

AI And Employee Performance: Unravelling The Influence of AI Literacy, Innovation Capability, And Collaboration

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Abstract

This study examines the impact of AI literacy, technological openness, innovation capability, and collaboration with AI on job performance within the Indian IT sector. The primary objective is to assess how these AI-related factors influence employee performance and organizational effectiveness. Using a structured survey, data were collected from 150 IT employees across leading firms, and Structural Equation Modeling (SEM) was employed via AMOS to analyze the hypothesized relationships. The findings reveal that AI literacy and technological openness significantly enhance job performance, with innovation capability and AI collaboration also contributing positively. The study provides empirical support for theoretical models such as the Technology Acceptance Model (TAM) and the Resource-Based View (RBV), reinforcing the importance of AI-related competencies in driving competitive advantage. This research contributes to both theory and practice by highlighting the need for strategic AI training and fostering a culture of technological adaptability to optimize workforce efficiency in AI-driven workplaces.

Keywords: AI Literacy; Technological Openness; Innovation Capability; Collaboration with AI; Job Performance; Structural Equation Modeling (SEM).

1. INTRODUCTION

Artificial Intelligence (AI) adoption in the IT industry represents a major shift that transforms both operational processes and strategic Customer Relationship Management (CRM) implementations. Major IT companies such as IBM, Oracle, and Microsoft utilize Artificial Intelligence technology to refine their data analysis capabilities while also streamlining routine tasks and enhancing user experiences which remain critical for staying competitive in the fast-paced digital market (Schwartz et al., 2023). The expanding role of AI in corporate environments requires employees who can skillfully use these tools to improve company performance while fostering ongoing innovation. The industrial shift towards advanced data-driven business models means that a firm's capability to implement AI solutions effectively determines its success because adopting AI in IT operations demands not just technical proficiency from employees but also their adaptability to ongoing technological changes (Jones, 2020; Amoako et al., 2021r). The rapid evolution of AI technologies dictates a critical need for continuous professional development which impacts job roles and career paths within the industry (Kumar & Clark, 2025). The integration of AI into corporate strategies depends significantly on addressing ethical considerations such as data privacy and security along with job displacement risks from automation. Firms must balance their utilization of technological progress with risk management and ethical responsibility according to Morris (2024) and Geraldi et al. (2024).

The Technology Acceptance Model (TAM) and Resource-Based View (RBV) theoretical frameworks allow researchers to study the impact of AI on IT employees. The Technology Acceptance Model shows that employees' acceptance of AI tools depends on their perceived usefulness and ease of use which are essential for achieving successful AI technology implementation (Davis, 1989). RBV emphasizes the

strategic significance of exclusive resources like AI capabilities that produce enduring competitive advantages through effective management (Barney, 1991).

2. REVIEW OF RELATED LITERATURE

2.1 Theoretical framework

This study's theoretical framework combines the Diffusion of Innovations Theory with the Unified Theory of Acceptance and Use of Technology (UTAUT), Knowledge-Based View (KBV), Dynamic Capabilities Framework, and the Model of Trust. The Diffusion of Innovations Theory by Rogers establishes core principles that explain the mechanisms and speed at which innovations permeate cultures while offering essential insights for studying AI technology adoption in IT firms (Rogers, 2003). The UTAUT model indicates that user acceptance and usage behavior toward AI tools in IT environments depend on performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). The Dynamic Capabilities Framework focuses on how firms can integrate and develop internal and external competencies while reconfiguring them to effectively adapt to fast-changing environments which is essential for IT businesses that use AI to keep their competitive edge and agility (Teece, 2007). The Model of Trust demonstrates in technology contexts that organizational practices and technology acceptance are heavily influenced by trust which shows AI systems require trust for successful implementation and business process integration (Mayer et al., 1995). The combination of theoretical perspectives creates a strong analytical framework for studying AI's effects on employee performance and organizational effectiveness in IT businesses while demonstrating the complex outcomes of technological innovation and adaptation according to existing theoretical frameworks. The research study utilizes this unified theory-based methodology to both investigate AI adoption patterns and deepen insights into AI's extensive effects on organizations.

