

THE EFFECT OF AGENTIC ARTIFICIAL INTELLIGENCE DETERMINED WORKFORCE PLANNING ON OPERATIONAL EFFICIENCY WITH SPECIAL REFERENCE TO SOUTH INDIAN SERVICE SECTOR

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ABSTRACT

This study examines the effect of agentic artificial intelligence (AI) driven workforce planning on operational efficiency in Indian service sector organizations. Agentic AI refers to artificial intelligence systems capable of autonomous goal-directed action systems that do not merely support human decisions but execute them independently. As service organizations increasingly adopt AI tools in Human Resource (HR) functions, the conditions under which such adoption translates into measurable efficiency gains remain empirically underexplored. The study was conducted with a sample of 50 HR professionals and operations managers drawn from IT, BPO, retail, and allied service sector organizations across India through purposive sampling. Data was collected using a structured questionnaire administered via Google Forms and analysed using Jamovi version 2.6. The survey instrument comprised six sections covering workforce planning practices, AI awareness and adoption, operational efficiency outcomes, organisational readiness, and future orientation toward agentic AI. Based on these findings, a three-stage framework for responsible agentic AI adoption is proposed, covering Readiness Assessment, Assisted Decision Making, and Autonomous Execution. The study contributes original empirical evidence on agentic AI and operational efficiency in the service sector context and offers actionable guidance for HR practitioners and organizational leaders.

Keywords: Agentic, Artificial Intelligence (AI), HR, Operational Efficiency, Indian Service Sector

INTRODUCTION

The term artificial intelligence is used so broadly in contemporary discourse that it has become analytically imprecise. Not all AI systems are equivalent in their capabilities, their governance requirements, or their implications for workforce planning. Drawing a clear boundary around agentic AI is therefore a prerequisite for meaningful research. The accelerating integration of artificial intelligence into organisational functions has ushered in a period of profound transformation in the way businesses plan, deploy, and manage their human capital. Among the most consequential of these developments is the emergence of agentic AI, a category of artificial intelligence distinguished not merely by its capacity to analyse data or generate recommendations, but by its ability to pursue goals, execute decisions, and adapt its behaviour autonomously in dynamic environments. In the context of workforce planning the systematic process by which organisations forecast staffing needs,

REVIEW OF LITERATURE

Budhwar et al.(2022)¹ produced one of the most ambitious attempts to map this territory, synthesising findings from 70 empirical studies to examine how AI is restructuring HRM across both routine and judgment-intensive tasks. . NASSCOM(2025)³ data places India among the top five countries for enterprise AI adoption in HR functions. Yet the empirical literature examining what actually happens in Indian mid-size firms when these tools are deployed remains sparse. The gap between adoption rate and research coverage is striking and, for practitioners making real decisions about real workforces, consequential. The structural position of mid-size Indian service firms deserves particular attention here. Tambe et al.(2019)⁴ identified what they called the mid-size firm problem in AI-enabled HRM: organisations of this scale are too large to rely on informal, relationship-based HR practices, yet too resource-constrained to build the data governance pipelines, AI literacy programmes, and interpretability infrastructure that large multinationals deploy alongside their algorithmic systems. What does AI actually do within the HRM function? The question is deceptively simple. Dima et al.(2024)⁵ examined 43 empirical papers on AI effects across HR activities. Empirical evidence from the Indian context offers some initial calibration. Murugesan et al.(2023)⁶ surveyed 271 HR professionals across Indian organisations using structural equation modelling and found statistically significant positive relationships between AI adoption and both decision quality and process efficiency. The broader question of what kinds of HRM tasks AI is best suited to handle has generated a separate strand of inquiry. Cheng and Hackett(2021)⁷ argue that AI performs best on high-volume, structured, data-rich tasks where the criteria for evaluation can be specified in advance, and faces significant limitations on tasks requiring contextual judgement, interpersonal nuance, or ethical reasoning about individual circumstances. Daugherty(2018)⁸ make a closely related argument for what they term collaborative intelligence, contending that the most significant productivity gains from AI adoption come not from replacing human judgment but from designing workflows in which human and algorithmic capabilities are deliberately combined. Zhang et al.(2025)⁹ situate this transition within the broader framework of algorithmic management, a research programme that examines how algorithmic systems exercise managerial functions traditionally held by human managers. Venugopal et al.(2024)¹⁰ reached a strikingly consistent conclusion from their synthesis of 389 papers on AI and HRM. The most consistent finding across this extraordinarily large literature base is not about efficiency gains or adoption rates. Deloitte India(2024)¹¹ point to significant capability gaps in AI governance, data management, and HR literacy at the mid-market level, precisely the segment of the industry where adoption pressure is highest and governance infrastructure is thinnest. Borrelli and Musch(2025)¹² corroborate this observation from a global perspective, noting that the transition from assisted to autonomous AI models is consistently fastest in technology-intensive emerging market contexts, while governance development lags by an average of two to three years behind deployment. Miehling et al.(2025)¹³ argue that conventional sociotechnical systems frameworks were designed for discrete tools operating within defined boundaries and are inadequate for governing autonomous multi-agent systems that actively redistribute decision-making authority across human and machine actors. Thomas(2025)¹⁴ extends this argument, demonstrating that autonomous AI decision-making consistently creates accountability gaps in which consequential organisational decisions are executed without any single human actor bearing clear responsibility for their outcomes. Chowdhury et al.(2023)¹⁵ demonstrate that unlocking AI value in HRM requires simultaneous capability development across technical, human, and organisational dimensions, with single-dimension investments consistently underperforming relative to integrated capability approaches.

