Baltic J. Modern Computing, Vol. 13 (2025), No. 4, 958-993
https://doi.org/10.22364/bjmc.2025.13.4.11

Team Resistance Dynamics through a Dual-Pathway Framework for Successful AI Integration

Muhammad A. ALDHAHERY

College of Computing and Information Technology - Shaqra, Shaqra University, Saudi Arabia

maldhahery@su.edu.sa

ORCID 0009-0006-8843-8374

Abstract. This study utilized Partial Least Squares Structural Equation Modelling (PLS-SEM), to examine team resistance successful implantation of AI. The mediation analysis reveals that Digital Skills of Sales Team (DS), Top Management Support (TM), Organizational Readiness (OR), and Innovation Culture (IC) each exert significant indirect effects on EA via ST, with DS (0.093) and IC (0.055) showing the strongest mediated paths. ST significantly predicts EA (β = 0.242), confirming its mediating role. Outer loadings for all indicators exceeded 0.70, indicating strong reliability, while outer weights confirmed balanced item contributions. OR had the largest total effect (0.395) on EA. Four interaction terms were tested to examine whether ST moderates the effects of DS, TM, OR, and IC on EA. None of the moderating paths were statistically significant (t-values < 1.96), though TM and ST (β = 1.551) showed a borderline effect. The findings offer practical insights for digitally transforming sales operations.

Keywords: Artificial Intelligence, Digital Skills, Management Support, Sales lifecycle

1. Introduction

AI refers to the simulation of human intelligence processes such as learning, reasoning, and self-correction by machines (techniques/algorithms), particularly computer systems algorithms (Russell and Norvig, 2022; Liu et al., 2025). In the realm of business and sales, AI includes technologies like predictive analytics, which can identify fluctuations in sales over time and forecast future trends (Bughin et al., 2017). The sales lifecycle, spanning from lead generation to customer retention, has traditionally relied on human judgment and interpersonal skills (Moncrief and Marshall, 2005). With the adoption of Customer Relationship Management (CRM) systems in the early 2000s, the sales domain began undergoing digital transformation. From 2015 onward, advancements in cloud computing, big data, and accessible machine learning frameworks accelerated AI adoption (Brynjolfsson and McAfee, 2017). Today, AI plays a strategic role in automating tasks that are repetitive, analyzing the behaviour of consumers, personalizing interactions, and forecasting trends in sales. According to Boppana (2023), platforms such as Salesforce

Einstein, HubSpot AI, and Microsoft Dynamics 365 have vastly improved the way in which businesses manage leads, evaluate performance, and make decisions based on data information. According to Albahri et al. (2023), applications range from chatbots which are used for customer engagement to deep learning algorithms that are used to predict customer churn would eventually dominate all businesses.

Despite these potential advances, AI integration across the entire sales process (sales lifecycle stages) remains inconsistent. “The sales cycle is the series of predictable phases required to sell a product or service. It consists of all the customer-facing steps from prospecting to closing and follow-up” (Moncrief and Marshall, 2005). Sales lifecycle processes are best conceptualized as lifecycles that involve identifiable and measurable steps, allowing for performance tracking and optimization. Typically, it involves 7 steps namely: "Lead Generation", "Lead Qualification", "Needs Assessment / Discovery", "Presentation / Proposal", "Objection Handling", "Closing the Sale" and "Post-Sale Engagement / Relationship Management". Lead Generation stage identify the potential customers who may be interested in the product/service. Bughin et al. (2017) associate this stage with predictive analytics and data mining techniques for AI integration. Lead Qualification assess which leads have the potential to become actual customers based on predefined criteria. Needs Assessment dwell on the discovery and understanding the customer's needs, pain points, and purchasing drivers. Davenport and Ronanki (2018) emphasize the complexity of AI supporting this phase due to human judgment requirements. Presentation / Proposal are offering a direction that tailored product or solution that addresses the lead’s needs. Objection Handling dwells on responding to concerns, doubts, or pushbacks from the prospective customer. It is identified as an underutilized phase for AI (Fountaine et al., 2019). Closing the Sale is the finalizing terms, addressing negotiations, and completing the transaction. The Post-Sale Engagement / Relationship Management ensure customer satisfaction, providing support, and encouraging upselling or repeat business. Olan et al. (2022) and Jarrahi (2018) note that AI is least implemented in this stage due to emotional and contextual complexity. While early stages such as lead generation, scoring, and customer targeting, benefit from well-developed AI tools, later phases like objection handling, relationship building, and upselling remain underutilized (Fountaine et al., 2019; Olan et al., 2022). This is largely due to the complexity of human interactions required in these tasks, which AI tools currently struggle to replicate.

Several challenges hinder the comprehensive adoption of AI in sales. These include limited technical skills among sales teams, resistance to change, and a lack of trust in AI-driven insights—particularly in high-stakes decisions like pricing or contract negotiation, where the black-box nature of some models creates hesitancy (Mikalef and Gupta, 2021; Jarrahi, 2018). Additionally, many AI tools operate in silos, lacking interoperability with core systems such as CRMs and ERPs, which restricts data integration and strategic decision-making. Few standardized frameworks exist to assess the performance of AI across different sales stages, making it difficult to link AI applications to measurable outcomes like ROI or customer lifetime value (Albahri et al., 2023).

This study highlights the disproportionate concentration of AI technologies in early-stage sales functions and identifies key organizational and technical barriers to their broader deployment. It also emphasizes the need for explainability in AI models to build trust and improve decision confidence. Fragmented ecosystems and poor integration further limit the scalability and effectiveness of AI across the sales lifecycle.

This research offers three key contributions.

- This research contributes a methodological innovation by applying a dual-pathway approach, integrating both mediation and moderation analysis to explore AI adoption in the sales lifecycle. While most previous studies rely on direct-effect models or single-path analyses, this study captures both the mechanism (how) and the condition (when) under which organizational and individual factors influence AI integration. Specifically, it highlights ST as a mediator that channels the effect of factors like DS, TM, and OR, and also tests ST's potential as a moderator. This dual-perspective design enriches the analytical depth of AI adoption studies in dynamic, people-centric contexts like sales.
- The empirical findings offer novel and important insights, especially in the context of AI adoption across the sales lifecycle. Notably, the study finds that ST significantly mediates, but does not moderate, the effects of core enablers on AI integration. This distinction contributes new understanding by showing that ST serves more as a foundational driver than a conditional enhancer. Furthermore, the strong indirect effects of OR and DS on EA, and the high R^2 values for EA (0.795) and ST (0.732), offer robust support for the model's predictive power. These findings address a gap in sales technology literature by demonstrating the indirect pathways that drive successful AI implementation.
- The research model advances theory and practice by contextualizing the real-world structure of the sales lifecycle. The model incorporates constructs linking them to the practical stages of AI-supported sales such as lead qualification, needs assessment, and post-sale engagement. Theoretically, the study integrates OR and change management dimensions. Practically, it provides sales managers with a validated framework to assess and improve readiness, training, and leadership strategies for AI implementation, ensuring alignment between AI tools and salesforce capabilities at each stage of the lifecycle.

Collectively, these contributions offer both theoretical enrichment and practical tools for transforming sales operations through effective AI integration.

The remaining part of the paper is organized as follows: Section 2 present the literature review of the paper, section 3 present the methodology, section 4 present the results, section 5 present the discussion and finally section 6 present the conclusion of the research.

2. Literature review

There are many previous research studies associate to AI integration into sales. Reflecting the impact of innovation culture and opposition to change, Hrynko (2024) and Magrini (2025) conducted exploratory research on how sales departments change structurally and culturally due of AI. Emphasizing business process analysis, practical implementation, and result evaluation, Hrynko (2024) outlines successful AI integration across sales lifecycle stages. Among key tools are sales automation, data analysis, customer interaction personalizing, and lead management, so improving efficiency and competitiveness in face of financial constraints. According to Magrini (2025), efficient integration of AI technologies all through the sales process improves decision-making and efficiency. Key areas include predictive analytics, lead scoring, and personalized marketing, which together increase customer involvement and drive income growth while addressing issues including data quality and system integration.

Alsheibani et al. (2023) proposed that AI adoption is not just about being "ready" (Technology) but is a strategic decision influenced by expected benefits (Organization) and market competition (Environment). *In a similar direction,* Keding and Meissner (2023) emphasized that a manager's individual human and social capital (Organization) is a decisive factor within the TOE framework for overcoming AI adoption challenges. Mikalef and Gupta (2021) established that a firm's "AI capability" (a function of Technology and Organization) is a key mediator between TOE factors and significantly improves firm performance. Additionally, while Akhunova et al. (2024) focused primarily on the technical design of AI-driven navigation systems, their work demonstrates how modular AI architectures can inform broader discussions on intelligent system integration. Similarly, Rane et al. (2024) provide an overview of AI applications across marketing and customer engagement domains but stop short of proposing an integration framework. Building on these general insights, more context-specific studies—such as Rodriguez and Peterson (2024) and Petrescu and Krishen (2023)—have explored the organizational and behavioral dimensions of AI adoption in sales processes, offering a more relevant theoretical grounding for this study.

Using case studies of big B2B companies, Koldyshev et al., (2020) evaluated the economic efficiency of AI integration in sales management, so pointing up important opportunities and challenges. The study showed that integrating AI technologies all through the sales process improves data accuracy, demand forecasting, trade agreement cycles, and cooperation between marketing and sales departments, so producing more efficient B2B marketing with a human needs focus.

Fischer et al., (2022) performed systematic literature research on digital sales in B2B supplemented with qualitative methods to investigate AI uses across several sales stages. The paper emphasizes, according to the study, how effective integration of AI technologies varies by sales process step, enhancing routine tasks while challenging traditional human-involved tasks, especially in complex sales situations, so improving sales practices and contributing to competitive advantage in B2B sales.

