker criterion and heterotrait–monotrait (HTMT) ratio.

The data analysis strategy and modeling framework

The quantitative analysis is conducted in multiple stages. First, descriptive statistics summarize enterprise AI maturity levels and growth performance indicators. Second, Pearson correlation analysis evaluates preliminary associations among constructs. Third, structural equation modeling (SEM) is

employed to test hypothesized relationships among AI capability, integration maturity, governance readiness, and scalability outcomes. Model fit indices include CFI, TLI, RMSEA, and SRMR.
To assess predictive strength and variable importance, machine learning techniques such as Random Forest regression are applied to identify key drivers of marketing scalability. Feature importance scores are compared with SEM path coefficients to enhance robustness. Additionally, hierarchical regression analysis tests moderation effects of leadership readiness and governance frameworks.

The qualitative analysis and triangulation process

Interview transcripts are analyzed using thematic coding supported by qualitative data analysis software. Codes are categorized under AI implementation challenges, integration bottlenecks, data governance issues, and growth acceleration mechanisms. Thematic patterns are triangulated with quantitative findings to validate causal interpretations and identify contextual nuances.
The robustness checks and sensitivity analysis
Robustness is ensured through bootstrapping (5,000 resamples) to confirm path stability. Multicollinearity is examined using variance inflation factors (VIF). Sensitivity analysis is performed by comparing early and late adopters of AI systems to evaluate temporal bias. Common method bias is assessed using Harman's single-factor test and marker variable techniques.
The ethical considerations and data governance compliance
All participants provide informed consent, and organizational data are anonymized to ensure confidentiality. The study adheres to enterprise data governance standards, ensuring compliance with data privacy regulations and ethical AI principles. Algorithmic transparency and bias mitigation strategies are incorporated in model interpretation.

Results

The descriptive statistics presented in Table 1 indicate that the sampled B2B enterprises demonstrate moderate-to-high levels of AI adoption and enterprise integration maturity. The mean AI Capability Index (M = 3.80, SD = 0.60) suggests that most firms have implemented predictive analytics, automation systems, and AI-supported personalization tools beyond experimental stages. Enterprise Integration Maturity (M = 3.50, SD = 0.70) reflects substantial but not fully optimized synchronization across CRM, ERP, finance, and sales functions. Governance and Leadership Readiness (M = 3.70, SD = 0.50) indicates relatively strong structural preparedness for AI-driven growth initiatives. In performance terms, firms report an average Revenue Growth Rate of 14.20% (SD = 4.80), a CLV/CAC ratio of 3.40 (SD = 0.90), and a Marketing ROI of 128.50% (SD = 22.30), collectively suggesting that AI-enabled enterprises achieve favorable scalability outcomes.

Table 1. Descriptive Statistics of Core Constructs (N = 250)

Variable	Mean	Standard Deviation
AI Capability Index	3.80	0.60
Enterprise Integration Maturity	3.50	0.70
Governance & Leadership Readiness	3.70	0.50
Revenue Growth Rate (%)	14.20	4.80
CLV/CAC Ratio	3.40	0.90
Marketing ROI (%)	128.50	22.30

Correlation analysis in Table 2 reveals strong and statistically significant positive relationships among the core constructs. AI Capability is strongly correlated with Revenue Growth (r = 0.71), indicating that higher AI maturity aligns with improved financial performance. Enterprise Integration Maturity also demonstrates a robust association with Revenue Growth (r = 0.68), confirming the importance of cross-functional synchronization in scaling marketing operations. Governance Readiness shows a meaningful relationship with both AI Capability (r = 0.58) and Revenue Growth (r = 0.60), suggesting that leadership and compliance structures contribute to performance stability.

Table 2. Pearson Correlation Matrix

Variable	AI Capability	Integration Maturity	Governance Readiness	Revenue Growth
AI Capability	1.00	0.62	0.58	0.71
Integration Maturity	0.62	1.00	0.64	0.68
Governance Readiness	0.58	0.64	1.00	0.60
Revenue Growth	0.71	0.68	0.60	1.00

The structural equation modeling (SEM) results summarized in Table 3 further validate the proposed growth architecture. AI Capability significantly predicts Enterprise Integration Maturity ($\beta = 0.64$, $p < 0.001$), confirming that AI adoption strengthens internal system alignment. Integration Maturity, in turn, significantly predicts Revenue Growth ($\beta = 0.52$, $p < 0.001$), supporting its mediating role. AI Capability also exerts a direct positive effect on Revenue Growth ($\beta = 0.41$, $p < 0.01$), indicating partial mediation rather than full dependence on integration. Additionally, the interaction term between Governance Readiness and AI Capability significantly influences Revenue Growth ($\beta = 0.28$, $p < 0.05$), demonstrating a moderating effect. Model fit indices (CFI = 0.94; RMSEA = 0.048; SRMR = 0.041) confirm strong model adequacy.

