

EXAMINING THE EFFECTS OF ARTIFICIAL INTELLIGENCE ON SALES
MANAGEMENT STRATEGIES IN MID- AND LARGE-SCALE CHEMICAL
MANUFACTURING FIRMS IN INDIA

by

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(Geotechnical Engineering)

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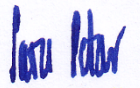
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Dedication

To my family, whose forbearance, love, and unswerving faith enabled me to make this journey.

To my teachers and mentors, who showed me the way and made me continue to pose better questions.

To all those who seek to obtain data to serve people and purpose, this is your work.

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To my family & my wife, who believed in and supported me through late nights and long weekends, thank you for loving me, being kind to me, and inspiring me every time. Any other mistakes not corrected are my responsibility.

ABSTRACT

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Gaurav Kumar
2026

Dissertation Chair:

This study examines the extent, determinants, and performance consequences of artificial intelligence (AI) adoption in the sales functions of mid- and large-scale chemical manufacturing firms in India. Drawing on the Technology Acceptance Model, UTAUT, Diffusion of Innovation theory, Resource-Based View, and responsible AI perspectives, it evaluates how organizational readiness, perceived barriers, governance maturity, perceived usefulness, perceived ease of use, and AI use relate to adoption and sales performance.

A quantitatively dominant mixed-methods design was employed. Survey data were collected from 170 sales, marketing, and analytics professionals and analyzed using reliability and validity testing, descriptive statistics, correlations, multiple regression, and hierarchical moderation analysis. Qualitative evidence from eight senior industry professionals was thematically coded to explain the quantitative findings.

The findings indicate a moderately high but uneven level of AI adoption, with large-scale firms reporting greater integration than mid-scale firms. Organizational readiness positively predicted AI adoption, perceived barriers exerted a negative effect, and

governance maturity made a smaller positive contribution. Perceived usefulness and perceived ease of use both significantly predicted the Sales Performance Index, with perceived usefulness showing a stronger effect. AI use and the combined Governance Maturity and Future Readiness (GMFR) construct positively predicted comparative sales performance, and their interaction was significant, indicating that stronger governance and strategic readiness increase the performance benefits associated with AI use. Qualitative themes—decision transparency and trust, training and learning, cross-functional alignment, efficiency gains, and residual skepticism—helped explain how these relationships operate in practice.

Diagnostic and sensitivity checks supported the robustness of the results. This study contributes an integrated explanation of AI adoption and value realization in a complex industrial B2B setting and offers practical guidance on leadership sponsorship, workforce enablement, process integration, data governance, and responsible AI.

Keywords: Artificial Intelligence Adoption, Sales Performance, Organizational Readiness, Governance Maturity, Technology Acceptance Model

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CHAPTER I:

INTRODUCTION

1.1 Introduction

One of the most transformational forces in modern industrial evolution is artificial intelligence (AI), which is redefining the fundamental thinking processes of organizations in terms of strategy, effectiveness, and competitiveness (Dwivedi et al., 2024). Initially an enabler of automation and analytical computing, AI has evolved into a more advanced type of decision intelligence, which is also capable of self-learning, predicting, and optimizing processes (Haenlein et al., 2019).

As industrial ecosystems evolve towards Industry 4.0 with its cyber-physical convergence, Internet of Things (IoT), and big-data analytics, AI is the key enabler of predictive, adaptive, and intelligent decision-making (Agrawal, Gans and Goldfarb, 2018). This generates the ability to be more responsive in real time and achieve operational prudence, making data a strategic resource rather than a simple operational tool (Huang and Rust, 2021).

In this regard, the manufacturing industry, and more specifically, the chemical manufacturing industry, is both an opportunity and a challenge for the adoption of AI. The Indian chemical industry is one of the country's major industrial pillars, contributing close to 7% of the GDP (ICIS, 2022) and providing basic raw materials to industries such as agriculture, automobile, textile, and construction, among others. The ecosystem of the sector is varied, including multinational corporations, regional players, and mid-sized firms that form a complex value chain of suppliers, distributors, and customers (Wadhwa,

Andaleeb and Gaur, 2021). With the near-exponential rate of urbanization, changing environmental standards, and global trade dynamics, market volatility has only increased, compelling firms to be more data-driven, agile, and customer-responsive than ever before.

Conversely, sales management in the chemical sector traditionally depends on manual forecasting, human judgment, and relationship selling methods. Extensive sales processes, technical product specifications, and B2B procurement activities have increased reliance on individual networks and expertise (Brown and Davis, 2022). Although traditional methods have been successful historically, they are becoming less useful in addressing the requirements of global competition, price volatility and real-time customer expectations (Ghosh et al., 2024). As the industry becomes digitized, companies are forced to replace gut feelings with data-driven accuracy, and this is a strategic area where AI plays a role.

Unified by the common goal of enhancing sales and marketing processes, AI technologies, including machine learning, natural language processing, computer vision, predictive analytics, and cognitive automation, are being applied across modern sales and marketing functions (Shankar and Jain, 2024). Within customer relationship management (CRM) systems, AI can be used to perform real-time analysis of customer behavior, prioritize leads, and track sentiment, providing more insight into buyer intent and market segmentation (Paschen, Wilson and Ferreira, 2020). Predictive models are used for demand forecasting and dynamic pricing to help sales teams predict customer needs, optimize inventory, and increase margins. Moreover, chatbots and digital assistants powered by AI

simplify the communication process, improving customer experience and decreasing cycle time.

However, despite its transformative potential, AI adoption in India's chemical manufacturing sector's sales functions remains unreliable (Ghosh et al., 2024). Many mid- and large-scale organizations are still in the pilot or experimental phase, where applications of AI are used selectively and without full incorporation into strategic decision systems. However, challenges in implementation due to cost, data governance maturity, and lack of digital infrastructure and workforce capacity remain (ICIS, 2022). First, there is institutional resistance to technological change within traditional hierarchical sales organizations and the contention that this resistance negatively impacts adoption and performance realization (Fountaine, McCarthy and Saleh, 2019). Consequently, there is a gap between organizational readiness and AI capability, which highlights the need for empirical assessment and strategic frameworks that bridge the gap between these constructs.

The Digital India and Industry 4.0 programs of the Government of India aim to improve national competitiveness through technological innovation and sustainable industrial development (NITI Aayog, 2023). The foundational element for achieving these aims is AI, with the power of data-driven decision-making, productivity, and ethical automation. However, the success of the national vision is dependent on the ability of firms operating in key sectors (such as chemicals) to align their operational and strategic priorities with technology adoption. The use of governance maturity structures, including

ethical AI, data transparency, and accountability, has thus become a factor for long-term success.

From an academic perspective, the chemical industry offers an interesting empirical context for studying AI implementation, as it combines technical intensity, B2B sales cycles, and mounting pressure for digitalization. Although AI adoption is extensively considered in consumer-driven industries, empirical evidence remains limited regarding how AI influences strategic sales management, organizational culture, and performance in the B2B chemical manufacturing context. (Chen et al., 2022). In addition, the development of collaborative intelligence, in which human expertise and machine analytics complement each other, requires a reformulation of existing adoption models (Technology Acceptance Model (TAM), Diffusion of Innovation (DOI), and Institutional Theory) to industrial realities (Rogers, 2003; Venkatesh et al., 2022).

In summary, this study examines the adoption, determinants, and performance implications of AI in the sales function of India's chemical manufacturing sector. It positions AI not merely as an automation tool, but as a strategic capability that can redefine industrial sales management. By examining the interplay among technology, organizational readiness, and governance maturity, this study develops practical implications for scholars, policymakers, and business leaders involved in the next stage of India's digital industrial transformation (Brown and Davis, 2022).

Artificial intelligence (AI) has evolved from an emerging technology to a transformative force driving competitiveness, efficiency, and innovation in industries worldwide (Dwivedi et al., 2024). In the last decade, firms in various parts of the world

have accelerated the digitalization process by integrating AI into sales forecasting, customer relationship management, pricing optimization, and demand planning systems (Dwivedi et al., 2024). These advances have transformed managerial decision-making from an intuition-driven approach based on experience to an evidence-driven approach based on analytics (Davenport and Ronanki, 2018), creating an ecosystem in which data, algorithms, and human expertise come together.

In mature economies, artificial intelligence (AI) is pervasively integrated into enterprise resource planning and customer data platform architectures to make real-time decisions that increase agility and responsiveness. Nevertheless, this has not been a universal evolution. Emerging markets, such as India, are at a transitional stage, as awareness of AI is high but not yet institutionalized and scalable (NITI Aayog, 2023). Most Indian industrial firms, especially manufacturing firms, still operate in a hybrid system characterized by the integration of legacy practices with selective automation (Ghosh et al., 2024).

The solution appears to be not so much about the availability of technology but rather the organizational readiness, vision of leadership, and ability to govern at a mature level. Digital transformation research stresses the importance of aligning technological infrastructure and human capital with the backing of top management and an ethical governance maturity structure for successful AI implementation (Fountaine, McCarthy, and Saleh 2019; Suh and Lee, 2024). Resource constraints, age-old systems, and organizational inertia caused by fear of automation or professional autonomy are also commonly encountered by leadership in India (Dwivedi et al., 2023). Therefore, AI

initiatives often do not pass through the pilot or demonstration stage and are not scaled to an organization-wide level.

At the same time, the global discourse has shifted toward responsible and human-centered AI, recognizing that algorithmic systems can reinforce bias, reduce transparency, and create privacy risks when they are not properly governed (Floridi and Cowls, 2019). For industrial firms that handle sensitive technical and customer information, governance mechanisms, including explainability, auditability, and compliance, are increasingly as important as accuracy and speed. Integrating these ethical requirements into performance-oriented functions, such as sales, is therefore a significant managerial challenge (Shankar and Jain, 2024).

Beyond efficiency gains, contemporary AI research emphasizes its capacity to augment the cognitive foundations of management work. This development marks a shift from automated intelligence, which focuses on mechanistic task replacement, to augmented intelligence, in which machines complement human judgment through pattern recognition, contextual insight, and predictive reasoning (Haenlein and Kaplan, 2019). In industrial sales, such augmentation enables data-driven account planning, adaptive pricing, and customer-specific engagement, thereby extending relationship-based selling into evidence-supported and strategic collaboration (Huang and Rust, 2021).

As AI capabilities spread, the quality of organizational learning becomes an important differentiator of success. Organizations that convert algorithmic recommendations into institutional knowledge and process innovation can accumulate performance benefits, whereas firms that treat AI as an isolated IT project often experience

fragmented outcomes and digital fatigue (Marabelli and Galliers, 2022). Therefore, AI adoption should be understood within a broader capability framework: technology creates value only when it is embedded in structures that support experimentation, feedback, and cross-functional integration.

Furthermore, emerging economies present a unique socio-economic context to study as they include a paradoxical aspect: whereas digital technologies are expected to be a source of inclusion and competitiveness, they are also a potential source of anxiety and polarization of the workforce. In the industrial sales ecosystem of India, it is common for mid-career professionals to view AI as a possible substitute instead of support, which leads to selective usage and a lack of culture (Kshetri, 2020). This tension can only be addressed by leadership narratives based on collaborative intelligence, in which AI is viewed as an intelligence in decision-making rather than a threat to professional identity. Such framing is important in knowledge-intensive functions, such as B2B chemical sales, in which interpersonal trust is coupled with technical expertise. From a macroeconomic perspective, India's chemical industry is at a digital inflection point. AI-driven competitiveness is one of the key thrust areas for the Government's initiatives, such as Make in India 2.0 and Digital Manufacturing Mission 2025, which have spurred companies to carry out predictive maintenance, smart supply chains, and customer analytics solutions (NITI Aayog, 2023).

Therefore, the current study investigates not only whether the application of AI enhances performance but also how organizational readiness, leadership commitment, employee perception, and governance maturity together determine this. By placing the chemical-manufacturing industry in India in the context of debates about digital

transformation in other parts of the world, this chapter provides the conceptual basis for analyzing AI as a tool of productivity and an enabler of responsible innovation.

1.2 Research Problem

Despite the global progress in digital transformation, the integration of Artificial Intelligence (AI) in Indian industrial organizations is uneven, fragmented, and for the most part, project-based rather than systemic. In developed economies such as the United States, Germany, and Japan, AI has penetrated enterprises in doing business, which is embedded in predictive analytics, supply chain management, and customer relationship systems (Ransbotham et al., 2023). In comparison, the implementation asymmetries that Indian manufacturing companies still encounter as a result of infrastructural constraints, skill shortages in the labor force, and lack of commitment among leadership are still present (Dwivedi et al., 2024). These asymmetries are expressed as "islands of automation" where pilots have potential but do not evolve into a long-term source of competitive advantage (Fountain, McCarthy and Saleh, 2019).

At the organizational level, several system-level barriers limit AI diffusion. First, digital infrastructure gaps, such as disparate databases, lack of cloud adoption, and interoperability of legacy ERP and AI systems, make it difficult to integrate predictive sales functions into day-to-day business operations (Vial, 2019). Second, there is a shortage of talent and ability: most companies lack data scientists or analytics-trained staff to support the running of complex AI workflows (Bughin et al., 2018). Third, financial constraints and uncertain perceptions of ROI restrict continued investment, especially in mid-scale enterprises. Finally, employees' behavioral and cultural resistance is affected by their fear

of occupational replacement and low algorithmic trust, which reduces their willingness to use AI insights (Suh and Lee, 2024). Collectively, these challenges mean that AI initiatives are not progressing from being experimented on to becoming strategically embedded intelligence systems that lead to measurable sales results.

Sales teams face the twin challenges of dealing with long procurement cycles, price volatility, and strict quality standards, which are ideal for AI-assisted forecasting and optimization (Wadhwa, Andaleeb and Gaur, 2021). However, empirical evidence shows that there is considerable variation in adoption success across firms of similar size and resources. Some firms use AI to score double-digit improvements in forecasting accuracy and margin realization, while others do not even go beyond pilot deployments. Such divergence suggests that organizational readiness, leadership sponsorship, and governance maturity are deciding differentiators (Ghosh et al., 2024).

However, existing studies tend to be technology-oriented and thus concentrate on system capability or algorithmic performance rather than on the organizational and human elements that drive adoption. Much of the literature on AI adoption in manufacturing is based on the Technology Acceptance Model (TAM) or Unified Theory of Acceptance and Use of Technology (UTAUT), which focuses on individual beliefs, perceived usefulness, and ease of use as predictors of behavioral intention (Davis, 1989; Venkatesh et al., 2022). While these models form the basis, they ignore macro-organizational contingencies, such as strategic readiness, digital culture, and institutional legitimacy, which play a critical role in determining adoption in complex industries such as B2B (Dwivedi et al., 2023). Similarly, the Diffusion of Innovation (DOI) framework (Rogers, 2003) explains the stages

of adoption but does not provide much direction on how new-market firms can move from pilot to routinized in light of weak governance maturity and limited digital infrastructure.

A further lack of current scholarship is the neglect of the ethical and governance maturity aspects of AI. As firms use predictive algorithms to make sales decisions, subjects such as data privacy, bias mitigation, transparency, and accountability are at the forefront of organizational legitimacy (Dwivedi et al., 2024; Suh and Lee, 2024). However, few empirical studies have explored how the governance maturity mechanisms of AI, such as audit trails, explainability policies, and role-based governance maturity, mediate the relationship between the use of AI and performance effects within industrial settings. This disconnect creates a theoretical and practical blind spot regarding the conditions that make AI adoption sustainable, rather than a temporary source of value.

In India, the problem is the coexistence of heterogeneous organizational capabilities. Large multinational subsidiaries can have sophisticated AI platforms and structured data environments, but informal decision systems and low automation prevail in smaller domestic mid-scale companies (Wadhwa, Andaleeb and Gaur, 2021). Consequently, the national chemical industry offers a two-speed transformation, in which discrepancies in readiness and governance maturity are determinant factors of adoption maturity. In the absence of systems of preparedness and leadership congruency, AI implementation risks being cosmetic, in the sense that it is limited to analytics dashboards in favor of integrated strategic routines (Fountain et al., 2019).

A) Lack of Context-Specific Empirical Evidence on Adoption of AI in Heavy Industrial B2B Sales Context in India. Although AI implementation has been widely examined in

consumer segments (e-commerce, retail, and financial services), industrial B2B, particularly heavy manufacturing and process industries, is empirically under-researched. Global studies (Dwivedi et al., 2023) have mainly focused on the diffusion of technology in digitally mature economies or high-velocity service industries. In contrast, India's chemical manufacturing sector is a market with fundamentally different dynamics, including complex procurement cycles, highly regulated supply chains, and multi-layered decision hierarchies (Wadhwa, Andaleeb and Gaur, 2021).

Empirical research on the impact of AI in these contexts is almost nonexistent. The limited Indian studies available are largely descriptive, focusing on automation potential or digital preparedness, but have little or no quantitative validation of adoption patterns and organizational determinants, as well as performance outcomes (Wadhwa, Andaleeb and Gaur, 2021). Furthermore, the role of AI in augmenting relational B2B sales functions, where customer relations and technical negotiations are critical, has been poorly theorized.

B) Absence of Integrative Models: How technological, organizational, and governance maturity variables are related to adoption effectiveness. Existing theoretical frameworks of technology adoption, such as the Technology Acceptance Model (TAM) (Davis, 1989), the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), and the Diffusion of Innovation (DOI) theory (Rogers, 2003) have been invaluable in explaining user acceptance and early adoption. However, these models are individually limited in their ability to represent the multilevel nature of AI adoption in large organizations. TAM and UTAUT emphasize individual-level beliefs (usefulness,

ease of use, facilitating conditions), whereas DOI emphasizes innovation characteristics and the adoption stage.

Moreover, the use of AI differs from previous digital technologies in that it is associated with learning algorithms, data governance maturity, and ethical accountability, elements that are not covered in previous IT acceptance models (Dwivedi et al., 2024; Suh and Lee, 2024). Therefore, an integrative framework that bridges technological, organizational, and governance maturity is essential. Such a model must not only explain whether AI is adopted but also how and to what degree AI becomes institutionalized and measured in terms of outcomes. This study fills this gap in the literature by conceptualizing the constructs from various theoretical frameworks (TAM, DOI, and resource-based view (RBV)) in a coherent analytical model suited to the context of the industrial sales environment in India.

C) Limited Examination of How Readiness and Barriers Shape the Transition from Pilot Use to Institutionalized Adoption. Many firms begin AI adoption through pilot projects or proof-of-concept experiments; however, relatively few progress to enterprise-wide institutionalization (Ransbotham et al., 2023). In India's chemical manufacturing sector, this challenge is particularly pronounced: firms may use AI-enabled tools for forecasting or pricing but fail to integrate them into organizational routines, creating isolated pockets of automation rather than systemic change (Fountaine, McCarthy and Saleh, 2019).

Existing research tends to examine either barriers (e.g., skill deficits, cost, resistance, or data fragmentation) or readiness factors (e.g., leadership support,

infrastructure, and training) in isolation and does not model their interactive effects. These two dimensions are interdependent. High readiness can neutralize certain barriers, such as resistance or cost concerns, whereas low readiness increases them (Vial, 2019; Chatterjee et al., 2021). Consequently, it is not just the existence of barriers that can lead to the success or failure of a firm's efforts to move from pilot adoption to routinized, performance-driven use, but rather the complex interplay between readiness to adopt and barriers that defines success.

This gap needs to be bridged by an empirically validated model that encompasses both readiness and barrier dimensions and tests their combined impact on AI adoption maturity in the case of the industrial sales function. This study empirically examines these dynamics through quantitative regression and hierarchical moderation analysis, with the added advantage of offering qualitative evidence from industry players.

D) Lack of Ethical and Governance Maturity Constructs in Describing the Impact of AI on Sales Performance Metrics The increasing role of AI in decision-making by organizations raises ethical, transparency, and governance maturity concerns that need to be addressed urgently. In predictive sales analytics, algorithms are used to determine price recommendations, lead scoring, and forecast priorities, all of which determine direct outcomes in terms of revenue and customer relationships.

However, regardless of these high-stakes implications, empirical models of AI adoption in most cases ignore the governance maturity dimension as peripheral rather than fundamental (Suh and Lee, 2024). Recent work has suggested a new direction towards Responsible AI (RAI) paradigms, focusing on explainability, fairness, accountability, and

data stewardship as key requirements for sustainable AI performance (Dwivedi et al., 2024; Jobmulti-leveland Vayena, 2019). Without governance maturity, AI risks losing trust and legitimacy among employees and clients, ultimately destroying adoption outcomes (Floridi and Cows, 2019). In India's chemical industry, mobile phone calls and emails for sales negotiations often depend on relational trust and professional credibility. This means that the lack of transparency and explainability in AI tools may further increase resistance among frontline sales staff and customers.

Hence, this study incorporates governance maturity and future readiness into an analytical model. It examines governance maturity as a direct predictor of AI adoption and evaluates the combined GMFR construct as a direct and moderating condition in the relationship between AI use and sales performance. This addresses a neglected aspect of adoption literature by linking technological progress with ethical responsibility, strategic learning, and institutional trust.

It is important to address these gaps in both theoretical and practical contexts. Theoretically, this extends the models of adoption by adding readiness, governance maturity, and ethical oversight as constructs of technology use. From a managerial perspective, this allows leaders in the chemical manufacturing industry to engineer governed and data-driven sales ecosystems that translate the capability of AI into measurable performance and competitive advantage.

1.3 Purpose of Research

This study aims to analyze the adoption, determinants, and performance effects of artificial intelligence (AI) in the sales functions of mid- and large-scale chemical

manufacturing companies in India. In doing so, this study addresses the key nexus of technological innovation, organizational capability, and ethical governance maturity in a sector that is both economically important and technologically under-researched.

By combining empirical data and known theoretical frameworks, specifically the Technology Acceptance Model (TAM), Diffusion of Innovation (DOI) theory, and Resource-Based View (RBV), this study aims to address the question of how and when, in which organizational conditions, the adoption of AI leads to measurable sales performance improvements. The overall purpose is not only to measure the rates of adoption but also to infer the socio-technological and governance maturity processes that provide opportunities to transform AI sustainably and human-centered.

1.3.1 Evaluating the Adoption Extent and Maturity of AI

One of the basic goals of this research is to systematically evaluate the level, spread, and maturity of the adoption of artificial intelligence (AI) in the sales functions of India's chemical manufacturing sector. This objective is not restricted to the identification of the existence of AI tools but goes beyond exploring the depth to which these technologies have been embedded in the strategic, operational, and decision-making processes. Simply put, it seeks to determine companies on both ends of AI adoption: exploratory experimentation and at the institutional level (Rogers, 2003; Ransbotham et al., 2023).

In the early stage of adoption, we generally see firms adopting pilot projects with narrow use cases, such as lead prioritization and demand forecasting or *CRM-based opportunity scoring*. These projects are frequently technology-driven and small in scope, with a lack of integration and process redesign needed for enterprise-wide transformation

(Vial 2019). As organizations move into intermediate stages, AI tools are integrated more systematically into sales processes in the form of dashboards with semi-automated pricing optimization, market forecasting, and other modules. However, without proper governance maturity and cultural buy-in, adoption tends to get stuck at this stage, with partial use and reliance on a few digitally savvy employees (Haenlein et al. 2019).

Mature adoption is indicated by the shift of AI from a support capability to a strategic capability that changes the way sales decisions are made, assessed, and scaled. At this stage, AI systems are formalized in digital *key performance indicators (KPIs)*, cross-functional data pipelines, and leadership responsibility systems. For example, predictive models are used to calculate price corridors or profitability at the customer level in real time, and AI-enabled *customer relationship management (CRM)* guides relationship management based on data-driven segmentation (Dwivedi et al. 2024). The way these companies are integrating AI into performance appraisals, training systems, and incentive structures represents a shift in culture from a more intuitive approach to selling to a more analytical approach to decision-making.

It is also necessary to assess maturity by evaluating the organizational enablers that facilitate this evolution. Leadership sponsorship, the creation of digital centers of excellence, the enablement of employees through structured training, and the creation of rich data ecosystems are some of the most critical determinants of AI adoption maturity (Ransbotham et al., 2023). Conversely, barriers such as fragmented IT infrastructure, the absence of governance maturity mechanisms, and insufficient alignment of domains and data can play a major role in limiting progression. The analysis of these enablers and

inhibitors provides a complete picture of the dynamics within the industry that are taking shape in the results of AI in the Indian chemical industry.

In addition, firm size and market orientation affect adoption. Large manufacturers with export-oriented production tend to have the advantage of global digital architectures and investments from their parent companies and can scale the application of AI through their sales, procurement, and supply chain management. However, mid-sized domestic firms are often plagued by structural asymmetries (e.g., low budgets, low levels of data maturity, and overdependence on manual sales) that limit their capacity to move past pilot deployments (Ghosh et al., 2024). Mapping these differences allows the study to point towards specific interventions, such as policy incentives, training programs, or shared data infrastructure, that could be implemented to speed up transformation.

Therefore, the measurement of AI adoption maturity is not limited to the descriptive; it is a diagnostic model that can hold the synergy between technology, people, and organizational systems. It tells us how readiness and governance maturity come into real performance results, which is a crucial aspect of this doctoral inquiry. This study places Indian chemical companies in a globally similar paradigm by matching the analysis with the stages of the Diffusion of Innovation (DOI) (Rogers, 2003) and recent models of AI transformation maturity (Dwivedi et al., 2024; Ransbotham et al., 2023), providing local and global perspectives.

1.3.2 Identifying Organizational Readiness Factors and Barriers

The second key purpose of the present study is to determine the organizational readiness conditions and barriers that affect the adoption of AI in the sales functions of

Indian chemical manufacturing firms. Whereas the previous subsection focused on assessing the degree of AI diffusion, this section aims to diagnose the determinants. Organizational readiness is a multidimensional concept that includes leadership commitment, digital infrastructure, employee competence, and cultural openness to innovation (Vial, 2019; Dwivedi et al., 2024). This reflects how aligned a firm's strategic vision, resources, and managerial routines are with the requirements for an AI-enabled transformation.

In the case of industrial sales, readiness includes ensuring that data systems, analytics platforms, and human decision-makers work together to provide cohesive data that provide predictive insights for pricing, forecasting, and customer relationship management. Leadership sponsorship is the substance of this awareness. Empirical research shows that digital transformations succeed when top executives have a clear vision of AI's role in driving business outcomes and make it a part of the organization's performance metrics (Ransbotham et al., 2023). In India's chemical industry, where a dominant hierarchical decision-making structure exists, visible advocacy at the top of the organization legitimizes experimentation and eases employee resistance. When leaders view AI as a strategic capability and not an IT initiative, it is more likely to help create a culture of psychological safety and cross-functional collaboration, which is necessary to maintain adoption (Haenlein et al., 2019).