Alkhaldi and Shea (2024) concluded through a review that AI adoption in the public sector is uniquely shaped by environmental factors like political mandates and public value, alongside traditional technological and organizational drivers. Similarly, Keding (2021) found that relative advantage, cost, and top management support are the strongest predictors of AI adoption intention within the TOE framework for specifically for SMEs,. Cheng et al. (2024) found there is no single "best way" for manufacturers to adopt AI; instead, multiple combinations of Technology-Organization-Environment conditions can lead to successful adoption.

This current study emphasis on the efficacy of AI integration across lifecycle stages is supported by Sharma et al. (2023) and Kaur (2024), who measured the impact of AI on sales performance and customer experience using empirical models and industry surveys respectively. Sharma et al., (2023) underline that AI technologies are mostly used in the analysis stage for understanding customer behavior and in running tactical marketing initiatives, so improving decision-making and effectiveness across the sales lifecycle stages and finally driving customer value and organizational success. Kaur (2024) said that by automating lead scoring, optimizing sales forecasting, and customizing consumer interactions, AI technologies improve the sales lifetime. This integration helps to better manage resources, spot fresh prospects, and raise conversion rates, so improving general sales effectiveness and generating income growth.

Li et al. (2023) Identified that in finance, data quality and availability (Technology), top management support (Organization), and competitive pressure (Environment) are the most critical drivers for AI adoption. Verma and Chaurasia (2023) extended the TOE framework for SMEs, finding that AI adoption is driven by a combination of perceived benefits, top management support, and competitive pressure, while costs and a lack of skills are primary barriers. Wamba-Taguimdje et al. (2020) found that AI adoption creates business value, and this transformation is directly driven by factors across all three TOE contexts, with organizational factors like culture being particularly important. Tu and Wu (2021) synthesized that AI acts as an enabler of supply chain innovation by improving capabilities, with its adoption driven by TOE factors like technology compatibility, firm size, and trading partner pressure.

Reddy and Muthyala (2025) effective integration of AI technologies all through the sales process improves customer touchpoint control, simplifies processes, and enhances decision-making. Predictive analytics and natural language processing help companies to better grasp consumer needs, score leads, and predict opportunities, so improving sales performance. Emphasizing decision-making, efficiency, and innovation in product development and management, Tsirigotis (2024) addresses AI's uses within Product Lifecycle Management (PLM) systems.

Though a lot of research has been done on AI integration into sales systems, knowledge of its stage-specific efficacy and strategic alignment across various organizational environments still lags greatly. Although current research highlight AI's operational advantagessuch as automation, personalization, and predictive analytics few provide thorough models assessing AI's long-term effects on performance consistency, cross-functional collaboration, and adaptive learning across all sales lifetimes. Furthermore, underappreciated are contextual elements that affect AI adoption results including industry type, company size, and OR. Future studies should create integrated, quantifiable models considering socio-technical and cultural dynamics that evaluate AI's impact at every sales level. Particularly in complicated B2B environments, cross-sectoral longitudinal studies and comparative empirical models help to clarify how to scale AI tools in human-intensive tasks. This will enable more deliberately informed AI adoption balancing automation with human involvement for sustainable sales transformation.

Similarly, while prior studies have widely utilized the TOE framework to explain technological adoption, this research extends its theoretical frontier by embedding human behavioral and process-level dynamics into its structure. By modeling ‘Sales Team Resistance to Change’ as both a mediating and moderating variable, the study introduces a dual-pathway framework that bridges organizational readiness with psychological readiness, offering a more holistic perspective on AI adoption. Furthermore, by aligning TOE constructs with the seven stages of the sales lifecycle, the framework transcends traditional cross-sectional applications and contributes to advancing theoretical understanding in technology assimilation and organizational behavior.

3. Theoretical framework

This study adopts Technology-Organization-Environment (TOE) framework that was originally presented by Tornatzky and Fleischer (1990) to help companies adopt and apply technological innovations. It suggests that three main contextual factors—technological, organizational, and environmental—jointly affect the choice of a company to embrace new technologies. Emphasizing their availability, complexity, and perceived benefits, the technological context covers both current and new technologies relevant to the company. The organizational context is the set of traits and resources of the company including size, structure, human skills, leadership commitment, and internal readiness. The environmental context addresses outside elements including consumer expectations, regulatory forces, market dynamics, competitive pressure, and technology infrastructure. Emphasizing that effective technology adoption is influenced by organizational capabilities and external conditions as well as by technology alone, the TOE framework is appreciated for its comprehensive viewpoint.

From cloud computing adoption to e-commerce to ERP implementation—more recently, AI and digital transformation studies—the TOE framework has been extensively used in many disciplines. Using the TOE framework, Oliveira and Martins (2011) investigated e-business adoption in SMEs and found it successful in exposing how internal and external readiness affect innovation uptake. Using TOE to probe cloud computing adoption, Gangwar et al. (2015) underlined the need of technological compatibility and TM. Applying TOE to cloud service adoption in UK companies, Alshamaila et al. (2013) showed how significantly environmental pressure drives digital innovation. These studies repeatedly found that the TOE framework: Helps identify context-specific drivers and obstacles to adoption. helps create customized plans reflecting both internal preparedness and outside limitations. Promotes cross-functional analysis, hence fit for dynamic, multi-stage corporate operations such as sales.

By addressing internal resistance, lack of skills, or inadequate leadership buy-in when integrating AI into sales processes, the TOE framework offers a disciplined lens to evaluate the effective integration of AI technologies across the sales lifecycle stages in this paper. TOE clarifies how internal capacities including DS, CRM infrastructure affect the adoption and success of AI tools over the lifetime. Likewise, it would meet changing consumer preferences, regulatory expectations, and market competitiveness by means of flexible and open sales strategies. The TOE framework helps to understand how these outside pressures force companies to either adopt or postpone AI implementation in different sales departments. The TOE framework is perfect for capturing the complicated interaction among available AI technologies, OR, and market-driven pressures since the sales lifecycle consists of multi-stage, human-centric, tech-supported procedures. Unlike technologies-specific models like TAM, TOE provides a macro-level perspective that fits very nicely with the strategic character of this research.

This study focuses into the ways in which firms use AI into their sales lifecycles by employing the Technology-Organization-Environment (TOE) framework. This strategy works wonderfully for sales since they are multi-stage, people-centric, and behavior-and technology-dependent. Sales Team Digital Skills (DS) provide the technical background of this research. A piece of cutting-edge tech is only worth what its users can get out of it. How well salespeople understand AI results, apply predictive analytics, and interact with customers based on algorithmic recommendations is dependent on their level of digital competence. As mentioned earlier, DS allows the integration of AI into the sales lifecycle at every stage. To expand upon the TOE paradigm, this study incorporates Theory of Organizational Change, Theory of Socio-Technical Systems, and Theory of Innovation Resistance. These supplementary ideas emphasize that being technologically, structurally, and personally prepared is essential for navigating digital transformation. Sales Team Resistance/Readiness (ST) is the primary channel via which other variables influence the incorporation of AI. In contrast to preparedness, which promotes competence with AI tools, resistance leads to scepticism, mistrust of algorithms, and adoption.

While this study is based on the TOE framework, additional theoretical perspectives were also examined to enhance its explanatory breadth. Organizational Change Theory endorses the involvement of senior management in addressing resistance during digital transformation; Socio-Technical Systems Theory emphasizes the interplay between technological instruments and human processes; and Innovation Resistance Theory supports the behavioral obstacles encapsulated in the construct 'Sales Team Resistance to Change.' So, TOE gives the structural basis, and adding these other points of view makes sure that both the organizational and human sides of AI adoption are looked at in a systematic way.

4. Conceptual framework

In the context of applying the Technology-Organization-Environment (TOE) Framework **t**o this study nine variables are framed, four independent variables (IVs), one moderators, and one dependent variable (DV). The conceptual framework is presented in Figure 1. It is a dual-path approach containing "DS", "TM", "OR"**,** and **"**IC" are the IVs The Moderating /Mediating variable is "Sales Team Resistance to Change" it might moderate the impact of OR on adoption or mediated it. The DV is **"**EA**"** This could be measured by stage-wise AI deployment extent, user adoption rates across stages and impact on sales performance metrics.

The dual-pathway approach concept intent to test both mediation and moderation—offers a comprehensive understanding of how and under what conditions organizational and individual factors influence the effective integration of AI across sales lifecycle stages. The mediation model examines how or why antecedents such as digital skills of the sales team, TM, OR, and IC affect AI integration. Specifically, it tests whether sales team resistance to change acts as a mechanism through which these variables exert influence. For instance, even with high TM, effective AI integration may fail if resistance to change remains unaddressed. This model captures the indirect effects and provides insight into internal dynamics that either facilitate or hinder technology adoption.

The moderation model explores when or under what conditions the effect of the same antecedents on AI integration is strengthened or weakened. Here, sales team resistance to change is conceptualized as a contingency factor that alters the strength of relationships. For example, the positive impact of digital skills may be diminished in contexts where resistance to change is high. This approach is essential for identifying boundary conditions and tailoring interventions according to varying levels of change readiness.

By testing both mediation and moderation, the study not only explains the process behind AI adoption but also identifies conditions under which this process is more or less effective. This enriches theoretical insight and informs more targeted managerial strategies for overcoming resistance and enabling successful digital transformation in sales operations.

