ARTIFICIAL INTELLIGENCE (AI) ADOPTION AND EMPLOYEE TASK PERFORMANCE: UNPACKING THE ROLES OF WORK ENGAGEMENT AND DIGITAL LEADERSHIP IN THE INDIAN IT SECTOR

Md Alijan Arif and Mohammed Kamalun Nabi
Department of Commerce and Business Studies, Jamia Millia Islamia, India

Abstract

The increasing adoption of artificial intelligence (AI) in workplaces has transformed organisational processes and employee work experiences. However, limited research has examined the mechanisms through which AI adoption influences employee performance. Drawing on the Job Demands–Resources (JD-R) theory, this study investigates the effect of AI adoption on employee task performance, the mediating role of work engagement, and the moderating role of digital leadership in the Indian IT sector. A quantitative research design was employed, using survey data from 245 employees working in Indian IT organisations, which were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM). The findings indicate that AI adoption positively influences work engagement and employee task performance, and that work engagement, in turn, significantly enhances task performance. The results further reveal that work engagement partially mediates the relationship between AI adoption and employee task performance. In addition, digital leadership strengthens the positive effect of AI adoption on work engagement, thereby amplifying its indirect effect on employee task performance. This study extends JD-R theory by conceptualising AI adoption as a technological job resource and highlights the importance of leadership support in maximising AI-related workplace outcomes. The findings offer practical insights for organisations seeking to improve employee engagement and performance in AI-enabled work environments.

Keywords:

Artificial Intelligence (AI), Work Engagement, Employee Task Performance, Digital Leadership, JD-R theory, Indian IT Sector

1. INTRODUCTION

The rapid advancement of artificial intelligence (AI) has transformed workplaces by reshaping organisational operations, communication, and value creation. Organisations increasingly integrate AI-driven systems to automate repetitive tasks, improve decision-making, and enhance productivity [1], [2]. The information technology (IT) sector, due to its digitally intensive nature, has emerged as a major adopter of AI-enabled technologies. AI applications such as automation, predictive analytics, generative AI, and machine-learning systems are increasingly embedded in employees' daily activities, thereby influencing job structures and work experiences [3], [4].

Despite growing investment in AI, an important question remains: Does AI adoption improve employee performance? Although AI may enhance efficiency and reduce workload, its effects on employees are often shaped by psychological and organisational conditions [5], [6]. Employees may experience uncertainty, technological anxiety, resistance, or concerns regarding job displacement, which may affect work attitudes and behaviours [7]. Consequently, understanding the mechanisms through which AI adoption influences employee outcomes has become increasingly important.

Existing studies suggest that AI-enabled systems improve productivity by supporting decision-making and reducing repetitive work [8]. However, prior research has primarily focused on technological outcomes and paid limited attention to the psychological mechanisms underlying employee performance [4]. In particular, little evidence exists regarding how employees' motivational states influence the effectiveness of AI implementation.

Among motivational factors, work engagement has been widely recognised as a key predictor of employee performance. Work engagement refers to a positive psychological state characterised by vigour, dedication, and absorption [9]. Engaged employees invest greater effort in their work, resulting in enhanced performance [10]. However, limited evidence exists regarding whether work engagement mediates the relationship between AI adoption and employee task performance, particularly in digitally intensive sectors such as IT [6], [8].

Successful AI implementation may also depend on supportive leadership. In digital workplaces, digital leadership facilitates employees' adaptation to technological change by promoting innovation, technological readiness, and confidence in digital systems [11]. Leadership support is particularly important during AI implementation because employees' perceptions of technological usefulness are often shaped by managerial guidance [12]. Nevertheless, limited research has examined digital leadership as a contextual factor that influences the relationship among AI adoption, engagement, and performance.

Several gaps remain in prior studies. Existing research primarily emphasises direct relationships between AI and employee performance while overlooking motivational mechanisms [5]. Studies also rarely integrate AI adoption, work engagement, employee task performance, and digital leadership within a unified framework. Moreover, empirical evidence from the Indian IT sector remains limited despite increasing AI adoption, creating an important contextual gap.