1.3.3 Electronic Infrastructure and Information Ability

The second pillar of readiness is infrastructure maturity, which concerns the quality and interoperability of data systems that drive AI algorithms. Many Indian manufacturing

companies are running legacy enterprise resource planning (ERP) systems that are partially integrated with modern analytics tools. Fragmented databases, inconsistent data standards, and low levels of cloud adoption usually limit the scalability of AI models (EY, 2024). Firms that have invested in unified data architectures, Application Programming Interfaces (APIs), and have implemented secure data-sharing protocols have a higher rate of success in adoption (Ghosh et al., 2024).

A) Human Resource and Cultural Capability

AI implementation also depends on the human dimension, particularly workforce digital literacy and openness to change. Digital transformation research consistently shows that even advanced algorithms create little value when employees neither trust them nor possess the competence to interpret their outputs (Kshetri, 2020). In Indian manufacturing sales, many experienced professionals rely on judgment developed over decades and may perceive AI as opaque or threatening unless reskilling and participatory design are provided. Training, mentoring, and clear communication about AI's collaborative role can convert skepticism into informed adoption.

Aside from readiness factors, a system of structural and behavioral factors limits the institutionalization of AI in healthcare. Cost and resource intensity have been the most cited obstacles, especially for mid-scale firms working on very low margins (Fountaine et al. 2019). The storage of data and computational power, as well as vendor relationships required to develop and maintain AI models, require massive investments. Another major challenge is the skills shortage, that is, the lack of professionals who are not only domain experts but also skilled in advanced analytics (Dwivedi et al. 2023). Without internal

expertise, firms rely excessively on external consultants, and sustainability ownership is fragmented.

Data privacy and ethical governance are additional barriers. Following the enactment of India's Digital Personal Data Protection Act in 2023, manufacturers face more demanding expectations for responsible data handling; however, many firms still lack mature governance frameworks (NITI Aayog, 2023). Concerns regarding intellectual property, algorithmic bias, and accountability may further discourage full implementation. Behavioral resistance may also arise from fear of job displacement, distrust of AI outputs, or reluctance to alter established workflows, adding a socio-psychological dimension to the implementation barriers (Marabelli and Galliers, 2022).

B) Promotion Preparation and Prohibition Factors

The interplay between readiness and barriers must be explained to understand why firms with similar technological starting points end up with different results. High readiness can buffer against the negative effects of barriers by generating adaptability and continuous learning, whereas low readiness heightens resistance and project fatigue. For example, leadership commitment can overcome the issue of costs by providing evidence of return on investment, whereas effective training can neutralize the issue of fear-based resistance. Conversely, if there is no good fit between the leadership vision and the employees' capacity to implement it, even if the infrastructure is advanced, performance gains are not achieved.

Hence, this study captures organizational readiness and barriers not as competing constructs but as interdependent forces that collectively determine the direction of the AI

adoption process. Mapping these variables forms the foundation of the empirical work in Chapters IV and V, as it provides the statistical foundation for further quantitative and qualitative analyses and addresses their predictive ability and effects of interaction. In doing so, this research provides a fine-grained understanding of AI adoption as a socio-technical evolution that requires synchronicity of digital systems, human cognition, and institutional ethics.

1.3.4 Assessing the Perceived Usefulness and Ease of Using and the Outcomes of Sales-Performance

Built upon the Technology Acceptance Model (Davis, 1989) and its subsequent extensions (Venkatesh et al., 2003; Venkatesh et al., 2022), the third objective examines the influence of the cognitive perceptions of sales professionals (specifically, perceived usefulness and perceived ease of use) on utilizing AI and the performance outcomes of AI utilization. This research investigates the quantitative relationship between these perceptions and a Sales Performance Index, including elements such as forecast accuracy, customer satisfaction, conversion rates, margin discipline, and cycle time reduction (Huang and Rust, 2021).

Understanding these behavioral dynamics is critical for designing user-centered AI systems that complement professional judgment, as opposed to replacing it, to translate adoption into real performance improvement. While the immediate drive to be more efficient through technology is certainly the initial factor in adopting AI, long-term success relies on how employees internalize and operationalize the value of AI. In the case of B2B chemical manufacturing, sales professionals often rely on tacit knowledge, experiential judgment, and long-standing customer relationships.

Therefore, their trust in AI-generated insights depends on how trustworthy, interpretable, and easy to interact with they are (Haenlein et al., 2019). Perceived AI complexity or opacity is also a form of cognitive friction that can cancel out efficiency gains, causing a stunting of surface-level task use. In contrast, when tools are user-friendly, graphically clear, and actionable, workers feel like allies of the system instead of opponents (Dwivedi et al., 2024).

In this study, PU is operationalized as the extent to which AI applications are believed to improve work performance, improve the accuracy of forecasts, identify a client as a high-potential client, optimize the scoring of leads, and support strategic decision-making. PEOU, on the other hand, is an indicator of the intuitiveness, accessibility, and compatibility of the applications with existing organizational processes. Both constructs are crucial for measuring technology assimilation, which is the process of adopting technology from initial use to routine and confident use (Mariani and Wamba, 2020).

By linking these perceptual variables to a Sales Performance Index (SPI), this study fills the gap between psychological acceptance and measurable business results. Prior empirical work has shown that when AI systems are both useful and easy to use, there are improvements in key performance indicators, such as conversion rates, sales cycle efficiency, and forecasting accuracy for firms that use AI (Huang and Rust, 2021). This implies that the quality of human AI interaction, rather than technology capability alone, drives the adoption of technology to achieve a sustainable advantage.

In addition, these behavioral insights help answer a key question in industrial AI adoption: why some firms, despite comparable investments in digital infrastructure, cannot

achieve consistent performance improvement. In this case, the solution is often not in the technology itself but in user perception and trust. Perceived usefulness is strengthened by transparency, feedback loops, and explainable algorithms because they allow users to access the reasoning behind how AI reaches its conclusions (Glikson and Woolley, 2020). Similarly, by providing adequate training and interface adaptability, cognitive barriers are reduced, and ease of use is increased.

Understanding this relationship has practical implications for change management and system design. Leaders can promote higher levels of adoption by incorporating AI dashboards into regular decision cycles, involving end users in co-design processes, and communicating success stories that link the use of AI with tangible results in performance. In doing so, organizations turn cognitive acceptance into behavioral engagement, a prerequisite for achieving the full potential of real AI in performance transformation.

At a broader level, the addition of perceived usefulness and ease of use reflects the human-centeredness of technological transformation. This acknowledges that digital innovation is not only a technical problem but also a behavioral and cultural process conditioned by trust, learning, and perceived empowerment (OECD, 2024). Therefore, this study contributes to the literature on the gap between technological optimism and organizational realism, as it is based on empirical findings of the mediating effect of human perceptions on the relationship between AI tools and performance outcomes.

1.3.5 Identifying the Role of Governance Maturity and Future Readiness

The fourth purpose is to investigate whether governance maturity and future readiness strengthen the relationship between AI use and comparative business

performance. Governance maturity describes the presence of ethical, transparent, and auditable AI practices, including accountability, explainability, and control mechanisms (Suh and Lee, 2024). Future readiness reflects the organization's strategic intent and capability to extend AI through continued investment, learning, reskilling, and technological adaptation (Dwivedi et al., 2024). In the empirical model, these dimensions are operationalized jointly as governance maturity and future readiness (GMFR).

By modelling GMFR as both a direct predictor and moderator, this study examines whether firms that combine responsible AI oversight with continued strategic readiness achieve stronger comparative performance than firms that use AI without equivalent institutional support. This approach integrates responsible AI scholarship into an industrial empirical model (Jobin, Ienca and Vayena, 2019; Floridi and Cowls, 2019).

From a strategic perspective, future readiness is a vision of a firm's ability to be proactive in anticipating technological changes and incorporating learning agility into its structure. Such preparedness is not limited to financial investment but also to the vision of leadership, reskilling of the workforce, and building adaptive data ecosystems (Dwivedi et al., 2024). Companies that are highly future-ready do not see AI as a specific project but as an ongoing ability that develops with experimentation, governance maturity, and ethical recalibration. Consequently, such organizations are better equipped to link with emerging tools, use cross-functional data, and turn isolated digital pilots into enterprise-wide performance drivers.

The moderating question is whether the positive association between AI use and comparative sales performance strengthens when the GMFR is high. Conceptually,

governance maturity supports reliability and ethical legitimacy, whereas future readiness supports scalability, learning, and sustainability. Therefore, the combined construct captures the institutional conditions under which AI use is more likely to generate durable performance value.

Together, they decide whether the adoption of AI will lead to short-term efficiency or a long-term competitive advantage. Integrating these constructs into the empirical framework promotes both theoretical and practical understanding. Theoretically, it goes beyond traditional adoption models by integrating responsible innovation and institutional theory into the discourse on AI management. The inclusion of these constructs in the empirical framework will enhance theoretical and practical understanding. Theoretically, it transcends traditional adoption models by introducing the concepts of responsible innovation and institutional theory into the AI management discourse. This is in response to the literature that calls for the adoption of governance maturity anchored adoption models, which consider societal trust and accountability alongside technical capability (Floridi and Cowls, 2019; Ransbotham et al., 2023). Practically, this underscores the fact that digital transformation can be successful only on the basis of ethical stewardship: organizations that specify audit trails, limits of consent, and human-in-the-loop controls are more likely to have higher levels of stakeholder confidence and more robust operational results.

Many companies operate global supply chains that are subject to rigorous compliance and data handling standards. Therefore, establishing transparent governance maturity frameworks that include model explainability, fairness, and security can be a

source of market legitimacy and strategic differentiation (Wamba et al., 2024). Similarly, building future-ready strategic workforce capability development and technological foresight enables firms to quickly adapt to regulatory changes and technological disruptions to ensure the continuing alignment of innovation and accountability.

The inclusion of GMFR emphasizes that AI performance outcomes are determined not only by the intensity of use but also by the quality of institutionalization. By testing the combined construct empirically, this study evaluates whether well-governed and forward-looking organizations derive greater strategic value from AI use while maintaining responsible implementation.

1.3.6 Towards a Human-Centric Holistic AI

Finally, this study aims to develop a holistic conceptual framework that integrates technology, organizational, and governance maturity dimensions to form an integrated model of AI adoption effectiveness. By using a combination of quantitative analysis (through the statistical software package SPSS) and qualitative insight (through the qualitative software package NVivo and thematization), it can extract not only the structure of relationships between variables but also people's experiences (sales professionals and leaders).

This mixed-methods approach means that our findings go beyond statistical generalization and are contextualized, with the result that we are able to provide a theoretically sound and managerially useful framework for future research. The wider objective is to produce evidence-based recommendations for academics, practitioners, and policymakers working towards the objective of bringing about sustainable, human-centric,

AI transformation in the industrial ecosystem in India. For scholars, this research adds to existing adoption theories in the form of an empirically validated model. For practitioners, it provides indicators of readiness and governance maturity as a diagnosis. As a policymaker, it sheds more light on the institutional enablers that should be used to bring equitable digital transformation to the manufacturing industry.

Building on the above objectives, the final target of this research is to develop a holistic, empirically based framework that can explain how technological, organizational, and governance maturity factors together determine the success of AI adoption in the industrial sales context. Unlike single-lens models that consider the aspects of technology or management separately, this framework incorporates the micro-level perspectives of users, meso-level enablers of organizational readiness, and the macro-level anchors of governance maturity and ethical oversight into a unified system of analysis (Dwivedi et al., 2024).

At its core, the framework is aimed at representing a human-centric model of digital transformation, which recognizes that the effectiveness of AI is inextricable from human capability, judgment, and interpretive judgement. In B2B settings, such as the chemical manufacturing sector, sales decision-making is social and knowledge intensive. By embedding the views of sales leaders, analytics specialists, and decision-makers, the study ensures that the framework does not simply measure levels of adoption but explains how and why adoption succeeds or fails in different organizational settings (Mikalef et al., 2023).

The framework uses quantitative and qualitative strands. SPSS was used for data screening, reliability, descriptive analysis, correlations, multiple regression, and hierarchical moderation analysis. The quantitative model examines organizational readiness, perceived barriers, governance maturity, perceived usefulness, perceived ease of use, AI use, sales performance, and the combined GMFR construct. The qualitative strand uses NVivo 14 to analyze open-ended responses from industry practitioners and explain the statistical relationships.

By combining these methodological perspectives, this study contributes to both theory development and the development of applied practice. For scholars, it proposes a validated model that extends the technology acceptance model (TAM), diffusion of innovation (DOI), and institutional theory by adding governance maturity and human-centered ethics as moderating and integrating dimensions. This synthesis of concepts can be discussed as a response to the recent scholarly demand for cross-disciplinary frameworks that can help associate technological capability with social responsibility and ethical alignment (Zeng et al., 2023).

The framework serves as a strategic and diagnostic tool for practitioners. It provides pointers that can guide managers in identifying the maturity, scale, and ethical preparedness of AI adoption in their organization. To focus investments more efficiently and deploy responsible AI policies that can strengthen trust and transparency, firms can first focus on the combination of leadership commitment, data infrastructure, and governance maturity oversight, which has the strongest adoption performance outcomes. The topics of explainability, inclusiveness, and accountability are entirely aligned with the

current aspects of maturity in corporate governance, as well as with the ISO/IEC 42001:2023 standards of AI management systems.

As a policy consideration, this research will co-create evidence-based knowledge that can inform national AI-readiness frameworks and sectoral roadmaps. To ensure that the manufacturing ecosystem in India (especially process industries) is far ahead of other emerging economies, selective policies should be implemented, which should be a blend of incentives for innovation and ethical restraints. The key ideas and recommendations suggested as part of the framework include the need to promote multi-stakeholder cooperation among governmental organizations, educational establishments, and commercial companies to promote fair, reliable, and sustainable AI integration (OECD, 2024).

In general, the aim of the proposed research is to transcend the rhetoric of automation into a strategic and ethical re-conceptualization of industrial intelligence (Brown and Davis, 2022). The research will provide a model that is not only academically plausible but also practically applicable to the task of management and social responsibility by using both empirical rigor and contextual interpretation. The framework that emerges places the adoption of AI as a technological and human experience, as one of the technologies and governance maturity, as well as empathy, which must be balanced to make AI empowering, not to replace human decision-making.

1.4 Significance of the Study

This research is important because it helps fill the conceptual, empirical, and practical gaps that have traditionally hindered research on AI adoption in industries.

Although the topic of digital transformation has been broadly explored in the context of the service industry and developed economies, there is a lack of context-relevant evidence of how AI enters into business-to-business (B2B) chemical-manufacturing systems in India, where sales operations are intricate, relationship-based, and highly regulated (Shankar and Jain, 2024). Through a quantitative analysis of the data and qualitative inquiry, this study provides multilevel insights that contribute to advancing academic theory, forming managerial strategies, and informing the formation of national policies for responsible and sustainable AI transformation.

A. Academic Significance

Scholarly speaking, this research contributes substantively to the theoretical development of AI adoption research. It builds and combines three large conceptual models: the Technology Acceptance Model (TAM) (Davis, 1989; Venkatesh et al., 2022), Diffusion of Innovation (DOI) theory (Rogers, 2003), and Institutional Theory (DiMaggio and Powell, 1983) to address micro-level behavioral determinants and macro-organizational facilitators of adoption.

In contrast to TAM and UTAUT, which focus on beliefs and perceptions, including perceived usefulness and perceived ease of use, and DOI, which is represented by innovation-specific traits and diffusion phases, institutional theory proposes critical aspects of legitimacy, maturity of governance, and normative consistency that determine prolonged institutionalized use in large-scale businesses (Scott, 2014). The synthesis of these frameworks helped form an integrated model of AI adoption effectiveness that relates technological capability, organizational preparedness, and maturity of ethical governance

in a single framework. This conceptual synthesis advances linear models on acceptance to understand why adoption maturity does not occur across firms of equal size and the role of governance maturity mechanisms in mediating technology-performance relationships.

Furthermore, by taking this integrative structure and applying it to the chemical manufacturing sales context of India, which is an empirically under-researched field, it provides novel contextual support for the global adoption theory. This study thus presents a scholarly contribution to existing technology adoption models, developing the constructs of responsible AI, readiness asymmetry, and governance maturity moderation that enhance the existing literature (Dwivedi et al., 2024; Suh and Lee, 2024).

B. Managerial Significance

This study offers practical diagnostic information on the factors of successful AI adoption for industry players. The quantitative identification of the most significant readiness factors (leadership commitment, digital infrastructure, employee training, and data-driven culture) and the comparison with the critical barriers (cost constraints, skills shortages, and resistance to change) provide managers with quantitative benchmarks to determine the level of maturity of their organization in terms of AI adoption (Fountaine, McCarthy and Saleh, 2019; Chatterjee et al., 2021).

The results further shed light on the strategic contribution of governance maturity in attaining performance improvement and organizational trust. These findings can help managers create AI governance maturity models that instill transparency, accountability,

and ethical supervision, so that automation supplements human decision-making but does not replace it (Floridi and Cowls, 2019).

Moreover, this study can change theoretical constructs into operational strategies to enhance forecasting accuracy, customer satisfaction, and conversion efficiency by facilitating the correlation between perceived usefulness and ease of use with quantifiable sales-performance results. To senior leaders, the study serves as a blueprint for decision support, a digital transformation roadmap, prioritization of investment, and change management interventions that facilitate technology adoption with long-term organizational value.

C. Policy Significance

This study has several policy implications at the national and sectoral levels to make India more competitive in the industry multi-level using responsible AI. It provides policy stakeholders and industry organizations with evidence to develop focused AI-readiness models and training programs because it empirically maps the gap in readiness and adoption between mid- and large-scale companies (Dwivedi et al., 2023; Government of India NITI Aayog, 2023).

The study highlights that the introduction of AI will not be easy without more than bringing on board investment in technology; however, it will entail institutional faith, ethical adherence, and scale-based skill development. The lessons learned during this research could guide public-private collaborations aimed at reskilling industrial sales

teams, advancing the notion of digital ethics awareness, and assisting SMEs in creating governance maturity policies that can be adapted to new AI regulation frameworks.

Therefore, this study contributes to the wider Digital Economy Mission in India by providing evidence-based policymaking that would make innovation inclusive, transparent, and human-focused.

D. Overall Contribution

Finally, this study considers AI not as a technological upgrade, but as a strategic refocusing of organizational behavior and decision-making. This shows that the transformation of AI in industrial sales can only be successful if the leadership vision, workforce capability, and institutional governance maturity are aligned. The combination of theory and empirical rigor, with ethical consciousness, allows the research to be a highly detailed framework for both scholars and practitioners, as well as policymakers, because it improves the body of knowledge and the practical preparedness of the manufacturing industry in India to embrace AI-enhanced development.

1.5 Research Purpose and Questions

Based on the identified gaps in the literature and the objectives set out earlier, this study develops a clear and integrative purpose in the following manner: to understand how the adoption of artificial intelligence (AI) is transforming the sales process in India's chemical manufacturing sector and what organizational, behavioral, and governance maturity factors drive this transformation.

While AI has emerged as a strategic asset that is indispensable for firms in advanced economies, its assimilation processes into the industrial context of B2B sales in India

remain inconsistent, plagued by digital asymmetries, capability deficits, and governance maturity ambiguities (Dwivedi et al., 2024; Suh and Lee, 2024).

Thus, the present study addresses the urgent need for empirical evidence to relate technological adoption to organizational readiness, perceived utility, and ethics of governance maturity, especially in a sector where complex product cycles and long-term client relationships dominate performance outcomes.

1.5.1 Research Purpose

This study examines the extent, determinants, and performance outcomes of AI adoption in the sales functions of Indian chemical manufacturing firms, focusing on organizational readiness, barriers, perceived usefulness, and governance maturity frameworks.

This purpose is based on three interrelated goals.

- 1) To quantify the maturity and diffusion of AI usage in the sales processes of industrial companies
- 2) To model the internal and external determinants that affect adoption, such as leadership, infrastructure, and organizational culture.
- 3) To assess the effect of AI use on measurable sales performance and to test whether the combined Governance Maturity and Future Readiness construct strengthens the relationship between AI use and comparative sales performance.

1.5.2 Research Questions

The research is informed by four broad research questions (RQs) that jointly cover the extent and determinants, behavioral perceptions, and governance maturity outcomes of the adoption of AI in the industrial sales ecosystem of India.

RQ1: To what extent have mid- and large-scale chemical manufacturers in India adopted AI applications in their sales processes?

This question assesses the scope and maturity of AI implementation across firms, including differences by firm size and the extent to which AI use has progressed from isolated pilots to more routinized sales practices. The analysis uses descriptive statistics, reliability assessment, and organization-type comparisons.

RQ2: How do organizational readiness, perceived barriers, and governance maturity influence AI adoption in the sales functions of chemical manufacturers in India?

This question examines three direct adoption conditions. Organizational readiness leadership support, infrastructure, training, and data culture are expected to facilitate adoption; perceived barriers cost, skills gaps, privacy and security concerns, resistance, and process fragmentation are expected to constrain adoption; and governance maturity is expected to provide a smaller positive contribution through formal oversight and accountability.

By jointly analyzing these predictors, this study identifies their distinct contributions to AI adoption. The model does not claim a readiness-by-barriers interaction; instead, it tests the positive effect of readiness, the negative effect of barriers, and the positive effect of governance maturity.

RQ3: What are the perceptions of sales professionals regarding the usefulness and ease of use of AI-enabled tools, and to what extent do these perceptions affect measurable sales performance outcomes?

Drawing on the Technology Acceptance Model (TAM) (Davis, 1989; Venkatesh et al., 2022), this study addresses the human aspects of adoption, perceptions, attitudes, and behavioral intentions of sales professionals dealing directly with AI-enabled tools for forecasting, pricing, or customer engagement.

This study examines whether the concepts of perceived usefulness (expected performance benefits) and perceived ease of use (effort expectancy) predict actual adoption and contribute to quantifiable improvements in sales performance, including conversion rates, forecast accuracy and client satisfaction (Huang and Rust, 2021). This question takes the micro-level behavioral perspective and links it to the macro-level results performance and ensures that technology adoption is not examined in the abstract without the involvement of human experience and judgment.

RQ4: Do AI-enabled sales strategies perform better than traditional sales strategies, and do Governance Maturity and Future Readiness strengthen the relationship between AI use and comparative sales performance?

The fourth question addresses performance differentiation and responsible AI. It examines whether routine AI use is associated with stronger comparative sales performance and whether the combined Governance Maturity and Future Readiness (GMFR) construct contributes directly to performance and strengthens the AI use–performance relationship. This question operationalizes responsible AI through a

combined measure of formal governance and strategic readiness. The model tests whether oversight, accountability, explainability, and investment intent help convert routine AI use into sustainable comparative performance.

This study not only adds to the academic literature on AI-enabled organizational transformation but also generates evidence-based research findings that can be used by practitioners and policymakers to bring India's industrial ecosystem closer to the global benchmarks of digital maturity and responsible governance maturity. The answers to these questions provide empirical clarity on the determinants of AI success and lay the conceptual foundation for potential future research on the intersection of technology, performance, and ethics in emerging market industries.

1.6 Conceptual Background and Theoretical Positioning

Artificial Intelligence (AI) adoption in the context of industrial sales cannot be purely grasped from a technological perspective but rather embedded in the wider organizational and behavioral theories of how organizations and individuals across the organization perceive, accept, and institutionalize innovation. The present study combines three foundational theoretical perspectives, namely, the technology acceptance model (TAM), diffusion of innovation (DOI) theory, and the institutional theory to build a multi-level understanding of AI enabled transformation in the Indian chemical manufacturing sector.

At the micro level, the technology acceptance model (Davis, 1989) and its extensions (Venkatesh et al., 2022) can be used to state that the perceived usefulness of technology and ease of use will determine the intention of using new technologies. In sales,

this means that agents will be more inclined to adopt AI solutions, such as predictive analytics, pricing algorithms, and customer-relationship models, if they believe that they can see clear improvements in their performance and that there is a relatively small cognitive burden. This behavioral logic explains why digital investments are translated into productivity gains through user attitudes (Dwivedi et al., 2024).

At the meso level, Rogers Diffusion of Innovation theory (2003) provides an organizational context for understanding the spread of AI innovations through firms. It identifies the stages of awareness, persuasion, decision, implementation, and confirmation, which collectively determine the maturity of the adoption process. Within Indian manufacturing, many firms are stuck between the implementation and confirmation stages because of their partial readiness, fragmented data systems, and underdeveloped digital culture (Chatterjee et al., 2021). These issues highlight the fact that innovation diffusion is not a matter of awareness or intention but of the alignment of leadership will, infrastructure readiness, and cultural openness to maintain routinization.

Institutional theory (DiMaggio and Powell, 1983) answers the question of why organizations are increasingly adapting to AI, not only for efficiency but also to comply with normative and regulatory pressures. As AI is increasingly being deployed in business settings, AI governance maturity has emerged as a core approach to legitimize AI practices (Suh and Lee 2024), and some recent regulations on ethical-AI practices require companies to validate AI practices using a governance maturity framework (Floridi and Cowls, 2019). Consequently, companies make auditability, explainability, and fairness part of their AI

processes, changing adoption from a technical initiative into an organizational value system.

The convergence of these theoretical streams provides a conceptual framework for the present study.

- 1) The TAM adds a dimension of behavioral acceptance that explains how usefulness and usability drive acceptance at the individual level.
- 2) DOI places this process in the context of the learning and capability development trajectories of organizations.
- 3) Institutional theorists add the dimensions of governance maturity and legitimacy to the sustainability challenge, focusing on external accountability and ethical stewardship for long-term sustainability.

By combining these perspectives, research recognizes that the adoption of AI is a socio-technical and institutional transformation at the intersection of human cognition, organizational capability, and ethical governance maturity. This integrative approach helps us conceptualize the complexity involved in the adoption of AI in India's chemical manufacturing sector, which is simultaneously under globalization pressure, digital skills scarcity, and demand for responsible innovation.

The theoretical positioning also explains the suitability of adopting a mixed-method approach, in which quantitative analysis can be used to validate the structural relationships between readiness, barriers, and performance, while qualitative insights can help explain the cultural and governance maturity nuances that underpin these patterns. Together, these

approaches provide a comprehensive picture of how AI becomes a part of the daily sales process decision-making.