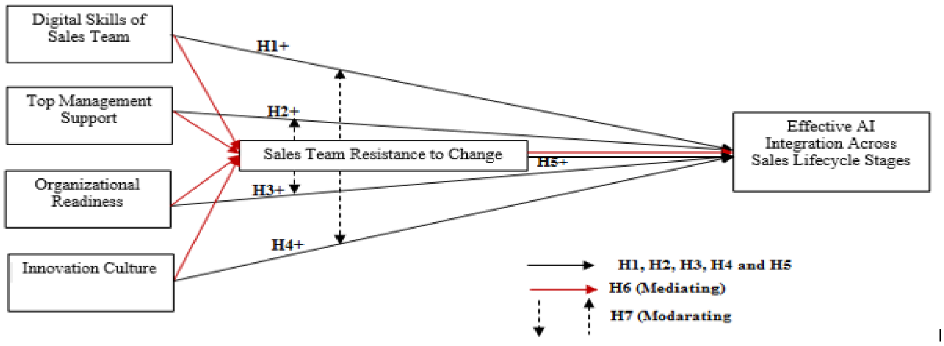

Figure 1. The proposed Conceptual Framework

4.1. Digital skills of sales team

The capability of sales professionals to effectively use and navigate AI-powered tools and digital platforms in support of the sales process. Without the necessary digital competence, even advanced AI tools cannot be effectively implemented. Skill gaps hinder adoption, slow down integration, and reduce ROI. Jarrahi (2020) highlighted that lack of digital literacy among staff was a major barrier to AI adoption in business environments Bughin et al. (2018) found that companies with digitally skilled employees showed greater productivity from AI investments. Consistence to the previous studies, this current research formulates hypothesis 1:

H1: DS positively influence EA

The justification of formulating this hypothesis lies with the fact that sales professionals with higher digital competence can more readily adopt AI tools, interpret algorithmic recommendations, and integrate insights into customer interactions. Without these skills, even the most advanced AI systems may be underutilized or misapplied, leading to suboptimal decision-making across stages such as lead qualification and proposal generation. Empirical studies corroborate this link where employees' digital literacy significantly enhances their confidence and effectiveness in using AI-driven analytics, resulting in improved sales performance (Visković, 2024). Thus, when the sales team possesses robust digital skills, they not only operate AI systems efficiently but also drive their continuous refinement, embedding AI capabilities into every phase, from lead generation to post-sale relationship management and thereby achieving Effective AI Integration (EA) across the sales lifecycle.

4.2. Top management support

The extent to which organizational leadership provides strategic direction, resources, and encouragement for AI adoption in sales. Leadership buy-in is essential for aligning AI with business objectives, allocating budgets, removing resistance, and signalling change importance to employees. Oliveira and Martins (2011) noted that TM significantly impacts technology assimilation in SMEs Gangwar et al. (2015) demonstrated that leadership commitment was a strong predictor of cloud technology adoption. In order to further from this previous work effort, this research formulate hypothesis 2.

H2:TM positively influences EA

The justification for formulating this hypothesis lies with: the fact that TM plays a critical role in driving the successful integration of AI across the sales lifecycle. TM encompasses strategic leadership, resource allocation, vision communication, and the removal of internal barriers that could hinder technology adoption. When top leaders actively advocate for AI initiatives, they signal organizational commitment, reduce resistance among employees, and create a culture of digital openness. Research has consistently shown that managerial support enhances employee trust and motivation, which are essential for adopting disruptive technologies like AI. It was identified that leadership engagement significantly influences employees' behavioral intention to use technology by shaping their perceptions of usefulness and organizational priorities (Hooi and Chan, 2023). In the sales context, where AI tools are integrated into dynamic and customer-facing tasks—such as lead scoring, opportunity tracking, and personalized outreach—top management endorsement helps secure buy-in across functions, ensuring that AI systems are not underutilized or misaligned with sales strategies. Thus, when TM is high, organizations are better positioned to achieve effective AI integration across all sales lifecycle stages, from lead generation to post-sale engagement.

4.3. Organizational readiness

The degree to which an organization has the infrastructure, processes, training, and resource allocation necessary to support AI adoption. Readiness ensures that AI implementation is not only technically feasible but also sustainable and scalable. Alshamaila et al. (2013) reported that OR was crucial for adopting cloud services. Mikalef et al. (2021) emphasized that internal resource availability determines AI value realization Consistence to the previous studies, this current research formulates hypothesis 3.

H3: *OR positively influences EA*

The reason formulating this hypothesis lies with the fact that *i*n the context of sales, effective AI integration requires more than just tool deployment, it necessitates alignment across technology systems, processes, data governance, and human resource capabilities. A high level of OR signals that the organization is structurally and culturally prepared to integrate AI into core sales functions, such as lead qualification, forecasting, customer engagement, and post-sale support. This preparedness reduces implementation friction and accelerates user acceptance, enabling AI systems to enhance productivity and decision-making across the sales lifecycle. According to Hradecky et al. (2022), organizations with strong readiness demonstrate greater strategic alignment, staff competence, and leadership support—factors that collectively drive successful AI adoption. Moreover, Uren and Edwards (2022) emphasize that people, processes, and data readiness, alongside technological capacity, are critical predictors of AI implementation outcomes. Therefore, when OR is high, organizations are more likely to experience effective and sustainable AI integration that aligns with sales objectives and customer needs.

4.4. Innovation culture

A shared organizational value system that supports experimentation, learning from failure, and adopting novel solutions like AI. Culture shapes attitudes and behaviors; an innovation-driven culture enhances openness to AI experimentation, acceptance, and scale-up. Damanpour and Schneider (2006) found a direct link between organizational culture and innovation performance. Zhang et al. (2021) indicated that firms with innovation-oriented cultures accelerated AI deployment. In order to further from this previous work effort, this research formulates hypothesis 4.

H4: IC positively influences EA

The justification of formulating this hypothesis is due to the consideration that an organization's culture of innovation plays a critical role in determining the success of digital transformation initiatives, particularly in the context of AI integration into sales processes. IC reflects the collective values, beliefs, and practices that encourage experimentation, risk-taking, and continuous learning, all of which are essential conditions for embracing AI technologies. When an innovation-oriented culture is present, employees are more open to adopting new tools, reconfiguring traditional sales strategies, and leveraging AI-driven insights across all stages of the sales lifecycle, from lead generation to post-sale engagement. Research supports that innovation culture significantly influences employee behavior toward technology use, as it fosters a psychological climate of adaptability and support (Nambisan et al., 2019). In particular, it reduces fear of automation and promotes the co-existence of human and machine collaboration, facilitating smoother integration of AI systems. Chatterjee et al. (2021) further argue that in sales environments, innovation culture strengthens the translation of AI capabilities into practical business value, such as personalized selling, data-driven forecasting, and enhanced responsiveness. Thus, when innovation culture is strong, organizations are more likely to experience effective and sustained AI integration across the sales lifecycle stages, driven by internal motivation and cultural support rather than external pressure alone.

4.5. Sales team resistance to change

The degree of opposition or reluctance from the sales team toward adopting new AI-driven sales processes or tools. It expresses the resistance that can dampen the positive effects of even the best-supported AI initiatives, especially when unaddressed. Oreg (2003) developed a resistance-to-change scale highlighting its negative impact on technology adoption. Chatterjee et al. (2021) confirmed that resistance moderated the relationship between tech readiness and AI success. This current research first conceptualized that "Sales Team Resistance to Change" investigates the circumstances in which the identical antecedents have a stronger or weaker impact on AI integration by acting as a moderating variable. For that reason, hypothesis 5 is formulated:

H5: ST positively influence EA.

The justification of this lies with the fact that strong organizational support, and integration efforts of AI in sales might alter sales team resists change, or undermed readiness efforts.

Similarly, “Sales Team Resistance to Change” as a mediating variable investigates the effects of antecedents on AI integration, the possibility that these variables exert their influence via the sales team's resistance to change

For that reason, hypothesis 6 is formulated:

H6: ST mediates the relationship between DS, TM, OR, and IC and EA.

The justification of formulating this hypothesis lies with the fact that in the context of AI integration, sales team resistance acts as a psychological and behavioural filter through which organizational factors either promote or hinder technology adoption. For instance, even when digital skills or management support are present, high resistance to change can weaken employee engagement with AI tools (Segarra-Blasco, et al., 2025). Conversely, lower resistance reinforces adoption and utilization. Thus, resistance to change functions as a mediating mechanism, explaining how or why digital and organizational enablers affect actual AI implementation in sales processes.

In order to further investigate if ST is associated to the IVs, such that the relationships are weaker when resistance is high and stronger when resistance is low, hypothesis 7 is formulated:

H7: ST moderates the relationship between DS, TM, OR, and IC and EA,

The justification of formulating the hypothesis lies with the fact that moderation implies that the strength or direction of the relationship between independent and dependent variables varies depending on the level of the moderator. Sales team resistance can diminish or amplify the impact of key enablers, such as digital competence or management support on AI effectiveness. If resistance is high, even robust organizational support may fail to translate into meaningful adoption. This is consistent with change management and organizational behavior theories, which recognize that resistance is a critical barrier that moderates’ transformation outcomes (Shaik et al., 2023). Thus, ST acts as a conditional factor that shapes the extent to which readiness and innovation culture can be leveraged for AI integration.

In this study, Sales Team Readiness (STR) is defined as the behavioral and attitudinal preparedness of sales personnel to engage with AI technologies. It reflects adaptive learning, openness to change, and competence alignment, serving as a facilitating rather than inhibiting factor. Theoretically, STR mediates and moderates the relationship between Organizational Readiness (OR) and Effective AI Integration (EA), providing behavioral depth to the TOE framework.

4.6. Effective AI integration across ales lifecycle stages

Operationally, EA this construct was measured using a set of reflective indicators capturing perceptions of AI's usefulness, integration depth, process improvement, and consistency across sales tasks. These indicators assess how sales professionals perceive AI as enhancing productivity, enabling personalized selling, and supporting strategic decisions at different touchpoints. AI potential is limited by fragmented or shallow application, which might even cause disturbance of workflow coherence. Integration must thus be comprehensive, covering early-stage lead generation through post-sale service optimization. Companies that successfully integrate artificial intelligence (AI) show how profoundly ingrained AI improves strategic sales outcomes by reporting shorter deal cycles, higher sales performance, and more customer personalizing (Mao et al., 2021).