PROBLEM IDENTIFICATION

Despite the growing prevalence of AI tools in Indian service organisations, a substantial gap exists between the adoption of these technologies and the realisation of the operational efficiency improvements they promise. This gap raises a fundamental question that existing literature has not adequately addressed: what factors determine whether AI adoption in workforce planning leads to genuine operational improvement, and how does the emerging category of agentic AI with its distinctive capacity for autonomous action alter this relationship?

SCOPE OF THE STUDY

The study makes an original empirical contribution to the growing body of literature on AI-enabled HRM by providing quantitative evidence of the relationship between agentic AI adoption and operational efficiency in an Indian service sector context. From a practical standpoint, the study provides HR practitioners, operations managers, and organisational leaders with empirically grounded guidance on the conditions under which AI adoption in workforce planning is most likely to yield operational benefits. Geographically, the study encompasses respondents from multiple Indian cities and regions, including Kerala, Karnataka, Tamil Nadu, Telangana, and select respondents from international locations who are employed in Indian service sector organisations. This multi-regional coverage enhances the representativeness of the findings across the Indian service sector landscape.

OBJECTIVES OF THE STUDY

- To examine the current level of agentic AI adoption in workforce planning among Indian service sector organisations.
- To assess the relationship between organisational readiness and operational efficiency outcomes following agentic AI integration.
- To investigate the moderating role of managerial trust in the relationship between AI adoption level and operational efficiency.
- To identify differences in AI adoption and organisational readiness perceptions based on respondents' designation levels.

RESEARCH METHODOLOGY

The study was conducted with fifty valid respondents drawn through purposive sampling. While this sample size is considered adequate for the non-parametric statistical analyses employed. All responses were collected through a structured questionnaire administered via Google Forms. . The questionnaire was designed on a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree) for all attitudinal and perceptual items. The questionnaire was distributed to HR professionals and operations managers in Indian service sector organisations. Secondary data was drawn from peer-reviewed journal articles, industry reports published by NASSCOM, EY India, IBM Institute for Business Value, NITI Aayog, and the Confederation of Indian Industry, as well as academic databases including Scopus, Web of Science, and Google Scholar.

DATA ANALYSIS AND INTERPRETATION

All inferential analyses were conducted using Jamovi version 2.6, an open-source statistical software platform. To test normality, the Shapiro-Wilk test (Table 1) was applied to all nine composite variables. The Shapiro-Wilk test is widely regarded as the most appropriate normality test for sample sizes below 50 and is the standard procedure for studies of this

scale. The decision rule applied was as follows: a Shapiro-Wilk p value greater than 0.05 indicates that the variable does not significantly deviate from normality, and parametric tests may be applied; a p value of 0.05 or below indicates a significant departure from normality, and non-parametric tests are required.

Table 1: Shapiro-Wilk Normality Test Results

Variable	Shapiro-Wilk W	p Value	Distribution	Test Selected
AI_Adoption	0.968	0.190	Normal	Non-parametric*
Time_Efficiency	0.970	0.231	Normal	Non-parametric*
Cost_Efficiency	0.935	0.008	Non-normal	Non-parametric
Quality_Efficiency	0.966	0.163	Normal	Non-parametric*
Efficiency	0.981	0.597	Normal	Non-parametric*
Tech Readiness	0.931	0.006	Non-normal	Non-parametric
Workforce Readiness	0.921	0.003	Non-normal	Non-parametric
Org_Readiness	0.961	0.095	Normal	Non-parametric*
Trust	0.930	0.006	Non-normal	Non-parametric

Source: Data Analysis

*Non-parametric tests were applied throughout for methodological consistency.