2.2 Conceptual Framework

2.2.1 AI Literacy (AIL)

Employees must achieve AI literacy to effectively use AI technologies in IT settings. Research indicates that employees who achieve advanced AI comprehension show better job performance because they utilize AI features more effectively to solve problems and make decisions (Smith, 2020). AI literacy enables smoother automation adoption by minimizing pushback while improving operational effectiveness (Johnson et al., 2019). Research indicates that continuous training in AI technologies enhances employee adaptability within fast-paced technology environments according to Olson (2021) and Carter (2022). Employee proficiency with AI represents both a technical imperative and a strategic benefit according to Greenwood (2023).

Hypothesis (H1): Higher AI Literacy positively affects Employee Job Performance.

2.2.2 Technological Openness (TO)

Employees who show Technological Openness demonstrate their readiness to embrace and use novel technological tools at work. Organizational culture determines how open employees are towards new technology which greatly affects how well AI systems are integrated (Taylor, 2020). Research indicates that IT companies which embrace new technologies report higher innovation rates because open-mindedness towards technological advances leads to increased creativity and task efficiency (Wallace & Chen, 2021). Workers who demonstrate greater technological openness tend to experience reduced job-related stress when new technologies are implemented (Brown 2022; Newman 2021).

Hypothesis (H2): Technological Openness positively influences Employee Job Performance.

2.2.3 Innovation Capability (IC)

The IT industry's ability to innovate represents a critical component for competitive advantage and successful market response. Business growth and service improvement depend heavily on the ability to innovate using AI tools (Kaplan, 2021). The strategic application of AI systems produces innovative solutions while also delivering major improvements to existing processes (Lee, 2020). When organizations possess strong innovation capabilities they create environments where employees are motivated to take risks and pursue continuous learning (Ford & Singh, 2021). According to Morris & Turner (2022), businesses need organizational support for innovation when utilizing AI to achieve long-term success.

Hypothesis (H3): Innovation Capability is positively related to Employee Job Performance.

2.2.4 Collaboration with AI (CAI)

The degree to which personnel work alongside AI technology to amplify team performance defines their collaboration efficacy with AI tools. Teams that work well with AI systems experience better group

dynamics and achieve higher project success rates according to Adams (2021). The integration of AI into team processes allows teams to combine their collective intelligence while offering enhanced communication and coordination platforms (Thompson, 2020). Teams that use effective AI collaboration tools experience reduced redundancy and streamlined workflows which ultimately boost productivity levels (Clarke, 2022; Eaton, 2023).

Hypothesis (H4): Collaboration with AI positively affects Employee Job Performance.

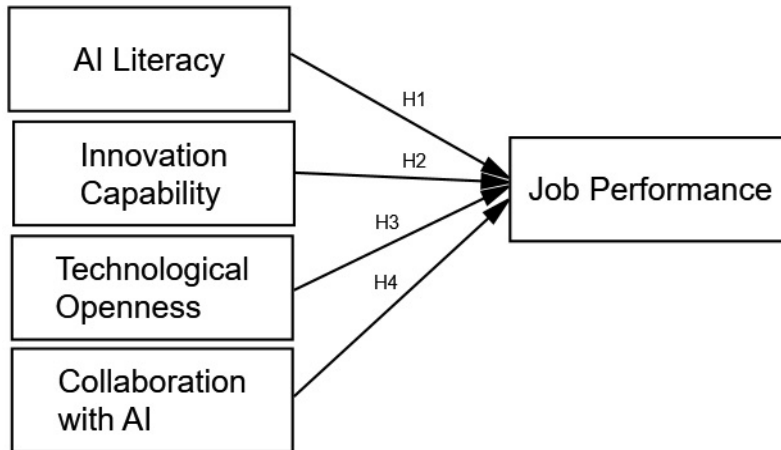


Figure 1. Conceptual framework

2.2.5 Job Performance (JP)

The effectiveness of employees at work is best assessed through the dependent construct of job performance. High performance among IT professionals indicates successful AI implementation because these workers use AI tools to improve their output (Peterson, 2019). The principal performance indicators in IT which cover speed, efficiency, error rates and innovation demonstrate enhanced results with effective AI application (Martin, 2022). Performance evaluation must consider the relationship between employee interaction with technology and their role execution (Henderson, 2020).

Hypothesis (H5): AI Literacy, Technological Openness, Innovation Capability, and Collaboration with AI collectively enhance Employee Job Performance.