Table 3. Structural Equation Modeling (SEM) Results

Structural Path	Standardized Coefficient (β)	p-value
AI Capability → Integration Maturity	0.64	<0.001
Integration Maturity → Revenue Growth	0.52	<0.001
AI Capability → Revenue Growth	0.41	<0.01
Governance Readiness × AI Capability → Revenue Growth (Moderation)	0.28	<0.05

Model Fit Indices; CFI = 0.94, TLI = 0.92, RMSEA = 0.048, SRMR = 0.041

The machine learning-based driver analysis presented in Table 4 identifies Predictive Analytics Usage (importance score = 0.27) and CRM–ERP Integration (0.22) as the strongest predictors of Revenue Growth. Lead Automation Systems (0.19), Governance Framework Strength (0.17), and Real-Time Personalization (0.15) also contribute meaningfully, highlighting that both technological sophistication and structural governance jointly drive scalable marketing performance.

Table 4. Random Forest Feature Importance for Predicting Revenue Growth

Predictor	Feature Importance Score
Predictive Analytics Usage	0.27
CRM–ERP Integration	0.22
Lead Automation Systems	0.19
Governance Framework Strength	0.17
Real-Time Personalization	0.15

The distributional differences across AI maturity levels are visually illustrated in Figure 1, which presents a boxplot of Revenue Growth across low, medium, and high AI Capability groups. Firms with high AI maturity demonstrate substantially higher median growth rates and tighter interquartile ranges compared to low-maturity firms, indicating not only superior performance but also greater predictability and reduced volatility.

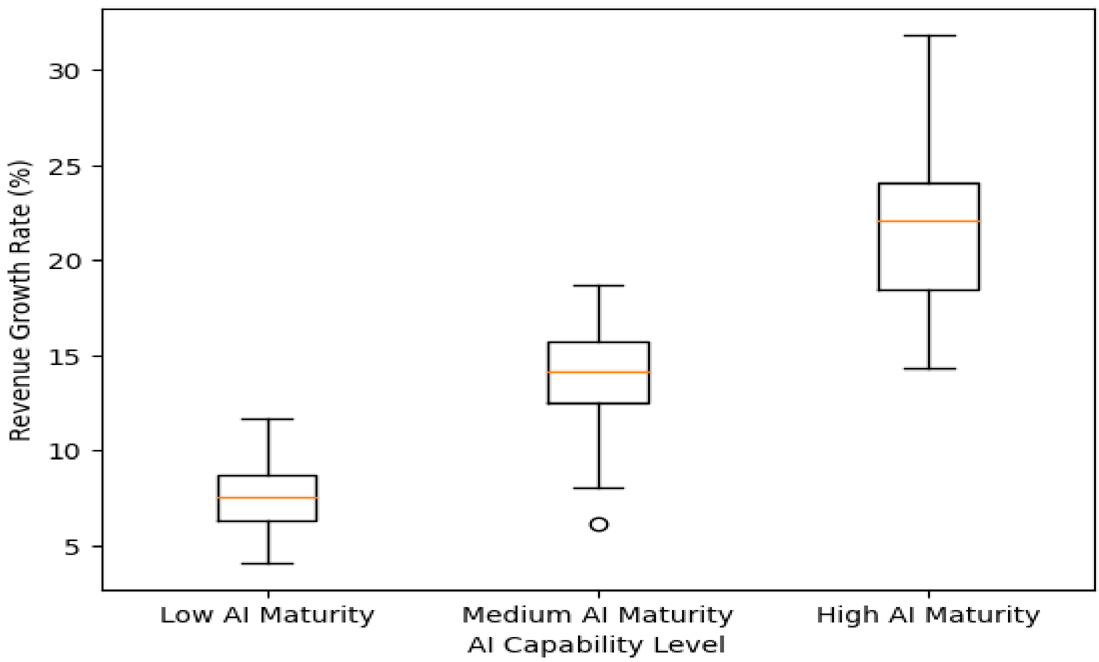

Figure 1. Revenue growth distribution across AI capability levels

Finally, the interaction surface shown in Figure 2 illustrates the synergistic relationship between AI Capability and Enterprise Integration Maturity. The three-dimensional surface demonstrates a nonlinear upward trajectory, where revenue growth increases most sharply when both AI capability and integration maturity are high. This confirms the compounded growth effect hypothesized in the framework, emphasizing that technological adoption alone is insufficient without enterprise-wide synchronization.