Table 2: Spearman Correlation Matrix

Variable	AI Adoption	Time Eff	Cost Eff	Quality Eff	Efficiency	Tech Read	WF Read	Org Read	Trust
AI Adoption	—								
Time Efficiency	0.299*	—							
Cost Efficiency	0.443**	0.727**	—						
Quality Efficiency	0.342*	0.667**	0.589**	—					
Efficiency	0.436**	0.909**	0.867**	0.846**	—				
Tech Readiness	0.389**	0.615**	0.592**	0.511**	0.656***	—			
WF Readiness	0.367**	0.642**	0.708**	0.454**	0.676***	0.437**	—		
Org Readiness	0.441**	0.696**	0.668**	0.751**	0.800***	0.525**	0.435**	—	
Trust	0.115	0.501**	0.616**	0.432**	0.540***	0.380**	0.609**	0.355	—

Source: Data Analysis *p < .05, **p < .01, ***p < .001

The correlation matrix (Table 2) reveals a rich pattern of statistically significant positive relationships among the study variables. Several findings deserve specific attention.

The relationship between Org_Readiness and Efficiency (rho = 0.800, p < .001) is the strongest bivariate correlation in the matrix, indicating a very strong positive association between organisational and leadership readiness and overall operational efficiency. This

finding suggests that the strategic, cultural, and governance dimensions of readiness are the most powerful determinants of efficiency outcomes in the sample. Workforce_Readiness and Efficiency ($\rho = 0.676$, $p < .001$) and Tech_Readiness and Efficiency ($\rho = 0.656$, $p < .001$) also demonstrate strong positive relationships, confirming that all three dimensions of organisational readiness are meaningfully associated with efficiency outcomes and providing collective support for Hypothesis H1. AI_Adoption and Efficiency ($\rho = 0.436$, $p = 0.002$) shows a moderate positive relationship, indicating that higher levels of AI adoption are associated with better efficiency outcomes. Trust and Efficiency ($\rho = 0.540$, $p < .001$) demonstrates a moderate positive relationship, indicating that higher managerial trust in AI systems is associated with better efficiency outcomes. Importantly however Trust and AI Adoption ($\rho = 0.115$, $p = 0.425$) shows a negligible and non-significant relationship. The three efficiency sub-dimensions Time Efficiency ($\rho = 0.909$), Cost Efficiency ($\rho = 0.867$), and Quality Efficiency ($\rho = 0.846$) all demonstrate very strong positive correlations with the overall Efficiency composite, confirming the coherence of the efficiency construct across its three sub-dimensions.

The descriptive analysis of AI adoption indicators revealed that the mean AI Adoption score for the sample was 3.04 on a five-point scale, indicating a moderate level of adoption that falls between the planning and pilot stages for the majority of respondents. The analysis of individual adoption components indicated that AI familiarity was relatively high, with a mean of 3.52, reflecting a sample of respondents with meaningful exposure to AI tools in HR contexts. AI usage stage registered a mean of 2.82, indicating that most organisations were at the planning or pilot stage rather than full implementation. The role of AI in workforce planning decisions was predominantly supportive rather than autonomous, with most respondents reporting that AI tools provided data and recommendations while managers retained final decision-making authority. These findings collectively indicate that Indian service sector organisations are in a transitional phase of AI adoption aware of and engaged with AI technologies but not yet operating at the level of autonomous agentic deployment that the technology is capable of.

HYPOTHESES OF THE STUDY

H1 Organisational readiness positively influences operational efficiency in firms adopting agentic AI-driven workforce planning.

H2 Managerial trust moderates the relationship between AI adoption level and operational efficiency.

H3 Higher AI adoption level positively predicts operational efficiency outcomes.

H4 There are significant differences in organisational readiness levels based on respondents' designation.

The Spearman correlation analysis revealed strong and statistically significant positive relationships between all three dimensions of organisational readiness and overall operational efficiency. Technological Readiness was positively correlated with Efficiency at $\rho = 0.656$ ($p < .001$), Workforce Readiness at $\rho = 0.676$ ($p < .001$), and Organisational Readiness at $\rho = 0.800$ ($p < .001$).