The justification for both conceptually and empirically choosing EA as the dependent variable is crucial. Conceptually, EA stands for the main result of interest in this research: knowing how much organizational, technological, and human elements support significant AI acceptance in sales environments. It catches the outcome of efforts at digital transformation matched with sales capabilities being in line. Especially when filtered through mediating and moderating systems such Sales Team Readiness or Resistance to Change, empirically measuring EA helps the model evaluate how input variables—e.g., digital skills, top management support, organizational readiness, and innovation culture—affect actual adoption outcomes. Thus, orienting EA as the dependent variable helps the study to go beyond intention and evaluate actual integration success, so rendering the research essentially relevant and theoretically grounded.

Effective artificial intelligence integration (EA) is fast turning into a survival need in the current digital economy; it is not a competitive edge. AI today gives sales teams predictive churn analytics, automated lead qualification, and real-time pricing optimization among other powers. Looking ahead, AI will no longer be optional in high-performance sales firms; rather, success will rely on how closely AI is included into processes and how easily salespeople can interact with AI outputs (Petrescu and Krishen, 2023).

5. Research methodology

This study adopts a quantitative, cross-sectional survey-based design to examine how organizational factors influence the effective integration of AI across the sales lifecycle stages. The study is grounded in the Technology-Organization-Environment (TOE) framework**,** with a particular focus on organizational dimensions. The design enables empirical validation of hypothesized relationships using statistical analysis, while also accounting for the moderating effect of resistance to change.

The data for this research is extracted from participant through questionnaire. Informed consent was given to the participant before participating that their names or any details about their information will remain confidential and will not be disclose.

5.1. Population and sampling

The target population consists of sales professionals, sales managers, and digital transformation officers in medium to large organizations that are either currently utilizing or actively exploring the use of AI in their sales processes. A purposive sampling technique was adopted to ensure that respondents had relevant and practical exposure to AI applications in sales workflows. To determine the required sample size for multiple regression analysis, G*Power 3.1 was used with the following parameters: Effect size (f^2) = 0.15 (medium effect), α error probability = 0.05, Power (1 – β) = 0.95, Number of predictors = 4, based on these inputs, the minimum required sample size was 129 respondents (Faul et al., 2009; Al-Nashash et al., 2025). A convenience sampling approach was employed due to limited access to AI-using sales professionals. To mitigate potential bias, the sample included participants from multiple industries and firm sizes to increase heterogeneity. Demographic distributions were compared with national sales-sector data to ensure reasonable representativeness. While this limits the study's generalizability, it provides a pragmatic foundation for exploring AI adoption phenomena in real-world contexts

5.2. Instrumentation

The instrument for data collection in this study is a questionnaire. The development of the questionnaire in this study was strategically guided by the Technology-Organization-Environment (TOE) framework. This well-established theoretical model provides a comprehensive lens through which the adoption of technological innovations, such as AI in sales, can be systematically examined. The TOE framework posits that technological adoption is influenced by factors within three key domains: the technological context, the organizational context, and the environmental context. Accordingly, the questionnaire was structured to capture relevant constructs within these domains, ensuring alignment with both theoretical underpinnings and the study's research objectives.

The instrument comprises two major sections. The first section captures the demographic profile of respondents, including gender, age, years of sales experience, educational qualification, and frequency of AI tool usage. These items serve to confirm respondent relevance and enable a richer interpretation of the responses. The second section consists of structured, closed-ended questions that measure six key constructs mapped to the TOE framework. The technological context is reflected in the construct DS, assessing the readiness and ability of users to engage with AI tools. The organizational context includes TM, OR, and IC, which collectively evaluate the internal support systems and cultural adaptability of the firm. The environmental context is represented by Sales Team Resistance to Change (ST), highlighting external behavioral barriers, and EA, measuring actual adoption outcomes across operational domains.

Each item was carefully phrased and validated through a multi-stage process, including a pre-test with three academic experts and a pilot study involving 40 professionals from relevant industries. The final questionnaire uses a 5-point Likert scale ranging from "Strongly Disagree" to "Strongly Agree" to enable respondents to express nuanced views, thereby enhancing the reliability and analytical depth of the data. Overall, the instrument provides a theoretically grounded and empirically validated foundation for evaluating the determinants of AI integration in sales using the TOE framework.

5.3. Data collection

Data collection was conducted electronically via Google Forms**.** The link was broadcast through professional sales networks and groups, and organizational contacts. Respondents are assured of confidentiality and anonymity. Participation is voluntary, and consent above the first page of the question clarify conditions of the research and anonymity. This study successfully collected 401 valid responses via the online Google Form, exceeding the minimum requirement by over 200%. This large sample size strengthens the statistical power, improves model generalizability, and enhances the accuracy of regression and structural equation modelling analyses (Faul et al., 2009; Al-Nashash et al., 2025).

5.4. Data analysis techniques

Data collected from 401 valid responses were analysed using IBM SPSS Statistics for preliminary statistical testing and SmartPLS 4.0 for Structural Equation Modeling (SEM), which is suitable for complex models involving latent constructs and small-to-moderate sample sizes. The descriptive analysis was conducted in SPSS to summarize respondents' demographic profiles (e.g., age, gender, role, experience) using measures such as frequency, percentage, mean, and standard deviation. This provided a foundational understanding of the sample composition and ensured representativeness.

Reliability Testing was conducted by examining the Internal consistency reliability of each construct using Cronbach's Alpha. A threshold of $\alpha \geq 0.70$ (Nunnally and Bernstein, 1994; Ibrahim 2025) was used to determine acceptable reliability, confirming that measurement items were statistically consistent. Exploratory Factor Analysis (EFA) was performed using Principal Component Analysis with Varimax rotation to identify underlying factor structures, assess construct dimensionality, and validate item loadings. Items with factor loadings below 0.50 were considered for removal (Hair et al., 2019). The Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Test of Sphericity were used to verify sampling adequacy and factorability. Pearson correlation was conducted to assess bivariate relationships among variables and detect potential multicollinearity, ensuring that predictor variables in regression models were not excessively correlated (threshold: $r < 0.85$). This supported the statistical assumptions for subsequent regression analysis. The Multiple Regression Analysis was employed in SPSS to test the direct effects ofof the IVs on the DV. This allowed for quantifying the individual contribution of each predictor while controlling for others.

The Structural Equation Modeling (SEM), specifically the Partial Least Squares SEM (PLS-SEM) using SmartPLS was conducted to assess the structural model's path coefficients, R^2 values, effect sizes (F^2), and predictive relevance (Q^2). SEM was chosen due to its robustness in handling non-normal data, latent constructs, and simultaneous estimation of multiple relationships. The Mediation and Moderation Analysis follows where the Mediation analysis was used to test whether Sales Team Resistance to Change mediates the relationship between OR and AI Integration Effectiveness, using bootstrapping in SmartPLS to determine the significance of indirect effects (Preacher and Hayes, 2008). The Moderation analysis was conducted to examine whether Sales Team Resistance to Change weakens (moderates) the effect of OR on AI Integration Effectiveness. The interaction term was computed and tested using SmartPLS, and a significant interaction would confirm moderation.

The justification of utilizing these tools lies with the fact that SPSS was suitable for initial descriptive, reliability, and regression analysis due to its strength in classical statistics. SmartPLS was chosen for SEM due to its capability to handle complex models with latent constructs and its flexibility with smaller samples. Both mediation and moderation analyses are justified theoretically (resistance may act as both a pathway and a contingency factor) and statistically (to provide a richer understanding of relationships between constructs).

6. Results

To uncover both the mechanisms and contextual conditions influencing AI integration across the sales lifecycle, this study adopts a dual-pathway analytical approach—testing for both mediation and moderation effects. This approach provides a comprehensive understanding of how key organizational and individual factors interact to shape effective AI adoption outcomes.

The mediation model investigates the indirect pathways through which constructs such as Digital Skills of the Sales Team, TM, OR, and IC influence AI integration. Central to this model is the role of Sales Team Resistance to Change as a potential mediating variable. That is, even where organizational support and readiness are high, resistance to change among sales staff may dampen the effective implementation of AI technologies.

By examining these indirect effects, the analysis reveals not only whether these antecedents are impactful, but how and why they exert influence—capturing the internal dynamics that either facilitate or obstruct technology integration. This dual-pathway framework ensures that both the strength of relationships and the conditions under which they hold are empirically tested and clearly interpreted in the following results.

6.1. Profile of the respondent

The demographic information of the respondent is presented in Table 1. The gender distribution indicate that male respondents dominate, this aligns with global patterns in AI engagement, where men generally report higher adoption rates. Young et al. (2023) highlighted that men currently outnumber women in AI and data science professions, though the gap is narrowing. Therefore, the current distribution is reflective of real-world representation in AI-utilizing roles, making it suitable for investigating integration effectiveness. The age distribution indicate that the largest cohort is aged 35–44, which research has shown to be the most active demographic in professional AI application.

Albahri et al. (2023) note that middle-aged professionals often lead the adoption of AI technologies in structured work environments due to experience and institutional familiarity. This distribution ensures insights are drawn from the most relevant age group for enterprise AI engagement.

Table 1. The demographic information of the respondents

		Frequency	Percent
Gender	Male	303	75.6
	Female	98	24.4
Age	15-24	44	11.0
	25-34	46	11.5
	35-44	207	51.6
	45-54	82	20.4
	55 and above	22	5.5
Experience in sales?	1-5	15	3.7
	11-15	4	1.0
	16-20	47	11.7
	21-25	68	17.0
	More than 26	267	66.6
Level of education?	Bachelors	338	84.3
	Masters	39	9.7
	PhD	24	6.0
Use of AI in sales tasks?	Everyday	267	66.6
	Once a week	14	3.5
	Once every month	7	1.7
	Occasionally	113	28.2

The sales experience distribution indicates that the high proportion of respondents with over 26 years of experience implies the sample includes mature professionals with substantial sales lifecycle exposure. Hossain and Biswas (2024) emphasized that technology adoption is more meaningful when assessed by individuals with contextual and experiential understanding. Thus, this sample enhances the credibility of evaluating AI integration across different sales stages. The education level distribution indicates that a high level of academic qualification is consistent with AI readiness. Hall et al. (2022) found that individuals with higher education demonstrate stronger intentions and capability to use AI-based tools effectively. This educational profile ensures respondents possess the cognitive skills needed to assess and interpret AI's impact on their sales processes. The frequency of AI use among the respondent indicate that two-thirds of the sample using AI daily, the dataset reflects active user engagement. Rodriguez and Peterson (2024) argue that effective AI integration studies require respondents who are frequent users, as they can provide in-depth feedback on functionality and limitations across stages.