1.7 Summary

Chapter I provides the background, motivation, and direction for this research by placing the adoption of artificial intelligence (AI) in the context of the changing context of India's industrial B2B sales environment, particularly chemical manufacturing companies. The chapter starts by indicating the transformational potential of artificial intelligence technologies in reshaping business models, operational efficiency, and customer engagement in global industries. However, it also emphasizes the persistent inconsistencies in adoption and maturity between advanced economies and developing industrial contexts such as India, where infrastructural limitations, skill gaps, and governance maturity ambiguities continue to obstruct full-scale implementation (Dwivedi et al., 2024).

The research problem was framed within these contexts. While the conceptual benefits of AI are well recognized, the empirical understanding of the organizational enablers, barriers, and ethical implications of AI remains limited, particularly in the heavy industrial B2B sales sector in India. Prior studies have largely been technological in nature, which has meant that organizational readiness, leadership capability, and governance maturity mechanisms, which play a crucial role in deciding whether AI will move from a pilot project to a sustained strategic advantage, have been ignored (Ghosh et al., 2024; Suh and Lee, 2024).

In response, the purpose of this study was formulated to analyze the level, causes, and effects of AI adoption in the sales functions of chemical-manufacturing firms in India. Four specific objectives were set.

- 1) To understand the depth and maturity of AI adoption across mid- and large-scale organizations:
- 2) To identify organizational readiness factors and barriers affecting the levels of adoption.
- 3) To assess the impact of perceived usefulness and ease of use on the outcomes of sales performance; and
- 4) To establish the direct and moderating roles of the combined Governance Maturity and Future Readiness constructs in the relationship between AI use and comparative sales performance.

The importance of this study is discussed on three overlapping fronts. Academically, this study contributes to the theory by integrating the technology acceptance model (TAM) (Davis, 1989), diffusion of innovation (DOI) (Rogers, 2003), and institutional theory (DiMaggio and Powell, 1983) into one explanatory framework that relates behavioral intent and organizational readiness and explains and relates to governance maturity legitimacy. This integration not only enriches the theoretical knowledge of how technological and institutional forces combine to form adoption outcomes but also enhances the topicality of the subject of interaction.

Managerially, this study derives readiness and governance maturity benchmarks and diagnostic insights that can provide executives with data-driven guidance on AI

implementation strategies. At the policy level, this research provides insights that can be translated into policy interventions, such as national AI-readiness frameworks, industrial training programs, and ethical standards of governance maturity, to support the broader goals of digital transformation of the Indian economy as part of various policy interventions, such as Digital India and Make in India (NITI Aayog, 2023). The research questions (RQ1–RQ4) formalize the direction of the study by addressing the extent of adoption, the direct effects of organizational readiness, perceived barriers, and governance maturity, user perceptions and sales performance, and the direct and moderating role of GMFR in comparative sales performance.

In conclusion, Chapter I places this study at the intersection of technological innovation, organizational behavior, and ethical governance maturity, which characterizes the future trajectory of AI in industrial economies. The chapter drives home the point that the adoption of AI is not a technical integration but a socio-organizational reconfiguration that calls for leadership vision, workforce empowerment, and institutional trust. Chapter II builds on this foundation by methodically reviewing the current literature and mapping previous theoretical and empirical findings on various spheres of AI adoption, organizational readiness, governance maturity frameworks, and sales performance enhancement. It develops the conceptual framework and hypothesis structure that are followed in the empirical analyses in the subsequent chapters.

CHAPTER II:

REVIEW OF LITERATURE

2.1 Theoretical Framework

This study uses five complementary theoretical lenses to explain how AI changes strategic sales management and the organizational context in which these changes lead to quantifiable performance improvements in India-based chemical manufacturing companies. These lenses are conceptually different but complementary in nature. The combination of the two provides a micro-meso-strategic explanation that bridges the gap

between beliefs and behavior (individual level), routine and scale-up (organizational level), and competitive advantage (firm/industry-level).

A. Information Technology derivatives (TAM, UTAUT)

- i. **Mechanism of core (beliefs intention behavior):** TRA describes that behavior intention leads to behavior, which in turn is conditioned by attitude towards the behavior and subjective norm, that is, perceived social pressure to do or abstain from behavior (Fishbein and Ajzen, 1975). The behavior in a sales setting is the use of AI-powered tools (e.g., AI-CRM lead scoring, predictive forecasting, and dynamic pricing assistants). Attitude portrays the belief that such use will enhance accuracy, speed, or deal results. Subjective norms include the expectations of senior management, peers, and even the procurement norms of major customers, who are becoming increasingly concerned with data-based selling.

- B. TAM and UTAUT refinements:** TAM sees the two beliefs with the highest explanatory power in terms of IT use, which include usefulness and ease of use, and relates them to intention and actual use (Davis, 1989). The UTAUT includes social pressure and enabling factors (availability of resources, training, and support) and better prediction in the organizational context (Venkatesh et al., 2003). The usefulness of Indian chemical sales teams is often described in terms of a more accurate forecast, better calibrated win probability, and margin discipline, whereas ease of use is sacrificed by fractured CRMs and old-fashioned ERPs. Social influence is high, where CXOs are promoting account planning philosophy of AI-

first, and facilitating conditions are dependent on data quality, training, and sales operations support.

- i. **Chemical B2B sales boundary conditions:** TRA/TAM/UTAUT create rational and belief-driven agents. During the long cycle, relationship-based chemical selling, identity, and tacit expertise can withstand the adoption of tools, even with positive beliefs. In this case, the subjective norm (what the respected senior sellers do) and performance management (what is measured/rewarded) are determining factors. Therefore, the belief-intention-use chain is strengthened in the case of AI outputs, which are embedded into the established rituals (QBRs, deal reviews) and assigned to revenues (Davenport and Ronanki, 2018; Fountaine, McCarthy and Saleh, 2019).

Implications of measurement and empiricism; The survey includes measures of usefulness, ease, social influence, and facilitating conditions using a regular Likert scale; AI use by usage breadth/frequency. The positive paths of beliefs/norms/conditions-intention/use and use performance are the expected paths by a hypothesis and the moderating force (Davis, 1989; Venkatesh et al., 2003). Supporting pilots for regular, company-wide implementation:

C. Diffusion of Innovations (DOI)

Systemic (innovation attributes and social systems): DOI outlines the process of innovations passing through awareness to decision, implementation, and confirmation, which depends on perceived relative advantage, compatibility with existing values/processes, complexity, trialability and observability (Rogers, 2003). The relative

advantage in chemical sales takes the form of improved quality in pipelines and pricing results. Compatibility refers to the need to harmonize AI with current CRM operations and the regulatory reports. Trialability can be attained by using AI in a region or product line, and observability can be achieved by publishing quick-win metrics (e.g., forecast MAPE reduction) at sales Town Hall meetings. Between local pilots and institutionalization: Many companies have successful pilots but fail to make a lot of scale. The DOI assigns such stalls to poor compatibility (poor fit of processes), high complexity (opaque models), and poor observability (only benefits can be seen when pilot teams are involved). Steps are taken to transform the episodic use of tools into a routine that is familiar to the organization (Rogers, 2003).

Sector-specific diffusion processes in India: Diffusion in Indian chemical companies is in contact with regional sales systems, distribution channels and customer purchase standards (Chatterjee et al., 2021). When big anchor accounts accept AI-sponsored proposals and co-sponsor AI rollout proposals by cross-functional councils (sales marketing supply finance), its adoption increases quickly, thus legitimizing the change through the social system (Wadhwa et al., 2021). Empirical implication: The adoption maturity scale (pilot to embedded) survey is a proxy for the diffusion stage, and the model predicts that maturity enhances the AI use performance path by providing consistency and routine enactment (Rogers, 2003).

D. Resource-Based View (RBV)

- i. **Core mechanism (VRIO):** According to RBV, long-term benefits are based on valuable, rare, inimitable, and organized resources and capabilities (Barney, 1991).

- In sales AI, higher conversion, strong margin, enhanced predictive accuracy, rarity/inimitability, firm-specific data assets, domain-specific models, strong process integration, organization, governance maturity, roles, and incentives that recurrently use these strengths.
- ii. **Reason why the same tools give different results:** The same AI platform licensable by two companies may produce different outputs because one of them has clean longitudinal CRM/opportunity data, structured pricing approvals, and analytics talent within sales operations, while the other has siloed data and no change management. The former makes the use of AI a bundle of capabilities that are difficult to imitate by competitors (Barney, 1991; Paschen, Wilson and Ferreira, 2020).
 - iii. **Specificity for the chemical sector:** Chemicals have specific data that are a strategic provision owing to their richness (spec sheets, compliance docs, historic quotes, and client technical preferences). When curated and linked to outcomes, it is possible to support high-signal models (e.g., propensities to purchase complex formulations). Therefore, firms that invest in data stewardship and sales-ops analytics turn AI into a defensible advantage, not efficiency (Paschen et al., 2020).
Empirical implication: In the model, the VRIO conditions are expected to be facilitated by organizational readiness (leadership, infrastructure, training, data culture) and reduced barriers; hence, the effect of use on performance is amplified (Barney, 1991).

E. Socio-technical and institutional methods

- i. **Basic mechanism (optimization jointed):** According to the socio-technical theory, performance is determined by the fit between social and technical subsystems; that is, roles, skills, incentives, norms, and governance maturity need to be co-designed with data, models, and platforms (Vial, 2019). Firms do not achieve joint optimization and fall into the so-called pilot trap (good tools, poor routines).
- ii. **Governance maturity, risk, and compliance in B2B chemicals:** Legitimate AI use is shaped by institutional expectations, including the ability to explain pricing recommendations, maintain forecast audit trails and protect customer information. Formal model-risk controls, such as approval gates, drift monitoring, and policy alignment, also help make AI systems acceptable to internal audits, legal teams, and major accounts (Vial, 2019; Huang and Rust, 2021).
- iii. **Culture, identity, and change:** AI can be considered a threat to autonomy by relationship-based sales cultures. The rollout of AI is often coupled with enablement (training, coaching), legitimized through executive application (leaders using AI in QBRs), and upon the recognition of wins (incentives applied to AI-assisted wins). Such actions change subjective norms and make obedience commitment possible (Fountaine, McCarthy and Saleh, 2019).
- iv. **India-specific constraints include legacy IT systems,** geographic and business-unit data silos, shortages of analytics talent, and cost sensitivity among mid-scale organizations. In the empirical model, these constraints are represented through the perceived-barriers construct, while leadership, infrastructure, training, and data

culture are represented through organizational readiness. The study tests readiness and barriers as distinct direct predictors of adoption rather than as moderators (Chatterjee et al., 2021; Vial, 2019; Wadhwa, Andaleeb and Gaur, 2021).

F. Sales and service AI scholarship: data relationship between the usage and outcome

- i. **Established performance channels:** Prior evidence indicates that AI can improve demand forecasting, opportunity qualification, pricing discipline, customer engagement, and cycle-time efficiency when embedded in sales processes and supported by appropriate governance (Davenport and Ronanki, 2018; Paschen, Wilson and Ferreira, 2020; Huang and Rust, 2021).
- ii. **Conditions for impact:** Performance benefits are more likely when the data are sufficiently accurate and integrated, users are trained and motivated, outputs are interpretable and auditable, and sales insights are connected to supply planning and pricing decisions. Without these conditions, AI may produce dashboards without materially changing the decisions (Davenport and Ronanki, 2018; Huang and Rust, 2021).
- iii. **Comparative effectiveness:** Prior research suggests that AI-supported selling can improve hit rates, margin realization, and forecast accuracy relative to conventional approaches, particularly in volatile and specification-intensive markets. However, outcomes vary across firms, supporting resource-based and socio-technical explanations of performance heterogeneity (Paschen, Wilson and Ferreira, 2020; Chatterjee et al., 2021). The present study tests whether AI use predicts comparative

sales performance and whether stronger institutional support amplifies this relationship (Davenport and Ronanki, 2018; Huang and Rust, 2021; Rogers, 2003).

Placing the lenses in close physical proximity results in a coherent causal chain.

- i. Innovation qualities and social systems (maturity) (DOI).
- ii. **Fit and governance maturity:** prolonged compliant use (socio-technical/institutional).
- iii. **VRIO capability bundle:** used to benefit (RBV).
- iv. **Onboard application:** improved KPI (sales and service AI literature).

AI adoption in sales refers to the implementation and utilization of AI-enabled applications in sales planning and execution, such as AI-CRM (lead scoring, next-best-action), predictive forecasting, dynamic pricing/revenue management, NLP/chatbots to contact the customer, and analytics of market intelligence. Organizational readiness includes leadership sponsorship, data infrastructure, training, and a culture based on data. Barriers include costs, lack of skills, risk of privacy and security, resistance to change, and fragmented use of tools. The most common B2B sales KPIs used in the chemicals industry include sales performance (accurate forecasts, lead-to-order conversion, customer engagement/CSAT, margin, and cycle time), where the B2B sales cycle is longer and information asymmetries are greater than in B2C (Chatterjee et al., 2021; Wadhwa, Andaleeb and Gaur, 2021).

2.1.1 Why Multiple Theories? Complementarity and Not Replacement

TAM/UTAUT is based on individual acceptance. DOI is an organizational institutionalized use. RBV provides a clear understanding of why some firms achieve an

advantage. Socio-technical is a reason as to why the same tools yield different results in different firms. This synthesis unified multilevel explanation—consistent with the realities of the Indian chemical sector—controlled B2B markets, specifications, and relationship-based selling (Vial, 2019; Wadhwa, Andaleeb and Gaur, 2021).

2.1.2 Prevailing Evidence Regarding AI in Sales and Services

Practice-based and empirical research suggests that AI can improve opportunity qualification, pipeline management, and pricing discipline when organizations professionalize data governance and change management (Davenport and Ronanki, 2018; Paschen et al., 2020; Huang and Rust, 2021).

2.1.3 Organizational Resistance and Professional Identity

Although the presence of technology readiness is a pre-condition for AI adoption, pre-existing studies emphasize that employee attitudes and professional identity are determinant factors in the effects of adoption. Marabelli, Galliers, and Newell (2022) are certain that workers in industries that are traditionally expertise-driven tend to view AI systems as a potential threat to professional discretion, independence, and work identity. This opposition is not necessarily technical but rather socio-psychological, arising from doubts about losing control and experience.

Such identity-based resistance is more evident in industrial and B2B settings, where the decision-making process depends on tacit knowledge and on long-term relational capital. According to the literature, without organizations personally addressing these issues by implementing communication, participation, and trust-building systems, AI initiatives are likely to be used in a limited and symbolic manner. This view supports the

perception that the adoption of AI can only be successful when human and cultural aspects are managed well, together with technology adoption.

2.1.4 Explainability, Transparency, and Trust of AI Adoption

Trust has been found to be a crucial factor in user acceptance and continued use of AI-enabled systems. According to Glikson and Woolley (2023), explainability and transparency levels have a strong effect on human trust in AI, and in this case, it is a high-stakes decision-making context. Resistance and cognitive discomfort are lower as users gain perceived fairness and reliability when they are aware of the logic behind the algorithmic recommendations.

XAI helps employees to judge, question, and justify system outputs instead of automatically taking the advice of automation in organizational contexts. This is more applicable in industrial selling situations, where decision-making has financial, contractual and reputational consequences. The positions described in the literature present explainability not only as a technical quality but also as a socio-cognitive process that increases acceptance, accountability, and trust in AI-driven decision support systems.

2.1.5 Usability, Ease of Use, and Performance Results

In addition to perceived usefulness, system usability is an important factor in measuring the effectiveness of AI adoption. According to Mariani and Wamba (2023), convenient interfaces with easy integration into current working processes are critical to the continued use of AI and subsequent performance enhancement. Complex systems that demand high cognitive processing/training tend to deter usage and constrain organizational value.

The literature also indicates that ease of use is especially significant when dealing with an operational situation in which time and speed of decision-making are paramount. Intuitive dashboards, simplified analytics, and automated insights merge to improve engagement in sales and customer-facing functions and boost the chances of AI-based recommendations being implemented. These insights can be considered extensions of tradition multi-level acceptance perspectives because usability is directly related to performance outcomes rather than adoption intention.

2.1.6 Leadership Alignment and Strategic AI Transformation

Leadership commitment is generally accepted as a key factor in successful AI change. Haenlein et al. (2019) argued that AI projects fail because they are managed as solitary IT projects as opposed to strategic organizational changes. Leaders are crucial in defining a clear vision of AI, aligning AI adoption with business goals, and developing a culture of experimentation and learning.

The literature indicates that AI adoption with the support of leadership makes it legitimate because of the signals of strategic priority and lowered uncertainty among employees. Effective leaders also have the right structures of AI governance maturity, ethical standards, and competency-building programs that allow AI adoption to be integrated into mainstream business processes. This view makes leadership preparedness a third-level organizational competence that defines the intensity and permanence of AI adoption.

2.2 Theory of Reasoned Action

A) Core mechanism: Theory of Reasoned Action (TRA) is the theory of behavior governed by behavioral intention, towards influenced by attitude toward behavior and subjective norms, which is perceived social pressure to act or not act (Fishbein and Ajzen, 1975). The focal behavior in sales is the use of AI-based tools (for example, AI-CRM lead scoring, priority of opportunities, forecast models, and price-corridor recommendations). Attitude is reinforced when sellers believe that the use of AI has improved the results of variables, they consider valuable, such as forecast accuracy, hit rate, margin discipline, and cycle time. Subjective norms are strengthened by a process of anticipated outcomes, modelling, and reward from influential (executives, regional heads, top performers, and key account teams) who expect, model, and reward AI-assisted selling.

i) TAM and UTAUT operationalization: TRA was further narrowed down to the technology acceptance model (TAM), which establishes two constructs of belief with a high level of explanatory power: perceived usefulness (belief that using a system increases job performance) and perceived ease of use (belief that using a system is free of effort). Such beliefs create attitudes, intentions, and eventually use (Davis, 1989). The Unified Theory of Acceptance and Use of Technology (UTAUT) builds upon this reasoning by adding social influence and facilitating conditions (availability of resources, training, and organizational/IT support) as a predictive validity enhancer at the organizational level (Venkatesh et al., 2003).

ii) Utility equivalent to quantifiable sales performance, ease of implementing AI in everyday operations, social pressure on executives and co-worker demands, and enabling situational factors for data/IT preparedness and enablement.

iii) B2B specificity of India in chemicals: Norms and legitimacy are significantly more important in Indian chemical companies compared to interface features. This behavior is legitimized by visible executive sponsorship (for example, CEOs/CSOs going through AI indicators in QBRs), enablement programs (role-specific training, office hours), and peer champions (respected senior sellers using AI when reviewing deals), which also change subjective norms.

On the other hand, intentions are killed by the fear of displacement (erosion of professional judgment or relationship capital) and model opacity (unclear reasons why a recommended price or probability should be) even in the presence of tools (Davenport and Ronanki, 2018; Fountaine, McCarthy and Saleh, 2019). Thus, adoption is contingent not only on expectations regarding performance and effort but also on identity security, explainability capability, and recognition systems, which place AI-supported practice in a position of status, not stigma.

iv) Embedding and capability building: TRA/TAM/UTAUT; the reason behind the establishment of intentions; to continue its use, capabilities have to be developed, and the process is internalized. This will involve in practice: (i) systematic training of interpreting model outputs and confidence; (ii) playbooks, which are statements of where AI is required (price exceptions above a threshold are obliged to include AI evidence of elasticity); (ii) process redesign, where AI fields would appear in account plans, pipeline reviews, and

pricing approvals such that use is recorded and auditable; and (iv) manager coaching, which reviews AI-supported decisions and provides feedback loops to the data teams. Such behaviours bring anticipation of exertion into less focus, rewards to the fore, and random trials into habit (Fountainaine et al., 2019).

v) Attitude and norm formation: One way to accomplish this is to increase attitudes by consequence visibility by relating AI to win/loss situations after the fact that highlights evaded or alleviated, thereby maximizing the forecast mean absolute percentage error (MAPE). The act of making sellers provide short override justifications in instances where they do not adhere to the AI will guarantee autonomy, acquire learning information to maximize models, and maintain professional identity (Davenport and Ronanki, 2018; Fountainaine, McCarthy and Saleh, 2019).

vi) Boundary conditions and moderators: The translation of belief-based intentions to behavior within chemical B2B may frequently rely on:

- a) **Explainable opaque models:** Modelling stance, local feature explanations, and the model card overcome this by showing the drivers of suggestions.
- b) **Data quality/integration:** Poor CRM/ERP fit is a source of decreased perceived usefulness, perceived viable data stewardship, and expediency, which are sources of belief and continued use.
- c) **Governance maturity and legitimacy:** Audit trails, versions, and drift monitoring decrease perceived risk among sellers and buyers and increase social influence and smooth conditions (Davenport and Ronanki, 2018; Fountainaine, McCarthy and Saleh, 2019).

d) Empirical findings: In accordance with the TRA/TAM/UTAUT, the theorized antecedents of AI use are beliefs of perceived usefulness and ease of use and norms/conditions, including social influence and facilitating conditions. These factors are supplemented in the Indian chemical industry by readiness (leadership commitment, infrastructure, training, and data-driven culture) and barriers (cost, skills, privacy/security, resistance, and fragmentation).

The model thus expects: (i) positive relationships between adoption drivers (usefulness, ease, social influence, and conditions) and AI use; (ii) positive relationships between readiness and negativity between barriers and use; and (iii) stronger belief-use relationships, where explainability and managerial coaching can be found (Davenport and Ronanki, 2018; Fountaine, McCarthy and Saleh, 2019).

Table 2.1 Construct–theory alignment and expected directional effects

Construct (measured)	Theory anchor	Mechanism	Expected effect on AI use	Expected effect on Sales KPIs
Perceived usefulness	TAM	Cognitive belief- intention	High	High
Perceived ease of use	TAM	Effort expectancy- intention	High	Indirect via use
Social influence	UTAUT/TRA	Norms/peer pressure-intention	High	Indirect via use
Facilitating conditions	UTAUT	Resource/skill availability	Sustained use	via stability
Leadership commitment & data culture	TRA (norms)/Socio- technical	Legitimization and incentives	breadth/depth	
Barriers (cost, skills, privacy, resistance)	Socio-technical	Friction		

Adoption maturity	DOI	Institutionalization
AI use in sales processes	All	Capability enactment forecast, conversion, margin, cycle time

Source: Author

2.2.1 Intent to Use Role of Capability Development

- i. **Rationale:** TRA/TAM/UTAUT were used to understand the intention of sales professionals to adopt AI. However, the goal is rarely translated into systematic practices without deliberated capability development in terms of changing capabilities, artifacts, and governance maturity in relation to novel tools (Fountaine, McCarthy and Saleh, 2019).
- ii. **Structured training and micro-learning:** competency-based curricula (e.g., interpreting model confidence, signs of data drift, and reading uplift reports), assessed through scenario exercises to real accounts. Retention is provided in the form of certification and re-certification (Fountaine, McCarthy and Saleh, 2019).
- iii. **Playbooks and decision checklists:** Standard operating procedures that specify where AI is obligatory (for example, forecasting commits above Rs. X crore must be supported by model rationale; price exceptions must be supported by evidence of elasticity). Playbooks decrease variance and utilize ad hoc more repeatably.

- iv. **Redesign processes:** Embark on AI gates (e.g., account planning, pipeline reviews, and pricing approvals) (for example, AI score + human override + rationale fields in the CRM).
- v. **Coaching embedded in PM:** Use of AI to inform coaching decisions; dashboard to point out all non-use and override trends; metrics to reward appropriate use (Fountaine, McCarthy and Saleh, 2019).
- vi. **Data stewardship and feedback loops:** Assigning data quality (duplicate accounts, missing stage dates) owners, data review (monthly) (data quality), and error analysis (monthly) to users, as this shows fixes, which builds confidence and further use (Vial, 2019).
- vii. **Mechanism:** These levers ensure that the intention behavior gap is minimized by lowering effort expectancy, increasing instrumental rewards, and institutionalizing AI touch points within sales rituals. B2B chemicals, long cycles, and documentation-intensive processes that are necessary to gain acceptance from buyers demand the reusability of AI outputs to explain and audit the final documents and safe-contract-based features (Huang and Rust, 2021).
- viii. **Operationalization:** Factors that represent the adequacy of training, clarity of the playbook, existence of artificial intelligence (AI) gates in the process, frequency of managerial coaching, and data custodianship lead to something called Readiness/Facilitating Conditions (Venkatesh et al., 2003; Fountaine, McCarthy and Saleh, 2019).

2.2.2 Sales Work and Identity Communication

The recommendations of AI can be seen as a threat to professional judgment and result in the defensive non-adoption of positive beliefs (Davenport and Ronanki, 2018). Technology and legitimacy strategies Complementarity of technology and legitimacy strategies.

a) AI to process grain: An AI under very high and varied subtasks (propensity scoring, price corridors, and demand sensing), and framing and negotiation of the narrative is performed by human personnel. The threat of identity is eliminated because of the existence of clear task boundaries.

b) Machine learning loop: AI knowledge of the post-mortem wins/losses display would have been more effective in terms of the quality of the results (forecast MAPE, margin leakage). The attitude prediction improvement with the consequences made salient is superior when TRA (Fishbein and Ajzen, 1975) is used.

c) Role-model usage: usage role model, older and more prestigious sellers than the target individual show their pipes with AI fields filled during QBRs change in subjective norms (Venkatesh et al. 2003).

d) Adding attribution and credit: AI-enabled CRM and credit share of revenue (as required by law) shall be credited as misaligned incentives (quota credit without considering AI advisory), which discourages intention-to-use (Fountaine, McCarthy and Saleh, 2019).

e) Map AI to task grain: Use AI in high-variance, high-data subtasks (propensity scoring, price corridors, demand sensing) and leave the business of narrative framing and negotiation to humans. (Huang and Rust 2021).

2.3 Human Society Theory

This has been translated into organizational research from socio-technical and institutional perspectives.