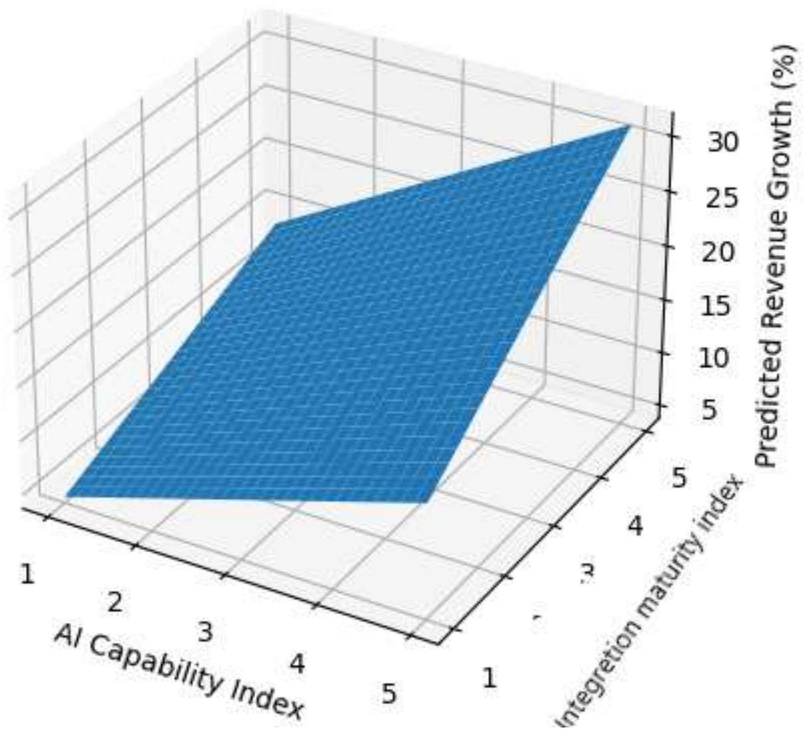

Figure 2. Surface relationship between AI, integration, and growth

Discussion

The strategic role of AI capability in driving scalable B2B growth

The findings demonstrate that AI capability functions as a foundational growth accelerator within B2B marketing ecosystems. The strong correlation between AI Capability and Revenue Growth ($r = 0.71$, Table 2), along with the significant direct structural effect ($\beta = 0.41$, Table 3), confirms that AI maturity independently contributes to enterprise-level performance. This suggests that predictive analytics, automated lead scoring, and AI-driven personalization are not merely operational enhancements but strategic enablers of revenue expansion (Patel & Trivedi, 2020). The boxplot in Figure 1 further reinforces this interpretation, as firms with high AI maturity exhibit substantially higher median growth rates and lower dispersion. This indicates not only improved financial performance but also enhanced stability and predictability; two critical attributes in B2B environments characterized by long sales cycles and high transaction values (Ye et al., 2020).

The mediating influence of enterprise integration maturity

While AI adoption demonstrates a direct performance impact, the results also reveal that enterprise integration maturity plays a central mediating role. The significant path from AI Capability to Integration Maturity ($\beta = 0.64$, Table 3) indicates that AI implementation often necessitates structural alignment across CRM, ERP, sales, and finance systems. Moreover, the strong effect of Integration Maturity on Revenue Growth ($\beta = 0.52$, Table 3) confirms that scalable growth is amplified when AI-driven insights are embedded within interconnected enterprise architectures. The surface interaction shown in Figure 2 illustrates a nonlinear synergy effect, where revenue growth accelerates most steeply when both AI capability and integration maturity are high. This finding suggests that technological sophistication without systemic alignment yields suboptimal outcomes (Liang et al., 2017). In practical terms, enterprises must move beyond siloed AI experimentation toward unified data environments and synchronized performance dashboards to unlock full scalability (Kaklauskas & Gudauskasm, 2016).

