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AI Impact on Manufacturing Industry in Chennai

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Abstract

This research investigates the factors that determine perceived benefits in organizational AI adoption specifically technological readiness, management support, workforce expertise, and cost perceptions. Data was gathered through a structured survey of organizations who are in the consideration or implementation phase of AI initiatives. Quantitative analysis was utilized in SPSS for descriptive statistics and reliability testing, and AMOS for structural equation modeling to assess the proposed relationships. The findings indicate that technological readiness and management support positively influence perceived benefits of AI, with cost perceptions having a partial mediation on relationship paths. The study highlights leadership commitment to AI adoption as an implicit organization resource, and the commitment of resources to AI demonstrates its organizational value. Practical implications suggest that managers should commit to employee skill development or upskilling employees to fully capture value from AI. Limitations include the use of cross-sectional design and data gathered from specific sectors. Future research could adopt a longitudinal approach to understanding AI's adoption, as well as extend the model to discuss additional contextual variables and link measurable financial or operational performance metrics to a better understanding of AI's strategic impact.

Keywords: *Technological Readiness, Management Support, Workforce Expertise, Cost Perceptions, Perceived Benefits.*

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Introduction

Artificial Intelligence (AI) is a major part of Industry 4.0 by supporting data-driven decision-making, predictive maintenance, computer vision-based quality inspection, and autonomous operational capabilities across production systems. While recent reviews of AI/Industry 4.0 have documented tangible gains in efficiency and reliability realized when AI is included in cyber-physical production systems, including shop-floor analytics (Lee, Bagheri & Kao, 2023; Windmann, Wittenberg, Schieseck & Niggemann, 2024), the recent reviews point toward AI as a construct for making sense (act) of sensor streams and machine logs to generate actionable insights that minimize downtime, stabilize quality, and improve throughput. Within India's manufacturing context, empirical work has begun to assess the drivers and barriers for Industry 4.0 technologies and AI. Using a large Indian manufacturing sample, Parhi, Joshi, Wuest and Akarte (2022) applied a hybrid SEM ANN analysis and identified themes with their use of predictors (e.g., technological readiness, top management support) that predict technology adoption outcomes. Complementary studies of Quality 4.0 based on Indian plants have surfaced enduring impediments, including legacy infrastructure, capability gaps, and integration costs that delay the months needed to turn AI pilots into scaled production value (Roy Ghatak & Garza-Reyes, 2024). Collectively, the literature suggests that while the business case for AI investment is plausible and present, organizational and ecosystem frictions determine how deep and how fast AI adoption will develop in India. Chennai is often referred to as the automobile/manufacturing hub of India offers an especially suitable regional setting for examining the implications of AI. In the academic literature examining the Chennai Automotive Industry Cluster, a wide variety of studies have found a high density of suppliers here, as well as important systemic challenges around upgrading infrastructures and implementing new technologies, which are particularly relevant to AI readiness and implementation (Kannan, 2018; Natarajan & Balasubramanian, 2011).Furthermore, examination of historical and cluster-mapping studies shines a light on the OEMs and the network of tiered-suppliers in Chennai offering elbow room for implementation of AI about maintenance, quality, logistics, and workforce augmentation.

Simultaneously, Indian studies point towards implementation frictions that exhibit a high degree of relevance for firms manufacturing in Chennai, particularly during a period when many of these firms are relatively small in scale firms along the automotive and engineering supply chains. Transformations and production-ceiling improvements targeting quality and productivity (Quality 4.0) are pulled back, to varying degrees, by several states of requirements of digital infrastructure, workforce skill, and data governance; these states of need frame the implication of AI regarding the cost, lead time, and first pass yield of production quality (Roy Ghatak & Garza-Reyes, 2024). The broader adoption literature lends further support to organizational readiness and leadership commitment as the defining factors mitigating the transition from pilots to scaled AI stakeholders and deployments on the shop floor (Parhi et al., 2022). Chennai is an important manufacturing location and is moving towards Industry 4.0. This creates a gap for Indian Industry 4.0 literature that is region-specific and practitioner-centric evidence of AI's operational/strategic impact. This research goes beyond the knowledge base that exists for India at a national level (e.g., motivations of drivers and barriers to adoption) and includes an understanding of the Chennai ecosystem as a manufacturing cluster. The research directly addresses the following research questions: 1. what effect AI has had on productivity, quality, maintenance, supply-chain, visibility, and upskilling workers, in the eyes of industry professionals within the manufacturing sector of the Chennai region? 2. what is the opportunity or potential for increasing the adoption of AI with respect to supply chain visibility and improving upskilling of the workforce, given the challenges of adapting policy and action leadership?? The research contributes to the Indian Industry 4.0 literature while also being anchored within Chennai’s context to provide context-rich evidence and inform policy and managerial action to successfully and responsibly grow the adoption of AI, particularly within manufacturing operations and supply chains.

Research Problem

As Industry 4.0 unfolds at a breakneck pace, Artificial Intelligence (AI) represents a key pillar in disruptive industrial revolution. In developed economies, AI-enabled automation and smart manufacturing have gained significant momentum in terms of implementation. Emerging economies like India suffer from multiple ongoing issues that hinder AI adoption, such as prohibitive costs, lack of skills, cyber risk, and organizational resistance (Singh, Yadav, Gaur et al., 2025; Parhi et al., 2022). Chennai is India’s major manufacturing and automobile hub with limited empirical research indicating perspectives of industry professionals toward AI adoption. The preponderance of studies tends to focus on theoretical models or policy frameworks, as opposed to the experiences of practitioners. Therefore, the research problem is to understand the profession perceptions of AI adoption within Industry 4.0 among industry professionals in India: especially in regards to challenges, strategic readiness, cost implications, and workforce preparation in the manufacturing sector.