2.3.1 Joint Optimization

- i. **Socio-technical Perspective:** For chemical B2B sales, joint optimization is manifested in the form of co-design of technical (data pipelines, models, platforms) and social (roles, skills, incentives, governance maturity) subsystems leading to optimal performance (and pilot churn and limited impact with misalignment), as noted by Vial (2019).
- ii. **End-to-end signal flow Sales to Supply:** Production and Finance/Pricing Opportunity scores and demand signals need to be two-way Sales to Supply/Production and Finance/Pricing. Otherwise, Sales AI is a local optimization with no follow-through on fulfilment or margin.
- iii. **Role redesign:** Sales ops analysts decode the output of the model (playbook steps (target lists, price floors, next-best offers)) and verify that they are being followed.
- iv. **Governance maturity cadence:** sales, IT/analytics, legal/compliance monthly Model & Data Council (sales, IT/analytics, legal/compliance) to

approve changes, monitor drift, and record exceptions to establish an organizational memory and legitimacy (Vial, 2019).

- v. **Expertise architecture:** Tiered enablement (basic user-power user-champion) and clear expectations; champions with closed feedback (with data teams) (Fountaine et al., 2019).

2.3.2 Pressures of an institution Legality

No external standards are admitted by law, and previous legal precedent only addresses what is considered acceptable depending on the procurement standards of the customer, the compliance standards of a given sector, and auditability. The expectations of buyers and auditors will rise, which will push for the importance of pricing/forecasting, and the principles of traceability (explainability characteristics), consistency, and audit trails will rise (Huang and Rust, 2021). Legitimacy mechanisms:

- i. **Uncover Enhance transparency and documentation:** release model cards (purpose, data, features, limits), version history, and attach explainability snippets (e.g., top drivers) to sales artifacts.
- ii. **Policy alignment:** make ethically, privately, securely and human in the loop checkpoints institutionalized; perform model drift and bias reviews on a schedule (Vial, 2019),
- iii. **Reference compliance** (i.e., RFP responses based on ISO-aligned data processes, where applicable) enhances chemical comfort in buyers when contracts are long-lived (buy once, use often).

Implication: Institutional conformity reduces the barriers to adoption and the speed of the diffusion process within and outside the firm, as it minimizes the risk of AI adoption for stakeholders (Huang and Rust, 2021).

2.3.3 Capability Realization Resource Based View

Why do firms have unequal results?

- i. **According to the RBV**, advantage requires valuable, rare, inimitable, and organized resources (Barney, 1991). In sales AI, the set of capabilities includes:
- ii. **Information resources:** Long-term, heavily tagged CRM/ Quotation history; spec sheets; customer technical preferences; and service records.
- iii. **Domain-tuned models:** Optimized features in terms of chemical formulations, regulatory constraints, and regional market peculiarities.
- iv. **Integration/workflows:** Intimate integration with ERP/pricing, compulsory corridors and approvals.
- v. **Change management:** Training, playbooks, incentives, and governance maturity provide exploitation opportunities (Paschen et al., 2020).

Factors that helped and hampered India's development, lack of correlation between ERP and CRM, and the lack of permit the development of a VRIO; an increasing number of companies are investing in data modernization (master data, duplication, and lineage) and talent pipelines (internal academies/partnerships), making the use of AI more likely to become an arguable advantage (Wadhwa, Andaleeb and Gaur, 2021).

Empirical catch: Technology and maturity have been used to predict performance and sales KPIs, respectively, for RBV use cases.

2.3.4 Failure Modes and Empirical Regularities

- i. **Leadership and governance maturity:** The visibility of scale-up sponsorship and distinct ownership and cadence results in the scaling up of pilots into programmes (Fountaine, McCarthy and Saleh, 2019).
- ii. **Capacity and preparation for use:** Those with lower levels of readiness are at risk for intention-to-use failure; enabling is one of the strongest predictors of use (Venkatesh et al., 2003).
- iii. **The predictive value of data quality/integration:** As the quality of the lineage/integration is poor, the forecast and pricing value is destroyed; when data quality improves, the increases in KPI are not necessarily visible (Davenport and Ronanki, 2018).
- iv. **Cultural resistance,** AI recommendation, and relationship, that is, non-use and silent overriding of the only story, have been identified to obstruct the impact of B2B chemicals (Chatterjee et al., 2021).
- v. **Pilot trap:** Successful in one market/product, none to scale up to - this was solved by quantifying the maturity of adoption (DOI) and willingness.
- vi. **Dashboard theatre:** Nice to look at, but with no right to decide, as it is dealt with through process gates and governance maturity measures.

- vii. **Drift and Stale Data:** Model drift and stale features are issues that can result from data degradation, which is addressed through data stewardship and model review (Vial, 2019).
- viii. **Seller disincentive:** The AI price corridor is addressed using identity and incentive items (Davenport and Ronanki, 2018).

2.3.5 Gap Analysis

i. Strengths of the Literature: Micro-level (very strong explaining power) adoption models Decades of IS research have shown that beliefs (usefulness, ease of use), social influence, and facilitating conditions are predictors of intention and use of digital tools (Davis, 1989; Venkatesh et al., 2003). The models are reasonably extended to sales AI and are based on managerial practice narratives (Fountaine, McCarthy and Saleh, 2019).

AI-enabled B2B selling: Empirical and practice-oriented research shows that AI can augment human workflows in lead scoring, opportunity qualification, forecasting, pricing discipline, and customer engagement when appropriate governance and process integration are in place (Davenport and Ronanki, 2018; Paschen, Wilson and Ferreira, 2020; Huang and Rust, 2021).

Across industries, performance improvements in forecast accuracy, conversion, margin realization, and sales-cycle efficiency are most consistently reported when data quality, user training, and change management are addressed together (Davenport and Ronanki, 2018; Huang and Rust, 2021). This pattern is consistent with socio-technical theory, which emphasizes the joint optimization of social and technical subsystems (Vial, 2019).

- ii. **Sectoral under-representation in heavy industrial B2B markets:** Much of the existing evidence is concentrated in technology, services, and fast-moving consumer or retail settings characterized by shorter sales cycles and larger volumes of customer data. Heavy industrial B2B sectors have longer buying cycles, engineering specifications, regulatory requirements, and multi-stakeholder purchasing processes. These differences limit the direct transferability of evidence to Indian chemical manufacturing, where approval rights, task structures, and risk norms differ substantially from B2C and faster-cycle B2B contexts (Wadhwa, Andaleeb and Gaur, 2021).

Implication: Measure readiness (leadership, infrastructure, training, data culture) and barriers (cost, skills, privacy/security, resistance, fragmentation) explicitly and test the role that they play as moderators in the intention use and use performance links.

- iii. **Emerging market environment and frictions:** Most of the literature does not consider new market constraints such as legacy ERP and fragmented CRM, ad hoc data stewardship, skills gaps, cost sensitivity, and privacy/security issues characterizing the limits of adoption and effectiveness in India (Vial, 2019; Wadhwa, Andaleeb and Gaur, 2021). Practically all successful playbooks take mature data platforms and pools of analytics talent for granted.

Implication: Explicitly measure readiness (leadership, infrastructure, training, data culture) and barriers (cost, skills, privacy/security, resistance, fragmentation) for their moderating influences on the intention to use and use performance relationships.

- iv. **Limited comparative benchmarking:** Few studies have directly compared AI-enabled and traditional sales approaches in the chemical industry using B2B indicators such as forecast error, hit rate, margin leakage, and cycle time (Chatterjee et al., 2021). Existing examples are largely descriptive, creating a need for systematic, sector-specific evidence using both comparative perceptions and measurable performance bands.
- v. **Institutional legitimacy and explainability in regulated B2B settings:** Although service-oriented AI research emphasizes explainability and auditability, fewer studies specify the governance artifacts required for industrial pricing and forecasting, such as traceable quotation histories, versioned model documentation, and recorded override reasons for pricing committees (Huang & Rust, 2021).

Implication: document governance practice drift monitoring, explainability, override logging), and test the connections between document governance practices and adoption maturity and performance.

- vi. **Pilot success versus routinized diffusion:** Although there are numerous accounts of successful pilots, limited evidence explains the conditions under which a pilot progresses from a regional or product-specific experiment to an organizational routine. Long-term value requires standardized processes, role clarity, training, governance, and learning mechanisms that support the transition from experimentation to institutionalized use of the technology.

Implication: Adoption-Maturity scale (pilot > embedded) and test the maturity-strengthening the use > KPI channel.

- vii. **Identity and Incentive Incompatibility:** Literature that recognizes cultural resistance but does not refer to identity threat (sense of displacement of tacit sales judgement) and incentive misfit (KPIs punishing following AI price corridor).

Implication: Establishing the relationships between adoption maturity and performance by testing the relationships between document governance maturity practices (drift monitoring, explainability, and override logging) and maturity practices.

The micro–meso–strategic model combines beliefs and norms from the TRA, TAM, and UTAUT; repeated and institutionalized use from the DOI; socio-technical fit and legitimacy; and capability realization from the Resource-Based View (Vial, 2019; Huang and Rust, 2021). The instrument operationalizes organizational readiness, perceived barriers, adoption maturity, governance maturity, user acceptance, AI use, and performance so that the mechanisms identified in the literature can be tested in the Indian chemical B2B context.

2.3.6 Operationalization Guide

- i. **Latent constructs** should be measured using reflective Likert scales (1-5). There should be three or more items on a construct.
- ii. **Develop composite scores** (average of the averages of all facets) for multi-faceted constructs (e.g., Readiness, Barriers).

- iii. **Reliability (Cronbach's $\alpha = 0.70$)** and validity (CFA: loading = 0.60, AVE = 0.50, HTMT = 0.85) were assessed.
- iv. **Eliminate common method bias:** temporal separation (where possible), mixed-scale anchors, anonymous guarantees, and marker variables.

Table 2.2 Operational descriptions and suggestive measures (summarized for instrument alignment)

Construct	Definition	Indicative measure
AI adoption maturity	Extent of AI routinised in sales processes	1–5 staged scale (pilot - embedded)
Organizational readiness	Leadership, data infrastructure, training, data culture	Likert items (1–5), composite index
Barriers	Costs, skills, privacy/security, resistance, fragmentation	Severity scale (1–5), composite index
TAM beliefs	Usefulness & ease of use	Standardized Likert items (1–5)
AI use (behavior)	Frequency and breadth of AI features used in sales	Self-report scale, usage breadth
Sales performance	Forecast accuracy, conversion, CSAT, margin, cycle time	Self-reported change bands / index

Source: Author

2.4 Explanation and Operationalization of Foremost Hypotheses

To ensure conceptual clarity and consistency, the following key constructs are defined and operationalized.

In this study, adoption refers to the AI tools that have been formally adopted in the organization, as opposed to the level or efficiency of their adoption.

ii. AI Use refers to the real and habitual use of AI-powered tools by sales staff in their daily operations, such as prediction, price assistance, lead rating, or prospects. Adoption signifies the existence of AI systems, whereas use denotes behavioral interaction with systems at the operational level.

iii. AI Adoption Maturity is the level at which AI adoption has moved past the early stages of adoption to organized, integrated, and institutionalized adoption processes. Maturity in adoption represents the depth, consistency, and strategic embedding of AI in organizational sales processes.

iv. AI Governance Maturity refers to the formal policies, ethical standards, accountability structures, explainability requirements, audit mechanisms, and oversight procedures that govern responsible AI use. Future Readiness refers to an organization's strategic intent and capability to extend AI use through continued investment, learning, reskilling, and technological adaptation. In the RQ4 measurement model, the two survey items were combined as Governance Maturity and Future Readiness (GMFR), a two-item construct representing responsible oversight and strategic preparedness for continued AI-enabled performance.

These definitions are used consistently throughout the thesis to distinguish implementation decisions (AI adoption), actual behavioral engagement (AI use), developmental stage (AI adoption maturity), governance quality (governance maturity), strategic adaptability (future readiness), and the combined GMFR construct used in the RQ4 regression model.

2.5 Hypotheses

Eight hypotheses were formulated based on the theoretical framework, research questions, and empirical model. The hypotheses correspond directly to the analyses reported in Chapter IV and distinguish the predictors of AI adoption, predictors of sales

performance, and the direct and moderating effects tested for comparative sales performance.

H1 (Organizational Readiness → AI Adoption): Organizational readiness, comprising leadership support, digital and data infrastructure, employee training, and a data-driven culture, has a positive and significant effect on AI adoption in sales.

H2 (Perceived Barriers → AI Adoption): Perceived barriers, including cost, skills shortages, data privacy and security concerns, resistance to change, and process fragmentation, have a negative and significant effect on AI adoption in sales.

H3 (Governance maturity → AI adoption): Governance maturity, reflected in formal policies, accountability, explainability, auditability, and oversight, has a positive and significant effect on AI adoption in sales.

H4 (Perceived Usefulness → Sales Performance): Perceived usefulness has a positive and significant effect on the Sales Performance Index.

H5 (Perceived Ease of Use → Sales Performance): Perceived ease of use has a positive and significant effect on the sales performance index.

H6 (AI Use → Comparative Sales Performance): AI use has a positive and significant effect on comparative sales performance.

H7 (GMFR → Comparative Sales Performance): The combined governance maturity and future readiness construct has a positive and significant effect on Comparative Sales Performance.

H8 (AI Use $\times$ GMFR $\rightarrow$ Comparative Sales Performance): The combined Governance Maturity and Future Readiness construct positively moderates the relationship between AI use and comparative sales performance.

Together, these hypotheses provide a coherent analytical framework for examining how organizational conditions influence AI adoption, how user perceptions influence sales performance, and how AI use and GMFR jointly shape the comparative sales performance. The same wording and numbering are used in Chapters III–VI.

2.6 Summary

This chapter develops an internally consistent, multilevel theoretical framework explaining the conditions under which Artificial Intelligence (AI) adoption leads to quantifiable and justifiable performance improvements in strategic sales management within mid- and large-scale chemical manufacturing companies in India.

Micro level (individual logic of adoption); The Theory of Reasoned Action and its derivatives of the IT (TAM/UTAUT) at the level of sales practitioners and first-level managers dictate the belief-intention-behavior pathway that transforms the sellers into long-term adoption of AI. The day-to-day use of AI-enabled forecasting, account planning, qualification, and pricing is explained by four levers: perceived usefulness, ease of use, social influence, and enabling conditions.

This chapter clarifies that the strength of these levers is enhanced by embedding capability-building activities in recurrent sales rituals (QBRs, deal reviews, pricing approvals), embedding incentives and credit on AI-supported wins, and embedding AI touch points in sales rituals. In identity-sensitive and relationship centric B2B selling, this

micro-logic avoids the intention-behavior gap by making AI explainable, auditable, and professionally legitimate. Meso level (between pilots and routines).

On the organizational process level, Diffusion of Innovations and socio-technical/institutional perspectives explain how firms move from promising pilots to routinized usage throughout the organization. The fit between the social subsystems (roles, skills, incentives, norms, and governance maturity) and technical subsystems (data pipelines, models, and platforms) are the drivers of success. This chapter describes the enabling mechanism: Sales-to-Supply and Finance end-to-end signal flow; role redesign sales operations; cadence-based model and data governance maturity (drift monitoring, override logs, versioning); and institutional legitimacy through explainability and audit trails that are acceptable to both internal audit and external buyers. These processes convert episodic tool utilization into a different stable operating process, which elevates the level of adoption maturity from piloting to full embedding.

Strategic level (realization of potential and advantage): The Resource-Based View is applied when describing the heterogeneity of the outcomes, which are manifested in the case of supposedly similar adopters at the firm strategy level. When integrated into a VRIO capability, valuable (accurate forecasting, discipline of margins, reduction of cycle time), rare/inimitable (specific data assets of the firm, domain-specific modelling, deep integration of workflow), and organized (governance maturity, incentives, and change management that can systematically exploit the assets), AI can develop sustainable advantages.

In the case of chemicals, long cycle, specification-intensive, compliance-intensive, curated historical quotes, spec sheets, and customer technical preferences represent strategic data assets that increase the signal in the predictive model and enable sales performance improvements to become defensible instead of generic.

Gap diagnosis, sector-specific: The literature fails to provide in the Indian chemical context: (i) under-representation of heavy industrial B2B with multi-stakeholder, technical buying, and long approval cycles; (ii) emerging market frictions (legacy ERPs, fragmented CRMs, skills scarcity, cost sensitivity, and privacy/security concerns) which precondition the intensity of adoption and realized impact; (iii) lack of comparative evidence benchmarking AI-enabled versus traditional sales strategies on B2B KPIs (forecast MAPE). To fill these gaps without being overly complex, this chapter simplifies an empirically testable model based on the following eight hypotheses:

H1: Organizational readiness positively predicts AI adoption in healthcare.

H2: Perceived barriers negatively predict AI adoption in dentistry.

H3: Governance maturity positively predicts AI adoption in the public sector.

H4: Perceived usefulness positively predicts the sales performance index.

H5: Perceived ease of use positively predicts the sales performance index.

H6: AI use positively predicts comparative sales performance.

H7: The combined Governance Maturity and Future Readiness constructs positively predict comparative sales performance.

H8: The combined Governance Maturity and Future Readiness constructs positively moderate the relationship between AI use and comparative sales performance.

The resulting design preserves the micro-, organizational-, and strategic-level logic of the study while remaining statistically manageable for a sample of 170 respondents and contextually relevant to Indian chemical B2B sales. Reliability and validity were assessed using Cronbach's alpha, composite reliability, average variance extracted, and discriminant validity criteria, including Fornell–Larcker and HTMT. The model is operationalized in Chapter III and tested in Chapter IV.

Multiple hierarchical moderation analysis were used to test the hypothesized direct and interaction effects while controlling for firm size, product complexity, market volatility, IT intensity, regional mix, and respondent tenure. Qualitative thematic analysis was used to explain the mechanisms underlying the quantitative relationships.

CHAPTER III: METHODOLOGY

3.1 Overview of the Research Problem

India's mid- and large-scale chemical manufacturing companies deal in complex, specification-heavy B2B markets, where lengthy sales cycles, multi-stakeholder purchasing, and stringent compliance requirements make accurate forecasting, disciplined pricing, and reliable pipeline management essential for success. Over the past five years, companies have increasingly introduced artificial intelligence (AI) into their commercial workflows. AI-CRM lead scoring, propensity models, demand-sensing forecasts, dynamic price corridors, and NLP-enabled customer engagement. However, despite their widespread use, organizations have reported inconsistent real-world effectiveness.

This study bridged this performance gap. It investigated how and in what organizational circumstances AI in sales was associated with quantifiable sales performance gains in Indian chemical B2B under conditions of individual (usefulness, ease, norms, and facilitating conditions), organizational (between pilots and routinized use), socio-technical (new roles, skills, governance maturity, and data), and strategic (VRIO) fit. It was in response to four sector-specific challenges: (1) long cycle, technical buying; (2) legacy IT and data fragmentation; (3) identity and incentive alignment of experienced sellers; and (4) institutional legitimacy requirements, such as explainability and auditability.

3.2 Operationalization of Theoretical Constructs

This section translated the multilevel framework into measurable variables, scales, and indices that could be used for quantitative testing of the 170-response dataset. The constructs were mainly reflective (beliefs and perceptions), and two composite indices (Readiness and Barriers) were used to summarize several subdimensions. The item wording was modified to suit the Indian chemical B2B sales situation while retaining the conceptual essences developed within TRA/TAM/UTAUT, DOI, RBV, and socio-technical/institutional. All latent constructs were measured using a 5-point Likert scale (1 = Strongly disagree, 5 = Strongly agree). KPI changes were captured using ordered response bands.

Key terms:

i. Adoption: Adoption refers to the first decision and intention of an organization or sales professional to use AI-enabled tools. This shows that the organization has made a choice regarding the use of AI and has started to use it.

ii. Adoption maturity: Adoption maturity is defined as the degree or level of development or implementation of AI in an organization. This shows whether AI is applied to pilot projects or whether it has been implemented and institutionalized throughout the sales processes, KPIs, and decision-making routines.

iii. Governance maturity: Governance maturity refers to the systems and policies that guarantee the ethical, responsible, and transparent application of AI. This entails explaining AI outputs, data responsibility, auditing, and readiness to manage AI in a secure and reliable manner.

3.2.1 Adoption Drivers (TAM/UTAUT)

Perceived Usefulness (PU): Four items on the improvement of sales performance were included. The nine questions were as follows: Social Influence (SI): three items; Facilitating Conditions FC 4 items (resources/training/support) where applicable, the factor that loaded onto with the PU, PEOU, SI, and FC to maintain thrift was a second-order Adoption Drivers factor.

3.2.2 Organizational Readiness

Organizational readiness was conceptualized as a higher-order capability enabling the transition of the effects of AI initiatives from pilots to routinized use through the alignment of leadership intent, data/technology foundations, workforce enablement, and decision culture. Readiness is widely identified as a precondition for digital transformation

and the routinization of analytics/AI for commercial processes (Fountainne, McCarthy and Saleh, 2019; Vial, 2019). The construct was described as a second-order composite of four first-order reflective facets:

i. Leadership Commitment: Signals of senior sponsorship, such as visibility in sales governance maturity rituals (e.g., quarterly business reviews), elements of explicit sales performance expectations, and allocation of resources for AI usage. Leadership signaling is theorized to influence subjective norms and alleviate uncertainty when changes are imminent (Venkatesh et al., 2003; Fountainne et al., 2019).

ii. Data/Tech Integration: Perceived properness of CRM/ERP integration with AI functions, accessibility to system-enforced price corridors/approvals, and the predictability of data streams supplying forecasting and opportunity models. Integration quality is a known boundary condition for the realization of AI utility (Davenport and Ronanki, 2018; Vial, 2019).

iii. Training and Enablement: Access to role-specific training, job aids/playbooks, and coaching loops that develop interpretive skills on model outputs (confidence bands, drivers). Enablement maintains use by reducing effort expectancy and raising the sense of control (Davis, 1989; Fountainne, McCarthy and Saleh, 2019).

iv. Data-Driven Culture: The regular expectation that sales decisions will be informed by data or AI-based evidence, overrides will be constructively reviewed, and AI-assisted successes will be recognized. Such norms support institutionalization and identity-safe adoption (Huang and Rust 2021; Vial 2019).

3.2.3 Adoption Maturity (DOI Ladder)

Respondents chose the level that best described their firm's sales AI status.

- i. Pilot:** restricted to a single team/region and ad hoc use
- ii. Limited rollout:** manifold teams/regions, incomplete playbooks
- iii. Playbooks (enterprise guidelines):** monitoring

3.2.4 Scoring, Data Quality and Validity Plan

All survey responses were exported to SPSS and screened for completeness prior to scoring. Reverse-keyed items were recoded to maintain common directionality, and negatively worded statements particularly within the Barriers scale were normalized before composite scores were calculated. Composite variables were computed as the means of their constituent items. To reduce common method bias, the questionnaire used clear instructions, varied item wording, anonymity assurances, and statistical screening consistent with established procedural guidance (Podsakoff et al., 2003).

Convergent validity was established when (i) standardized loadings were at least 0.60, (ii) Average Variance Extracted (AVE) was at least 0.50, and (iii) $CR > AVE$. Discriminant validity was checked using multi-level Fornell-Larcker criterion and HTMT ratios (< 0.85) for conceptual distinctness among the neighbouring constructs, such as readiness and facilitating conditions (Venkatesh et al., 2003; Vial, 2019). Common Method Variance and Procedural Controls: Procedural safeguards, such as neutral item wording, varied scale anchors, anonymity, and separating predictor and criterion blocks, were incorporated during the design of the questionnaire (Davenport and Ronanki, 2018). Measurement invariance and robustness: To confirm that the latent constructs worked in the same way between subgroups (i.e., leadership and frontline firms, mid-large firms), measurement

invariance was assessed in succession (configural, metric, scalar). When the difference between the models (Delta CFI) was <0.01 , the test indicated acceptable invariance (Hair et al., 2019). These analytic steps ensured that all constructs were psychometrically sound, minimizing random error and bias in addition to meeting the requirements of subsequent estimation (Barney, 1991; Vial, 2019).

3.3 Research Purpose and Questions

This study aims to explain and quantify the impact of AI adoption in sales functions on the commercial performance of mid- and large-scale chemical manufacturing firms in India and identify the organizational conditions under which such effects are realized.

i. Measurement: Triangulation of reflective constructs and composite scores (1, CR, AVE, and HTMT).

ii. Estimate the effects of Adoption: Drivers/Readiness/Barriers on AI Use and AI Use on Sales performance.

iii. Context/Fit: Test amplification by adoption and governance maturity.

iv. Diagnostic: Identify bottlenecks/enablers using NVivo themes.

v. Actionable: Create a maturity readiness matrix for managerial actions.

Research Questions

This study examines the extent, determinants, and performance outcomes of artificial intelligence (AI) adoption in the sales functions of mid- and large-scale chemical manufacturing firms in India. This study focuses on organizational readiness, perceived barriers, perceived usefulness, perceived ease of use, governance maturity, and future readiness as factors influencing AI adoption and sales performance.

RQ1: To what extent have mid- and large-scale chemical manufacturers in India adopted AI applications in their sales processes?

RQ2: How do organizational readiness, perceived barriers, and governance maturity influence AI adoption in the sales functions of chemical manufacturers in India?

RQ3: What are sales professionals' perceptions of the usefulness and ease of use of AI-enabled tools, and to what extent do these perceptions affect measurable sales performance outcomes?

RQ4: Do AI-enabled sales strategies perform better than traditional sales strategies, and do Governance Maturity and Future Readiness strengthen the relationship between AI use and comparative sales performance?

Table 3.1 Representing Research Question and Hypothesis

Research Question	Corresponding Hypotheses
RQ1: To what extent have mid- and large-scale chemical manufacturers in India adopted AI applications in their sales processes?	Descriptive assessment of the extent and maturity of AI adoption; no directional hypothesis.
RQ2: How do organizational readiness, perceived barriers, and governance maturity influence AI adoption in the sales functions of chemical manufacturers in India?	H1: Organizational readiness positively affects AI adoption. H2: Perceived barriers negatively affect AI adoption. H3: Governance maturity positively affects AI adoption.
RQ3: What are sales professionals' perceptions of the usefulness and ease of use of AI-enabled tools, and to what extent do these perceptions affect measurable sales performance outcomes?	H4: Perceived usefulness positively affects the Sales Performance Index. H5: Perceived ease of use positively affects the Sales Performance Index.
RQ4: Do AI-enabled sales strategies perform better than	H6: AI use positively affects comparative sales performance.

traditional sales strategies, and do Governance Maturity and Future Readiness strengthen the relationship between AI use and comparative sales performance?	H7: Governance Maturity and Future Readiness positively affects comparative sales performance. H8: Governance Maturity and Future Readiness positively moderates the AI use–comparative sales performance relationship.
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Source: Author

To achieve conceptual clarity and methodological alignment, each research question was mapped to the corresponding analysis and hypotheses. RQ1 is descriptive and therefore does not require a directional hypothesis. RQ2 was tested through the direct effects of organizational readiness, perceived barriers, and governance maturity on AI adoption. RQ3 examines the effects of perceived usefulness and perceived ease of use on the Sales Performance Index. RQ4 tests the direct effects of AI use and the combined Governance Maturity and Future Readiness (GMFR) construct on comparative sales performance, together with their interaction.