To address these limitations, this study draws on the Job Demands–Resources (JD-R) theory to explain how AI adoption influences employees' task performance through work engagement across varying levels of digital leadership. Within the JD-R framework, AI adoption is conceptualised as a technological job resource; work engagement serves as the motivational mechanism; and digital leadership functions as a contextual resource that strengthens employees' ability to benefit from AI-enabled systems [10], [13]. Accordingly, this study examines the effect of AI adoption on employee task performance, the mediating role of work engagement, and the moderating role of digital leadership in the Indian IT sector. The study extends JD-R theory by conceptualising AI adoption as a technological job resource and provides practical insights for organisations seeking to enhance engagement and performance in AI-enabled workplaces.

1.1 RESEARCH OBJECTIVES

The present study aims to achieve the following objectives:

1. To examine the effect of artificial intelligence (AI) adoption on employee task performance in the Indian IT sector.
2. To investigate the effect of artificial intelligence (AI) adoption on work engagement.
3. To assess the effect of work engagement on employee task performance.
4. To examine the mediating role of work engagement in the relationship between AI adoption and employee task performance.
5. To investigate the moderating role of digital leadership in the relationship between AI adoption and work engagement.
6. To examine the conditional indirect effect of AI adoption on employee task performance through work engagement under varying levels of digital leadership.

2. THEORETICAL FRAMEWORK

This study is grounded in the Job Demands–Resources (JD-R) Model, which explains how workplace resources influence employee motivation, well-being, and performance. Developed by Bakker and Demerouti [13], the model categorises work characteristics into job demands and job resources. Job demands require sustained effort and may generate psychological or physiological costs, whereas job resources facilitate goal attainment, reduce work strain, and support employee development [13], [14].

A key assumption of JD-R theory is the motivational process, whereby job resources enhance employee engagement and improve performance outcomes [10]. Employees with sufficient resources experience greater vigour, dedication, and absorption, resulting in improved effectiveness and productivity. Consequently, JD-R has been widely applied to explain employee attitudes and behaviours in technology-enabled workplaces [15].

In digitally transformed environments, AI adoption can be conceptualised as a technological job resource. AI-enabled systems assist employees by automating repetitive work, improving information processing, supporting decision-making, and increasing task efficiency. Such support reduces cognitive burden and allows employees to focus on higher-value activities. From a JD-R perspective, AI adoption improves work experiences by facilitating task completion and reducing strain [5], [6]. Prior studies increasingly recognise AI as a workplace resource that enhances employee effectiveness, particularly in knowledge-intensive sectors such as IT [4], [8].

The benefits of AI adoption, however, may not emerge automatically but operate through employees' motivational states. In this regard, work engagement acts as an important mechanism linking workplace resources with performance. Work engagement reflects a positive psychological state characterised by vigour, dedication, and absorption [9]. Engaged employees invest greater effort into their work, resulting in improved task effectiveness. Existing research consistently shows that strong workplace resources foster engagement, which subsequently enhances performance outcomes [4], [10].

This study further conceptualises employee task performance as the primary behavioural outcome. Task performance refers to employees' effectiveness in performing formal job responsibilities [16]. Under the JD-R theory, performance improves when employees possess adequate resources and higher motivational engagement. Thus, AI adoption may directly improve task performance through efficiency gains and indirectly through enhanced work engagement.

The effectiveness of AI adoption may also vary according to organisational context. JD-R theory highlights the importance of contextual resources in shaping employee responses to workplace changes [10]. In digital workplaces, digital leadership functions as an important contextual resource by promoting technological readiness, reducing uncertainty, encouraging innovation, and strengthening employees' confidence in technology use [11]. Employees working under digitally competent leaders are therefore more likely to perceive AI adoption positively, thereby increasing work engagement. Overall, integrating AI adoption, work engagement, employee task performance, and digital leadership within the JD-R framework provides a coherent explanation of employee behaviour in digital workplaces. Specifically, AI adoption serves as a technological job resource; work engagement represents the motivational mechanism; employee task performance reflects the behavioural outcome; and digital leadership acts as a contextual boundary condition, strengthening the effectiveness of AI-related resources. Thus, JD-R theory provides a strong theoretical basis for explaining how AI adoption influences employees' task performance through work engagement across varying levels of digital leadership. The proposed research framework is presented in Fig.2.

3. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

This study is grounded in the Job Demands–Resources (JD-R) theory, which suggests that job resources can foster employee motivation, engagement, and performance. In digitally transformed workplaces, AI adoption can be understood as a technological job resource because it may reduce repetitive effort, support decision-making, improve efficiency, and free employees to concentrate on more meaningful tasks. At the same time, digital leadership can be conceptualised as a contextual resource that facilitates the effective use of digital technologies and shapes how employees respond to AI-enabled work environments. Recent studies have increasingly supported the resource-based view of AI in the workplace, showing that AI can enhance engagement and performance when employees perceive it as useful, supportive, and well-led [4]-[6], [11].

3.1 AI ADOPTION AND WORK ENGAGEMENT

AI adoption is likely to positively influence work engagement by simplifying processes, reducing workload, and enabling employees to complete tasks more efficiently. When employees experience AI as a useful resource rather than as a threat, they are more likely to feel energetic, dedicated, and absorbed in their work. Empirical evidence supports this reasoning. For example, Korzynski et al. [4] showed that AI-enabled knowledge management and organisational support can strengthen intrinsic motivation and work engagement among software engineers. Similarly, Liu and Li [7] found that AI usage has a meaningful effect on work engagement, although this effect may depend on boundary conditions such as core task characteristics substitution. Manresa et al. [17] also argued that humanised GenAI in the workplace can bridge the gap between technological innovation and employee engagement. On this basis, AI adoption should enhance employees' psychological connection with their work.

- H1: AI adoption has a positive and significant effect on employee work engagement.

3.2 WORK ENGAGEMENT AND EMPLOYEE TASK PERFORMANCE

Work engagement is widely recognised as a key driver of task performance because engaged employees invest more energy, show greater persistence, and concentrate more fully on work responsibilities. Under the JD-R theory, engagement serves as the motivational mechanism by which job resources translate into positive outcomes. Engaged employees are more likely to maintain focus, complete assigned tasks effectively, and meet formal performance requirements. Prior research strongly supports this relationship. Korzynski et al. [4] found that work engagement mediates the relationship between AI-related motivation and productivity. Prentice et al. [6] similarly showed that job engagement contributes to employee performance in an AI-enabled context. In addition, Marimon et al. [18] reported that engagement is positively associated with workplace performance, while Khan et al. [19] found that work engagement contributes to employee performance alongside knowledge sharing. Therefore, higher work engagement should lead to better task performance.

- H2: Work engagement has a positive and significant effect on employee task performance.

3.3 AI ADOPTION AND EMPLOYEE TASK PERFORMANCE

AI adoption may also directly affect employee task performance. AI tools can automate repetitive activities, reduce error rates, support information processing, and improve decision quality, all of which can directly enhance task effectiveness. In workplace settings, AI can therefore operate as a performance-enabling resource. This relationship has been confirmed in several studies. Su et al. [20] found that artificial intelligence facilitates task performance in knowledge workers. Prentice et al. [6] similarly reported that AI functions as a boundary-crossing object that supports employee performance. Vuong [8] found that GenAI usage positively influences job performance, and Khan et al. [19] showed that AI in the workplace drives employee performance through knowledge sharing and work engagement. Likewise, Marimon et al. [18] demonstrated that trust in generative AI is linked to stronger employee performance. These findings suggest that AI adoption may improve performance both directly and indirectly.

- H3: AI adoption has a positive and significant effect on employee task performance.

3.4 MEDIATING ROLE OF WORK ENGAGEMENT

The mediation argument follows naturally from JD-R theory. AI adoption is expected to provide resources that enhance work engagement, which, in turn, should translate into better task performance. In other words, AI adoption may influence performance not only directly but also indirectly by increasing employees' motivation. This logic is consistent with prior research showing that engagement is a central psychological mechanism underlying AI-related work outcome. Korzynski et al. [4] found that engagement fully mediates the relationship between intrinsic motivation and productivity in AI-enabled knowledge management. Vuong [8] reported that work engagement partially mediates the effect of GenAI usage on job performance. Prentice et al. [6] also showed that employee engagement and service performance mediate the relationship between AI and job performance. Together, these studies indicate that engagement is an important explanatory pathway through which AI adoption can improve employee task performance.