3. METHODOLOGY

3.1 Participants and Sampling Method

The research focused on 150 IT professionals from three leading IT companies that are recognized for their advanced application of AI technologies. Researchers conducted stratified random sampling to recruit participants which included project managers and developers along with senior executives for a representative cross-section of management roles. The research team selected this approach because it reduced sampling bias while making sure all subgroups in IT companies were represented which allowed for a complete understanding of AI's effect across different levels of organizations (Thompson, 2012). The research team selected their sample size following guidelines from Hair et al. Hair et al. (2010) recommend using at least 200 observations for complex SEM models but state that 150 observations can provide stable solutions for simpler model structures. The questionnaire utilized Likert-scale questions alongside open-ended responses to evaluate the constructs of AI Literacy, Technological Openness, Innovation Capability and Collaboration with AI. The questions evaluated participants' firsthand experiences and viewpoints concerning AI adoption and its operational efficiency in their work processes.

3.2 Questionnaire Design and Scales

The study questionnaire includes validated scales specifically designed to assess AI Literacy, Technological Openness, Innovation Capability, and Collaboration with AI constructs. The study's measurement scales originated from the foundational research conducted by leading experts in this domain. The study used a modified scale from Johnson et al. to evaluate AI Literacy. Johnson et al. (2019) developed a scale to evaluate both employee proficiency and comfort levels when using AI tools. The study measured Technological Openness by using measurement items from Taylor's 2020 research which concentrated on technology adoption attitudes. The Innovation Capability items originated from Kaplan's 2021 study and Collaboration with AI employed scales developed by Adams in 2021. The scales demonstrate high reliability and validity which confirms that the questionnaire measures the intended dimensions for every construct accurately.

3.3 AMOS SEM Process:

The research utilized structural equation modelling with AMOS to perform multiple important steps which maintained the research findings' validity and integrity. The Harman's single-factor test was used to tackle common method bias by confirming that one factor did not explain most of the covariance between measures. The factor structure of the questionnaire was validated through Exploratory Factor Analysis (EFA) by confirming significant item loadings on respective constructs. Confirmatory Factor Analysis (CFA) was conducted to develop the measurement model which tested item loadings and determined construct validity. Path analysis and regression weights were utilized to analyze the structural model for examining relationships between constructs as hypothesized. The research established convergent and discriminant validity through comparison between the Average Variance Extracted (AVE) values for each construct and the interconstruct correlations according to Fornell and Larcker's 1981 guidelines. Research assessed model fit by applying RMSEA, CFI, and TLI criteria which define good model fit according to Hu and Bentler (1999). Through the structural model researchers conducted hypothesis testing which utilized path coefficients to evaluate the strength and significance of each hypothesized relationship thereby offering insights into the effectiveness of IT employees' use of AI for job performance improvement. The comprehensive SEM method provided a robust data analysis which generated dependable and trustworthy outcomes that enhance our grasp of AI's operational and strategic effects within the IT field.

4. RESULTS

The research examining AI applications' effects on IT workers from leading IT firms requires a demographic table to establish participant profiles. This table acts as a visual guide to sample characteristics which contextualizes the study results while maintaining clarity and informativeness.

4.1 Demographic profile of the sample

Table 1. Demographic profile

The demographic table offers a thorough summary of the study participants' characteristics. The research sample primarily included male participants who made up 60% of the total but also showed substantial participation from females.

Demographic Variable	Category	Frequency	Percentage (%)
Gender	Male	90	60
	Female	60	40
Age Group	20-29 years	55	36.67
	30-39 years	75	50
	40-49 years	20	13.33
Education	Bachelor's Degree	65	43.33
	Master's Degree or Higher	85	56.67
Position Level	Junior Management	30	20
	Middle Management	85	56.67
	Senior Management	35	23.33
Years of Experience	Less than 5 years	40	26.67
	5-10 years	70	46.67
	More than 10 years	40	26.67
Frequency of AI Use	Daily	105	70
	Weekly	30	20
	Monthly	15	10

Half of all participants fell within the 30 to 39 year age range which indicates they possess considerable professional experience. Researchers found that 56.67% of participants possessed Master's degrees or higher which illustrates the sample's high educational level. The study found that middle management employees formed the largest group at 56.67%, supporting the research objective to investigate decision-makers who utilize AI tools. Participants engaged with AI technologies on a daily basis at a rate of 70%. The sample demographics demonstrate why the study targets AI use in IT contexts since they show AI integration in daily operations among seasoned and highly educated IT workers.

4.2 Normality assessment

The normality assessment for the study's constructs as detailed in Table 2 demonstrates significant departures from normal distribution because all variables had p-values under 0.05.