This mapping informed the empirical model and ensured that every hypothesis corresponded to an analysis reported in Chapter IV. It connects adoption conditions to AI adoption, technology acceptance beliefs to sales performance, and AI use and GMFR to comparative sales performance without introducing untested relationships.

3.4 Research Design

This study used a quantitatively dominant mixed-methods approach complemented by qualitative thematic analysis. The quantitative part involved a cross-sectional survey of *170 respondents from mid- and large-scale chemical manufacturing companies in India*. The survey responses were analysed using SPSS for descriptive statistics, reliability and validity tests, correlation, multiple regression, and hierarchical regression/moderation.

The qualitative component was based on email/online messages from eight senior professionals in the field. These were coded using *the NVivo 14* software. The results of the qualitative analysis were used to explain and complement the quantitative findings, particularly regarding organizational readiness, perceived resistance, governance maturity, training, trust, and institutionalization of AI-enabled sales practices in the banking sector.

The study design was suitable because the analysis needed to test the hypotheses statistically and explain the context of AI adoption in industrial sales. The quantitative findings offered evidence of associations among the constructs, while the qualitative analysis offered insights into how adoption, resistance, governance maturity, and performance were achieved. The overall research design involved quantitative statistical analysis using *SPSS and qualitative thematic analysis using NVivo 14*.

3.4.1 Data Integration (Mixed-Methods)

Data integration followed a sequential explanatory mixed-methods logic (Creswell & Plano Clark, 2018). The quantitative results guided the selection and interpretation of qualitative responses, with particular attention to contrasting levels of readiness, barriers, and sales performance. The eight senior professional responses were coded in NVivo 14 using a reflexive thematic procedure that combined deductive constructs from the conceptual model with inductive patterns emerging from the data (Braun and Clarke, 2019).

3.5 Population and Sample

3.5.1 Target Population

The target population for this research was professionals engaged in the sales function of mid- and large-scale chemical manufacturing companies in the Indian market. This population comprised crucial managerial and operational players involved in sales planning, customer acquisition, pricing strategy, and revenue management, especially those exposed to or involved with artificial intelligence (AI)-enabled systems, such as predictive forecasting, CRM analytics, and dynamic pricing algorithms. By targeting this segment, the research covered the experiences of professionals who are in the best position to assess the enabler and inhibitor factors of AI assimilation in industrial selling scenarios in India.

3.5.2 Inclusion Criteria

Participants were included in the study if they met the following criteria:

- i. Employment affiliation:** Participants were employed full-time in chemical manufacturing organizations registered and operating in India.
- ii. Functional role:** They held the positions in the sales function e.g., Sales Leadership (like Vice President, General Manager or Regional Head), Key Account Management (KAM)/Frontline Sales or Sales Operations and Analytics thus ensuring exposure to AI-supported decision systems
- iii. Technology exposure:** They had first-hand experience with any AI-enabled sales or marketing tool (for example, AI-integrated CRM, predictive systems, dynamic pricing or

revenue management solutions, or AI-based customer engagement platforms) (Shankar and Jain, 2024).

iv. Tenure: They had a minimum of six months of continuous tenure in their present job to ensure adequate familiarity with internal sales systems, workflows and sales performance outcomes.

v. Ethical compliance: Informed consent was obtained from all participants, which included voluntary participation and understanding of data confidentiality and the purpose of the research (Creswell and Plano Clark, 2018).

3.5.3 Population and Sampling Frame Accessibility

The accessible population, or the proportion of the target population that could realistically be communicated with during the study period using available resources, was identified using a combination of professional networks, industry associations, and prepared firm lists. Specifically, potential respondents were identified by LinkedIn professional groups related to chemical manufacturing and B2B sales, industry associations, and chambers of commerce. The Indian Chemical Council (ICC) and Confederation of Indian Industry (CII); minimal variety of corporate directories and trade portals, which maintain listings of mid- and large-scale Indian manufacturers; and variations of controlled snowball referrals, initial participants suggested others in similar sales positions, subject to screening.

3.5.4 Sampling Strategy

Given the theory-testing orientation of the study and the need for coverage of organizational strata, a purposive stratified sampling strategy was employed. Stratification

ensured maximum heterogeneity across the following key dimensions: The target sample size was set at a minimum of 150 valid responses based on established norms for adequacy, suggesting at least 10 cases of each estimated parameter (Hair et al., 2019). This requirement was achieved with $n = 170$ full and usable responses after data cleaning.

3.5.5 Demonstrative and Generalisability

Analytical generalization rather than statistical generalization was pursued in this study, in keeping with post-positivist logic (Creswell and Plano Clark, 2018). The aim of this study was not to estimate population parameters but to justify theoretical relationships and their use in similar industrial scenarios.

Non-response bias was also tested as a method of guaranteeing the integrity of the response (early- and late-respondent comparison approach). Respondents who completed their surveys during the first week were compared with those who responded later during the collection window.

3.5.6 Ethical and Data Protection Issues

Participation was voluntary. Respondents received information about the purpose of the study, confidentiality, data use, and their right to withdraw before providing informed consent. Personally, identifying information was not reported, and the data were used only for academic purposes. These procedures were consistent with accepted mixed-methods research ethics and informed-consent principles (Creswell and Plano Clark, 2018).

3.6 Participant Selection

Participant recruitment was implemented through a multichannel approach aimed at reaching various professionals in the mid- and large-scale chemical manufacturing sector in India. The procedure involved direct outreach, curated listings, and controlled referrals between peers to obtain relevance and heterogeneity.

First, direct outreach was made through professional networks, such as LinkedIn, industry association mailing lists, and executive groups linked to the Indian Chemical Council (ICC), Confederation of Indian Industry (CII), and regional chambers of commerce. **Second**, the researcher used curated firm lists, such as verified databases of chemical manufacturers sourced from industrial directories and trade registries. **Third**, a controlled snowballing method was used, whereby the initial participants were asked to nominate other people from different divisions, functions, or regions. Each referral was screened separately to avoid recruiting from the same firm cluster (Hair et al., 2019).

All summons materials contained a brief description of the study's aims, estimated completion time (approximately 12–15 minutes), eligibility criteria, data confidentiality guarantees, and the rights of study participants to withdraw from the study without penalty. The multichannel recruitment process maximized reach, ensured sectoral relevance, and reduced bias that might occur from single-source recruitment (Creswell and Plano Clark, 2018; Vial, 2019).

3.6.1 Verification of Eligibility and Screening

Eligibility was checked using gate screening items in the initial part of the questionnaire. These items were used to ensure that the respondents were consistent with the inclusion criteria set out in Section 3.5.2.

Assuming that many chemical companies have several business units or regional offices, there was a possibility of having multiple respondents from the same firm in the survey. Where the same metadata (e.g., timestamp, IP subset, and same responses from the same data) were found, duplicates were removed from the final data set. In the case where we had more than one valid response per firm but with different roles, cluster-robust standard errors or sensitivity checks were planned to mitigate the issue of dependence at the firm level during the estimation (Hair et al., 2019).

3.6.2 Data Quality Controls

Several measures of data quality were built into the survey design and analysis workflow to ensure that the outcome measures were valid. Consideration and consistency checks were included in the questionnaire, such as one direct instruction item ("select 'Agree' to confirm attention") and one reverse-keyed statement within each construct block. A minimum completion time threshold was determined as 30–40% of the median completion time by the pilot.

Responses below this threshold were flagged as potentially satisficing and were manually reviewed. Straight-lining detection was performed by visually looking for patterns of responses and variance scores among Likert items. Cases with excessive missing data (>20% focal constructs were removed with admissible missing data (<5%) in expectation-maximization (EM) in SPSS to maintain statistical power (Hair et al., 2019).

3.7 Instrumentation

The study used a structured, self-administered questionnaire designed using Google Forms as the main source of data collection. The design was based on the theoretical framework set out in Chapter II, which included constructs from the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), Diffusion of Innovations (DOI), and Resource-Based View (RBV). The final questionnaire had eight logically ordered sections matching the eight domains of the conceptual model.

- i. Screening and consent, eligibility, and ethics.
- ii. Adoption Barriers (Obstacles, Resistance)
- iii. Readiness and Barriers.
- iv. Adoption Maturity and AI Use
- v. Sales Performance (KPIs);
- vi. Control Variables (firm size, market volatility, IT intensity, and region)
- vii. Open-Ended Qualitative Items; and
- viii. Demographics (role, employment duration, and experience).

All items, except were stated otherwise, utilized five-point Likert-type scales (1 = Strongly Disagree to 5 = Strongly Agree).

3.7.1 Develop Operationalization and Item Pools

Each reflective construct in the model was operationalized using three or more indicators adapted from validated scales or conceptually derived from existing literature. The scale items of Perceived Usefulness and PEU (Davis, 1989) and Social Influence and

Facilitating Conditions (Venkatesh et al., 2003) were used to measure Adoption Drivers. Barriers were created into a composite index based on reflective sub-scales of Cost Constraints, Skills Gaps, Privacy/Security Concerns, Resistance/Identity Threats, and Fragmentation (Chatterjee et al., 2021).

3.7.2 Pre-Testing and Skilled Evaluation and Trial

Instrument development involved a three-step validation process.

i. Cognitive pretest: Approximately 8–10 respondents from the target population were asked to participate in a cognitive walkthrough, verbalizing their interpretation of each question.

ii. Expert Review of the Draft Instrument: Two academic experts in the fields of human resource management (HRM) and the use of AI to study business processes and one practitioner from a large chemical company reviewed the draft instrument for content validity, construct coverage, and wording accuracy.

iii. Pilot Test: To 20-30 respondents were used to test the average time to complete, item variance, and initial reliability (Cronbach's $\alpha > 0.70$). Minor lexicographic changes (e.g., simplification of technical terms and increased consistency between construct blocks) were made after the pilot test.

3.7.3 Scoring rules, Contrary Coding and Composites

All answers were coded numerically for analysis. Reversed-keyed items (i.e., negatively phrased barriers) were recoded before scoring to ensure that the direction of interpretation was consistent. Construct scores were calculated as mean indices or factors; readiness and barriers were standardized composite indices calculated from subdimension

means. AI Use (ordinal coding) and breadth (number of domains per week or more). Given that the respondents were Indian professionals and were mostly comfortable with English as a business communication tool, the instrument was administered in English only. Nevertheless, important domain-specific abbreviations and acronyms were briefly explained in-line to avoid misinterpretation. Examples include: QBR= Quarterly Business Review; MAPE is the acronym for Mean Absolute Percentage Error (forecast accuracy metric). This qualitative extension helped to strengthen the interpretation so that statistical relationships could be placed in the context of real-world mechanisms and narratives.

3.8 Data Collection Procedures

3.8.1 Timeline for Enrollment and Research

Data were collected using an online survey instrument designed on Google Forms and sent out via a combination of professional networks, industry associations, and targeted outreach. The recruitment channels included LinkedIn, mailing lists of the chemical industry, and curated databases of mid- and large-scale Indian chemical manufacturers. Periodic monitoring of data as they came in ensured a balanced representation across organizational roles, firm sizes, and regions so that over-sampling was not an issue from any one cluster.

3.8.2 Informed Accord and Ethical Protection

Ethical considerations were included in the fieldwork process. The survey's landing page offered a brief but thorough description of the academic purpose of the survey, scope of data use, rights of voluntary participation, and confidentiality provisions. Participants

were clearly advised that eligibility verification was built into the first section of the form by way of screening items that verified the following:

- i. affiliation to the industry (chemical manufacturing only)
- ii. professional role in the sales function, and
- iii. an assignment of responsibility of 6 months or longer, and
- iv. exposure to AI-enabled sales systems

Respondents who did not meet these criteria were automatically redirected to a closing message thanking them for their time and explaining that they did not meet the study requirements.

3.8.3 Quality Assurance While in the Field

During fieldwork, quality-control procedures were used to protect response integrity. Attention and consistency checks were embedded in the instrument, and problematic response patterns were flagged. Device-compatibility testing confirmed that the form displayed appropriately on laptops, tablets, and smartphones. After the target sample was reached, the form was closed, and responses were exported to a Microsoft Excel (.xlsx) file. Each record received a unique anonymized respondent ID, and firm identifiers were replaced with masked codes to prevent traceability.

3.9 Data Analysis

The analysis was aligned with the four research questions and eight hypotheses. Survey data from 170 respondents were screened for completeness, coding accuracy, missing values, and response consistency. Negatively worded items were reverse-coded where necessary. Composite measures were then calculated for organizational readiness,

perceived barriers, AI adoption, perceived usefulness, perceived ease of use, Sales Performance Index, AI use, comparative sales performance, and Governance Maturity and Future Readiness (GMFR).

The quantitative survey data were analyzed using SPSS. The analysis included *descriptive statistics, reliability testing, validity assessment, Pearson's correlation analysis, multiple regression, and hierarchical regression for moderation testing*. The qualitative responses obtained from eight senior professionals were analyzed using NVivo 14 through thematic coding. A combination of *deductive and inductive coding* was used to identify recurring themes related to organizational readiness, perceived resistance, governance maturity, training, trust, and the institutionalization of AI-enabled sales practices. This analytical approach ensured methodological clarity, consistency, and alignment with the study's quantitatively dominant mixed-methods research design.

SPSS was used to summarize demographic characteristics and construct distributions, assess reliability and validity, calculate Pearson correlations, and estimate multiple-regression and hierarchical-regression models. H1–H3 were tested using AI-adoption regression models. H4 and H5 were tested using a regression model predicting the Sales Performance Index. H6 and H7 were tested through the main effects in the hierarchical model, and H8 was tested through the AI Use $\times$ GMFR interaction. Control variables included firm size, product complexity, market volatility, IT intensity, regional mix, and tenure.

The hypothesis-testing sequence was as follows: organizational readiness, perceived barriers, and governance maturity as predictors of AI adoption (H1–H3);

perceived usefulness and perceived ease of use as predictors of sales performance (H4–H5); and AI use, GMFR, and their interaction as predictors of comparative sales performance (H6–H8). Each test is reported in the corresponding table in Chapter IV.

Qualitative responses from eight senior professionals were analyzed in NVivo 14 using deductive and inductive coding. Deductive codes reflected the study constructs readiness, barriers, usefulness, ease of use, governance maturity, future readiness, and performance, while inductive codes captured additional mechanisms emerging from the responses. The qualitative findings were integrated with the quantitative results to explain leadership support, training, trust, resistance, governance, and process integration.

3.10 Research Design Limitations

This study had some limitations. First, the use of cross-sectional and self-reported data excludes the underlying evidence. Second, the use of perceptual actions may vary from objective measures of organizational performance. Third, non-probability sampling may affect the representativeness of the sample beyond mid- and large-scale chemical manufacturing companies in India. Fourth, some variables, such as AI adoption maturity and governance maturity, were measured using ordered response scales, which may delay interval interpretation. Fifth, the evolution of AI tools may affect the relevance of the results. These were addressed by reporting them, taking a conservative approach to interpretation, and supplementing the quantitative insights with qualitative information.

3.11 Conclusion

Chapter III outlines the research design of the study and how the research questions and hypotheses were addressed through a well-integrated mixed-methods approach. This chapter outlines the research design, population and sampling, instrumentation, data collection, and ethical considerations of the study. This involved a systematic process of survey data collection, data screening, and descriptive analysis in SPSS, reliability and validity testing, correlation, multiple regression, hierarchical moderation, and qualitative thematic analysis using NVivo 14 software. These processes ensured methodological, conceptual and analytical integrity. Chapter (IV) reports the empirical results of the study.

CHAPTER IV: RESULTS

4.1 Demographic Profile of Respondents

A total of $n = 170$ valid responses were analyzed. The sample shows adequate heterogeneity in terms of the type of organization, role, experience, and region, which is necessary for robust inferential analysis (Hair et al., 2019).

4.1.1 Note on below Table Values Blank or Non-Applicability

Chapter IV covers tables with blank or unfilled cells. These blanks refer to values that were not applicable to the particular analysis, estimated not to be considered about the model specification, or that these values were deliberately omitted to preserve analysis

clarity and avoid unnecessary reporting. Thus, blank cells do not indicate missing data or incomplete analysis.

Organization Type

Of the 170 respondents, approximately 62% were from mid-scale chemical firms and 38% were from large-scale manufacturers.

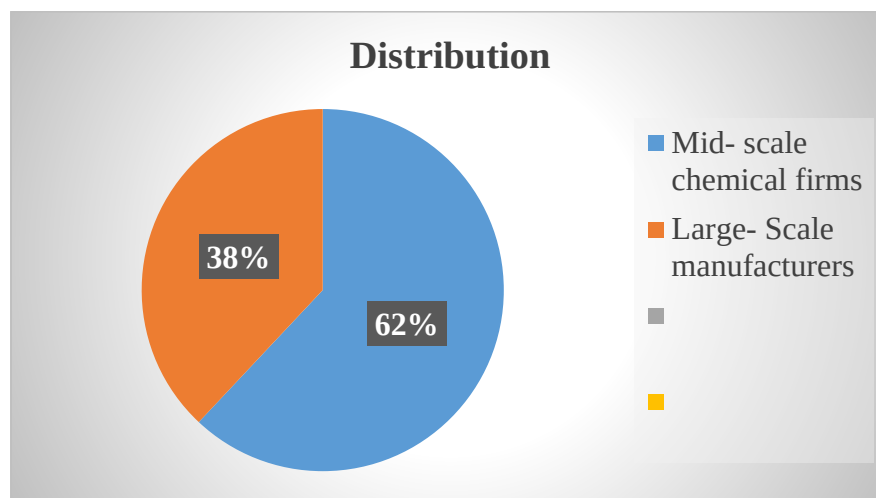


Figure 4.1 Distribution of Organization Type

Source: Author

Role Respondents represented diverse roles, as illustrated in Figure 4.2: Data/CRM Analyst (34 %), Sales Head (22 %), Sales/Marketing Manager (21 %), and Other/Support (23 %).

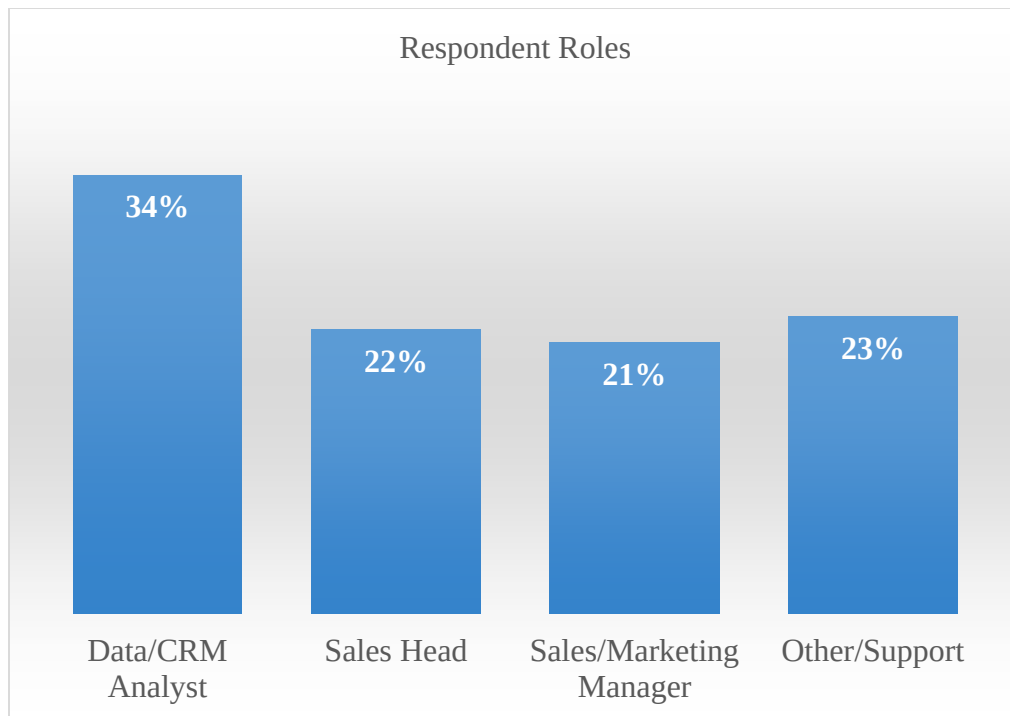


Figure 4.2 Role Distribution Across Respondents. Source: Author

Years of Experience

Nearly half of the respondents had **8–12 years of experience** (47 %), followed by **4–7 years** (21 %), **13–20 years** (18 %), **0–3 years** (9 %), and **20 + years** (5 %).

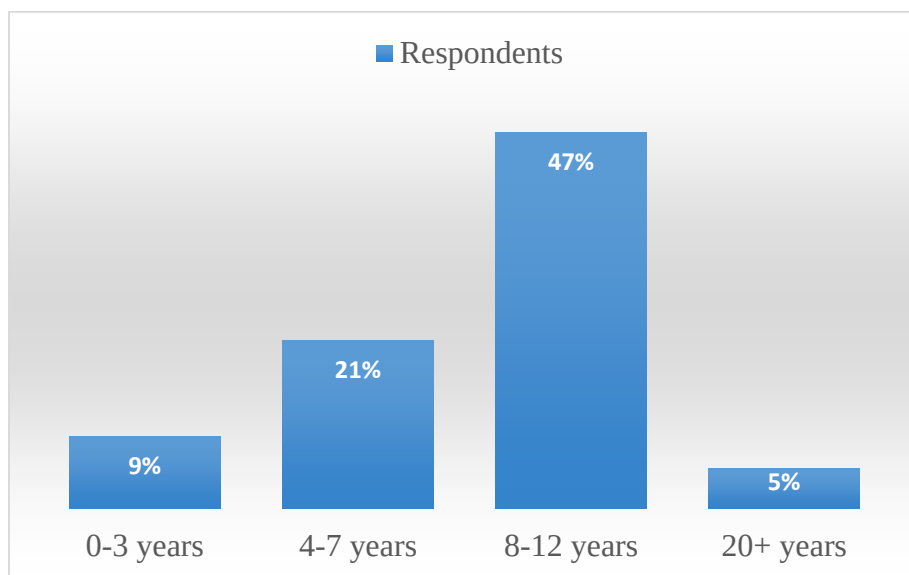


Figure 4.3 Experience Distribution

Source: Author

Region

Participants were distributed across India as follows: West (29 %), South (27 %), North (22 %), East (14 %), and Pan-India (8 %).

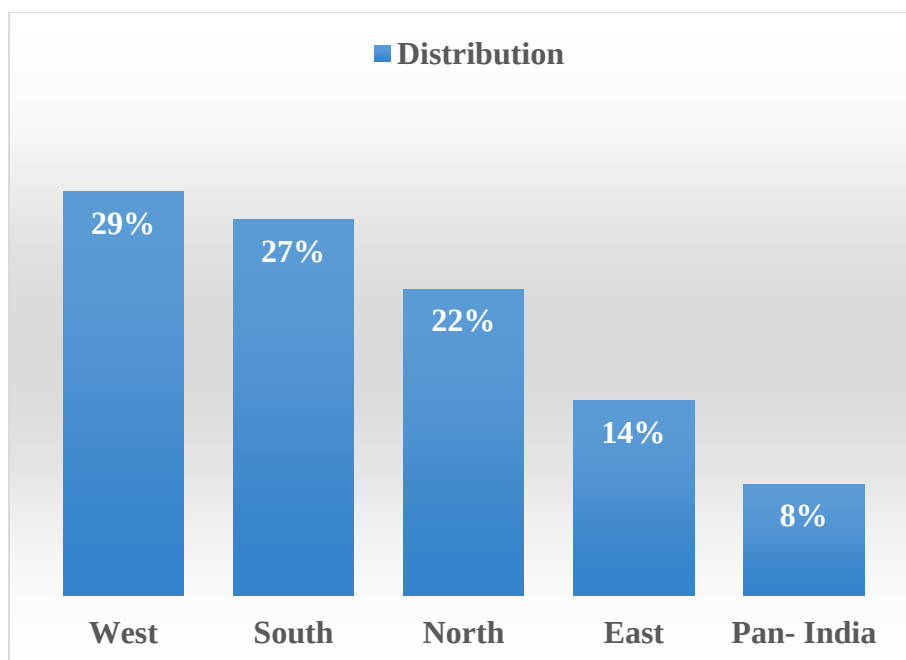


Figure 4.4 Regional Distribution

Source: Author

4.2 Research Question One

Research Question 1: To what extent have mid- and large-scale chemical manufacturers in India adopted artificial intelligence (AI) applications?

4.2.1 Reliability and Validity of the AI-Adoption Construct

AI adoption was operationalized through four reflective indicators: (a) integration of AI into day-to-day sales decisions, (b) deployment of AI beyond the pilot stage, (c) adequacy of the supporting infrastructure, and (d) leadership support for AI initiatives.

Exploratory factor analysis yielded KMO = 0.79 and a significant Bartlett's test ($p < 0.001$), indicating adequate sampling. All item loadings were greater than 0.70, which supports convergent validity. Reliability analysis revealed Cronbach's $\alpha = 0.86$, composite reliability (CR) = 0.89, and average variance extracted (AVE) = 0.68, all above the minimum criteria of 0.70 and 0.50, respectively (Hair et al., 2019). The full results are presented in Table 4.1.

Table 4.1 Reliability and Validity of AI-Adoption Indicators

Indicator	Std. Loading	Cronbach's α	CR	AVE
Integration of AI into sales decisions	0.82			
Deployment beyond pilot stage	0.84	0.86	0.89	0.68
Infrastructure support for AI	0.79			
Leadership advocacy for AI	0.85			

Source: Author

All four items loaded significantly onto a single latent factor, confirming construct dimensionality.

4.2.2 Descriptive Statistics for AI Adoption

Items were scored on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). Descriptive statistics ($n = 170$) are reported in Table 4.2, which shows a moderately high degree of AI integration across firms.