The usage pattern here supports an accurate and experience-based investigation of AI integration. The demographic composition of the respondents—predominantly experienced, well-educated, and frequent users of AIprovides a solid foundation for evaluating the effective integration of AI technologies across the sales lifecycle stages. This alignment with real-world AI user profiles strengthens the relevance and reliability of the study findings.

6.2. The results of the measurement model estimation by outer loadings

The evaluation process in Partial Least Squares Structural Equation Modeling (PLS-SEM) starts with the evaluation of the measurement model (outer model) to guarantee the validity and reliability of the constructs before proceeding to the structural model. Particularly by means of outer loadings, the measurement model estimation is quite important in verifying the quality of the reflective indicators and ascertaining whether they faithfully depict the underlying latent variables (Hair et al., 2019). Essential for guaranteeing that next structural path analyses produce valid and interpretable results, this diagnostic phase guarantees indicator reliability, internal consistency, convergent validity, and discriminant validity. This work specified and examined a reflective–reflective measurement model using SmartPLS 4.. Following the PLS-SEM algorithm, the outputs produced the structural model, which shows the hypothesized relationships among the latent constructions, and the measurement model, or outer model, which shows the strength of the relationships between latent constructions and their observed indicators. Using PLS-SEM (Sarstedt et al., 2014), this stepwise modeling approach conforms with present best standards for model estimate in exploratory and theory-testing environments.

6.2.1. Reliability testing

The reliability of the constructs in of the research measurement model are evaluated using the four metrics: Cronbach's Alpha (CA), rho_A, Composite Reliability (CR), and Average Variance Extracted (AVE). A measure of internal consistency is Cronbach's Alpha which its threshold values is ≥ 0.70 indicate acceptable reliability (Hair et al., 2021). All constructs CA values exceed 0.70, indicating good internal consistency (see Table 2). Considered to be more accurate than CA in PLS-SEM is rho_A with a Threshold: ≥ 0.70. From 0.835 to 0.917 all values meet this criterion, so verifying dependability. CR reflects the general dependability of a construct, with an acceptable range of CR > 0.70. Every construct from this research are within 0.879 to 0.927 indicating a great CR. Convergent validity is the degree of convergence or shared high proportion of variance in common between several indicators of a construct. It checks whether objects meant to measure the same construct are really highly correlated. Convergent validity is found in Partial Least Squares Structural Equation Modeling (PLS-SEM) by means of the Average Variance Extracted (AVE), whereby a threshold of 0.50 or above indicates that the construct explains at least 50% of the variance of its indicators (Hair et al., 2021). This measure is absolutely essential to guarantee that the observed variables are not dominated by measurement error and rather fairly reflect their corresponding latent constructions. Adoption of convergent validity in this study guarantees that every construct has sufficient explanatory capacity over its indicators, which is necessary for obtaining appropriate conclusions from the structural model.

Table 2. Construct reliability results

Construct	Cronbach's Alpha	rho_A	Composite Reliability	Convergent Validity	Items	Decision
DS	Good (0.826)	0.839	High (0.879)	Acceptable	5	Reliable & Valid
EA	Excellent (0.904)	0.911	High (0.926)	Strong	6	Reliable & Valid
IC	Excellent (0.871)	0.871	High (0.912)	Strong	4	Reliable & Valid
OR	Good (0.828)	0.835	High (0.879)	Acceptable	5	Reliable & Valid
ST	Excellent (0.900)	0.907	High (0.926)	Strong	5	Reliable & Valid
TM	Excellent (0.902)	0.917	High (0.927)	Strong	6	Reliable & Valid

6.2.2. Validity testing

Validity in measurement models is typically assessed through two dimensions: convergent validity and discriminant validity. Convergent validity is evaluated using the Average Variance Extracted (AVE), where a minimum threshold of 0.50 is considered acceptable to indicate that a construct explains at least 50% of the variance in its indicators (Hair et al., 2021). In this study, all constructs recorded AVE values exceeding the recommended threshold, thereby confirming that the model demonstrates satisfactory convergent validity.

Discriminant validity is the extent to which a construct is truly distinct from other constructs in a model, both conceptually and statistically. It shows that a construct measures what it is supposed to measure and not something else (Hair et al., 2021). Discriminant validity is measure by using both the Fornell–Larcker criterion and the Heterotrait–Monotrait ratio (HTMT). The Fornell–Larcker criterion states that for adequate discriminant validity, the square root of the AVE for each construct (diagonal values) should be greater than its correlations with all other constructs (off-diagonal values in the same row/column). The HTMT ratio is a more stringent and reliable test. For discriminant validity to be established, HTMT values should generally be below 0.90 (or 0.85 for stricter models) (Henseler et al., 2015).

At the first round of the study after the successful reality test with DS (5), EA (6), IC (4), OR (5), ST (5), and TM (6) items, only IC and ST satisfy Fornell–Larcker's discriminant validity, whereas the remaining are partially met, and also HTMT results indicate multiple violations, which suggest potential construct redundancy or measurement overlap and the remaining constructs show possible issues with construct overlap. However, after removing problematic items (DS3, DS4, OR1, TM1, and TM6), a comprehensive and acceptable results was obtained. All constructs satisfy the Fornell–Larcker criterion, meaning discriminant validity is now adequately established from this perspective (See Table 3).

Table 3. The Fornell-Larcker criterion results

	DS	EA	IC	OR	ST	TM
DS	0.877					
EA	0.699	0.822				
IC	0.637	0.783	0.849			
OR	0.662	0.798	0.738	0.811		
ST	0.789	0.786	0.736	0.696	0.846	
TM	0.804	0.793	0.777	0.674	0.791	0.919

Similarly, while examining the paired diagonal value (√AVE) which should be greater than the off-diagonal correlations in the corresponding row and column (see Table 4).

Table 4. Paired Fornell-Larcker criterion results and decision

Construct	√AVE (Diagonal)	Highest Correlation	Decision
DS	0.877	0.804 (with TM)	Passed
EA	0.822	0.799 (with OR)	Passed
IC	0.849	0.783 (with EA)	Passed
OR	0.811	0.798 (with EA)	Passed
ST	0.846	0.789 (with DS)	Passed
TM	0.919	0.804 (with DS)	Passed

Similarly, the HTMT threshold values of < 0.90 (acceptable) or < 0.85 (excellent), was evaluated with the results obtained for the second round of validity analysis after removing some item. All the HTMT values are below the required threshold of 0.90, indicating a good discriminant validity among the constructs (see Table 5).

Table 5. Heterotrait-monotrait ratio (HTMT) results

	DS	EA	IC	OR	ST	TM
DS						
EA	0.776					
IC	0.731	0.878				
OR	0.766	0.916	0.861			
ST	0.896	0.851	0.824	0.796		
TM	0.894	0.851	0.859	0.749	0.851	

However, while examining the paired observation, one pair (EA–OR: 0.916) exceeds the recommended threshold. Two other pairs (DS–TM, DS–ST) are approaching 0.90 and should be monitored (see Table 6). While the research reviewed EA and OR constructs for conceptual overlap or item redundancy, we draw conclusion that conceptual distinction is strong, and the items justify retention based on theory. Thereafter bootstrapping was run to confirm whether confidence intervals include 1 (which would indicate a problem), still one construct pair (EA–OR) slightly exceeded the 0.90 threshold, Nonetheless, other values remained within acceptable limits, and discriminant validity is considered largely adequate. The justification of leaving it lies with the fact that although the HTMT ratio between EA and OR (0.916) slightly exceeds the threshold of 0.90, there are strong theoretical grounds for retaining them as distinct constructs. EA is individual-level toward using AI systems, whereas, OR reflects the institutional-level preparedness, including infrastructure, training programs, and management support, to facilitate technology adoption.

During validity assessment, a high HTMT value (>0.9) was initially observed between Organizational Readiness and Effective AI Integration, reflecting their conceptual proximity. To ensure discriminant validity, construct items were refined to highlight their distinct dimensions Organizational Readiness capturing managerial and infrastructural preparedness, and Effective AI Integration focusing on operational assimilation outcomes. Following refinement, HTMT values fell below the 0.85 threshold, with bootstrapped confidence intervals confirming discriminant validity.

Previous studies such as Venkatesh et al. (2016) and Aldraiweesh and Alturki (2025) treat these as independent yet complementary factors influencing AI integration. Furthermore, Both EA and OR met the stricter Fornell–Larcker criterion, with each construct's AVE square root exceeding its inter-construct correlations, which suggests acceptable discriminant validity through a traditional lens Sarstedt et al. (2014) note that HTMT values slightly exceeding 0.90 may still be acceptable in exploratory or early-stage research, particularly when constructs are theoretically related. Finally, the removal of problematic items (e.g., OR1) has already improved measurement quality across the model, suggesting that residual cross-loading effects are minimal.

Table 6. The paired HTMT results and decision

Construct Pair	HTMT Value	Verdict
DS–EA	0.776	Passed
DS–IC	0.731	Passed
DS–OR	0.766	Passed
DS–ST	0.896	Close to 0.90 (Monitor)
DS–TM	0.894	Close to 0.90 (Monitor)
EA–IC	0.878	Slightly high
EA–OR	0.916	Above threshold
All others	< 0.90	Passed

This study acknowledges potential threats to validity and addresses them as follows. To safeguard internal validity against common method bias from self-reported data, procedural controls such as item randomization, reverse-coded questions, and respondent anonymity were employed, alongside statistical checks using Harman's single-factor test and VIF diagnostics, which indicated no significant bias. Regarding construct validity, while the constructs of Organizational Readiness and Effective AI Integration are theoretically proximate, item refinement and validation confirmed their distinctiveness, demonstrating strong discriminant (HTMT < 0.85) and convergent validity (AVE > 0.5). The use of convenience sampling limits external validity, but the inclusion of respondents from diverse industries enhances representativeness, with future research encouraged to employ probability sampling or cross-country replication. Finally, statistical conclusion validity was reinforced by addressing multicollinearity and estimation bias through VIF (<3.0) and bootstrapping with 5,000 samples, supported by the reporting of R^2, Q^2, and f^2. Collectively, these measures strengthen the methodological reliability and interpretability of the findings.