The moderating importance of governance and leadership readiness

The study further highlights the moderating role of governance and leadership readiness in AI-enabled growth. The significant interaction term ($\beta = 0.28$, Table 3) demonstrates that the impact of AI on revenue growth strengthens in organizations with robust governance frameworks and agile leadership cultures. This finding aligns with the notion that AI adoption is not purely a technical transformation but an organizational change process. Governance structures ensure ethical data usage, compliance adherence, and algorithmic transparency, while leadership readiness fosters experimentation, cross-functional collaboration, and rapid decision-making (Nwaimo et al., 2019). Without such institutional support, AI investments may fail to translate into measurable growth. Thus, governance maturity acts as a stabilizing amplifier, reinforcing the effectiveness of technological adoption (Fenwick et al., 2018).

Identifying primary growth drivers through machine learning insights

The Random Forest results in Table 4 provide additional nuance by identifying specific drivers of scalability. Predictive Analytics Usage and CRM–ERP Integration emerge as the most influential predictors of revenue growth. This indicates that enterprises deriving forward-looking insights and integrating them across commercial workflows achieve superior performance. Lead automation systems and real-time personalization also contribute meaningfully, suggesting that operational efficiency and tailored engagement enhance pipeline velocity and customer lifetime value. Importantly, governance framework strength ranks among the top predictors, reaffirming the structural interpretation of growth observed in the SEM model (Bergh et al., 2016). The convergence between statistical modeling and machine learning results strengthens the robustness of the findings and reduces the likelihood of model-specific bias (Wallert et al., 2017).

Advancing the AI-enabled enterprise growth architecture

Collectively, the findings support a compounded-growth architecture in which AI capability, enterprise integration, and governance readiness interact dynamically rather than independently (Mukherji & Mukherji, 2012). The evidence suggests partial mediation rather than full mediation, indicating that AI exerts both direct and indirect effects on growth (Rodríguez & Nieto, 2016). This layered structure challenges simplistic views that treat AI as a standalone tool. Instead, scalable B2B marketing

performance emerges from an ecosystem approach that combines analytical intelligence, cross-functional system alignment, and leadership-enabled governance mechanisms.
From a theoretical perspective, the results extend enterprise growth theory by positioning AI not only as a technological variable but as a structural catalyst embedded within organizational capability systems. From a managerial standpoint, the study emphasizes that scaling B2B marketing businesses requires synchronized investments in analytics infrastructure, integration platforms, and governance maturity. Firms that pursue isolated automation initiatives without enterprise-level synchronization may experience incremental gains but are unlikely to achieve sustained, predictable growth.

Conclusion

This study concludes that building and scaling marketing businesses across B2B environments require more than technological adoption, it demands integrated AI-enabled enterprise growth architecture. The findings demonstrate that AI capability significantly enhances revenue growth both directly and indirectly through enterprise integration maturity, while governance and leadership readiness strengthen and stabilize this impact. Firms that combine predictive analytics, automated marketing systems, and real-time personalization with synchronized CRM–ERP infrastructures achieve superior scalability, improved pipeline velocity, and stronger marketing ROI. Moreover, the interaction effects confirm that technological sophistication alone is insufficient without cross-functional alignment and structured governance mechanisms. Therefore, sustainable B2B marketing growth emerges from the convergence of analytical intelligence, systemic integration, and strategic leadership. Organizations seeking long-term competitive advantage must position AI not as an isolated tool but as a core structural driver embedded within enterprise-wide transformation frameworks.