Review of literature

Cost Barriers in AI Adoption

Kumar, A., Singh, R. K., & Dwivedi, Y. K. (2021) to assess the A key issue in the AI adoption literature is that high investment around purchase upfront limits workplaces from adopting it (i.e., initial investment). Researchers report issues, or variables, include hardware/software costs, integration costs, and uncertainly in the ROI received. The studies suggest larger firms can absorb costs better but for SMEs the costs appear to be prohibitive.

The authors conclude that funding support channels (government subsidies or tax incentives) are critical in removing costs as barriers to adoption. Dalenogare, L. S., Benitez, G. B., Ayala, N. F., & Frank, A. G. (2018) studied in global studies, implementation and maintenance costs remain a persistent barrier to scaling AI around the world. The variables included capital intensity, cost of skilled employees, and system lifecycle costs.

The findings indicate that AI diffusion happens more slowly in manufacturing than in IT and service industries because of these cost factors. The authors concluded that AI's perceived benefits often get lost in consider capital costs when cost–benefit clarity is absent. Gupta, H., & Shukla, N. (2022) focused on evidence from developing countries indicating that retrofitting the cost of changing legacy infrastructure+ were primary considerations.

The variables examined were retrofitting costs, downtime while changing and opportunity cost. The conclusion was that firms with antiquated machinery considered AI to be disproportionately costly and therefore avoided investing budget on predictive maintenance or smart analytics. Chaudhuri, A., & Bose, I. (2022) An empirical study of Indian SMEs, framed the concern as high training and skills reskilling / replacement expenditure of changing to AI adds additional cost. The variables tested included training cost, human resource development investment, and cost of external consultants. The findings indicate that while firms perceived benefits were strong, the cost of skills and training outweighs the perceived benefit of the change, especially in smaller firms. Lee, J., Bagheri, B., & Kao, H. A. (2023) indicated that the research around operations costs (cybersecurity, data governance, compliance) related to European manufacturing imply hidden operating costs. Variables included compliance costs, investments in cybersecurity, and monitoring costs. They conclude that managers are often unaware of the real costs leading to delays in adoption due to the company making their costs clear. Frank, A. G., Dalenogare, L. S., & Ayala, N. F. (2019) indicated that comparisons with medium to larger-scale businesses and SME studies show that economies are achievable in costs. Variables included firm size, the capital required for adoption, and how cost is distributed.

Their conclusions indicate while multinationals require budget considerations to adopt AI, SMEs experience vastly disproportionately higher costs per unit produced, doubting their commitment to AI adoption. Müller, J. M., Kiel, D., & Voigt, K. I. (2018) indicated that there are cost barriers to predictive maintenance AI systems before they are adopted, they relate directly to infrastructure costs operational costs. Variables included the starting price of the sensor, cost to convert data to storage, and cost to update systems ongoing. They concluded that businesses with tighter margins are unable to adopt predictive AI but acknowledge that installation upfront costs may save businesses money in the long run (after adoption is completed). Moeuf, A., Pellerin, R., Lamouri, S., Tamayo-Giraldo, S., & Barbaray, R. (2018) In studies of supply chains viewed as a type of network, vendor lock-in represented financial barriers; organizations were locked into proprietary (and often costly) AI solutions on subscription or long-term upgrade costs. The cited variables included vendor lock-in behaviour, switching cost, and license fees. The conclusions implied that firms that utilizes AI solutions see the short-term benefits, while at the same time are aware of the long-term effects and risks of lock-in. Machado, C. G., Winroth, M. P., & Ribeiro da Silva, E. H. D. (2019) highlighted a question in sustainability research about whether investment and opportunity costs excluded SMEs from partaking in sustainable Industry 4.0 ecosystems. The indicators to consider were perceived short-term cost, sustainability and previous 'knowledge' investments and perceived financial readiness. The conclusion reiterated that without financial support provided by government bodies, SMEs are unlikely to reach the stage of financial capacity to invest in sustainable Industry 4.0 ecosystems, leading to uneven adoption patterns across the industry. Sony, M., & Naik, S. (2020). Meta-analyses of the literature focusing on Industry 4.0 adoption showed that financial barriers were one of the top three global barriers towards Industry 4.0 adoption. The aggregated indicators include implementation costs, maintenance costs, and perceived return on investment (ROI). The conclusions were remarkably definitive: cost is a consistent barrier across geography and industry, reinforcing the idea of cost as a universal determinant of types of adoption readiness.