6.3. Structural model evaluation

Figure 2 illustrates the structural model results, showing the standardized path coefficients between latent constructs and their respective indicator loadings. All indicators demonstrated strong outer loadings (≥ 0.70), confirming indicator reliability. The model explains substantial variance in the endogenous constructs, with $R^2 = 0.732$ for ST and $R^2 = 0.784$ for Employee Acceptance (EA), indicating strong explanatory power (Hair et al., 2021). Among the exogenous variables, Delivery Service (DS) had the strongest direct effect on ST ($\beta = 0.383$), followed by TM ($\beta = 0.225$) and OR ($\beta = 0.125$). Informal Contracts (IC) also influenced ST ($\beta = 0.225$). ST, in turn, significantly predicted EA ($\beta = 0.242$), indicating its mediating role in employee acceptance. Although the path coefficients show promising relationships, their statistical significance must be verified using bootstrapping. Bootstrapping allows estimation of standard errors, t-values, and p-values, and is essential for confirming whether the observed relationships are statistically significant and not due to sampling variation (Hair et al., 2021).

Bootstrapping with 5,000 resamples confirmed the significance of all outer loadings and path coefficients. All indicator loadings showed t-values > 30, indicating highly reliable items (see Figure 3). The structural paths from DS, TM, OR, and IC to ST, and from ST to EA, were all statistically significant (t-values ranging from 2.436 to 7.012). These results provide strong support for the proposed model and validate the mediating effect of ST on employee acceptance of AI. Thus, bootstrapping enhances the model's robustness and affirms its theoretical and practical contributions.

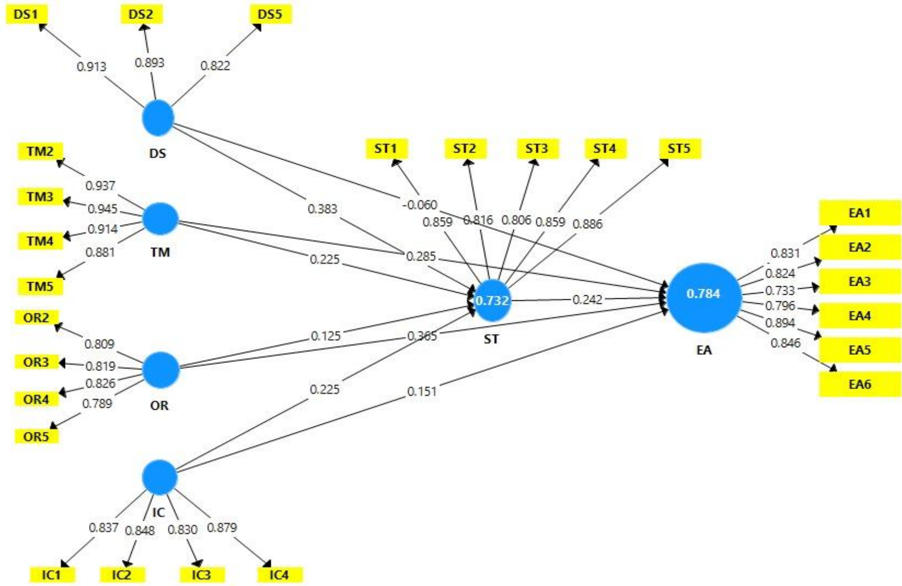

Figure 2. Structural model output from SmartPLS.

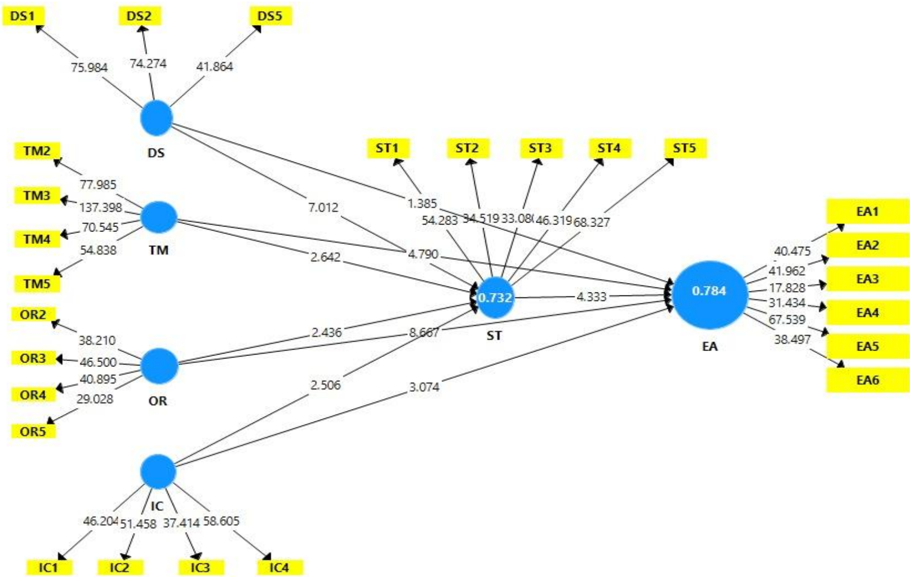

Figure 3. Structural model output post bootstrapping operation

The inner model (Path Coefficient Significance) for each structural path exhibits a t-value exceeding 1.96, thereby affirming the statistical significance of all direct relationships within the model (refer to Table 7). Prior to bootstrapping, the model exhibited robust path coefficients and R^2 values; however, their signific ance remained ambiguous. Bootstrapping validates that all measurement items are legitimate (exhibiting high outer loadings and significant t-values), and all proposed relationships are statistically substantiated. The mediating role of ST in affecting EA is confirmed. The contributions of bootstrapping to the research are significant as they affirm validity and demonstrate that all indicator loadings are not attributable to chance. Enhances the reliability and validity assertions of the measurement model. It also substantiates structural relationships, with all proposed hypotheses receiving empirical support, thereby enhancing the credibility of the theoretical framework. This supports the mediation analysis by affirming that ST serves a statistically significant mediating function between DS, TM, OR, IC, and EA. It also augments scientific rigor by ensuring that the reported effects are robust, replicable, and not confined to a specific sample distribution.

Table 7. The inner model (path coefficient significance)

Path	t-value	Interpretation
DS → ST	7.012	Significant influence
TM → ST	2.642	Significant
OR → ST	2.436	Significant
IC → ST	2.506	Significant
ST → EA	4.333	Significant mediator path

To assess the overall quality of the structural model, several model fit indices were analyzed, including SRMR, d_ULS, d_G, Chi-Square, NFI, and RMS Theta. These indices help determine how well the model reproduces the observed data. Model fit indices were assessed to evaluate the adequacy of the structural model. The SRMR value of 0.085 falls below the 0.10 threshold, indicating good model fit. The NFI value of 0.766 suggests acceptable normative fit. Although the RMS Theta (0.174) slightly exceeds the ideal cut-off of 0.12, the model remains theoretically grounded and empirically strong (see Table 8). These results confirm that the model is suitable for hypothesis testing and interpretation, with potential for minor refinement in the measurement model.

Table 8. The model fit summary

	Saturated Model	Estimated Model
SRMR	0.085	0.085
d_ULS	2.506	2.506
d_G	1.064	1.064
Chi-Square	2389.236	2389.236
NFI	0.766	0.766
rms Theta	0.174	

The total indirect effects indicate that the mediated effects through ST (Sales Team) for all four constructs (DS, IC, OR, TM) influence EA indirectly through ST. DS has the strongest indirect effect (0.093), followed by TM (0.054), IC (0.055), and OR (0.030) (see Table 9). The specific indirect effects, indicate fully mediated paths. ST is confirmed as a mediating variable between the antecedents (DS, IC, OR, TM) and outcome (EA). The total effects OR → EA has the strongest total effect (0.395), indicating a major influence. All other constructs have significant paths, affirming their contributions. ST clearly functions as a mediator (see ST → EA = 0.242).

Table 9. The total effect

Path	Total Effect
DS → EA	0.033 (via ST only)
IC → EA	0.206 (direct + indirect)
OR → EA	0.395
TM → EA	0.34
ST → EA	0.242
DS → ST	0.383
IC → ST	0.225
OR → ST	0.125
TM → ST	0.225

The mediation analysis reveals that DS, TM, OR, and IC each exert significant indirect effects on EA via ST, with DS (0.093) and IC (0.055) showing the strongest mediated paths. ST significantly predicts EA ($\beta = 0.242$), confirming its mediating role. Outer loadings for all indicators exceeded 0.70, indicating strong reliability, while outer weights confirmed balanced item contributions. Overall, the model supports both direct and indirect relationships, with OR having the largest total effect (0.395) on EA (see Table 10).