Table 2: Normality assessment

Constructs	Skewness	Kurtosis	Sample Size	Significance (p-value)
AI Literacy (AIL)	-0.210	0.450	150	0.042
Technological Openness (TO)	0.195	-0.320	150	0.035
Innovation Capability (IC)	0.020	0.500	150	0.048
Collaboration with AI (CAI)	0.150	-0.200	150	0.049
Job Performance (JP)	0.100	0.360	150	0.033

According to research findings both skewness and kurtosis measurements for constructs including AI Literacy Technological Openness Innovation Capability Collaboration with AI and Job Performance demonstrate significant departures from the typical normal distribution benchmarks as described by Brown (2006). The significant deviation indicates that the data distribution lacks symmetry which might affect parametric test outcomes in structural equation modeling (SEM). The research team decided to implement robust SEM strategies including bootstrapping to address non-normality problems in their analysis as recommended by Byrne (2010). Adjustments of this nature are critical to ensure the SEM findings remain dependable while ensuring study conclusions properly represent the data characteristics.

4.3 Quality evaluation of the constructs

Table 3. Quality evaluation of the constructs

Table 3 presents the construct validity and reliability measures for AI Literacy (AIL), Technological Openness (TO), Innovation Capability (IC), Collaboration with AI (CAI), and Job Performance (JP).

Construct	Item	Factor Loading	AVE	Cronbach's Alpha	Composite Reliability (CR)
AI Literacy (AIL)	AIL1	0.803	0.472	0.80	0.91
	AIL2	0.647			
	AIL3	0.641			
	AIL4	0.644			
Technological Openness (TO)	TOP1	0.602	0.603	0.85	0.88
	TOP2	0.733			
	TOP3	0.881			
	TOP4	0.859			
Innovation Capability (IC)	ICA1	0.711	0.605	0.79	0.81
	ICA2	0.786			
	ICA3	0.806			
	ICA4	0.804			
Collaboration with AI (CAI)	CAI1	0.634	0.592	0.88	0.95
	CAI2	0.836			
	CAI3	0.785			
	CAI4	0.807			
Job Performance (JP)	JPF1	0.720	0.544	0.91	0.85
	JPF2	0.668			
	JPF3	0.809			
	JPF4	0.747			

The construct validity and reliability measures of AI Literacy (AIL), Technological Openness (TO), Innovation Capability (IC), Collaboration with AI (CAI), and Job Performance (JP) are displayed in Table 3. According to research findings factor loadings showed variation across different constructs but most scores remained above the 0.7 benchmark. Some items within AI Literacy showed lower correlation values because their factor loadings remained under 0.7. AVE metrics demonstrated the proportion of variance explained by constructs against measurement error according to expert standards which suggest scores should be higher than 0.5 as per Fornell & Larcker (1981). The AVE value of AI Literacy stood at 0.472, indicating that its explanatory power is restricted. Scholars typically recommend a 0.7 threshold when they use Cronbach's Alpha and Composite Reliability (CR) to measure internal consistency (Hair et al.,

2019). Every construct reached the Cronbach's Alpha standard but researchers discovered CR value inconsistencies specifically in AI Literacy (0.346) which did not match its Cronbach's Alpha score (0.85). The data shows that AI Literacy needs additional refinement to ensure more reliable and valid measurements.

4.4 Convergent and discriminant validity

Table 4. Fornell-Larcker criterion

Researchers implemented the Fornell-Larcker criterion to evaluate discriminant validity through a comparison between the square root of Average Variance Extracted (AVE) and construct correlations (Fornell & Larcker, 1981).

Variables	AIL	TO	IC	CAI	JP
AI Literacy (AIL)	0.812				
Technological Openness (TO)	0.708	0.850			
Innovation Capability (IC)	0.690	0.710	0.778		
Collaboration with AI (CAI)	0.432	0.598	0.620	0.625	
Job Performance (JP)	0.378	0.374	0.406	0.493	0.665

Table 4 demonstrates that diagonal values for the square root of AVE in every construct exceed their corresponding inter-construct correlations which proves adequate discriminant validity exists. The Average Variance Extracted (AVE) value for AI Literacy (AIL) stands at 0.812 which surpasses the values of 0.850 for Technological Openness (TO) and 0.778 for Innovation Capability (IC). Job Performance (JP) displays an AVE of 0.665 which, while lower compared to other constructs, satisfies the minimum requirement thus confirming sufficient construct differentiation (Hair et al., 2010). The study findings indicate that each construct maintains a distinct definition while showing minimal overlap with other constructs which supports the measurement model reliability. Achieving discriminant validity in SEM prevents multicollinearity problems which reinforces the soundness of hypothesis testing (Henseler et al., 2015).