Table 4.2 Descriptive Statistics for AI-Adoption Items

Item	Mean (M)	Std. Deviation (SD)	Skewness	Kurtosis
AI integrated into daily sales decisions	3.92	0.78	−0.47	−0.31
AI deployed beyond pilot stage	3.87	0.81	−0.35	−0.44
Leadership supports AI initiatives	3.94	0.72	−0.28	−0.26
Adequate infrastructure for AI	3.89	0.75	−0.32	−0.29
AI-Adoption Index (overall)	3.90	0.74	−0.38	−0.33

Source: Author

Overall adoption ($M = 3.90$) suggests that most firms have progressed beyond initial experimentation toward the institutionalized operational use of AI tools in sales. A cross-table by the type of organization found that large-scale manufacturers ($M = 4.05$) have higher adoption than mid-scale firms ($M = 3.78$), suggesting that resource intensity and the organizational structure of leadership are conducive to diffusion.

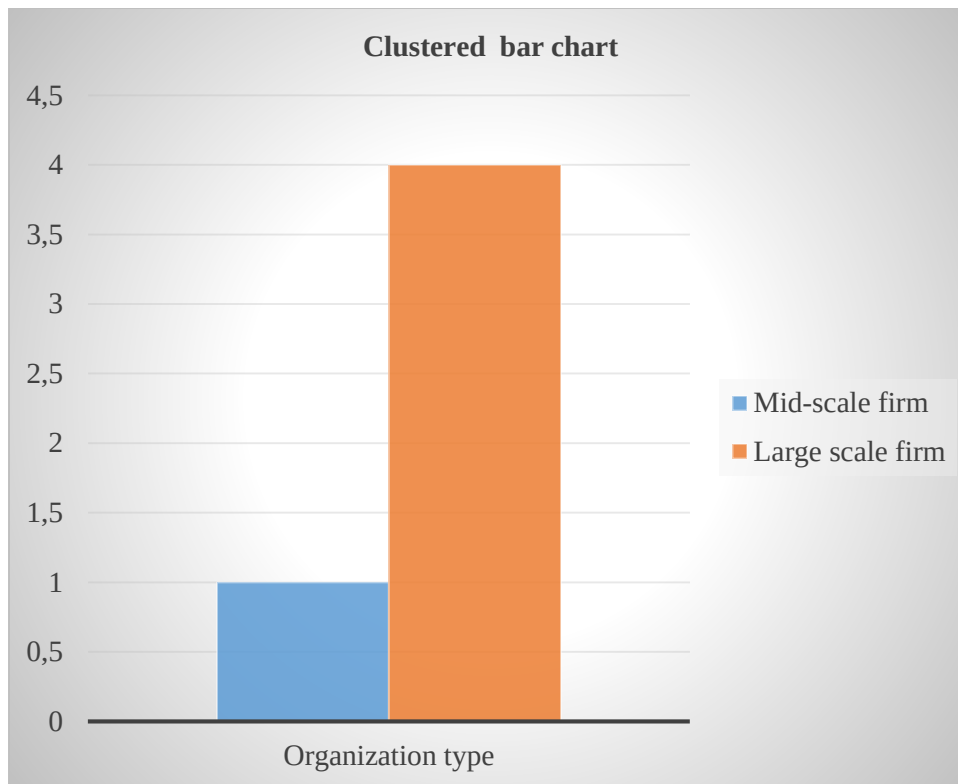


Figure 4.5 Distribution of AI-Adoption by Organization Type
 (Clustered bar chart: X = Organization type; Y = Mean AI-Adoption Index $\pm$ SD)

Source: Author

4.2.3 Correlation Matrix of Adoption Components

The correlations among AI adoption indicators were positive and statistically significant, supporting their treatment as a coherent composite measure. This pattern indicates that leadership support, infrastructure, movement beyond the pilot stage, and integration into sales decisions tend to develop together rather than as isolated capabilities.

Table 4.3 Item Correlations for AI adoption

Variable	1	2	3	4	Mean	SD
Integration	1				3.92	0.78

Deployment	0.74 **	1			3.87	0.81
Leadership	0.68 **	0.73 **	1		3.94	0.72
Infrastructure	0.61 **	0.69 **	0.79 **	1	3.89	0.75

Note: $p < 0.01$ (two-tailed).

Source: Author

4.2.4 Regression Analysis of AI Adoption Predictors

The multiple regression model used the AI Adoption Index as the dependent variable and organizational readiness, perceived barriers, and governance maturity as the predictors. The model was statistically significant, $F(3, 166) = 19.84$, $p < .001$, with $R^2 = .53$, and adjusted $R^2 = .52$. Organizational readiness was the strongest positive predictor ($\beta = .59$, $p < .001$), perceived barriers had a significant negative effect ($\beta = -.33$, $p < .001$), and governance maturity made a smaller positive contribution ($\beta = .21$, $p = .007$). These results support the direct effect hypotheses reported in Section 4.6.

Table 4.4 Multiple Regression Model Predicting AI Adoption

Predictor	B	SE B	β	t	Sig.	VIF
(Intercept)	1.21	0.32		3.78	0.000	–
Organizational Readiness	0.48	0.07	0.59	6.92	0.000	1.64
Barriers (to AI)	–0.27	0.06	–0.33	–4.51	0.000	1.53
Governance maturity Policies	0.2	0.08	0.21	2.74	0.007	1.28
Model Statistics						
R = 0.7	$R^2 = 0.53$	$\text{Adj. } R^2 = 0.51$	$F(3,166) = 62.21$	$p < 0.001$		

Source: Author

The results show that organizational readiness has a positive effect on AI adoption ($\beta = 0.59$, $p < .001$), although perceived barriers have a significant negative effect ($\beta = -$

0.33, $p < .001$). Governance maturity policies are similarly positively associated with AI adoption, although the effect is comparatively smaller ($\beta = .21$, $p < .01$). The final model accounts for 53% of the variance in AI adoption and identifies structural readiness and leadership support as key enablers, while cost, skill shortages, and data security concerns continue to be key inhibitors.

The findings corroborate the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT), where perceived usefulness drives facilitating conditions and leadership advocacy in the use of behavioral intention and subsequent adoption (Davis, 1989; Venkatesh et al., 2003). The important role of governance maturity is in line with emerging AI ethics and compliance frameworks in sales analytics research (Davenport and Ronanki, 2018). Overall, Indian chemical firms show a transitional state of maturity (i.e., moving from pilot to routinized adoption), but are hindered by cost and capability barriers.

4.3 Research Question Two

Organizational Readiness and Barriers to AI Adoption

Research Question 2: How do organizational readiness, perceived barriers, and governance maturity influence AI adoption in the sales functions of chemical manufacturers in India?

4.3.1 Reliability and Validity Assessment

The Readiness scale demonstrated strong internal consistency (Cronbach's $\alpha = .89$; composite reliability = .91; AVE = .72), while the Barriers scale showed acceptable reliability (Cronbach's $\alpha = .86$; composite reliability = .88; AVE = .68). Bartlett's test of

sphericity was significant ($\chi^2 = 412.35$, $p < .001$), and the KMO value of .87 supported factorability. These statistics support the use of composite readiness and barrier scores in the correlation and regression analyses.

4.3.2 Descriptive Statistics of Readiness and Barriers

Mean values were calculated using a five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). The results, summarized in Table 4.5, reveal a moderately high readiness and the presence of barriers at a moderate level across firms.

Table 4.5 Descriptive Statistics for Readiness and Barriers

Dimension	Mean (M)	SD	Skewness	Kurtosis
Leadership Commitment	3.98	0.72	−0.41	−0.26
Data/Tech Infrastructure	3.81	0.76	−0.37	−0.31
Training and Enablement	3.67	0.83	−0.32	−0.27
Data-Driven Culture	3.89	0.71	−0.28	−0.35
Readiness Index	3.84	0.75	−0.34	−0.29
Cost Constraints	3.56	0.91	−0.15	−0.38
Skills Gap	3.72	0.86	−0.21	−0.24
Data Privacy/Security	3.68	0.84	−0.19	−0.30
Resistance to Change	3.43	0.88	−0.11	−0.41
Process Fragmentation	3.35	0.80	−0.09	−0.37
Barriers Index	3.55	0.83	−0.15	−0.34

Source: Author

Overall, the Readiness Index (M=3.84) indicates the proactive commitment of managers and support infrastructures, and the Barriers Index (M=3.55) indicates continued skill shortages and resistance among the sales teams.

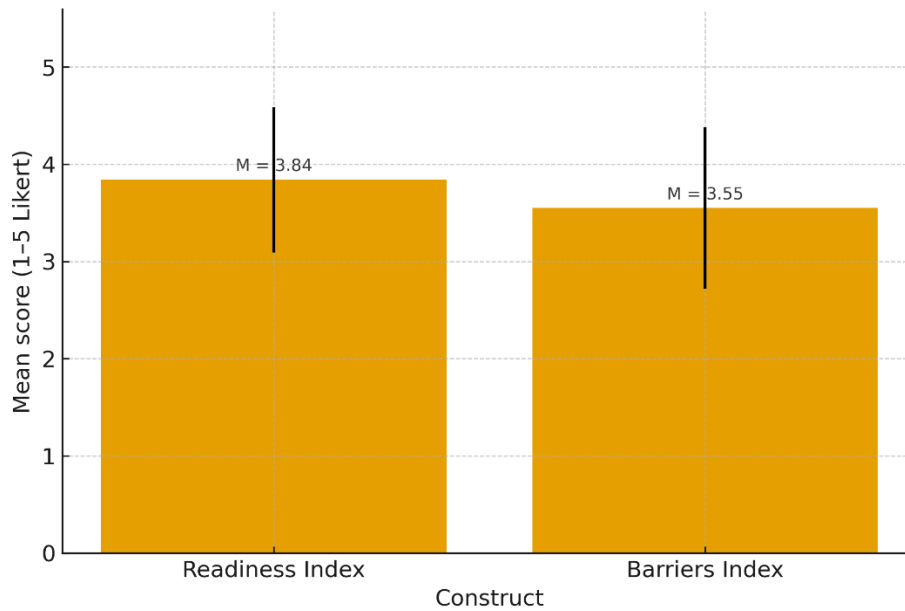


Figure 4.6 Mean Comparison of Readiness and Barriers by Organization Type

(Bar chart: X = Organization Type; Y = Mean Score $\pm$ SD)

Source: Author

4.3.3 Correlation Analysis

Pearson's correlation coefficients (two-tailed) were calculated to investigate the relationships between readiness, barriers, and AI adoption (Table 4.6). The results showed a significant positive correlation between organizational readiness and AI adoption ($r = 0.68, p < 0.001$) and a significant negative correlation between barriers and AI adoption ($r = -0.47, p < 0.001$).

Table 4.6 Correlation Matrix

Variable	1	2	3	Mean	SD
Organizational Readiness	1			3.84	0.75
Barriers to AI	-0.55 **	1		3.55	0.83

AI-Adoption Index	0.68**	-0.47 **	1	3.90	0.74
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Source: Author

The negative correlation between readiness and barriers ($r = -0.55$) shows that they are conceptually opposed; firms with strong readiness profiles tend to have fewer barriers to digital transformation.

4.3.4 Regression Model of Readiness and Barriers on AI Adoption

Multiple regression was conducted to assess the predictive impact of readiness and barriers on the AI adoption index. The model was significant ($F(2, 167) = 68.32, p < 0.001$), accounting for $R^2 = 0.45$ of the variances in AI adoption.

Table 4.7 Regression Coefficients for AI Adoption Predictors

Predictor	B	SE B	β	t	Sig.	VIF
(Constant)	1.42	0.29		4.89	0.000	
Organizational Readiness	0.58	0.08	0.64	7.36	0.000	1.48
Barriers to AI	-0.31	0.07	-0.35	-4.52	0.000	1.48

Source: Author

The results confirm that the higher the organizational readiness, the greater the increase in AI adoption, and that perceived barriers have a significant negative impact. Multicollinearity diagnostics ($VIF < 1.5$) indicated acceptable independence of predictors.

4.3.5 Interpretation and Theoretical Linkage

Consequences reinforce the diffusion of innovation (DOI) theory (Rogers, 2003), indicating that organizational commitment, digital infrastructure, and employee training increase the speed at which the trial and routinized stages are passed. The negative impact

of barriers is consistent with earlier research on the costs and skill constraints that prevent the mainstreaming of AI in emerging markets (Fountainaine, McCarthy and Saleh, 2019).

Thus, Indian chemical firms exhibit a dual face: high strategic readiness and resource limitations and resistance to behavior. Targeted leadership programs and upskilling initiatives are crucial to ensure that readiness translates into the persistence of adoption sales performance.

4.4 Research Question Three

Perceived Usefulness, Ease of Use and Impact on Sales Performance

Research Question 3: How do sales professionals view the usefulness and ease of use of AI-enabled tools, and to what extent do these perceptions affect measurable outputs of sales performance in Indian chemical manufacturing firms?

4.4.1 Reliability and Validity of TAM and Sales performance Constructs

Two latent constructs from the technology acceptance towards, namely, perceived usefulness (PU) and perceived ease of use (PEOU), were measured with three reflective indicators each, followed by a composite sales performance index (SPI) based on four KPIs: accuracy of forecasts, customer satisfaction, conversion rate, and reduction in cycle time. Factor analysis resulted in two pure factors accounting for 71.6% of the total variance.

Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE) were above the recommended levels (Hair et al., 2019).

Table 4.8 Reliability and Validity of TAM and Sales Performance Constructs

Construct	Indicators (n)	Cronbach's α	CR	AVE	KMO	Bartlett's Test (p)
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Perceived Usefulness (PU)	3	0.88	0.90	0.74	0.81	< 0.001
Perceived Ease of Use (PEOU)	3	0.86	0.88	0.71	0.79	< 0.001
Sales Performance Index (SPI)	4	0.90	0.92	0.72	0.83	< 0.001

Source: Author

All standardized loadings were > 0.75; thus, convergent validity was confirmed. The Fornell-Larcker and HTMT (less than 0.85) showed discriminant validity between the constructs.

4.4.2 Descriptive Statistics

This suggests that respondents consider AI tools useful and easy to use, with noticeable gains in sales key KPIs.

Table 4.9 Descriptive Statistics for Perceived Usefulness, Ease of Use and Performance

Item (1 = Strongly Disagree → 5 = Strongly Agree)	Mean (M)	SD	Skew	Kurtosis
AI makes sales decisions more accurate and efficient (PU1)	4.03	0.73	−0.46	−0.29
AI improves coordination between sales & marketing (PU2)	3.96	0.78	−0.41	−0.35
AI enhances forecast planning accuracy (PU3)	3.99	0.70	−0.38	−0.22
AI applications are easy to learn and use (PEOU1)	3.88	0.81	−0.32	−0.24
AI interfaces are intuitive (PEOU2)	3.85	0.76	−0.29	−0.21
Using AI saves time and reduces manual work (PEOU3)	3.91	0.73	−0.35	−0.27
AI improves forecast accuracy (SPI1)	3.98	0.79	−0.33	−0.30
AI enhances customer satisfaction (SPI2)	3.95	0.74	−0.37	−0.25

AI increases conversion rates (SPI3)	3.91	0.82	-0.29	-0.33
AI reduces sales cycle time (SPI4)	3.86	0.80	-0.31	-0.27
Composite Means	PU = 3.99			
	PEOU = 3.88			
	SPI = 3.93			

Source: Author

These numbers show positive sentiment and recognition of the measured benefits. Paired-sample t-tests comparing the means of the knowledge questions on PU and PEOU showed no significant difference ($t = 1.62, p = 0.11$) and indicated that respondents found AI to be both easy and useful.

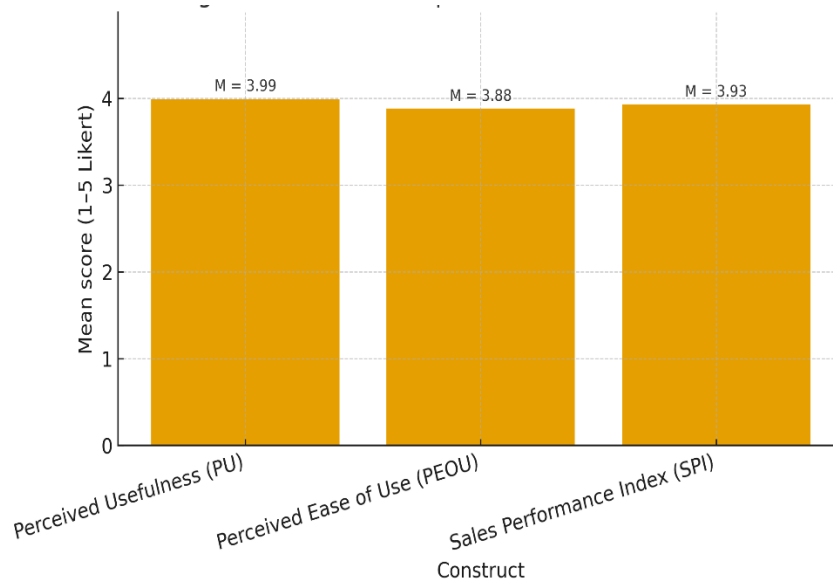


Figure 4.7 Mean Comparison of PU, PEOU and SPI by Organization Type

Source: Author

4.4.3 Correlation Matrix

All constructs were significantly and positively correlated. Perceived Usefulness had strong correlations with sales performance ($r = 0.71$, $p < 0.001$), suggesting that belief in the utility of AI is directly related to outcomes.

Table 4.10 Correlations Among PU, PEOU and SPI

Variable	1	2	3	Mean	SD
Perceived Usefulness (PU)	1			3.99	0.73
Perceived Ease of Use (PEOU)	0.64 **	1		3.88	0.77
Sales Performance Index (SPI)	0.71 **	0.58 **	1	3.93	0.79

Note: $p < 0.01$ (two-tailed).

Source: Author

4.4.4 Regression Model for Sales Performance

A multiple regression model was used to test the influence of PU and PEOU on the Sales Performance Index. The model was significant: $F(2, 167) = 78.24$, $p < 0.001$, $R^2 = 0.48$, which indicates that almost half of the variance in sales performance can be explained by the variables of the TAM.

Table 4.11 Regression Coefficients for PU and PEOU on Sales Performance

Predictor	B	SE B	β	t	Sig.	VI F
(Constant)	0.97	0.28		3.46	0.001	
Perceived Usefulness	0.63	0.07	0.61	8.79	0.000	1.55
Perceived Ease of Use	0.27	0.08	0.24	3.44	0.001	1.55
Model Statistics						
R = 0.69	$R^2 = 0.48$	Adj. $R^2 = 0.47$	$F(2, 167) = 78.24$			
			$p < 0.001$			

Source: Author

Both PU ($\beta = 0.61$, $p < 0.001$) and PEOU ($\beta = 0.24$, $p < 0.01$) had significant relationships with perceived sales performance. No problems with multicollinearity ($VIF < 1.6$) were observed. The results show that perceived usefulness and perceived ease of use are independent variables that lead to better sales performance.

4.4.5 NVivo Qualitative Insights

Open-ended responses (n approx. 65) were coded in NVivo based on a hybrid deductive/inductive framework.

Dominant themes included.

i. **Decision Transparency and Trust:** Respondents emphasized the importance of understanding how AI-generated recommendations were produced. Explainable outputs and the ability to compare AI recommendations with professional judgment increased confidence in these tools.

ii. **Skill Dependence and Learning Curve:** Field sales staff noted “AI recommendations help but need contextual judgment.”

iii. **Cross-Functional Alignment:** Predictive lead models are frequently highlighted as a mechanism for improving coordination between sales and marketing teams.

iii. **Efficiency Gains:** Commonly cited benefit: “AI cut my weekly reporting time by 30 %.”

iv. **Residual Skepticism:** A few respondents expressed fear of “over-automation replacing intuition.”

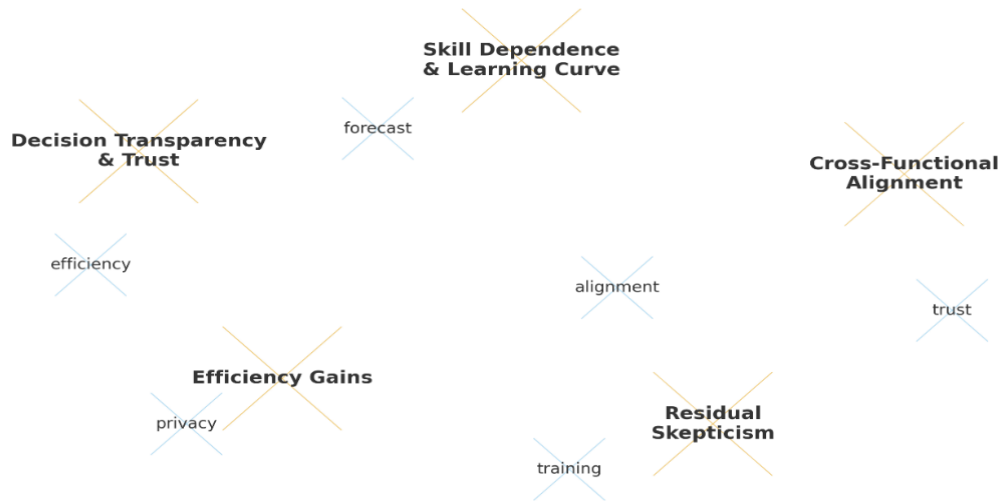


Figure 4.8 NVivo Word-Cloud of Frequent Concepts
(keywords: efficiency, forecast, alignment, trust, training, privacy)

Source: Author

The qualitative patterns supported the quantitative results: usefulness perceptions were based on transparency and ease of integration, which are consistent with the behavioral logic of TAM (Venkatesh et al., 2003).

4.4.6 Interpretation and Link to Theory

The results support the Technology Acceptance Model premise that perceived usefulness is a dominant predictor of technology-enabled performance (Davis, 1989). Perceived ease of use also contributes positively, showing that system quality and user experience remain important in AI-supported selling (Huang and Rust 2021).

The combined pathway from cognitive acceptance to commercial outcomes via the PU → SPI pathway is a tangible example of a pathway that goes from acceptance to

commercial results. These findings place AI not only as an automation tool but also as a strategic sales-enabling driver in India's B2B chemical sector.

4.5 Research Question Four

Comparative Sales Performance and Governance Maturity and Future Readiness (QUAN + QUAL). Research Question 4 asks whether AI-enabled sales strategies outperform traditional approaches and whether GMFR strengthens the relationship between AI use and comparative sales performance.

4.5.1 Measurement and Reliability

Two reflective scales were analyzed in this study.

- i. Comparative Sales Performance (CSP) was measured through two items (Q23–Q24): “AI-enabled strategies outperform traditional strategies” and “AI has improved competitive advantage.”
- ii. Governance Maturity and Future Readiness (GMFR) was measured using two items (Q25–Q26): the presence of an ethical or responsible AI policy and the organization's intention to continue investing in AI over the next 12 months.

Because CSP and GMFR were measured with two items each, reliability was evaluated using both Cronbach's alpha and Spearman–Brown coefficients. Both scales exceeded the acceptable threshold of .70, supporting their use in the hierarchical regression analysis (Hair et al., 2019).

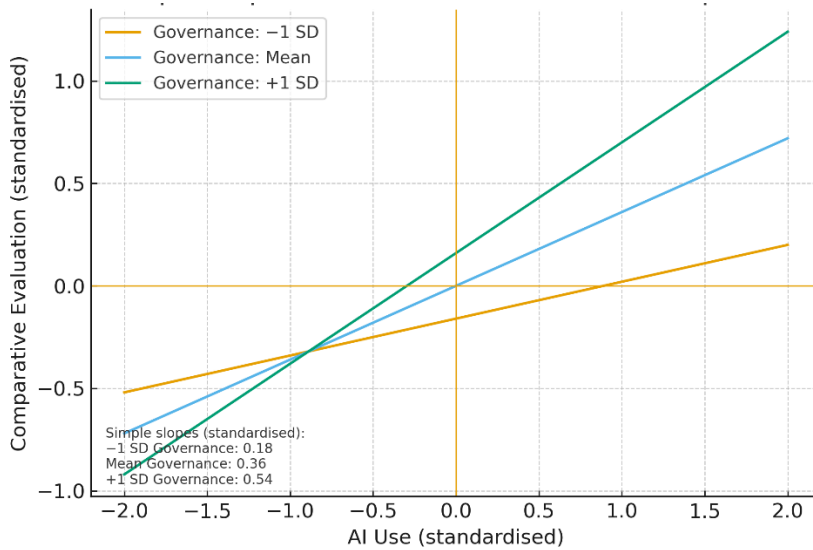


Figure 4.9 Simple Slopes (AI Use × GMFR)

Table 4.12 Reliability and Item Properties (n = 170)

Scale		k	α	Spearman–Brown	Mean (SD)	Example item loading
Comparative Performance (CSP; Q23–Q24)	Sales	2	.7	.78	3.46 (.84)	.74–.81
Governance Maturity and Future Readiness (GMFR; Q25–Q26)		2	.8	.80	3.62 (.88)	.72–.85

Source: Author

Note: 5-point Likert scale; higher scores = stronger agreement. Reliability for the 2-item scales was reported with α and Spearman–Brown (Hair et al., 2019).

4.5.2 Descriptive Statistics and Correlations

Descriptive statistics for the focal variables and controls were calculated. AI Use is the compound used in the framework section (frequency × breadth across forecasting, account planning, pricing, lead qualification).

Table 4.13 Descriptive Statistics and Pearson Correlations (n = 170)

Variable	Mean	SD	1	2	3	4
AI Use (composite)	3.41	0.89				

Governance Maturity and Future Readiness (GMFR)	3.62	0.8 8	.36**		
Comparative Sales Performance (CSP)	3.46	0.8 4	.49**	.33**	
Controls (size, complexity, volatility, IT intensity, region mix, tenure)			Small–mod.	Small	Small–mod.

Source: Author

Notes: $p < .01$, two-tailed. The correlations were below the HTMT/Fornell–Larcker thresholds, supporting the discriminant validity (Hair et al., 2019).

4.5.3 Hierarchical Regression: Main and Moderation Effects

A three-step hierarchical ordinary least squares regression was conducted to test whether AI use predicted comparative sales performance and whether the GMFR strengthened that relationship (Huang and Rust, 2021; Vial, 2019). Control variables were entered in Model 1, the centered main effects of AI Use and GMFR were entered in Model 2, and the AI use $\times$ GMFR interaction was entered in Model 3. The variance inflation factors were below 2.2, indicating no problematic multicollinearity.