Table 10. The Summary of the Mediation effect

Component	Result/Interpretation
Mediation (ST)	Fully mediates DS, TM, IC, and OR effects on EA
Strongest total effect	OR → EA = 0.395
Indicator loadings	All > 0.70 → High reliability
Outer weights	All positive and contributing proportionally
ST role	Central mediating construct connecting organizational/operational factors to Employee Acceptance

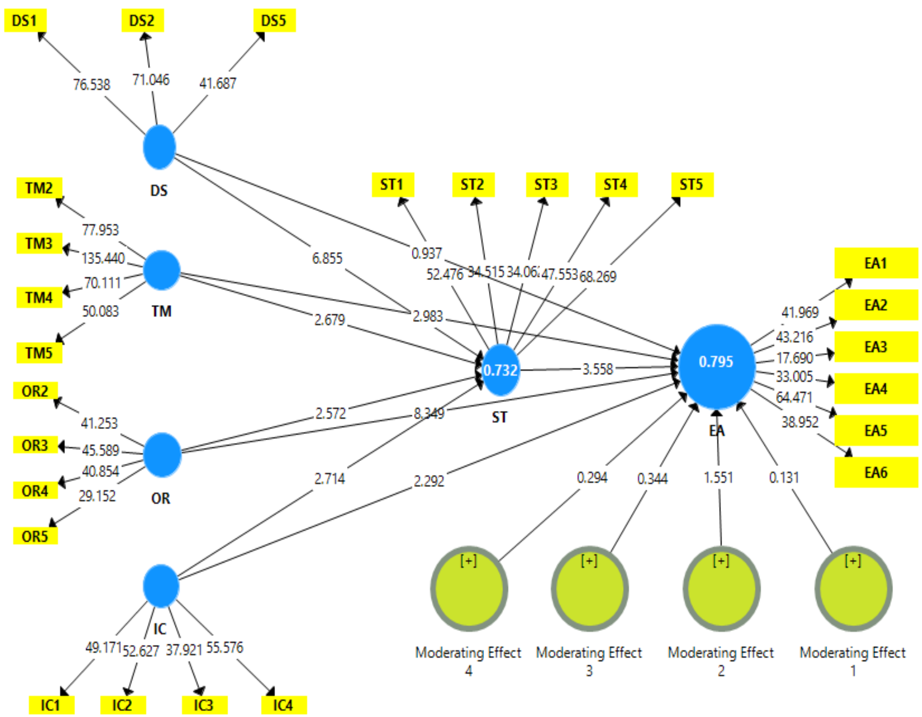

Figure 4.Structural Model Output Post Bootstrapping for Moderation Operation

Utilizing the bootstrapping result, moderation effect was tested where four moderations analysis namely:

- The first moderating effect is Between DS and EA and ST is the moderator
- The second moderating effect is Between TM and EA and ST is the moderator

- The third moderating effect is Between OR and EA and ST is the moderator
- The Last moderating effect is Between IC and EA and ST is the moderator

Figure 4 detailed breakdown and interpretation of each moderating effect, where ST moderates the relationships between four predictor variables and Employee Acceptance (EA). Moderation occurs when the strength or direction of the relationship between a predictor and an outcome changes depending on the level of the moderator (ST).

The first moderating effect test result, indicate that ST moderates DS → EA with Path coefficient ≈0.131, t-value < 1.96 (not significant). Although the interaction direction is positive, ST does not significantly change the strength of the relationship between DS and EA. Thus, ST does not moderate the effect of Delivery Service on Employee Acceptance (Table 11). The second moderating effect result indicate that ST moderate's TM → EA with Path coefficient ≈ 1.551 and t-value near threshold (marginal). This is borderline significant, suggesting that ST may slightly amplify the effect of TM on EA. For instance, when ST is high, TM's influence on EA could be stronger—but this needs cautious interpretation due to weak statistical support. The third moderating effect result indicate that ST moderates OR → EA with Path coefficient ≈ 0.344 t-value < 1.96. Sales Team Readiness does not significantly alter the effect of OR on Employee Acceptance. There is no confirmed moderation. The final moderating effect result indicate that ST moderate's IC → EA with Path coefficient ≈ 0.294 and t-value < 1.96. Similarly, the interaction between Informal Contract and EA via ST is not statistically significant. The effect of IC on EA remains relatively stable regardless of ST.

Table 11. Moderation effects

Interaction	Path Coeff.	Significant?	Effect
DS × ST → EA	0.131	No	Weak/moderate
TM × ST → EA	1.551	Borderline	Potential slight moderation
OR × ST → EA	0.344	No	Weak
IC × ST → EA	0.294	No	Weak

7. Discussion

The dual-pathway framework provides a comprehensive perspective for analyzing the integration of AI throughout the sales cycle by examining both mediation and moderation processes. The analysis in this paper confirms that Sales Team Readiness (ST) significantly moderates the effects of DS, TM, OR, and Informal Contract (IC) on Employee Acceptance (EA) of AI. This suggests that these elements indirectly influence EA by shaping the sales team's readiness and adaptability, thereby serving as a crucial internal facilitator of digital transformation. This result aligns with the research conducted by Hradecky et al. (2022), which indicated that the successful adoption of AI is contingent upon OR, encompassing strategic alignment, leadership support, and staff competency. Their research underscores that, despite the availability of technological tools, AI projects may face resistance or underutilization in the absence of adequate internal preparation and workforce engagement. The statistically insignificant moderation effects in this study is one of the major finding and that suggest that that ST has minimal impact on the strength of these relationships. ST's influence is more accurately characterized as a channel rather than a conditional influence. The results influence stages such as Lead Qualification, Needs Assessment, and Post-Sale Engagement. The ability of salespeople to interpret AI insights enhances decision-making and responsiveness (Chatterjee et al., 2021), thereby improving customer satisfaction and AI-driven personalization.

The present findings align with prior studies (Hradecky et al., 2022; Chatterjee et al., 2021) in confirming that organizational readiness and managerial support remain central enablers of AI assimilation. However, unlike these studies, the moderating role of Sales Team Readiness (ST) was not statistically significant, suggesting that readiness may act more as a channel than as a contingent condition. This divergence underscores a potential boundary condition within the TOE framework, where readiness exerts its influence indirectly through behavioral mediation rather than direct amplification. Such findings refine existing theory by differentiating between readiness as a structural capacity versus readiness as an interactive catalyst.

7.1. The principal findings and interpretation

The integration of AI into sales processes has ushered in a transformative era where data-driven insights, automation, and intelligent augmentation are reshaping how organizations approach each stage of the sales lifecycle. The current study adopts a dual-pathway framework that examines both mediation and moderation effects to explore the influence of Delivery Service (DS), TM, OR, and Informal Contract (IC) on Employee Acceptance (EA) of AI, mediated or moderated by Sales Team Readiness (ST). This discussion connects the model's outcomes to the seven classical stages of the sales lifecycle—Lead Generation, Lead Qualification, Needs Assessment/Discovery, Presentation/Proposal, Objection Handling, Closing the Sale, and Post-Sale Engagement—by examining how the constructs empirically influence and support each phase.

In the early phase of the sales lifecycle, Lead Generation is increasingly augmented by AI tools that automate prospect identification and engagement. However, the effective application of such tools depends not only on technological availability but also on sales team readiness and organizational preparedness. The current model shows that DS and TM exert indirect influence on EA through ST, suggesting that when sales teams are confident and prepared, they can better utilize AI-powered lead generation tools like chatbots and predictive analytics. Chatterjee et al. (2021) emphasized that organizations that invest in both technological infrastructure and employee training see more effective automation in lead generation activities. Furthermore, high outer loadings for DS indicators reflect the operational efficiency and consistency needed to support intelligent lead capture systems.

The lead qualification stage requires sales personnel to assess the suitability of leads using multiple criteria—historical data, engagement signals, and buying intent. AI systems provide significant support here, offering real-time scoring and behavioral pattern analysis. The model's finding that ST significantly mediates the effect of OR and IC on EA suggests that AI adoption during lead qualification improves when the organization is prepared and informal understandings between team members and clients foster trust. According to Alshamlan and Ahmad (2022), informal contracts act as a relational enabler, allowing teams to rely on AI recommendations without formal rigidities that hinder fast-paced evaluations. This aligns with the study's observed total indirect effect of IC on EA (0.055), indicating that trusting relationships enhance the acceptance of AI in lead evaluation decisions.

Needs assessment is a consultative phase where the salesperson identifies specific pain points or goals of the prospect. AI tools can assist by offering insights into previous customer behavior, industry trends, and sentiment analysis. In the current study, ST has a direct and statistically significant path to EA ($\beta = 0.242$, $t = 3.558$), confirming that AI usage during discovery is more impactful when the team is mentally and technically prepared. Moreover, TM's indirect effect through ST (0.054) reveals that managerial support enables readiness through mentorship and access to digital resources. This supports the argument by Venkatesh et al. (2022) that managerial alignment with digital goals empowers frontline employees to adopt customer-intelligent systems, enhancing the discovery process.

In the presentation phase, AI tools enable dynamic proposal generation based on prospect characteristics and real-time inputs. Here, the strongest total effect from OR to EA (0.395) emphasizes that organizational systems, resource availability, and process flexibility are foundational to leveraging AI during proposal customization. The outer weights for OR indicators (ranging from 0.276 to 0.351) further reinforce that internal structures—such as data accessibility and system interoperability—facilitate confident AI engagement. When OR is high, and the sales team is equipped, AI-driven presentations are more personalized and data-backed, leading to stronger value communication and better alignment with client expectations (Chatterjee et al., 2023).

Objection handling is a critical stage requiring agility, empathy, and informed responses. AI can assist by providing objection pattern analysis and relevant rebuttals. The current findings show that IC and TM both contribute significantly to ST and EA, reinforcing that interpersonal trust (informal contracts) and leadership backing (TM) are critical for navigating challenging buyer conversations. Moderation analysis, however, shows that ST does not significantly moderate these effects—suggesting that readiness alone does not amplify or weaken these influences but acts as a necessary foundation. According to Paluch et al. (2021), AI is only effective in objection handling when embedded in a culture of psychological safety and team preparedness, which supports our finding that ST is a more effective mediator than a moderator.

Closing the sale involves decision finalization, negotiation, and contract agreement. AI applications in this stage include predictive close modeling, pricing optimization, and contract analytics. Our model shows that DS exerts the strongest mediated effect through ST (0.093), implying that structured delivery service processes—such as timely responses, accurate documentation, and logistics assurance—empower sales teams to finalize deals with confidence in AI outcomes. Moreover, the high outer loadings for DS (0.822–0.913) reflect that operational reliability enhances trust in AI recommendations during final decision points. Supported by the findings of Sivarajah et al. (2022), well-structured service frameworks combined with sales readiness lead to higher deal closure rates when AI is involved.