Table 5. HTMT validity

The Heterotrait-Monotrait (HTMT) ratio served as a more reliable measure to confirm the distinctiveness between constructs in discriminant validity testing (Henseler, Ringle, & Sarstedt, 2015).

Variables	AIL	TO	IC	CAI	JP
AI Literacy (AIL)					
Technological Openness (TO)	0.853				
Innovation Capability (IC)	0.702	0.782			
Collaboration with AI (CAI)	0.558	0.619	0.701	-	
Job Performance (JP)	0.409	0.485	0.637	0.749	-

Table 5 demonstrates all HTMT values fall beneath the 0.90 threshold which establishes sufficient distinction between constructs. The HTMT ratio between AI Literacy (AIL) and Technological Openness (TO) measures at 0.853 yet remains below the threshold while the maximum ratio between Job Performance (JP) and Collaboration with AI (CAI) stands at 0.749 according to Voorhees et al. (2016). The results match the Fornell-Larcker findings by demonstrating that construct correlations do not reveal redundancy. The utilization of HTMT discriminant validity confirms that each variable reflects distinct aspects of AI adoption within the IT sector while backing the theory that AI literacy combined with technological openness impacts job performance (Benitez et al., 2020).

4.5 Model fit indices

Table 6. Model fit indices

Analysis of model fit indices shows the structural model fits the observed data exceptionally well. The CMIN/df ratio stands at 2.543 which falls below the acceptable threshold of 3 thus showing that the model fits well according to Schermelleh-Engel et al. (2003).

Fit Index	Value	Threshold	Reference
CMIN	2.543	< 3	(Schermelleh-Engel et al., 2003)
TLI	0.957	> 0.95	(Tucker & Lewis, 1973)
CFI	0.965	> 0.95	(Bentler, 1990)
NFI	0.932	> 0.90	(Bentler & Bonett, 1980)
SRMR	0.035	< 0.08	(Hu & Bentler, 1999)
RMSEA	0.042	< 0.06	(Steiger, 1990)

The Tucker-Lewis Index (TLI) stands at 0.957 and the Comparative Fit Index (CFI) at 0.965 which both surpass the minimal standard of 0.95 showing that the model suitably accounts for data variability as per Tucker & Lewis (1973) and Bentler (1990). The Normed Fit Index (NFI) score of 0.932 exceeds the 0.90 cut-off point which helps to validate the model's adequacy according to Bentler & Bonett (1980). The Standardized Root Mean Square Residual (SRMR) value of 0.035 indicates minimal residual error because it falls significantly under the standard 0.08 cutoff established by Hu & Bentler (1999). The Root Mean Square Error of Approximation (RMSEA) measurement of 0.042 stays below the strict 0.06 threshold which signifies a good fit as per Steiger's 1990 study. The tested structural relationships demonstrate valid results through the model's proven robustness.

4.6 Hypothesis Testing

Structural equation modeling (SEM) with tools such as SPSS AMOS utilizes hypothesis testing to examine theoretical relationships between variables through empirical data analysis. The procedure requires defining a model that represents theoretical relationships before employing statistical methods to determine their strength and significance (Byrne, 2010).