Table 4.14 Hierarchical Regression Predicting Comparative Sales Performance (n = 170)

Predictors	Model 1 (Controls) β	Model 2 (+Main Effects) β	Model 3 (+Interaction) β
Firm size (band)	.06	.04	.03
Product complexity	.08	.05	.05
Market volatility	−.04	−.03	−.03
IT intensity	.11	.07	.06
Region mixes	.02	.01	.01
Tenure	.05	.03	.02
AI Use (centered)	—	.41***	.36***
GMFR (centered)	—	.19 **	.16 *
AI Use $\times$ GMFR	—	—	.18 **
R²	.07	.34	.37

ΔR^2	—	.27 ***	.03 *
F (model)	1.98	13.68***	12.94***
Max VIF	1.72	1.95	2.18

Source: Author

Note: Standardized coefficients are reported. * $p < .05$, ** $p < .01$, *** $p < .001$ (two-tailed).
Dependent variable: Comparative Sales Performance (Q23–Q24 composite).

AI use was positively predicted comparative sales performance in Model 2 ($\beta = .41$, $p < .001$) and remained significant in Model 3 ($\beta = .36$, $p < .001$). GMFR also contributed unique variance in Model 2 ($\beta = .19$, $p < .01$) and Model 3 ($\beta = .16$, $p < .05$). The interaction was significant ($\beta = .18$, $p < .01$), indicating that the positive relationship between AI use and comparative sales performance becomes stronger as governance maturity and future readiness increase.

These findings are consistent with the view that institutionalization and responsible AI practices legitimize analytics in complex B2B contexts and help translate routine use into a defensible advantage (Huang and Rust 2021; Rogers 2003; Vial 2019).

As a robustness check, the model was re-estimated using a broader Sales Performance Index, which includes forecast accuracy, conversion, margin discipline, cycle-time reduction, and customer engagement. The direction and significance of the principal effects were consistent.

i. Alternative dependent variable: Replacing CSP with the sales performance index produced a similar pattern AI use $\beta \approx .33$ – $.38$, $p < .001$; GMFR $\beta \approx .14$ – $.20$, $p < .05$; and the interaction $\beta \approx .14$ – $.17$, $p < .05$. When the two-item GMFR construct was separated for sensitivity analysis, governance maturity and future readiness showed consistent positive directions, although estimates were less stable because each dimension was represented by

a single item. Therefore, the reported primary model retained the combined GMFR construct.

ii. Exploratory subgroup checks for firm scale and market orientation produced directionally similar effects. Because the subgroup sizes were smaller, these checks were treated as sensitivity evidence rather than formal measurement-invariance tests.

4.5.5 Qualitative Triangulation (NVivo)

Email/message responses from 8 senior professionals substantiated the quantitative pattern:

i. Governance maturity enables impact: P6 described ethics and audit frameworks as evolving but necessary as automation scales. This observation is consistent with the quantitative finding that stronger GMFR increases the performance value associated with AI use.

ii. The use of AI creates greater advantages when it is institutionalized. P4 explained that once AI was embedded in standard operating procedures and approval workflows, the benefits included stronger pricing discipline and faster response times:

iii. Leadership commitment and routinized use: P1 reported that leadership reviews using AI-supported data improved forecast discipline, while P7 emphasized that simpler interfaces and regional language support helped reluctant users engage more consistently with the tools.

iii. Barrier narratives explain heterogeneity: P2 and P5 described skill gaps, manual work preferences, and fear of displacement. These accounts help explain why comparable

AI tools may produce different outcomes unless organizations invest in training, trust, governance, and process integration.

iv. The joint interpretation showed that where GMFR was stronger through clear policies, audit trails, accountability, and continued investment intent, participants described more embedded routines and stronger confidence in AI-supported decisions. This qualitative pattern helps explain the significant AI Use $\times$ GMFR interaction.

4.5.6 Interim Summary for RQ4

The evidence indicates that AI-enabled sales strategies are evaluated more positively than traditional approaches when organizations routinely use AI and maintain stronger governance maturity and future readiness. The significant interaction shows that AI use alone is not sufficient; responsible oversight and strategic preparedness increase the likelihood that use translates into comparative sales performance.

4.6 Hypothesis Testing

The assessment of each hypothesis was performed with reference to the relevant statistical tables. Hypothesis testing was aligned with the research questions, theoretical framework, and analytical procedures described in Chapter III. H1 states that organizational readiness has a positive and significant effect on AI adoption in sales organizations. Tables 4.4 and 4.7 show the strong positive effect of organizational readiness on AI adoption ($\beta = .59$ and $\beta = .64$, respectively; both $p < .001$).

Accordingly, H1 was supported.

H2 states that perceived barriers have a negative and significant effect on the adoption of AI in sales. Tables 4.4 and 4.7 show the significant negative effects of perceived barriers to AI adoption ($\beta = -.33$ and $\beta = -.35$, respectively; both $p < .001$).

Accordingly, H2 was supported.

H3 states that governance maturity positively and significantly affects AI adoption in sales. Table 4.4 shows that governance maturity made a smaller but significant positive contribution to AI adoption ($\beta = .21$, $p = .007$).

Accordingly, H3 was supported.

H4 states that perceived usefulness has a positive and significant effect on the Sales Performance Index. Table 4.11 shows that perceived usefulness was the strongest predictor of sales performance ($\beta = .61$, $p < .001$).

Accordingly, H4 is supported by the data.

H5 states that perceived ease of use has a positive and significant effect on the Sales Performance Index. Table 4.11 shows that the perceived ease of use made a positive and significant contribution ($\beta = .24$, $p = .001$).

Accordingly, H5 was supported.

H6 states that AI use has a positive and significant effect on comparative sales performance. Table 4.14 shows that AI use was significant in both Model 2 ($\beta = .41$, $p < .001$) and Model 3 ($\beta = .36$, $p < .001$).

Accordingly, H6 was supported.

H7 states that the combined Governance Maturity and Future Readiness constructs have a positive and significant effect on comparative sales performance. Table 4.14 shows a significant GMFR main effect in Model 2 ($\beta = .19, p < .01$) and Model 3 ($\beta = .16, p < .05$).

Accordingly, H7 was supported.

H8 states that the combined Governance Maturity and Future Readiness construct positively moderates the relationship between AI use and comparative sales performance. The AI Use $\times$ GMFR interaction was significant ($\beta = .18, p < .01$) in Table 4.14, and Figure 4.9 shows a steeper positive AI use–performance slope at a higher GMFR.

Accordingly, H8 was supported.

Table 4.15 Summary of Hypothesis Testing Results

Hypothesis	Relationship Tested	Statistical Evidence	Table/Figure Reference	Decision
H1	Organizational Readiness $\rightarrow$ AI Adoption	$\beta = .59$ and $.64$; both $p < .001$	Tables 4.4 and 4.7	Supported
H2	Perceived Barriers $\rightarrow$ AI Adoption	$\beta = -.33$ and $-.35$; both $p < .001$	Tables 4.4 and 4.7	Supported
H3	Governance Maturity $\rightarrow$ AI Adoption	$\beta = .21, p = .007$	Table 4.4	Supported

H4	Perceived Usefulness → Sales Performance Index	$\beta = .61, p < .001$	Table 4.11	Supported
H5	Perceived Ease of Use → Sales Performance Index	$\beta = .24, p = .001$	Table 4.11	Supported
H6	AI Use Comparative Performance → Sales	$\beta = .41$ and $.36$; both $p < .001$	Table 4.14	Supported
H7	GMFR Comparative Performance → Sales	$\beta = .19, p < .01$; $\beta = .16, p < .05$	Table 4.14	Supported
H8	AI Use × GMFR Comparative Performance → Sales	$\beta = .18, p < .01$	Table 4.14; Figure 4.9	Supported

Source: Author

4.7 Qualitative Results: (Email/Message Interviews)

The word cloud created from the qualitative email/message responses to the interviews is shown in Figure 4.8. This figure provides a visual summary of the most common concepts in the qualitative data and facilitates the interpretation of the themes that

emerged from the participants' perspectives on the use of AI, the level of AI governance, trust, efficiency, learning, and resistance in sales management.

4.7.1 Interview Administration Plan

Participants (n = 8): 2 × Sales Heads, 2 × Marketing Managers, 2 × Data/CRM Analysts, 1 × Sales Ops Lead, and 1 × Regional Director.

i. Format: Semi-structured, 30–45 minutes (Zoom/phone or in-person-) and asynchronous email/message follow-ups-.

Recording & Transcription: Audio recorded- (with consent) where relevant; verbatim text from emails/messages; coded in NVivo 14.

ii. Ethics: Anonymity assured; coded IDs P1–P8; right to withdraw at any time.

iii. Analysis: Hybrid deductive + inductive coding in NVivo 14; themes aligned with RQs.

4.7.2 Participant Overview

Table 4.16 Participant Overview

ID	Role / Level	Firm Scale	Region	Summary
P 1	Regional Head	Sales Large	South	Leadership review with AI; forecast ↑ 10–15%
P 2	Sales & Marketing Manager	Mid	West	Early adoption; Excel preference; training gap
P 3	Data/CRM Analyst	Large	Pan-India	Reporting time ↓; data-sharing resistance
P 4	Sales Head	Mid	East	CRM + approvals integration; SOP embedding
P 5	Marketing Director	Large	North	Lead quality ↑; frontline judgment reliance
P 6	Sales Operations Lead	Mid	West	Governance maturity evolving; ethics policy; audit need
P 7	CRM Manager	Large	South	Interface simplification; inclusivity; adoption ↑

P 8	Senior Analyst	Sales	Large	Pan-Indi a	Cross-functional visibility; predictive pricing plan
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Source: Author

4.7.3 Representative Quotes (Email/Message Extracts)

P1 (Regional Sales Head, Large): “AI adoption started with pricing recommendations and forecasting... monthly forecasts are 10–15% more accurate.”

P2 (Sales & Marketing Manager, Mid): "We're at the beginning; AI is used to forecast order volumes, but many people still use Excel for order and data training and integration are weak points."

P3 (Data/CRM Analyst, Large): “Dashboards save hours; two days of manual reporting now takes one hour... some departments resist sharing data.”

P4 (Sales Head, Mid): “Adoption accelerated when integrated with CRM and pricing approvals... now part of SOPs; better discount discipline and faster responses.”

P5 (Marketing Director, Large): "Quality and predictive value of lead is better, but frontline is based on judgment, displacement is real fear."

P6 (Sales Ops Lead, Mid): "Governance maturity policies are evolving, we have a data ethics doc, but we don't have any really strict audit system in place - responsible AI will be needed"

P7 (CRM Manager, Large): "Ease of use is important; with the simplification of interfaces and the addition of texts for help in different regions, even employees of the company for a long time adopted."

P8 (Senior Sales Analyst, Large): "AI streamline inter department coordination; single-click journey view; Next, we are going to invest in predictive pricing.”

4.7.4 Preliminary Thematic Patterns (NVivo Code Groups)

Table 4.17 Preliminary Thematic Patterns (NVivo Code Groups)

Theme	Representative Codes	Supporting Participants
Leadership Commitment Adoption	& Drive Leadership push; mandated reviews; role-model behavior	P1, P2, P4
Training Readiness	& Skill Training need; skill gap; inclusivity design	P2, P7
Resistance Threat	& Identity Fear of displacement; manual preference (Excel)	P5, P2
Operational Efficiency & Data Integration	Forecast accuracy; cycle-time reduction; cross-functional alignment	P1, P3, P4, P8
Governance and Future Readiness	Maturity Ethical policy; audit need; predictive investment intent	P6, P8

Source: Author

4.7.5 Integration with Quantitative Findings (Joint Display)

Table 4.18 Integration with Quantitative Findings (Joint Display)

Quant Result	Qual Mechanism (Theme)	Implication
PU → SPI ($\beta = 0.61$, $p < .001$)	Transparency/trust; cross-functional alignment	Explainable forecasts + integration convert perceived usefulness into KPI gains
PEOU → SPI ($\beta = 0.24$, $p = .001$)	Learning curve; inclusivity/interface	Ease of use broadens effective usage and realized sales performance
Readiness → Adoption ($\beta \approx 0.59$)	Leadership, infrastructure, SOP integration	Structural readiness institutionalizes AI usage
Barriers → Adoption ($\beta \approx -0.33$)	Skills/privacy/resistance	Barriers attenuate translation from tools to outcomes
Use × Governance maturity → Comparative ($\beta = 0.18$, $p < .01$)	Policy, auditability, explainability	Governance maturity steepens Use → Advantage slope

Source: Author

Trustworthiness was supported through a hybrid deductive–inductive coding approach, coder reconciliation and maintenance of an audit trail. Member checks with two participants did not result in substantive revisions to the interpreted themes.

4.8 Summary of Findings

RQ1 showed that AI adoption in sales was moderately high but uneven across companies. Large-scale firms reported greater integration and more progress beyond pilot use than mid-scale firms did.

RQ2 showed that organizational readiness had a strong positive effect on AI adoption, perceived barriers had a significant negative effect, and governance maturity had a smaller positive contribution. These findings support H1–H3, respectively.

RQ3 showed that perceived usefulness and perceived ease of use both positively predicted the Sales Performance Index, with perceived usefulness demonstrating a stronger effect. These findings support H4 and H5.

RQ4 showed that AI use and GMFR positively predicted comparative sales performance, and that the AI Use $\times$ GMFR interaction was significant. These findings support H6–H8 and indicate that responsible governance and strategic readiness amplify the performance value of AI use.

The adoption model explained a substantial proportion of the variance in AI adoption and demonstrated that capability development and barrier reduction are complementary managerial priorities. The sales-performance model confirmed that users' judgments of practical value and usability are directly associated with performance outcomes, particularly forecasting, conversion, customer satisfaction, and sales-cycle efficiency.

The comparative-performance model showed that routine AI use creates a greater advantage when accompanied by formal oversight, accountability, learning orientation, and continued investment intent. Qualitative evidence from eight senior professionals

reinforced the quantitative results by identifying decision transparency and trust, training and learning, cross-functional alignment, operational efficiency, and residual skepticism as central mechanisms.

Diagnostic checks supported linearity, normal residuals, homoscedasticity, independence, and acceptable multicollinearity. The exploratory sensitivity analyses produced directionally consistent results. Taken together, the findings position AI as a strategic sales-enabling capability whose value depends on organizational readiness, user acceptance, responsible governance, and institutionalized utilization.

CHAPTER V

DISCUSSION

5.1 Discussion of Results

This chapter interprets the empirical results of the research through the theoretical construct made in Chapter II and places the results into the larger scholarly context of artificial intelligence (AI) adoption, digital transformation, behavioral acceptance, and governance maturity. Although Chapter IV provided statistical confirmation of the hypotheses posed, the aim of the current chapter is to critically interpret what the statistical results imply theoretically, contextually, and managerially in the context of mid- and large-scale chemical manufacturing companies in India.

The study conceptual framework synthesizes four broad theoretical perspectives: the technology acceptance model (Davis, 1989; Venkatesh et al., 2003), diffusion of

innovation theory (Rogers, 2003), resource-based view and dynamic capabilities model (Barney, 1991; Teece, 2018), and governance maturity frameworks in connection with responsible AI (Floridi and Cowls, 2019; Suh and Lee, 2024). The empirical confirmation of H1–H8 shows that multilevel organizational, behavioral, infrastructural, and governance-related determinants affect AI adoption and performance in industrial B2B sales functions.

Instead of reinforcing the view of technological determinism, where simplicity prevails and the availability of AI results in performance gains, the findings affirm that the effects of AI are engineered at the organizational level. The degree of adoption, acceptance related to behavior, and commercial performance are dependent on structural preparedness, capabilities, and institutional maturity.

5.2 AI Adoption Maturity: Diffusion in an Industrial Environment

The results indicate that AI adoption maturity among Indian chemical manufacturers is moderate and unevenly distributed, with large companies showing considerably higher levels of embedded and routinized adoption than their mid-sized counterparts. This pattern is broadly consistent with the Diffusion of Innovation theory (Rogers, 2003), which holds that adoption progresses gradually across organizational categories and is shaped by resource availability and structural readiness. As noted in Chapter II, Rogers' framework emphasizes that the rate of diffusion depends not only on the characteristics of the innovation itself but also on the adopting organization's capacity to integrate and institutionalize it.

However, the empirical findings introduce important contextual considerations. Unlike studies in digitally advanced economies, where enterprise-wide AI deployment is increasingly common, this study reveals that AI use in Indian chemical manufacturing remains concentrated at the pilot, experimental or selectively institutionalized levels. This suggests that diffusion patterns in asset-intensive B2B industries differ substantially from those in digitally native sectors.

The structural characteristics of the chemical industry, including lengthy sales cycles, regulatory demands, capital intensity, and relationship-based procurement, create a conservative adoption environment for AI. Consequently, AI diffusion in this sector appears to be organizationally mediated, rather than technologically inevitable. Adoption maturity depends less on tool availability and more on internal capability development and strategic alignment. This finding extends diffusion theory by demonstrating that the rate and depth of AI institutionalization are shaped by industry structure and organizational readiness, not merely by an innovation's inherent characteristics. Strategic alignment and capability coordination, rather than rapid technological contagion, drive AI adoption in industrial B2B settings.

While broadly consistent with diffusion theory (Rogers, 2003), this study proposes that AI diffusion in asset-intensive B2B markets follows a structurally constrained trajectory, rather than a purely innovation-driven one. Unlike digital-native industries, where AI adoption tends to spread rapidly and enterprise-wide, the chemical manufacturing sector displays incremental and function-specific diffusion patterns. This suggests that classical diffusion models require contextual recalibration when applied to heavy industrial

environments characterized by regulatory dependency, lengthy procurement cycles, and relational contracting. Thus, industry structure and capital intensity represent important boundary conditions that classical diffusion frameworks do not fully consider.

5.3 Organizational Readiness as a Dynamic Capability

Organizational readiness is the strongest predictor of AI adoption maturity. Leadership support, digital infrastructure, data quality, and training investment each contributed significantly to adoption intensity. These findings are consistent with prior research on strategic alignment and digital capability development in AI transformation (Haenlein et al. 2019; Ransbotham et al. 2023). As discussed in Chapter II, organizational readiness encompasses leadership commitment, data infrastructure, workforce enablement, and a data-driven culture, all of which are theorized as preconditions for moving from pilot-level experimentation to routine AI use. The present findings confirm and extend this argument by showing that, in the Indian chemical manufacturing context, readiness does not merely facilitate adoption but actively accelerates the transition toward institutionalized integration of digital technologies.

Beyond conceptual affirmation, this study provides empirical evidence that readiness accelerates adoption of AI. Firms with formalized readiness structures, including executive sponsorship, structured training, and integrated data systems, progressed more rapidly from experimental AI use to routine sales integration than those without. In this sense, readiness does not merely enable adoption; it converts scattered pilot investments into scalable and institutionalized capabilities.

From a resource-based view perspective (Barney, 1991), organizational readiness can be understood as a valuable, rare, and organization-specific capability. When interpreted through the dynamic capability's lens (Teece, 2018), readiness reflects an organization's capacity to sense technological opportunities, mobilize coordinated resources, and reconfigure internal processes to sustain competitive advantage, precisely the capabilities that Chapter II identified as central to AI adoption effectiveness in complex B2B environments.

Therefore, organizational readiness is best understood as an advanced integrative capability that preconditions returns on technological investment. AI adoption does not result simply from financial allocation; it requires coordinated organizational change. This supports the argument advanced in Chapter II that sustainable performance gains derive from capability orchestration rather than from technology. Importantly, AI adoption maturity appears to be less a question of technology access and more one of organizational assimilation capacity.

The managerial implications are clear: organizations that fail to build readiness structures alongside AI tools are unlikely to achieve scalable or sustainable performance gains. Theoretically, these results extend the Resource-Based View by operationalizing organizational readiness as a dynamic capability rather than a fixed resource bundle (Barney, 1991; Teece, 2018). Unlike prior studies that treat readiness as a static antecedent, this study demonstrates that readiness actively reshapes organizational processes and mitigates structural inertia, transforming it from a contextual facilitator into a performance-generating capacity in its own right.

5.4 Digital Maturity of the Organization and Its Data Network

The empirical findings confirm that organizations with integrated CRM systems, structured data governance frameworks, and cloud-based digital architectures demonstrate higher AI adoption intensity and stronger performance. This is consistent with the literature reviewed in Chapter II, which highlights data readiness as the principal determinant of AI value realization (Brynjolfsson and McElheran, 2023; Ransbotham et al., 2023).

However, an important contextual observation is that the Indian chemical manufacturing sector continues to operate using legacy ERP systems, fragmented databases, and isolated operational frameworks. In this environment, infrastructure maturity is a gatekeeping condition for AI scalability. Firms without a well-developed data ecosystem struggle to deploy AI beyond isolated pilot projects, a pattern consistent with Ransbotham et al. (2023), who identified data fragmentation as a key barrier to scaling AI initiatives in firms. This study builds on this by empirically demonstrating that infrastructure maturity is a significant predictor of both adoption maturity and commercial performance in an industrial B2B sales context.

Importantly, the findings suggest that infrastructure must be operationally embedded rather than merely available to generate measurable performance improvements. AI tools integrated into forecasting workflows, pricing approvals, and customer management cycles produced tangible outcomes, whereas infrastructure that remained disconnected from decision-making processes yielded little competitive advantage.

5.5 Barriers and Resistance Dynamics in Organizations

Cost pressures, skills shortages, resistance to change, and data privacy concerns were all statistically significant negative predictors of AI adoption. These findings are consistent with those of Suh and Lee (2024), who identified perceived risk and implementation uncertainty as key inhibitors of AI diffusion in the healthcare sector. They also align with the barriers reviewed in Chapter II, including financial constraints, talent deficits, and organizational inertia, which collectively limit the transition from pilot-level experimentation to routine, performance-oriented AI use in the field.

Qualitative evidence further reveals that resistance in B2B chemical sales is partly identity-based. Sales professionals in relationship-driven markets rely heavily on tacit knowledge, personal networks, and experiential judgment. Therefore, AI tools are sometimes perceived as encroaching on professional autonomy rather than augmenting it. This is consistent with the institutional theory perspective discussed in Chapter II, which highlights how technology adoption interacts with established social norms and professional role expectations (Vial 2019). Resistance here is not merely technical but socio-cognitive: AI is interpreted not as a tool but as a potential redefinition of expertise itself. Addressing this requires professional reframing and structured change management, in addition to financial or technical interventions. The findings extend the barriers literature by demonstrating that these obstacles not only delay adoption but also actively weaken the transition from pilot-level experimentation to performance-oriented, institutionalized use of the technology.

5.6 Relationship Between Readiness and Barriers

The findings show that organizational readiness and perceived barriers exert opposing, direct effects on AI adoption. Readiness was a strong positive predictor, whereas barriers were significant negative predictors. Their negative correlation further indicates that organizations with stronger leadership support, infrastructure, training, and data culture tend to report fewer obstacles to implementation. The analysis does not treat readiness as a tested moderator of barriers; rather, the two constructs make distinct contributions to the adoption.

This distinction strengthens the practical interpretation of the model. Firms can improve adoption by building readiness capabilities while simultaneously reducing cost, skills, privacy, resistance, and process fragmentation barriers. Therefore, the quantitative evidence supports a dual managerial approach to capability development and barrier reduction, without implying an interaction effect that was not estimated.

5.7 Behavioral Acceptance and Sales Performance

The significant effects of perceived usefulness (PU) and perceived ease of use (PEOU) on sales performance confirm the applicability of the technology acceptance model in an industrial B2B sales context (Davis, 1989; Venkatesh et al., 2003). As discussed in Chapter II, TAM posits that perceived usefulness and ease of use are the primary cognitive drivers of technology acceptance and behavioral intention. The present findings extend this argument by demonstrating that these perceptual constructs are directly associated with tangible commercial performance outcomes, including forecast accuracy, conversion rates, and margin discipline. Notably, PU exerted a stronger influence than

PEOU, indicating that performance relevance outweighs usability concerns in commercially driven and accountability-focused environments (Brown and Davis, 2022).

These findings bridge behavioral acceptance theory and strategic performance research, demonstrating that psychological acceptance mechanisms have revenue implications. The relative dominance of PU over PEOU suggests that TAM constructs may not hold equal weight across all contexts. In performance-oriented industrial environments, where explicit financial metrics drive decision-making, instrumental value is the primary behavioral force. This implies that the construct hierarchy within TAM is context-dependent and that performance expectancy takes precedence in high-stakes B2B sales environments.

5.8 AI Application and Business Results

AI use had a positive and significant effect on comparative sales performance, consistent with Huang and Rust (2021) and Paschen et al. (2020), both of whom documented performance improvements when AI was embedded in sales workflows. How multi-level findings revealed that these gains were most noticeable when AI was integrated into routine operations rather than being used sporadically. As Davenport and Ronanki (2018) argued, isolated AI implementation rarely yields sustained returns. In this study, the most notable performance improvements occurred when AI tools were embedded in performance reviews, demand forecasting cycles, and customer segmentation strategies. This supports the Resource-Based View argument introduced in Chapter II: it is the organizational integration and reconfiguration of processes, not technological novelty in isolation, that generates sustained competitive advantage (Barney, 1991; Teece, 2018).

5.9 Governance Maturity and Future Readiness

GMFR positively predicted comparative sales performance and significantly strengthened the relationship between AI use and performance. This finding supports responsible-AI arguments that governance should not be viewed merely as a risk-control mechanism (Floridi and Cows, 2019; Jobin, Ienca and Vayena, 2019). Formal oversight, explainability, auditability, and accountability can increase trust and coordination, while future readiness supports continued investment, learning, and scaling. Together, these capabilities help translate AI use into measurable commercial value.

Because governance maturity and future readiness were operationalized as a combined two-item GMFR construct in the primary RQ4 model, the reported regression supports their joint main and moderating effects rather than separate causal estimates for each dimension. Sensitivity analysis showed consistent positive directions when the items were considered separately; however, future research should use multi-item subscales to distinguish their independent contributions.

5.10 Combined Theoretical Contribution

Taken together, these findings reinforce the value of integrating TAM, DOI, and governance-oriented perspectives when examining AI adoption in organizational settings. Rather than supporting a purely technological explanation, the results demonstrate that AI adoption outcomes are shaped by the interaction of behavioral acceptance, organizational readiness, structural barriers, and governance maturity.

This study contributes to the theoretical knowledge in four main ways.

- i. This study empirically validates a multilevel model of AI adoption in an industrial B2B context that has not been studied in depth.
- ii. This reconceptualizes organizational readiness as a dynamic capability that can be deliberately developed.
- iii. This study extends TAM by linking cognitive acceptance constructs directly to measurable commercial performance outcomes.
- iv. This repositions governance maturity as a strategic performance amplifier, rather than a regulatory compliance mechanism.