References

1. Alluri, R. R., Venkat, T. A., Pal, D. K. D., Yellepeddi, S. M., & Thota, S. (2020). DevOps Project Management: Aligning Development and Operations Teams. Journal of Science & Technology, 1(1), 464-87.
2. Bergh, D. D., Aguinis, H., Heavey, C., Ketchen, D. J., Boyd, B. K., Su, P., ... & Joo, H. (2016). Using meta-analytic structural equation modeling to advance strategic management research: Guidelines and an empirical illustration via the strategic leadership-performance relationship. Strategic management journal, 37(3), 477-497.
3. Felzmann, H., Fosch-Villaronga, E., Lutz, C., & Tamò-Larrieux, A. (2020). Towards transparency by design for artificial intelligence. Science and engineering ethics, 26(6), 3333-3361.
4. Fenwick, M., Vermeulen, E. P., & Corrales, M. (2018). Business and regulatory responses to artificial intelligence: Dynamic regulation, innovation ecosystems and the strategic management of disruptive technology. In Robotics, AI and the Future of Law (pp. 81-103). Singapore: Springer Singapore.
5. GAFFAR, O., SIKIRU, A. O., OTUNBA, M., & ADENUGA, A. A. (2020). Autonomous Data Warehousing for Financial Institutions: Architectures for Continuous Integration, Scalability, and Regulatory Compliance.
6. John, B. I. (2020). Integration of intelligent scheduling optimization systems improving production flow, minimizing delays, and maximizing throughput across large-scale industrial operations. Global Journal of Engineering and Technology Advances, 5(3), 156-169.
7. Kaklauskas, A., & Gudauskas, R. (2016). Intelligent decision-support systems and the Internet of Things for the smart built environment. In Start-up creation (pp. 413-449). Woodhead Publishing.
8. Katuu, S. (2020). Enterprise resource planning: past, present, and future. New Review of Information Networking, 25(1), 37-46.
9. Liang, H., Wang, N., Xue, Y., & Ge, S. (2017). Unraveling the alignment paradox: how does business—IT alignment shape organizational agility?. Information Systems Research, 28(4), 863-879.
10. Mukherji, A., & Mukherji, A. (2012). Bihar: What went wrong? And what changed. National Institute of Public Finance and Policy (NIPFP),(Working Paper, (107).

11. Nwaimo, C. S., Oluoha, O. M., & Oyedokun, O. Y. E. W. A. L. E. (2019). Big data analytics: technologies, applications, and future prospects. Iconic Research and Engineering Journals, 2(11), 411-419.
12. Olayinka, O. H. (2021). Data driven customer segmentation and personalization strategies in modern business intelligence frameworks. World Journal of Advanced Research and Reviews, 12(3), 711-726.
13. Olszak, C. M., & Mach-Król, M. (2018). A conceptual framework for assessing an organization's readiness to adopt big data. Sustainability, 10(10), 3734.
14. Osho, G. O., Omisola, J. O., & Shiyanbola, J. O. (2020). A Conceptual Framework for AI-Driven Predictive Optimization in Industrial Engineering: Leveraging Machine Learning for Smart Manufacturing Decisions. Unknown Journal.
15. Papadas, K. K., Avlonitis, G. J., & Carrigan, M. (2017). Green marketing orientation: Conceptualization, scale development and validation. Journal of Business Research, 80, 236-246.
16. Patel, N., & Trivedi, S. (2020). Leveraging predictive modeling, machine learning personalization, NLP customer support, and AI chatbots to increase customer loyalty. Empirical Quests for Management Essences, 3(3), 1-24.
17. Rodríguez, A., & Nieto, M. J. (2016). Does R&D offshoring lead to SME growth? D ifferent governance modes and the mediating role of innovation. Strategic management journal, 37(8), 1734-1753.
18. Schoemaker, P. J., & Day, G. (2021). Preparing organizations for greater turbulence. California Management Review, 63(4), 66-88.
19. Tardieu, H., Daly, D., Esteban-Lauzán, J., Hall, J., & Miller, G. (2020). Deliberately digital. Cham: Springer International Publishing.
20. Valdez-De-Leon, O. (2019). How to develop a digital ecosystem: A practical framework. Technology Innovation Management Review, 9(8).
21. Wallert, J., Tomasoni, M., Madison, G., & Held, C. (2017). Predicting two-year survival versus non-survival after first myocardial infarction using machine learning and Swedish national register data. BMC medical informatics and decision making, 17(1), 99.
22. Wamba-Taguimdje, S. L., Fosso Wamba, S., Kala Kamdjoug, J. R., & Tchatchouang Wanko, C. E. (2020). Influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects. Business process management journal, 26(7), 1893-1924.
23. Yao, X., Jin, H., & Zhang, J. (2015). Towards a wisdom manufacturing vision. International Journal of Computer Integrated Manufacturing, 28(12), 1291-1312.
24. Ye, Y., Yeung, A. C., & Huo, B. (2020). Maintaining stability while boosting growth? The long-term impact of environmental accreditations on firms' financial risk and sales growth. International Journal of Operations & Production Management, 40(12), 1829-1856.
25. Zhang, Y., Ren, S., Liu, Y., Sakao, T., & Huisingh, D. (2017). A framework for Big Data driven product lifecycle management. Journal of Cleaner Production, 159, 229-240.