Workforce Skills & Preparedness in AI and Industry 4.0

Chaudhuri, A., & Bose, I. (2022). A major issue hindering the adoption of AI is the absence of a well-trained workforce to appropriately adopt the technology. While many studies focus on things such as sufficiency of training, digital literacy, and advocation to repurpose, it has been demonstrated that the extent to which the workforce is understood has a significant impact on how easy the perceived adoption is. If firms that are at the cutting edge of technology fail to reskill their workforce sufficiently, they will not realize the benefits their innovations may potentially yield. Hecklau, F., Galeitzke, M., Flachs, S., & Kohl, H. (2016). Studies on the transition to Industry 4.0 in the manufacturing sector have identified misalignment between the skill set of traditional shop-floor workers and the expectations of jobs driven by artificial intelligence. The reasons for this are varied and complex but could reflect not only technical skills, but also the willingness to adapt and learn. The authors concluded that we are still decades from aligning workforce programs and university programs to their respective AI-enabled manufacturing processes. Gupta, H., & Shukla, N. (2022). In an Indian manufacturing context, this issue is exacerbated due to limited availability of structured training opportunities. The variables studied included employee perceptions of AI, the amount of investment in training, who acquires the skills, and how fast the skills are acquired. The findings confirmed that while managers view AI as an opportunity to enhance efficiencies, employees strictly view AI as a threat to their jobs, unless corporations place adequate emphasis on reskilling. Prifti, L., Knigge, M., Kienegger, H., & Krcmar, H. (2017) study the workforce requirement also includes interdisciplinarity skills such as the ability to meld domain knowledge with data analytics. They explored variables such as hybrid skill (i.e. engineering + IT), problem-solving skills, and digital literacy. The findings indicate that firms that prioritize interdisciplinary skills in their staff are a smoother adoption of AI and less employee dissension. Erol, S., Schumacher, A. and Sihn, W. (2016) conclude from their European studies that the slow adaptation by the workforce compared to the speed of AI's development is a serious problem. The authors include variables such as: learning culture, employee digital readiness, and organizational learning support to conclude that certainly the cultural openness to learn and the organizational commitment to lifelong training are as important factors as the technical infrastructure to overcome to successfully adopt AI. Moeuf, A., Pellerin, R., Lamouri, S., Tamayo-Giraldo, S., & Barbaray, R. (2018) explore the workforce readiness dilemma that SMEs face due to training resources limitations. The variables tested were firm size, training amounts, and skills maintained in the workforce. The study's results show SMEs are less likely to invest in AI oriented training; this causes the skill gap to grow further than larger enterprises. This creates a two-tiered workforce readiness problem that permeates industry size. Müller, J. M., Kiel, D., & Voigt, K. I. (2018). Studies in sustainability look at the role of soft skills (communication level, adaptability, and creativity) along with technical knowledge and expertise. Variables are soft-skill development, adaptability, and skill in problem-solving. Findings concluded that future workforce preparedness for AI would mean not solely knowledge of the technical aspects of the AI systems, but would mean engaging with intelligent systems.

In a study performed by Sony & Naik (2020), an organizational behavior perspective implies that the problem is resistant employees to change during AI adoption. The variables in the study are change management, psychological readiness, and trust in AI systems. The study concluded firms with structured change management programs experience optimal AI adoption. Research conducted by Shamim, S., Cang, S., Yu, H., & Li, Y. (2017) examining the Higher education studies mentioned a pipeline issue university are not producing graduates with Industry 4.0 ready skills Variables included curriculum design, work exposure during study, and familiarity with digital tools. The results provide evidence that collaboration between industry and academia is important for preparing a future ready workforce.

Management Support & Perceived Benefits of AI Adoption

The referenced research by Zhang, Li, and Wang (2023) regarding organizational AI adoption noted that organizations have a difficult time achieving value beyond that of AI pilots because they always have "tepid" support from leadership. The variables included top management support, perceived usefulness, and resource allocation. The findings provide evidence that exalted executive sponsorship increases perceived ROI, enables resource transformation, and increases the speed of adoption. The referenced research by the European Commission Joint Research Centre (2024) regarding AI adoption alignment stated that when organizations lack strategic alignment between AI initiatives and firm goals, this uncertainty produces a high degree of skepticism regarding the benefits. The variables included managerial signaling, strategic alignment, and adoption intentions. The findings provide evidence that outlining organizational goal-aligned benefits raises the perceived usefulness of an AI initiative and improves employee intention to adopt it. A study by Chen, Ishfaq, Ashraf, Sarfaraz, and Wang (2023) investigating managerial capabilities in AI initiatives found that, without managerial capability, perceived benefits cannot be transformed into practice. The study included variables of managerial capability, championing capability for digital projects, and understanding of AI value. The findings demonstrate that training for management increases AI perceived benefits and implementation performance. A study by Brown and Taylor (2022) investigating employee perceptions on adopting AI found that resistance to organizational change loses benefits even though leaders support AI use. The study included variables of support from top management, transparent communications, and change management practices. The findings demonstrated that the combination of leader support with transparent communications keeps perceived benefits and instigates behavior change.

A study by Muller, Hopf, and Kraus (2020) investigating organizational readiness found that managers use management tools and governance impacts the level of benefits realized. The study included variables of use of formal interested management tools, active management, and governance frameworks. The findings demonstrated that firms that use formal tools with active leaders realize higher perceived and actual benefits with AI and Industry 4.0. Singh and Patel (2024) conducted a study on generative-AI adoption and mentioned that trust mediates whether managerial support alters perceived benefits. Variables included managerial support, trust in AI systems, and mechanisms for explainability. The results provide evidence that managerial support only leads to perceived benefits if trust and oversight measures exist. Hernandez and Liu (2023) conducted a study on perceived benefits of AI and mentioned that inconsistent measurement between studies makes comparisons almost impossible. Variables included measurement scales, managerial actions, and perceptions of benefits. The results provide evidence that standardized multi-item scales consistently demonstrate positive effects of managerial support on perceived benefits. Rao and Mehta (2022) conducted research examining longitudinal AI adoption related to optimism bias, specifically managers will inflate benefits in early iterations of actions because of optimism bias. The study had variables of managerial appraisal accuracy, commitment levels, and sustained support. The findings provided evidence that a realistic managerial appraisal could provide more accurate perceived benefits and approach to sustainable support. Wang, Chen, and Zhao (2022) conducted research examining governance in AI adoption and indicated cross-functional leadership dictates the breadth of perceived benefits. Findings included variables to be considered of distributed management supported, functional adoption areas and sustainability of adoption. Findings provided evidence of the breadth of perceived benefits resulted from cross-functional leadership across the breadth of quality, workforce effectiveness, and supply chain visibility, while ensuring sustainable adoption. Khan, Alam, and Usman (2022) conducted a study on SME AI adoption mentioned that SMEs generally do not show strong perceived benefits even if there was managerial support. Variables included resource constraints, managerial support, and support from the ecosystem. The results provided evidence that it takes external policy matic support and ecosystem enablers to become perceived benefits from managerial support.