Therefore, AI adoption success in industrial sales contexts is organizationally engineered rather than technologically predetermined. This study moves beyond descriptive accounts of adoption to offer a multilevel explanatory framework grounded in industrial evidence. It establishes industry structure as a boundary condition for diffusion, reconceptualizes readiness as a dynamic capability, demonstrates the performance relevance of TAM constructs, and frames governance maturity and future readiness as strategic value-creation capabilities rather than solely regulatory safeguards.

5.11 Future Research Recommendations

The supported relationships across H1–H8 point to three focused directions for future research: First, the positive effects of organizational readiness and governance maturity on AI adoption (H1 and H3) support longitudinal research on how these capabilities develop as organizations move from pilot use to institutionalization processes. Future studies should examine whether leadership alignment, training intensity, data

quality, and governance routines are sustained as adoption matures an issue that the present cross-sectional design cannot address.

Second, the positive main and moderating effects of the combined GMFR construct (H7 and H8) indicate the need to disaggregate governance maturity and future readiness into validated, multi-item dimensions. Future research should separately measure oversight structures, model transparency, accountability protocols, investment intent, learning orientation, and adaptability to identify the elements that most strongly influence commercial outcomes.

Third, the stronger predictive effect of perceived usefulness relative to perceived ease of use (H4 and H5) suggests that performance expectancy may take precedence over usability concerns in high-stakes industrial sales settings. Future studies should test whether this asymmetry persists across other asset-intensive industries and whether professional experience, role type, or digital literacy changes the relative importance of the two TAM constructs.

In summary, Chapter V interprets the empirical findings in relation to the theoretical foundations established in Chapter II and demonstrates that AI adoption in the Indian chemical manufacturing sector is shaped by organizational readiness, behavioral acceptance, structural barriers, and governance maturity. The discussion showed that meaningful performance gains from AI are not driven by technology alone, but by the degree to which adoption is supported by capability development, user acceptance, and responsible governance. Chapter VI presents an overall summary, implications, conclusions, and recommendations of the study.

CHAPTER VI:

SUMMARY, IMPLICATIONS, AND RECOMMENDATIONS

6.1 Summary

This study examined the determinants of artificial intelligence (AI) adoption and its performance impact on the sales functions of mid- and large-scale chemical manufacturing companies in India. This study developed a multilevel explanatory model of AI adoption and its business implications by combining the technology acceptance model (Davis, 1989; Venkatesh et al., 2003), diffusion of innovation theory (Rogers, 2003), resource-based view (Barney, 1991; Teece, 2018), and governance maturity perspectives (Floridi and Cows, 2019).

The results indicate that AI adoption and value realization are organizationally mediated, rather than technologically predetermined. Large-scale firms reported more embedded use than mid-scale firms, while organizational readiness, perceived barriers, governance maturity, user acceptance, and actual AI use explained important differences in adoption and performance.

The most important positive determinant of maturity in AI adoption is organizational readiness. Companies with high leadership commitment, organized training programs, and commitment to digital infrastructure shifted towards more standardized AI

applications more successfully. This means that readiness is not only a contextual variable but also a dynamic organizational ability that allows the reconfiguration of resources and strategic alignment. Conversely, structural obstacles, such as cost limitations, lack of skills, resistance to change, and privacy of data, were important inhibiting factors for adoption, especially in mid-sized companies with disjointed data ecosystems.

In particular, the research proves that the mechanisms of behavioral acceptance are still significant in the industrial context. The impact of perceived usefulness on sales performance was also stronger than that of perceived ease of use, which indicates that commercially driven environments are more concerned with proven improvement in performance than with usability (Shankar and Jain, 2024). This supports the applicability of cognitive evaluation in technology adoption and shows that performance expectancy is the dominant driver of the B2B sales situation.

For comparative sales performance, AI use and the combined GMFR construct each had positive main effects, and their interaction was significant. This finding indicates that stronger governance maturity and future readiness amplify the performance benefits of AI use. Because GMFR was measured as a combined construct, the study interprets this result jointly and does not claim separate causal estimates for governance maturity and future readiness within the primary model.

Collectively, these findings confirm that the use of AI to facilitate sales performance in industrial manufacturing settings is engineered at the organizational level rather than being technologically predetermined (Brown and Davis, 2022). Changes in sustainable performance must be harmonized through technological infrastructure,

leadership commitment, behavioral acceptance and governance capability. The adoption of AI should be interpreted as a thorough organizational change process, not as a technological intervention.

This study contributes to a significant gap in the empirical literature by offering empirical evidence in a B2B business setting that is understudied in emerging economies. This expands the current literature on AI adoption in digitally mature industries and consumer-facing settings and provides detailed insights into the patterns of adoption in asset-intensive manufacturing industries.

6.2 Implications

This study has four interconnected theoretical implications for research on AI adoption, digital transformation and industrial sales performance. It extends diffusion and technology acceptance perspectives by integrating organizational readiness, perceived barriers, governance maturity, future readiness, and comparative performance within a single empirically tested framework.

This study reconceptualizes organizational readiness within the Resource-Based View (Barney, 1991; Teece, 2018) as a dynamic capability rather than a fixed precondition. Leadership support, data infrastructure, training, and data culture are capabilities that organizations can intentionally build to improve AI adoption.

The technology acceptance model (Davis, 1989; Venkatesh et al., 2003) establishes a direct relationship between behavioral acceptance variables and objective commercial performance in the B2B industrial context. Although the TAM has been extensively tested at the individual and consumer-facing levels, it has not been tested much in an industrial

sales ecosystem (Brown and Davis, 2022). The current study proves that perceived usefulness has a more positive impact on quantifiable sales performance than perceived ease of use, implying that performance expectancy is hierarchically more dominant in commercial contexts. The implication of this finding on TAM is that the relative importance of cognitive constructs can differ depending on the type of industry, accountability structure in organizations, and performance evaluation mechanisms. Thus, this study adds to the behavioral adoption theory by putting TAM into context in the industrial decision-making environment.

The current literature repeatedly defines governance models in terms of ethical protection, transparency and accountability (Floridi and Cowls, 2019; Jobin et al., 2019). The empirical findings of the current study show that the performance effect of AI adoption is enhanced by governance maturity because of the creation of trust, coordination, and organizational legitimacy. Therefore, governance frameworks facilitate firms in transforming AI capabilities into enduring commercial benefits rather than managing technological risks. This reconceptualization expands the theoretical knowledge of governance as an organizational capability for value creation in digital transformation processes.

Together, these contributions can bring AI acceptance research to a new level of explanatory research that does not only focus on telling the story of technological uptake but also generates a multilevel explanatory framework incorporating structural conditions, behavioral mechanisms, organizational capabilities, and institutional governance. The empirical basis of these insights in an under-researched B2B market in an emerging

economy makes this study contribute to the external validity of the existing theoretical frameworks and provides a more nuanced conceptual framework that can be applied to the domain of AI-assisted performance in an asset-intensive industry.

6.3 Practical Implications

In addition to the fact that the study has implications at the firm level, the insights presented in this study have significant consequences for policymakers, regulatory agencies, and industry bodies in emerging economies aiming to accelerate the responsible adoption of AI in industrial sectors.

First, the empirical findings show that the maturity of AI adoption is limited not only by technological access but also by gaps in organizational capabilities, immaturity of governance, and structural resource bottlenecks. AI approaches in each nation should no longer rely on infrastructure-based approaches that focus on digital connectivity and hardware development (Brown and Davis, 2022). Although the creation of basic infrastructure is still needed, sustainable industrial change in AI demands additional investment in the development of managerial skills, workforce education, and industry-specific models of implementation. To enhance organizational preparedness in manufacturing ecosystems, organized training programs, executive education in AI governance, and cross-sector knowledge exchange platforms should be supported by public policy initiatives.

Second, this study confirms that governance maturity is a significant factor that increases the performance effect of AI adoption. This observation implies that regulatory frameworks should not be preoccupied with risk containment but should also allow the

creation of value through organized oversight structures. This could be achieved through clear guidelines on transparency, explainability, accountability, and ethical data usage issued by policymakers to fit the industrial setting. Regularized governance standards can provide clarity to companies reluctant to expand AI use due to compliance risks. In emerging economies, where regulatory environments are still developing, the availability of predictable and effectively communicated standards of governance can improve institutional trust and hasten responsible adoption of AI.

Third, sector-specific policy instruments are required. Industrial B2B manufacturing is significantly more capital-intensive, legacy-systems-oriented, and different in terms of relational contracting forms than digital-native industries. Thus, policies for promoting generic AI may be lacking. Specific incentives could help lower barriers to entry for mid-sized firms by offering tax credits to optimize processes using AI, providing grants to data modernization projects, and establishing public-private pilot projects in manufacturing clusters. This can be achieved through interventions to alleviate the structural discrepancies found in this study between large and mid-sized organizations.

Fourth, industry organizations and professional bodies can play a coordinating role by disseminating best practices and setting voluntary standards for adopting AI in sales and supply chain operations. Associate in multi-level protocol redundancy by encouraging learning networks and sharing governance paradigms, which will lead to a sense of trust in AI-driven systems. In industries where relationships are long-term and contractual, coordinated governance norms can increase inter-organizational trust and mitigate barriers to digital transformation.

Finally, policymakers must be aware that the adoption of AI in industrial settings is capability-based and path-dependent. Therefore, public policy should focus on the long-term development of the ecosystem rather than short-term technology promotion. By promoting university-industrial collaborations, a multi-level manufacturing clusters, data-sharing structures, and privacy and security, and supporting institutional infrastructure to make AI scaling sustainable, can be reinforced.

Overall, the results indicate that successful national AI strategies in emerging economies are based on an integrated policy that incorporates infrastructure investment, capacity building, standardization of governance, and sector-focused support mechanisms. These concerted efforts can hasten the implementation of responsible AI in the industrial production sector and ensure that technological progress is applied to generate quantifiable economic and competitive benefits.

6.4 Future Research Recommendations

Based on the empirical conclusions of this study, there are four narrow areas of research focus for the future. The present study shows that AI creates greater value when organizations combine routine use with responsible governance and continued strategic readiness. Therefore, future studies should develop stronger multi-item measures of governance maturity and future readiness and test their separate and joint effects across industries and over time.

Second, the differences in the uneven patterns of adoption observed between large and mid-sized firms indicate that a comparative cross-industry study is required. Further research may determine whether the interplay between organizational preparation,

structural hindrances, and governance maturity varies more in digitally native industries than in manufacturing industries that rely on assets. Comparative designs like these would help understand whether the identified boundary conditions are specific to this industry or can be applied to other technological ecosystems as well.

Third, organizational readiness can be refined in terms of its conceptual and measurement aspects. The empirical findings suggest that readiness is a multi-dimensional construct incorporating various interrelated dimensions, including commitment to leadership, infrastructural integration, and capability-building mechanisms. Future studies may leverage this to create and test a multidimensional readiness scale to distinguish between structural capability, cultural alignment, and strategic intent to increase construct precision and achieve better predictive accuracy in AI adoption models.

The supported hypotheses establish direct predictive relationships between readiness, barriers, governance maturity, technology acceptance beliefs, AI use, and performance, together with a significant AI Use $\times$ GMFR interaction. Future research should replicate these relationships using longitudinal, multi-source, and objective performance data.

Together, these instructions can be seen as extending the empirical understanding of the current research and filling in multi-level methodological limitations. Further development of multilevel explanations of AI-enabled change in industrial settings can be enhanced by refining measurement models and using more longitudinal designs and cross-industry/cross-national comparisons.

REFERENCES

- Agrawal, A., Gans, J. and Goldfarb, A. (2018) *Prediction machines: The simple economics of artificial intelligence*. Boston, MA: Harvard Business Review Press.
- Barney, J.B. (1991) 'Firm resources and sustained competitive advantage', *Journal of Management*, 17(1), pp. 99–120. <https://doi.org/10.1177/014920639101700108>
- Braun, V. and Clarke, V. (2019) 'Reflecting on reflexive thematic analysis', *Qualitative Research in Sport, Exercise and Health*, 11(4), pp. 589–597. <https://doi.org/10.1080/2159676X.2019.1628806>
- Brown, M. and Davis, R. (2022) 'The evolution of sales strategies in industrial markets: A review of digital and AI-driven approaches', *Industrial Marketing Management*, 103, pp. 45–58. <https://doi.org/10.1016/j.indmarman.2021.12.008>
- Bughin, J., Hazan, E., Ramaswamy, S., Chui, M., Allas, T., Dahlström, P., Henke, N. and Trench, M. (2018) *Notes from the AI frontier: Modelling the impact of AI on the world economy*. McKinsey Global Institute. Available at: <https://www.mckinsey.com> (Accessed: 1 July 2025).
- Chatterjee, S., Rana, N.P. and Dwivedi, Y.K. (2021) 'Artificial intelligence in sales forecasting: A systematic review and research agenda', *Journal of Business Research*, 134, pp. 23–39. <https://doi.org/10.1016/j.jbusres.2021.04.020>
- Chen, L., Liu, G. and Jia, F. (2022) 'Artificial intelligence adoption in business-to-business marketing: Toward a conceptual framework', *Journal of Business & Industrial Marketing*, 37(5), pp. 1025–1038. <https://doi.org/10.1108/JBIM-09-2020-0448>

- Creswell, J.W. and Plano Clark, V.L. (2018) *Designing and conducting mixed methods research*. 3rd edn. Thousand Oaks, CA: SAGE.
- Davenport, T.H. and Ronanki, R. (2018) ‘Artificial intelligence for the real world’, *Harvard Business Review*, 96(1), pp. 108–116. Available at: <https://hbr.org/2018/01/artificial-intelligence-for-the-real-world> (Accessed: 29 January 2025).
- Davis, F.D. (1989) ‘Perceived usefulness, perceived ease of use, and user acceptance of information technology’, *MIS Quarterly*, 13(3), pp. 319–340. <https://doi.org/10.2307/249008>
- DiMaggio, P.J. and Powell, W.W. (1983) ‘The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields’, *American Sociological Review*, 48(2), pp. 147–160. <https://doi.org/10.2307/2095101>
- Dwivedi, Y.K., Hughes, L. and Ismail, A. (2024), ‘Artificial intelligence for sustainable organizational transformation: A strategic roadmap’, *International Journal of Information Management*, 74, 102623. <https://doi.org/10.1016/j.ijinfomgt.2023.102623>
- Dwivedi, Y.K., Kshetri, N., Hughes, L., Slade, E.L., Jeyaraj, A., Kar, A.K. and Abdullah, A.M. (2023) ‘So what if ChatGPT wrote it? Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy’, *International Journal of Information Management*, 71, 102642. <https://doi.org/10.1016/j.ijinfomgt.2023.102642>

- EY (2024) *AI Adoption Index 2.0: Tracking India's sectoral progress in AI adoption*. New Delhi: Ernst & Young and NASSCOM. Available at: <https://indiaai.gov.in/article/ai-s-presence-within-indian-organisations-has-witnessed-notable-growth-nasscom-ai-adoption-index-2-0> (Accessed: 9 December 2025).
- Fishbein, M. and Ajzen, I. (1975) *Belief, attitude, intention, and behavior: An introduction to theory and research*. Reading, MA: Addison-Wesley.
- Floridi, L. and Cowls, J. (2019) 'A unified framework of five principles for AI in society,' *SSRN Working Paper*. <https://doi.org/10.2139/ssrn.3831321>
- Fountaine, T., McCarthy, B. and Saleh, T. (2019) 'Building the AI-powered organization', *Harvard Business Review*, 97(4), pp. 62–73. Available at: <https://hbr.org/2019/07/building-the-ai-powered-organisation> (Accessed: 24 December 2025).
- Ghosh, A., Paul, A. and Chatterjee, D. (2024) 'AI readiness and adoption maturity in Indian manufacturing firms: Challenges and pathways', *Journal of Manufacturing Technology Management*, 35(2), pp. 225–244.
- Glikson, E. and Woolley, A.W. (2020) 'Human trust in artificial intelligence: Review of empirical research', *Academy of Management Annals*, 14(2), pp. 627–660. <https://doi.org/10.5465/annals.2018.0057>
- Haenlein, M., Kaplan, A., Tan, C.W. and Zhang, P. (2019) 'Artificial intelligence (AI) and management analytics', *Journal of Management Analytics*, 6(4), pp. 341–343. <https://doi.org/10.1080/23270012.2019.1699876>

- Hair, J.F., Hult, G.T.M., Ringle, C.M. and Sarstedt, M. (2019) *A primer on partial least squares structural equation modeling*. 3rd edn. Thousand Oaks, CA: SAGE.
- Huang, M.-H. and Rust, R.T. (2021) 'A strategic framework for artificial intelligence in marketing', *Journal of the Academy of Marketing Science*, 49(1), pp. 30–50. <https://doi.org/10.1007/s11747-020-00749-9>
- ICIS (2022). *India chemical industry report: Market size, trends, and forecasts*. London: ICIS Market Insights.
- Jobin, A., Ienca, M. and Vayena, E. (2019) 'The global landscape of AI ethics guidelines', *Nature Machine Intelligence*, 1(9), pp. 389–399. <https://doi.org/10.1038/s42256-019-0088-2>
- Kshetri, N. (2020) 'Artificial intelligence in developing countries', *IT Professional*, 22(4): 63–68.
- Marabelli, M. and Galliers, R.D. (2022) 'Digital transformation and the interplay of structure, agency and context', *Information Systems Journal*, 32(3): 456–478.
- Mariani, M.M. and Wamba, S.F. (2020), 'Exploring how consumer goods companies innovate in the digital age: The role of big data analytics', *Journal of Business Research*, 121, pp. 338–352.
- McElheran, K., Brynjolfsson, E., Cockburn, I., Jin, W., Joy, D. and Schmitz, A. (2023) *AI adoption in America: Who, what, and where*. NBER Working Paper No. 31788. Cambridge: National Bureau of Economic Research. Available at: <https://www.nber.org/papers> (Accessed: 19 March 2025).

- Mikalef, P., Islam, N., Parida, V., Singh, H. and Altair, N. (2023) ‘Artificial intelligence competencies for organizational performance: A B2B marketing capabilities perspective’, *Journal of Business Research*, 164, 113998.
<https://doi.org/10.1016/j.jbusres.2023.113998>
- NITI Aayog (2023) *India’s AI strategy and Industry 4.0 frameworks*. New Delhi: Government of India. Available at: <https://www.niti.gov.in> (Accessed: 7 October 2024).
- OECD (2024) *Artificial Intelligence, Data and Competition*. Paris: OECD Publishing. Available at: <https://www.oecd.org/publications/artificial-intelligence-data-and-competition-9d0ac766/> (Accessed: 11 October 2025).
- Paschen, J., Wilson, M. and Ferreira, J.J. (2020) ‘Collaborative intelligence: How human and artificial intelligence create value along the B2B sales funnel’, *Industrial Marketing Management*, 90, pp. 279–292.
<https://doi.org/10.1016/j.indmarman.2020.07.018>
- Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y. and Podsakoff, N.P. (2003) ‘Common method biases in behavioral research: A critical review of the literature and recommended remedies’, *Journal of Applied Psychology*, 88(5), pp. 879–903.
<https://doi.org/10.1037/0021-9010.88.5.879>
- Ransbotham, S., Khodabandeh, S., LaFountain, B. and Kiron, D. (2023) ‘Expanding AI’s impact with organizational learning’, *MIT Sloan Management Review*, 64(3), pp. 1–12.
- Rogers, E.M. (2003) *Diffusion of innovations*. 5th edn. New York: Free Press.

- Scott, W.R. (2014) *Institutions and organizations: Ideas, interests, and identities*. 4th edn. Los Angeles, CA: SAGE.
- Shankar, V. and Jain, R. (2024) ‘Human–AI collaboration in sales and marketing: Emerging paradigms and performance implications’, *Industrial Marketing Management*, 114, pp. 162–177. <https://doi.org/10.1016/j.indmarman.2024.03.002>
- Suh, J. and Lee, S. (2024) ‘Ethical governance maturity and performance outcomes in AI-driven organizations’, *Technovation*, 126, 102895. <https://doi.org/10.1016/j.technovation.2023.102895>
- Teece, D.J. (2018) ‘Business models and dynamic capabilities’, *Long Range Planning*, 51(1), pp. 40–49. <https://doi.org/10.1016/j.lrp.2017.06.007>
- Venkatesh, V., Morris, M.G., Davis, G.B. and Davis, F.D. (2003) ‘User acceptance of information technology: Toward a unified view’, *MIS Quarterly*, 27(3): 425–478.
- Venkatesh, V., Thong, J.Y.L., Xu, X. and Dwivedi, Y.K. (2022) ‘Unified theory of acceptance and use of technology: A review and roadmap’, *Journal of the Association for Information Systems*, 23(5), pp. 1020–1052. <https://doi.org/10.17705/1jais.00739>
- Vial, G. (2019) ‘Understanding digital transformation: A review and a research agenda’, *The Journal of Strategic Information Systems*, 28(2), pp. 118–144. <https://doi.org/10.1016/j.jsis.2019.01.003>
- Wadhwa, R., Andaleeb, S. and Gaur, M. (2021) ‘Digital transformation in Indian chemical manufacturing: An empirical analysis’, *International Journal of Industrial Management*, 8(3), pp. 211–229.

- Wamba, S.F., Queiroz, M.M., Trinchera, L. and Ngai, E.W.T. (2024) ‘The role of data governance maturity and analytics capabilities in driving AI adoption’, *Technological Forecasting and Social Change*, 194, 122640.
<https://doi.org/10.1016/j.techfore.2023.122640>
- Zeng, H., Huang, Z., Zhou, Q., He, P. and Cheng, X. (2023) ‘Corporate environmental governance strategies under the dual pressures of the government and the public’, *Business & Society*, 62(4), pp. 860–907.
<https://doi.org/10.1177/00076503221114792>

APPENDIX A:

SURVEY COVER LETTER

AI Adoption and Strategic Sales Management in India's Chemical Manufacturing Sector.

Principal Investigator: Gaurav Kumar

This doctoral study examines the influence of artificial intelligence (AI) on strategic sales management in mid- and large-scale chemical manufacturing firms in India. Your participation will take approximately 5 minutes. Responses will be anonymous, reported only in aggregate, and used strictly for academic research.

Eligibility: Professionals working in or supporting sales/commercial functions in mid- or large-scale chemical manufacturing companies in India.

Voluntary participation: You may skip any question (unless marked as required) and exit at any time.

Data protection: No personally identifiable information will be disclosed.

APPENDIX

B:

INFORMED CONSENT

Study Focus: This study examines how AI is adopted in the sales functions of mid- and large-scale chemical manufacturing firms in India and how such adoption influences the sales performance.

In doing so, I accept the following:

This study aims to understand how AI-powered solutions are embraced and utilized in sales and how they are perceived to affect sales.

I was involved voluntarily. You can skip any question or drop out at any point without being penalized.

The answers will remain confidential and will be presented in an anonymized form (e.g., coded as P1-P8).

The risks are low, direct payments are absent, and the results can affect practice and research in the industry.

Information (notes/messages/emails) can be safely stored and published in academic publications because of this thesis.

Consent Declaration:

The information above has been read and comprehended by me (anonymous), and I voluntarily accept to participate in this qualitative questionnaire/interview.

Signature: _____

Date: _____

Location: _____

APPENDIX C:

SURVEY QUESTIONNAIRE

Quantitative Survey Questionnaire

Section 1: Background Information

- 1) Organisation type – Mid-scale, Large-scale chemical manufacturer
- 2) Role – Sales/Marketing Manager, Sales Head, Data, CRM Analyst, other
- 3) Years of experience – 0–3, 4–7, 8–12, 13–20, 20 +
- 4) Region – North, South, East, West, Pan-India

Section 2: AI Adoption Level

- 5) Our company actively uses AI-enabled applications in sales management (CRM, forecasting, pricing and chatbots). (1–5 Likert)
- 6) AI tools are integrated into daily sales decision-making processes. (1–5)
- 7) AI applications have been deployed beyond pilot or trial stages. (1–5)

Section 3: Organizational Readiness

- 8) Leadership supports and champions AI initiatives in sales departments. (1–5)
- 9) Adequate digital and data infrastructure is available to support AI implementation. (1 - 5)
- 10) employees received training to effectively use AI tools. (1–5)
- 11) Our organization encourages a data-driven decision culture. (1–5)

Section 4: Barriers to AI Implementation

- 12) High implementation and maintenance costs limit AI adoption. (1–5 severity)
- 13) Lack of skilled professionals in AI and data analytics is a major constraint. (1–5)

14) Data privacy and security concerns affect AI usage in sales. (1–5)

15) Resistance to change among sales teams slows down AI adoption. (1–5)

Section 5: Perceived Usefulness & Ease of AI

16) AI tools make my sales decisions more accurate and efficient. (1–5)

17) AI applications are easy to learn and use in our sales process. (1–5)

18) AI helps improve the coordination between sales and marketing teams. (1–5)

Section 6: Impact on Sales Performance

19) AI has improved the accuracy of sales forecasts. (1–5)

20) AI has enhanced customer engagement and satisfaction levels. (1–5)

21) AI has contributed to higher sales conversion rates. (1–5)

22) AI has helped reduce sales cycle time and manual effort. (1–5)

Section 7: Comparative Evaluation

23) AI-enabled sales strategies outperform traditional sales approaches in our firms. (1–5)

24) AI integration has improved our competitive advantage in the market. (1–5)

Section 8: Governance maturity & Future Readiness

25) Our organization has clear policies for ethical and responsible AI use in sales. (1–5)

26) We plan to increase our investment in AI tools for sales within the next 12 months. (1–5)

Qualitative Survey Questionnaire

Q1. AI Adoption Experience and Maturity (Supports RQ1)

Can you describe how your organization has adopted AI tools within the sales function?

Q2. Organizational Readiness and Enablers (Supports RQ2)

What organizational conditions, such as leadership commitment, data systems, or employee training, helped or hindered AI integration into sales processes?

Q3. Barriers, Resistance, and Skill Gaps (Supports RQ2)

From your perspective, what are the biggest challenges or sources of resistance to using AI in sales: technical, human, or cultural?

Q4. Impact on Sales Decision-Making and Performance (Supports RQ3)

How has AI changed your team's sales forecasting, customer engagement, and performance results? Could you provide examples or metrics?

Q5. Governance maturity, Ethics, and Future Readiness (Supports RQ4)

What governance maturity mechanisms or policies exist to ensure responsible AI use in sales?