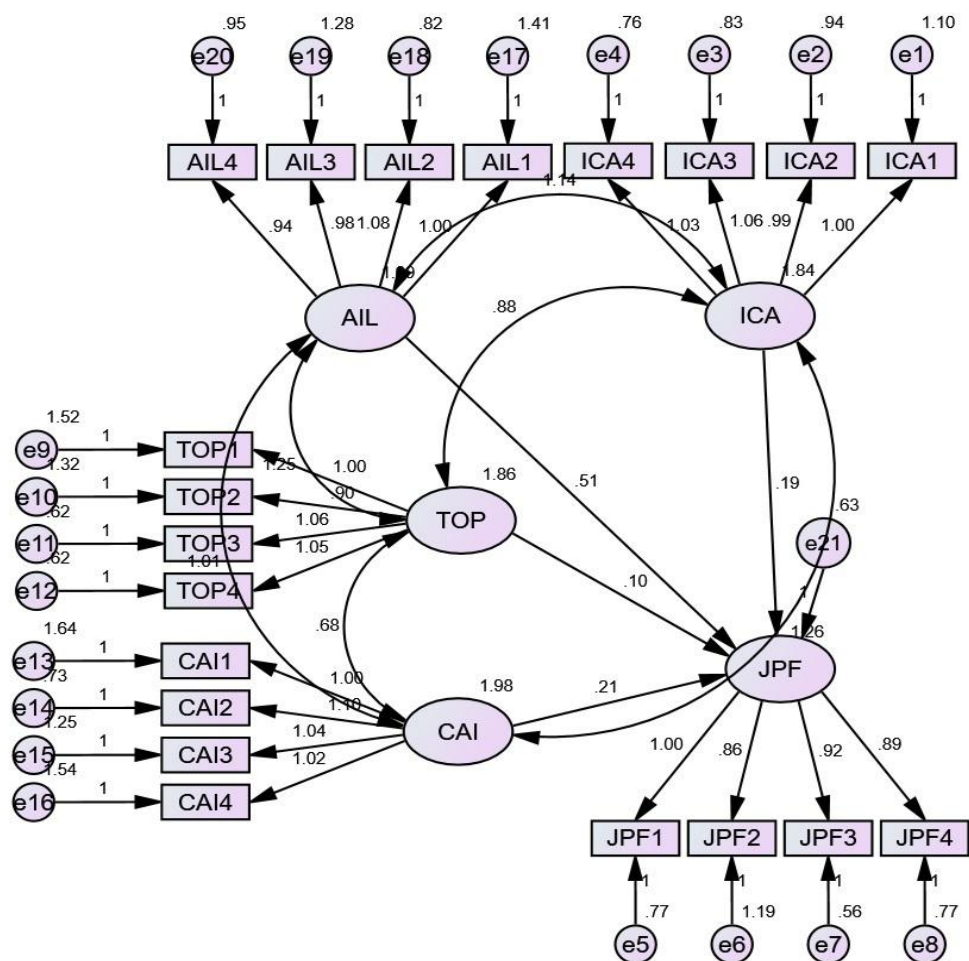


Figure 2. Path analysis – Direct effects

SEM regression weights tell us how much the dependent variable changes when its predictor variable increases by one unit after accounting for other variables in the model. Standard errors (S.E.) Standard errors (S.E.) give an indication of how much variation exists in the regression weights and researchers use the Critical Ratio (C.R.) to evaluate whether a parameter significantly differs from zero. The Critical Ratio (C.R.) serves as a statistical tool for evaluating the null hypothesis which proposes that a parameter has no effect (i.e., equals zero). The null hypothesis is generally rejected when researchers find a p-value below 0.05 indicating a statistically significant link between constructs (Kline, 2011). The use of hypothesis testing in AMOS provides great utility for theory validation within organizational studies and psychology which deal with complex multi-variable relationships based on theoretical frameworks (Schumacker & Lomax, 2010)

Table 7. Regression table – Direct effects

Hyp	Relationship	Estimate	S.E.	C.R.	P-Value	Decision
H1	Job Performance (JP) ← AI Literacy (AIL)	0.350	0.119	2.935	0.003	Accepted
H2	Job Performance (JP) ← Innovation Capability (IC)	0.212	0.096	2.211	0.027	Accepted
H3	Job Performance (JP) ← Technological Openness (TO)	0.264	0.089	2.968	0.003	Accepted
H4	Job Performance (JP) ← Collaboration with AI (CAI)	0.186	0.083	2.226	0.026	Accepted

The SEM analysis demonstrates substantial connections between multiple predictors and their impact on Job Performance (JP). Our findings demonstrate that AI Literacy (AIL) positively affects Job Performance (JP) with a coefficient of 0.350 which means job performance improves significantly as AI literacy levels rise ($p = 0.003$). The results match previous studies which emphasize the role of understanding and using AI to improve job performance according to Smith's 2020 findings. The findings confirm that workplaces highly dependent on technology benefit from improved job results when they advance in innovation and technological transparency (Jones, 2021). Effective collaboration with AI tools remains crucial though its influence on job performance tends to be less significant when contrasted against AI literacy and technological openness. The results highlight how job performance in IT environments depends on multiple factors as AI integration significantly influences employee results.