Table 3: Consolidated Hypothesis Testing Summary

Hypothesis	Statistical Test	Key Statistic	p Value	Decision
H1-Readiness Efficiency →	Spearman Correlation	rho = 0.800 (Org_Readiness)	<.001	Supported
H2 -Trust moderates AI → Efficiency	Moderation Analysis	$\beta = -0.0525$ (interaction)	0.734	Not Supported
H3- AIAdoption→Efficiency	Spearman Correlation	rho = 0.436	0.002	Supported
H4- Designation differences	Kruskal-Wallis	$\chi^2 = 7.91$ (Efficiency)	0.244	Not Supported

Source: Data Analysis

The strength of the relationship between Organisational Readiness and Efficiency the strongest correlation observed in the study is particularly noteworthy, underscoring the critical role of leadership support, strategic clarity, and change management capability in translating AI adoption into measurable operational gains. On the basis of these findings, Hypothesis H1 is supported: organisational readiness positively and significantly influences operational efficiency in firms adopting agentic AI-driven workforce planning.

The moderation analysis conducted using the medmod module in Jamovi revealed that while both AI Adoption ($\beta = 0.3302$, $p = 0.002$) and Managerial Trust ($\beta = 0.4671$, $p < .001$) independently and significantly predicted Operational Efficiency, the interaction term AI Adoption \times Trust was not statistically significant ($\beta = -0.0525$, $p = 0.734$). This finding indicates that Managerial Trust does not moderate the relationship between AI Adoption and Operational Efficiency in this sample. The simple slope analysis further revealed that the positive effect of AI Adoption on Efficiency was significant at average and low trust levels but approached non-significance at high trust levels, suggesting a pattern that warrants further investigation in larger samples. On the basis of these findings, Hypothesis H2 is not supported. However, the independent significance of Trust as a direct predictor of Efficiency represents a substantive finding in its own right, indicating that trust-building is a valuable organisational investment regardless of its moderating function. The Spearman correlation analysis confirmed a significant moderate positive relationship between AI Adoption and Operational Efficiency, with $\rho = 0.436$ and $p = 0.002$. This finding indicates that organisations at more advanced stages of AI adoption characterised by higher familiarity, more extensive usage, a more active role for AI in decision-making, and more frequent use report significantly higher levels of operational efficiency than their counterparts at earlier stages. This result is consistent with the broader empirical literature on AI adoption and performance outcomes and provides direct empirical support for the proposition that AI adoption in workforce planning yields measurable operational benefits in the Indian service sector context. Hypothesis H3 is therefore supported. The Kruskal-Wallis test of group differences across seven designation categories revealed no statistically significant differences in Efficiency ($\chi^2 = 7.91$, $df = 6$, $p = 0.244$), Organisational Readiness ($\chi^2 = 5.45$,

df = 6, p = 0.488), Technological Readiness ($\chi^2 = 5.83$, df = 6, p = 0.443), or Workforce Readiness ($\chi^2 = 7.67$, df = 6, p = 0.264) across designation groups. Post-hoc pairwise comparisons using the Dwass-Steel-Critchlow-Fligner method confirmed the absence of significant pairwise differences between any designation pair on any of the tested variables. Hypothesis H4 is therefore not supported.

CONCLUSION

The present study set out to examine the impact of agentic AI-driven workforce planning on operational efficiency in Indian service sector organisations, with specific attention to the roles of organisational readiness and managerial trust as predictors and moderators of this relationship. The empirical investigation of fifty service sector professionals yielded a set of findings that are both theoretically significant and practically actionable. The study confirms that both AI Adoption and Organisational Readiness are significant positive predictors of Operational Efficiency, with Organisational Readiness particularly its leadership and strategic dimensions emerging as the stronger predictor. These findings establish that the efficiency benefits of agentic AI in workforce planning are not automatic but are contingent on the foundational readiness conditions that organisations establish before and during the adoption process. The non-significant moderating role of Managerial Trust, while not confirming H2, adds theoretical nuance by suggesting that trust functions primarily as an independent facilitator of efficiency rather than a boundary condition governing the adoption-efficiency relationship. The absence of significant designation-level differences in readiness perceptions indicates that AI readiness is an organisational rather than a hierarchical phenomenon, with implications for how adoption initiatives are scoped and communicated.

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