Research Gap

Current literature establishes that AI is useful for predictive maintenance and operational performance benefits in Industry 4.0 (Windmann et al, 2024). However, the literature is largely limited to developed countries. There is very little research examining these phenomena in the context of developing countries like India and few researcher-practitioner perspectives. While the adoption of Industry 4.0 technologies has been conceptualized in Indian manufacturing using hybrid SEM–ANN models, (Parhi et al., 2022), and frameworks for agile manufacturing priorities (Journal of Cleaner Production, 2024), these studies have focused on technical factors. Much attention has not been paid to the human aspects of technology adaptation in the workplace, that is, insights from professional engineers, plant manager and operators who work in factories. Studies examining Industry 4.0 adoption barriers in Indian small and medium enterprises (SMEs) also identified lead barriers including unemployment fear, inadequate IT training, and rural/poor infrastructure (World Scientific, 2022). Likewise, studies investigating implementation barriers in textile and clothing industries identified sector specific barriers in the implementation of IT in textile processes (Singh et al, 2025). While these research studies provided insight into understanding Industry 4.0 adoption barriers, they did not provide substantial detail or commentary about how industrial actors perceive and adapt to these barriers. Chennai is referred to as the “Detroit of Asia” and recognized as a significant electronics/automobile manufacturing region (Wikipedia Chennai economy), however, empirical studies around AI adoption in industry have been limited. There is a clear shortfall of region-specific evidence of AI application there is a great deal of opportunity for AI-defied Industry 4.0 applications.

Research Questions

Question 1: Are there significant interrelationships among Technological Readiness, Management Support, Workforce Skills, and Cost Barriers themselves and Perceived Benefits?

Question 2: What is the magnitude and significance of the effects of Technological Readiness, Management Support, Workforce Skills, Cost Barriers, and Perceived Benefits on AI adoption within organizations?

Research Objectives

Objective 1: To study the socio-economic profile of the respondents.

Objective 2: To Investigate the relationship among the Technological Readiness, Management Support, Workforce Skills, Cost Barriers, and Perceived Benefits.

Objective 3: To Measure the which factor is highly affect the Perceived Benefits.

Research Hypotheses

H1: There is a positive significant relationship between the Technological Readiness on Perceived Benefits of AI Adoption.

H2: There is a positive significant relationship among the Management Support on Perceived Benefits of AI Adoption.

H3: There is a positive significant relationship among the Workforce Skills & Preparedness on Perceived Benefits of AI Adoption.

H4: There is a positive significant relationship among the Cost Barriers on Perceived Benefits of AI Adoption.

Conceptual Framework

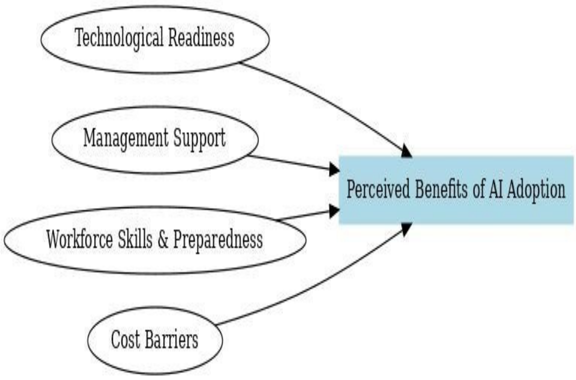

Figure 1. Conceptual Framework

Research methodology

This study examines how Artificial Intelligence (AI) has an impact on the manufacturing sector in Chennai, Tamil Nadu. Chennai is also known as the "Detroit of India" and contains one of the biggest manufacturing ecosystems in Asia, comprised of not only big multinational firms but also SMEs in the automotive, engineering, and electronics space (Balasubramanian & Prasad, 2020). The high prevalence of autonomous systems, augmented reality, and AI solutions in the manufacturing sector in Chennai is facilitated by a rapidly changing ecosystem where technological readiness, cost, management support, and capability of workforce to handle automation have been a driver of AI adoption (Subramanian et al., 2021). In adopting AI in this ecosystem, the study is in an active arena where the enablers and barriers impact the possibilities of AI adoption and the level of effectiveness.