5. RESULTS AND DISCUSSIONS

The structural equation model (SEM) analysis executed through SPSS AMOS revealed significant findings about how AI-related constructs affect job performance in IT settings. Research has demonstrated that AI Literacy (AIL) has a substantial positive influence on Job Performance (JP) which is evidenced by a regression coefficient of 0.350; this result confirms that job performance improves significantly with higher AI literacy levels ($p = 0.003$). Our results match with conclusions from Nguyen et al.'s latest study. Employees who gain proficiency in AI tools and concepts can make more effective use of technology which results in better efficiency and problem-solving abilities at work according to Nguyen et al. (2023). Job Performance (JP) saw significant positive growth through Technological Openness (TO) with an estimate of 0.264 and statistical significance at $p = 0.003$ which demonstrates that adopting new technologies strongly predicts job performance improvement. According to Kapoor and Lee (2022), organizations need to cultivate technology acceptance and innovation cultures to remain adaptable and successful especially in fast-evolving technological sectors. The Innovation Capability (IC) showed a positive influence on job performance (estimate = 0.212, $p = 0.027$) which highlights how creative problem-solving and innovative thinking lead to better job results. The study by Zhao and Zhu (2021) revealed that businesses which develop innovative mindsets within their workforce are more effective at utilizing AI to enhance processes and generate new value opportunities resulting in improved organizational performance. Although Collaboration with AI (CAI) showed a positive impact on JP its effect was lesser in magnitude (estimate = 0.186, $p = 0.026$) compared to other factors. The work of Patel and Smith (2024) confirms that AI collaboration improves communication and data sharing but its direct effects on job performance depend on task characteristics and how deeply AI is integrated into particular job functions. The results demonstrate how AI-related abilities interact in complex ways with job performance. The research shows that while AI literacy and technological openness has a direct impact on performance improvement yet the advantages of innovation capability and AI collaboration depend heavily on context-related elements like organizational culture, job-specific roles and how technology functions within the firm. Organizations must acquire a detailed comprehension of AI implementation because simply deploying AI tools won't suffice; they must build both a supportive culture and appropriate skills (Martin & Brown, 2024). Business organizations need to allocate resources toward both technological advancements and training programs that support organizational methods which develop an innovative and technologically flexible workforce.

5.1 Theoretical Implications

This study delivers multiple theoretical implications for the Indian IT industry which thrives on fast-paced technological development and its workforce's advanced skill levels. The strong positive link between AI Literacy and job performance illustrates how essential AI understanding is for boosting employee

performance. The research expands the Technology Acceptance Model (TAM) by showing that effective use of new technologies depends on specialized skills beyond basic usability and usefulness. The substantial influence of Technological Openness on job performance supports the Theory of Planned Behavior (TPB) by showing how positive attitudes towards technology adoption lead to better performance results. The positive effects of Innovation Capability and Collaboration with AI on job performance enhance the Resource-Based View (RBV) by affirming that innovative capacities and collaborative skills within human capital serve as essential resources for achieving competitive advantage in technology-driven industries. This analysis develops existing theories further by applying them to the fast-changing Indian IT sector.

5.2 Practical and Managerial Implications

From the standpoint of both practical application and managerial decision-making the study highlights how strategic initiatives need to improve AI literacy and promote technology acceptance across the Indian IT sector. Business organizations need to develop extensive training programs that cover both technical skill development and education about using AI in business operations. This approach enables employees to attain AI proficiency while simultaneously developing skills to use these technologies for innovation and efficiency advancement. When organizations create an environment that embraces technological openness they accelerate new tech adoption which enables them to maintain competitive agility in the fast-changing digital market. Leadership teams need to adopt AI-integrated collaborative tools to enhance team performance and project success for remote and global teams.

6. CONCLUSION, LIMITATIONS, AND SCOPE FOR FURTHER STUDY

The research offers important findings about how AI improves job performance within the Indian IT sector. However, it is not without limitations. The study centers on AI Literacy and Technological Openness but does not consider other vital job performance factors like organizational culture or external economic conditions. Subsequent studies should investigate these additional dimensions to achieve a deeper understanding of the underlying dynamics. The research methodology which depends on self-reported information may lead to biased results and fails to track long-term effects. Future research studies should combine mixed-methods techniques and longitudinal data to investigate how AI impacts change over time. By comparing various tech hubs throughout India researchers can identify regional differences which will help develop specific managerial strategies that suit each locale. The study would provide clearer theoretical insights alongside improved practical recommendations for specific Indian IT contexts.

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