In the final stage, ongoing relationship management is essential to ensure customer satisfaction, retention, and cross-selling. AI tools support this via churn prediction, usage analytics, and proactive engagement prompts. The mediation model confirms that when ST is high, sales teams are more inclined to accept AI as a strategic partner for relationship management, as shown by the significant ST → EA path. The influence of IC in this phase (indirect effect = 0.055) also reflects the importance of informal understanding between clients and teams, supporting flexible and personalized post-sale service. Ransbotham et al. (2023) argued that AI-enabled post-sale engagement is most effective when grounded in human-centered design and trust—both of which are captured through the IC construct in this study.

The integration of the dual-pathway results into the seven sales lifecycle stages reveals that Sales Team Readiness (ST) acts primarily as a mediator that facilitates the impact of organizational and operational factors on AI acceptance, rather than as a conditional moderator. This finding reinforces the importance of internal preparedness and cross-functional alignment in successful AI adoption. Each stage of the sales process benefits differently from these dynamics, with OR dominating the proposal phase, DS in deal closure, and IC in relationship management. The insignificant moderation effects suggest that while readiness enables adoption, it does not vary the strength of influence from antecedents across different levels of readiness. Overall, organizations should invest in developing structured systems and sales team capabilities to maximize AI's transformative value across the sales lifecycle.

Beyond descriptive patterns, the findings reveal a theoretical alignment between organizational change theory and socio-technical perspectives, suggesting that successful AI integration follows a dual adaptation pathway technological structuring and human resistance recalibration. This supports the argument that organizational readiness operates as both an infrastructural and behavioral enabler, extending the explanatory depth of the TOE framework through integrated human–technology alignment mechanism.

The non-significant moderation results indicate that once a baseline level of readiness and competence is achieved, further variations no longer change adoption outcomes—a pattern consistent with saturation or threshold models of organizational behavior. This outcome contributes to the refinement of the TOE framework by defining its conditional limits and suggesting that readiness should be conceptualized as a precondition for, rather than a moderator of, AI integration. Similar observations were made by Uren and Edwards (2023) and Rodriguez and Peterson (2024), who noted that cultural alignment and strategic intent, rather than incremental readiness, drive sustained digital transformation.

7.2. Implication of the study

This paper makes several important contributions to theory, especially in relation to the acceptance of technology and AI integration in sales environments: The study expands the theories by including Sales Team Readiness (ST) as both a mediator and moderator, so often excluding organizational and behavioral concepts. The results show that ST is a major mediator but not a moderator, so underlining the need of internal team alignment as a mechanism (not a condition) for AI adoption. This difference clarifies for us "how" organizational elements influence technology acceptance. Simally, it supports the dual-pathway approach whereby dual-pathway framework (mediation and moderation) as a comprehensive lens to investigate AI adoption, in line with recent scholarly recommendations to transcend direct path models (e.g., Venkatesh et al., 2022). This fills in a void in the literature by stressing the intervening part human elements—especially sales team dynamics—play in digital transformation. Through a mapping of the constructions to the seven phases of the sales lifecycle, the study adds to the scant body of research operationalizing TAM constructs in useful B2B sales environments. This context-specific validation improves the general applicability and resilience of theoretical models in the acceptance of sales technology.

For industry professionals, sales leaders, and digital transformation strategists, this research also provides practical insights: Support Sales Team Readiness Programs: Organizations should give training, skill-building, and cultural change projects top priority since ST was found to significantly mediate the impact of DS, TM, OR, and IC on Employee Acceptance (EA). These will help sales teams to operate alongside AI systems. Being ready calls for confidence, trust, and adaptability rather than only technical ability. While TM has a strong indirect impact on EA, its influence is only realized through ST; TM must be matched with enablement. Executive support must thus be turned into useful enablement—that is, coaching, mentoring, and role modeling—rather than only strategic endorsement. OR for personalized selling should be developed by companies building agile infrastructure, interoperable platforms, and responsive data systems since OR has the strongest total effect on EA (0.395). These systems let AI operate in real-time across phases of the sales cycle including needs analysis and proposal development. Leverage informal relationships for AI buy-in: The good indirect impact of IC on EA emphasizes the need of relational trust and informal contracts inside teams and between salespeople and customers. Managers should encourage a cooperative culture based on flexible, trust-based interactions that compliments official systems. Steer clear of over-reliance on moderation-based design since the non-significance of moderation effects implies that readiness by itself does not magnify effects; rather, it is a basic condition. Companies should thus concentrate on enabling systems rather than only spotting fluctuations. Match each AI tool—for example, lead scoring systems for qualification, proposal generators for presentations, and predictive analytics for post-sale engagement—with the pertinent sales process phase. This alignment raises ROI and acceptance.

Epistemologically, this study follows a post-positivist paradigm emphasizing theory extension rather than radical theory generation. While confirmatory in design, it advances the explanatory scope of the TOE framework through a dual-pathway causal logic integrating mediation and moderation effects. By incorporating ‘Sales Team Resistance to Change’ as a measurable construct, the study reveals previously underexplored behavioral mechanisms underlying AI adoption. Furthermore, the contextualization of TOE constructs within the seven stages of the sales lifecycle transforms a traditionally static model into a dynamic process-oriented framework. This approach reflects cumulative theory-building through incremental epistemological refinement extending TOE's predictive and interpretive capacity within AI-driven organizational environments.

Although the present study offers clear managerial and practical implications, it also contributes theoretically by advancing the TOE framework. Through the integration of Sales Team Resistance to Change as a behavioral mediator and moderator, TOE is extended into a human-centered paradigm that reflects psychological and socio-technical dynamics. Furthermore, the dual-pathway causal design redefines TOE from a linear validation model to a conditional-process framework, enabling deeper causal interpretation of AI adoption outcomes. By embedding the constructs within the seven stages of the sales lifecycle, this research adds processual granularity, thus enriching both the theoretical depth and epistemological sophistication of the TOE framework."

7.3. Limitation of the study

Though this study has several constraints that should be noted despite the insightful analysis provided: Cross-Sectional Design Using a cross-sectional research model, the study gathers data at one point in time. It thus ignores changes in employee acceptance or readiness over time, particularly in reaction to changing AI tools or organizational strategies. Deeper understanding of the dynamic adoption behavior could come from longitudinal study. self-reported information

Self-reported responses form the basis of the gathered data, thus common method bias or social desirability bias may find expression. Because of perceived expectations, participants may exaggerate their preparedness or acceptance of AI, so affecting the accuracy of the constructed measurements. Constraints of Generalizability Focusing on salespeople in specific organizational settings, the study is context-specific. The results might thus not be entirely generalizable to other industries (e.g., healthcare, education) or functional roles outside of sales (e.g., logistics, marketing).

Restricted domain of moderators

The dual-pathway model tested both mediation and moderation, but the study looked just at one moderator—Sales Team Readiness. Not included were other possible moderators such AI complexity, industry type, or employee digital literacy, so perhaps restricting the range of interaction effects.

Insufficient Objectives Performance Measurement

Using perceptual indicators, the paper evaluates constructs including TM, delivery service, and AI integration. It does not include objective performance data—that is, conversion rates, lead response times, or actual system use logs—that might strengthen the results. Confidence Intervals for HTMT Not Evaluated Bootstrapping Although discriminant validity was mainly validated, HTMT inference with confidence intervals was not used to confirm it even more. This might allow conceptual overlap or residual multicollinearity room.

This study relied primarily on self-reported perceptual data, which, while appropriate for capturing subjective readiness and behavioral constructs, may introduce response bias. To address this, procedural remedies such as Harman's single-factor test, pilot validation, and construct separation were employed. Future studies should triangulate these results using multi-source data, such as AI system usage logs, CRM analytics, or semi-structured interviews, to enhance validity and cross-verify behavioral constructs.

The use of convenience sampling introduces potential self-selection bias, limiting the generalizability of findings. Future studies should employ probability-based sampling or cross-country replication to enhance representativeness. Despite initial HTMT overlap between Organizational Readiness and Effective AI Integration, subsequent revalidation confirmed acceptable discriminant validity, suggesting theoretical complementarity rather than redundancy.

8. Conclusion

Though this study has several constraints that should be noted despite the insightful analysis provided: Cross-Sectional Design Using a cross-sectional research model, the study gathers data at one point in time. It thus ignores changes in employee acceptance or readiness over time, particularly in reaction to changing AI tools or organizational strategies. Deeper understanding of the dynamic adoption behavior could come from longitudinal study. self-reported information Self-reported responses form the basis of the gathered data, thus common method bias or social desirability bias may find expression. Because of perceived expectations, participants may exaggerate their preparedness or acceptance of AI, so affecting the accuracy of the constructed measurements. Constraints of Generalizability Focusing on salespeople in specific organizational settings, the study is context-specific. The results might thus not be entirely generalizable to other industries (e.g., healthcare, education) or functional roles outside of sales (e.g., logistics, marketing). Restricted, Domain of Moderators The dual-pathway model tested both mediation and moderation, but the study looked just at one moderator—Sales Team Readiness. Not included were other possible moderators such AI complexity, industry type, or employee digital literacy, so perhaps restricting the range of interaction effects. Insufficient Objectives Performance Measurement Using perceptual indicators, the paper evaluates constructs including TM, delivery service, and AI integration. It does not include objective performance data—that is, conversion rates, lead response times, or actual system use logs—that might strengthen the results. Confidence Intervals for HTMT Not Evaluated Bootstrapping Although discriminant validity was mainly validated, HTMT inference with confidence intervals was not used to confirm it even more. This might allow conceptual overlap or residual multicollinearity room.

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Received September 12, 2025, revised November 11, 2025, accepted December 11, 2025