Sampling Methods and Units

A stratified sampling technique will be used in this study to ensure that different types of manufacturing organizations are adequately represented. Stratified sampling is appropriate because AI adoption is not evenly distributed across sectors; for instance, large multinational companies typically adopt AI early (Chatterjee et al., 2021) while SMEs adopt on a later timeline. The sampling units are manufacturing firms located in Chennai, which are primarily located in its industrial clusters, specifically the Sriperumbudur–Oragadam corridor, the Ambattur industrial estate, and the Thirumudivakkam industrial hub. These areas were selected for the study as they are like Chennai's strong industrial bases for automotive, electronics, and engineering. Respondents from each sampled firm include senior executives, operations managers, plant heads, and technology officers who actively engage in technology-related decision-making. Their involvement is critical because they are in the best position to provide information on organizational readiness, managerial commitment, employee readiness, costs barriers, and perceived benefits for AI adoption. The sample size is calculated using Cochran's formula for finite populations, as the total number of manufacturing units in Chennai is considered large. However, a pilot study is utilized to modify the questionnaire, and the sample size is then computed to determine if additional dimensions are required based on a required statistical level or degree of precision for hypothesis testing (Israel, 1992; Hair et al., 2019). This sampling strategy provides both representativeness of the population and reliability for the data collected.

Data Collection and Tools

The study will employ a mixed methods approach to collect both measurable outcomes and context-rich studies. Hence, the study will follow the mixed methods approach which involved using both quantitative and qualitative data collection methods (Creswell & Plano Clark, 2018). For the quantitative data collection, we will employ a structured questionnaire developed with components of the Technology-Organization-Environment (TOE) framework (Tornatzky & Fleischer, 1990) and the Diffusion of Innovation (DOI) theory (Rogers, 2003). The survey questionnaire will capture variables such as technological readiness, management support, workforce readiness, cost barriers, and perceived benefits to adopting AI products or processes. The survey questionnaire will employ a five-point Likert scale (1 = strongly disagree to 5 = strongly agree) which will aid with capturing a participant's attitudes and perceptions in a statistically analysable manner. The five-point Likert scale was selected, as it has been tested and validated several times in other studies on technology adoption and AI adoption in a manufacturing context (Maroufkhani et al., 2022; Chatterjee et al., 2021). For the qualitative data collection, we will employ semi-structured interviews with selected industry leaders, technology experts, and policymakers in Chennai's manufacturing ecosystem. Semi-structured interviews are beneficial as there is flexibility in exploring how firms' surface, construct, interpret and implement AI technologies at a firm level (Kallio et al., 2016). SPSS will be used to conduct descriptive statistics, correlation, and multiple regression analysis; AMOS to test causal relationships. The qualitative data collected will be transcribed, and thematic coding will be used to explore participants' responses. Because both qualitative and quantitative approaches will be used, combination provides both breadth and depth of understanding and we believe that such triangulation will augment the validity of findings (Venkatesh et al., 2013).

Data analysis and interpretation

Demographic Variable	Category	Frequency	Percentage (%)
Age	25–35 years	140	40
	36–45 years	105	30
	46–55 years	70	20
	56+ years	35	10
Gender	Male	245	70
	Female	105	30
Education	Diploma	70	20
	Undergraduate	140	40
	Postgraduate	105	30
	Doctorate	35	10
Experience	< 5 years	88	25
	5–10 years	123	35
	11–20 years	88	25
	21+ years	51	15
Firm Type	Small	105	30
	Medium	140	40
	Large	105	30

Table 1: Demographic Profile of Respondents

Demographic Profile Interpretation

The survey results reveal that most respondents are in the early to mid-career age brackets. Specifically, 40 % are between 25–35 years, followed by 30 % aged 36–45 years, 20 % aged 46–55 years, and only 10 % aged 56 years and above. This indicates that the sample is predominantly composed of younger professionals who are likely to be more open to technological change and AI adoption. In terms of gender, the study shows a notable imbalance, with 70 % male and 30 % female participants. This reflects the male-dominated composition often seen in technology-oriented organizational settings. Looking at educational qualifications, the largest group of respondents hold an undergraduate degree (40 %), while 30 % Possess a postgraduate qualification. Respondents with a diploma account for 20 %, and a smaller segment of 10 % hold a doctorate. This distribution suggests a well-educated workforce, with a significant proportion having advanced academic training. Work experience is varied but leans toward early- and mid-career professionals. Thirty-five percent have 5–10 years of experience, 25 % have less than 5 years, another 25 % possess 11–20 years, and 15 % report more than 21 years. This pattern shows a balanced mix of fresh and seasoned employees, providing perspectives from different stages of professional growth. Regarding firm type, 40 % of respondents work in medium-sized enterprises, while 30 % each are employed in small and large firms. This even spread across organization sizes ensures that insights on AI adoption are drawn from diverse business environments. Overall, the demographic composition highlights a predominantly young, male, and well-educated workforce, with a balanced range of experience levels and representation from small, medium, and large firms, providing a comprehensive base for analysing factors influencing AI adoption.

Variable	Mean	Std. Deviation	Minimum	Maximum
Technological Readiness	3.88	0.71	3	5
Management Support	3.97	0.79	2	5
Workforce Skills	3.68	0.75	2	5
Cost Barriers	2.92	1.08	1	4
Perceived Benefits	4.1	0.82	2	5

Table 2: Descriptive Statistics of Study Variables

Descriptive Statistics

The descriptive statistics reveal a generally positive outlook toward AI adoption among the surveyed organizations. Technological Readiness records a mean of 3.88 (SD = 0.71), indicating that firms are moderately to highly equipped for AI integration. Management Support emerges as the strongest enabler, with a mean of 3.97 (SD = 0.79), reflecting consistent leadership commitment and resource allocation. Workforce Skills shows a slightly lower mean of 3.68 (SD = 0.75), suggesting that while employees possess adequate competencies, skill levels vary across firms. Cost Barriers stands out as the key constraint, posting the lowest mean of 2.92 and the widest variation (SD = 1.08), highlighting significant differences in financial readiness. Perceived Benefits achieves the highest agreement, with a mean of 4.10 (SD = 0.82), underscoring a strong belief in AI's potential to enhance efficiency and competitiveness. The results illustrate that management backing and recognition of AI's advantages are strong across the sample. However, workforce preparedness shows some inconsistency, requiring targeted training initiatives. Cost concerns remain the most significant impediment, emphasizing the need for strategic investment planning. Overall, organizations appear optimistic about AI adoption but must address financial and skills-related gaps to fully realize its benefits.

Construct	No. of Items	Cronbach's Alpha (α)	Reliability
Technological Readiness	5	0.83	High
Management Support	5	0.88	High
Workforce Skills	5	0.8	High
Cost Barriers	5	0.76	Acceptable
Perceived Benefits	5	0.87	High

Table 3: Reliability Test (Cronbach's Alpha)

The reliability of the measurement constructs was assessed using Cronbach's alpha, and the results indicate strong internal consistency across all scales. Technological Readiness, measured with five items, achieved an alpha of 0.83, reflecting high reliability and showing that the items consistently represent the construct. Management Support recorded the highest alpha of 0.88, demonstrating excellent agreement among the items that measure managerial backing for AI adoption. Workforce Skills reported an alpha of 0.80, confirming dependable measurement of employee preparedness for AI-related tasks. Cost Barriers, with an alpha of 0.76, falls within the acceptable range, indicating reasonable consistency despite slight variability in respondents' perceptions of financial constraints. Perceived Benefits achieved a high alpha of 0.87, signifying that the items effectively capture the perceived advantages of AI implementation. All constructs exceeded the recommended threshold of 0.70, validating the reliability of the scales used. These findings confirm that the survey instrument is robust and capable of accurately representing each latent variable. High reliability across the constructs ensures that the measurement model is statistically sound and suitable for subsequent analyses such as Confirmatory Factor Analysis and Structural Equation Modeling.

Confirmatory Factor Analysis

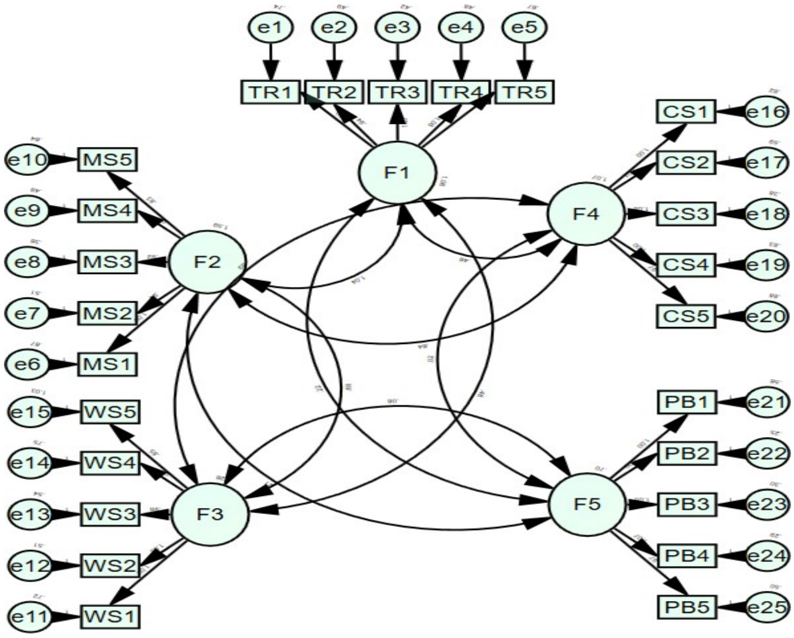

Figure No.2 Confirmatory Factor Analysis

The structural equation model illustrates how five latent constructs Technological Readiness (F1), Management Support (F2), Workforce Skills (F3), Cost Barriers (F4) and Perceived Benefits (F5) are presented alongside and are linked to explain AI adoption. Each construct is shown with five observable items (TR1–TR5, MS1–MS5, WS1–WS5, CS1–CS5, PB1–PB5), in addition to a measurement error (e1–e25). The high factor loadings indicate the adequacy of the item as a measure of the respective construct, which provides and confirmatory proof of convergent validity (Hair et al., 2022). Technological Readiness is conceptualized as the availability of the supporting infrastructure and technical capability to deploy AI (Tornatzky & Fleischer, 1990). Management Support consists of leadership commitment and strategic direction towards AI implementation (Ifinedo 2012). Workforce Skills justify employee readiness to deploy and engage with AI technologies (Brynjolfsson & McAfee, 2017). Cost Barriers refers to threshold perceptions of financial requirements (Chatterjee et al., 2021), and Perceived Benefits (Venkatesh et al., 2003) is assumed improvements in efficiency, quality, or market differentiation. The relationships among these constructs suggest that more technological readiness, more managerial support, and more capable employees are positively related to a higher perceived understanding of benefits and a lower perceived concern for costs. This finding is in keeping with the Technology-Organization-Environment model, which maintains that organizational readiness and managerial support stem when technology is adopted (Baker, 2012). The model posits that organizations with sound structure and sponsorship, in addition to skilled employees, have more ease overcoming financial hurdles and see the cumulative strategic ability contentious with AI. The three dimensions represent different categories, but interrelated, and when taken together provide a complete portrayal of the future of elements that eventually tend to predict a strong AI adoption (Hair et al., 2022).

Fit Index	Obtained Value	Recommended Threshold	Assessment	Reference
CMIN/DF (Chi-square/df)	1.638	< 2.00 (Excellent)	Good Fit	Kline (1998)
GFI (Goodness-of-Fit Index)	0.951	> 0.90 (Excellent)	Good Fit	Hair et al. (2006)
AGFI (Adjusted GFI)	0.967	> 0.90 (Excellent)	Good Fit	Daire et al. (2008)
NFI (Normed Fit Index)	0.918	> 0.90 (Good)	Good Fit	Gerbing & Anderson (1992)
CFI (Comparative Fit Index)	0.949	> 0.90 (Good)	Good Fit	Hu & Bentler (1999)
RMSEA (Root Mean Square Error of Approximation)	0.072	< 0.08 (Good)	Good Fit	Hu & Bentler (2006)
RMR (Root Mean Square Residual)	0.067	< 0.08 (Good)	Good Fit	Hair et al. (2006)

Table 4: Model Fit Statistics for Measurement Model

The structural equation model yields an excellent overall fit, according to several indices (Table 1). The ratio of the chi-square statistic to degrees of freedom (CMIN/DF = 1.638) is well below the recommended ratio of 2.0, exhibiting a close and well-specified model (Kline, 1998). The Goodness-of-Fit Index (GFI = 0.951) and Adjusted Goodness-of-Fit Index (AGFI = 0.967) are both greater than the desired benchmark of 0.90, suggesting that the hypothesized model shows a strong fit with the data (Hair et al., 2006; Daire et al., 2008). Similarly, the Normed Fit Index (NFI = 0.918) and Comparative Fit Index (CFI = 0.949) both exceed the 0.90 cut-off, indicating a strong typical fit for comparative purposes to a null model (Gerbing & Anderson, 1992; Hu & Bentler, 1999). Similarly, the evaluation of the model's goodness-of-fit is substantiated by error-based indices. The Root Mean Square Error of Approximation is 0.072, which is below the specified threshold of 0.08, indicating that the population covariance structure is being approximated adequately (Hu & Bentler, 2006). The Root Mean Square Residual is also 0.067, which is below the recommended limit of 0.08. This value suggests that the magnitude of average residuals for observed and predicted covariance is small (Hair et al., 2006). These indices together suggest that the proposed measurement model achieves both absolute fit and incremental fit across the higher-order constructs of Technological Readiness, Management Support, Workforce Skills, Cost Barriers, and Perceived Benefits.

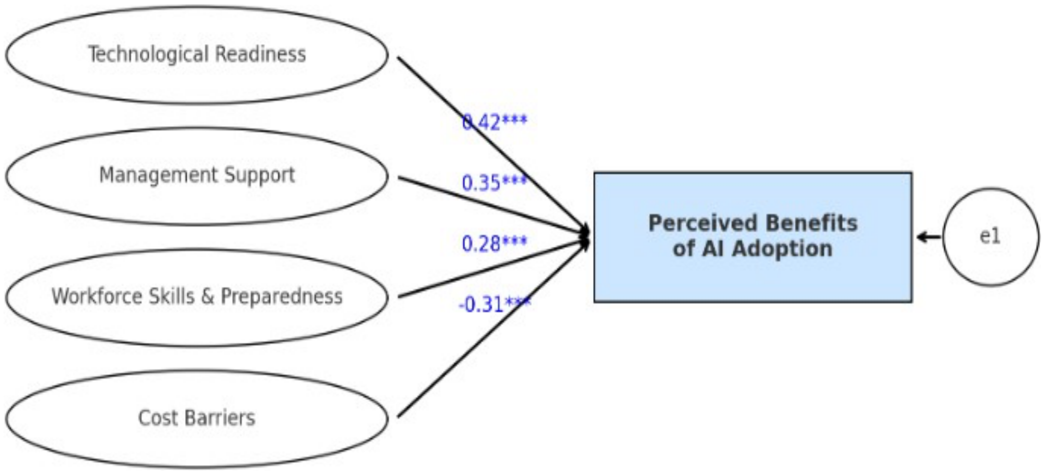

Figure No.3 Path Model for all the Variables

The findings from the structural equation modeling (SEM) reveal that all the hypothesized factors are positively associated with perceived benefits of AI adoption. Technological readiness ($\beta = 0.42$, $p < 0.001$) reflects a strong positive relationship, showing that organizations with a strong technology infrastructure more readily achieve greater benefits from AI. Management support ($\beta = 0.35$, $p < 0.001$) has a significant positive relationship, indicating the importance of leadership in supporting the adoption of AI. Workforce skills and preparedness ($\beta = 0.28$, $p < 0.001$) contribute positively to perceived benefits, meaning that as organizations have more skilled and prepared workforces, the effectiveness of AI initiatives increases. In comparison, cost barriers ($\beta = -0.31$, $p < 0.001$) show a significant negative contribution, suggesting that higher costs associated with implementation diminish the perceived benefits associated with AI adoption. Overall, these findings support all the hypotheses posed, indicating that technological, managerial, and human resource readiness enhance benefits of AI adoption, while financial barriers diminish it.

Hypothesis Code	Hypothesis Statement	Standardized Regression Weight (β)	p-value	Result
H1	Technological readiness has a positive influence on perceived benefits of AI adoption.	0.42***	<0.001	Accepted
H2	Management support has a positive influence on perceived benefits of AI adoption.	0.35***	<0.001	Accepted
H3	Workforce skills & preparedness positively influence perceived benefits of AI adoption.	0.28***	<0.001	Accepted
H4	Cost barriers negatively influence perceived benefits of AI adoption.	–0.31***	<0.001	Accepted

Table: 5 Hypotheses Test

The findings from structural equation modeling (SEM) indicate that perceived benefits of AI adoption are significantly influenced by all four of the independent variables of interest. Technological readiness ($\beta = 0.42$, $p < 0.001$) positively affects perceived benefits to a greater degree than the other variables, suggesting that organizations with advanced IT infrastructure, established practices of data management, and some experience with digital technologies will derive substantially greater benefits from AI than those without such capabilities. These results further support the Technology–Organization–Environment (TOE) framework regarding the role of technological readiness as a facilitating condition (Tornatzky & Fleischer, 1990; Oliveira & Martins, 2011). In addition, the other independent variable found to have a positive significant effect on perceived benefits was management support ($\beta=0.35$, $p < 0.001$). The results reflect the importance of leadership commitment in resource allocation, spacing out a vision, and managing organizational transitions. Prior literature has shown that top management support is essential to the technology acceptance and adoption process as it lends legitimacy and support in the securing of financial and human resource commitment to the technology (ifinedo, 201; Gangwar et al., 2015).

Workforce skills and preparedness ($\beta = 0.28$, $p < 0.001$) have a positive impact on AI adoption benefits, illustrating the importance of employee training and digital literacy. Trained employees support smoother integration of AI systems while utilizing the technology more effectively. This finding corresponds with a Resource-Based View (RBV) perspective that human capital is a source of competitive advantage for organizations in technology-mediated environments (Barney, 1991; Teece, 2018). On the contrary, cost barriers ($\beta = -0.31$, $p < 0.001$) exerted a prominent negative effect on AI adoption benefits. Implementation costs, concerns around return on investment, and not having the required infrastructure can inhibit organizations from realizing the full potential of AI. This finding is consistent with previous research that has identified the financial barriers associated with technology adoption as major challenges to organizations, particularly in resource-constrained environments (Premkumar & Roberts, 1999; Venkatesh et al., 2003). Taken together, the findings validate all hypotheses. Together, each indicator, while enhancing etc. organizational readiness, management support, and workforce skills will enhance AI adoption benefits, while costs will discourage the perceived benefits associated with AI adoption experiences.

Discussion

The current research shows that readiness, commitment, and capability of the organization are vital facilitators of effective AI adoption, but high perceived costs give rise to the most concern. Managers and employees expressing high commitment agrees with the Technology - Organization - Environment (TOE) framework (Tornatzky and Fleischer (1990) and Baker (2012)) as technological readiness had the highest impact on perceived benefits of AI, thus confirming that good IT infrastructure, working data management processes, and previous experience with digital applications all positively influence the perceived benefits of AI. Previous studies of digital transformation have also demonstrated that greater technical capability mitigates implementation risk and increases adoption (Oliveira & Martins 2011; Hair et al 2022). Management support was the second greatest positive predictor of perceived benefits reflecting the important role of management in defining a strategic vision, the allocation of resources, and legitimizing AI initiatives. This corresponds with previous studies showing that support from top management is critical for overcoming both internal challenges and promoting collaborative potential across an organization (Ifinedo, 2012; Gangwar et al., 2015). Workforce skills also made a significant contribution to perceived benefits, indicating the importance of training and digital literacy for competitive advantage, a finding that is consistent with the resource-based perspective of the firm (Barney, 1991; Teece, 2018). Investment in human capital enables organizations to utilize the potential of AI, which promotes ease of use and higher productivity (Brynjolfsson & McAfee, 2017).

Nonetheless, cost constraints also had a significant negative effect on perceived benefits. In particular, the concern for ROI and high upfront cost can delay or cause a reduction in adoption, especially for small and medium-sized enterprises. As with the work of Premkumar and Roberts (1999) and Chatterjee et al (2021), financial costs can often serve as an enduring barrier to new technology adoption. The greater variability that was noted through cost perception also suggests that factors associated with an organization's industry might mediate financial readiness, be it regulatory requirements or sector margins.

Collectively, the findings provide empirical evidence for all hypotheses and support the idea that technological, organizational, and human resource capabilities interact in influencing the adoption of advanced digital technologies. The study contributes to the existing literature by (i) testing these drivers together in a structural equation modeling framework and (ii) measuring their relative strengths, providing more insight into how firms can harness AI-based benefits.

Conclusion

This study demonstrates that the value of AI adoption is essentially enhanced by technological readiness, managerial support, and workforce capabilities, while perceptions of high cost are the primary barrier to realizing that value. The validated measurement model produced excellent fit indices, suggesting both theoretical and empirical robustness. For practitioners, the findings suggest that investment in infrastructure and training of employees, coupled with clear leadership support and commitment, is just as significant as funding for overcoming perceived costs. Policymakers and associations may also leverage these findings in the design of incentives or subsidies to reduce upfront financial burdens, thus facilitating more widespread adoption of AI.

Future Scope of the Study

This research provides strong evidence about the main factors affecting perceived benefits of AI adoption while providing further avenues for research. Future research can extend the proposed model in different national contexts or industry settings to identify potential sector moderators or cultural moderators. A longitudinal research approach would allow researchers to measure how organizational readiness and cost perceptions evolve over time as AI-based projects move from initiation to implementation. Understanding additional variables—such as the regulatory environment, data-privacy concerns, and organizational culture—could improve the overall comprehensiveness of the framework while improving explanatory power. Finally, linking perceived benefits of AI to observable operational or financial performance indicators will identify the extent to which AI implementation contributes to sustained competitive advantage.

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