- H4: Work engagement mediates the relationship between AI adoption and employee task performance.

3.5 MODERATING ROLE OF DIGITAL LEADERSHIP

Digital leadership is expected to strengthen the positive effect of AI adoption on work engagement. Leaders who are digitally competent can encourage experimentation, reduce uncertainty, and create a supportive climate for the effective use of AI tools. In such conditions, employees are more likely to perceive AI adoption as beneficial and motivating. By contrast, weak digital leadership may limit the motivational benefits of AI because employees may not receive sufficient guidance, support, or strategic clarity. This boundary condition is consistent with recent evidence. Nguyen et al. [5] found that leadership enhances engagement in AI-enabled work settings, while Gayathiri et al. [12] demonstrated that digital leadership and AI-related performance assessment significantly affect organisational performance through empowerment and engagement. Radic et al. [11] also linked AI-driven leadership with the JD-R framework, emphasising the role of leadership in shaping employee resources. Accordingly, digital leadership should amplify the positive relationship between AI adoption and work engagement.

- H5: Digital leadership positively moderates the relationship between AI adoption and work engagement.

3.6 MODERATED MEDIATION

Because digital leadership strengthens the AI adoption–work engagement link, it should also condition the indirect effect of AI adoption on employee task performance through work engagement. In other words, the beneficial impact of AI adoption on task performance through engagement should be stronger when employees perceive their leaders as digitally supportive and competent. This is a moderated mediation effect that follows logically from the earlier hypotheses. Evidence from digital transformation studies supports this reasoning.

Nguyen et al. [5] showed that leadership and AI jointly shape engagement and performance. Gayathiri et al. [12] further demonstrated that digital leadership strengthens employee outcomes through engagement-related pathways. Therefore, the indirect effect of AI adoption on employee task performance should depend on the level of digital leadership.

- H6: Digital leadership moderates the indirect relationship between AI adoption and employee task performance through work engagement.

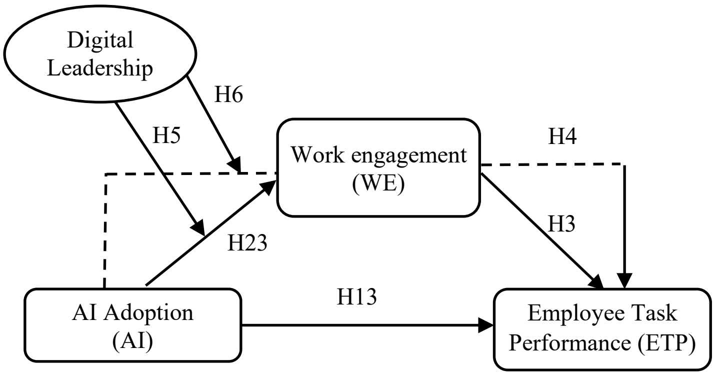


Fig.1. Conceptual Framework

Source: Developed by the authors.

4. METHODOLOGY

4.1 RESEARCH DESIGN

This study employed a quantitative cross-sectional survey design to examine the relationships among AI adoption, work engagement, employee task performance, and digital leadership in the Indian IT sector. A quantitative design was considered appropriate because the study aimed to empirically test hypothesised relationships among latent variables, including mediation and moderation effects [21]. The study is grounded in the Job Demands–Resources (JD-R) theory, in which AI adoption is conceptualised as a technological job resource, work engagement as the motivational mechanism, employee task performance as the outcome variable, and digital leadership as a contextual resource.

4.2 POPULATION AND SAMPLING PROCEDURE

The target population comprised employees in the Indian IT sector who had exposure to AI-enabled technologies at work. The IT sector was selected due to its rapid adoption of digital technologies and increasing reliance on AI-based systems. A combination of purposive and convenience sampling techniques was employed. Purposive sampling ensured that respondents had relevant experience with AI technologies, while convenience sampling facilitated access to participants across IT organisations. This approach is commonly used in organisational and behavioural research where access to a complete sampling frame is limited [22].

4.3 PILOT STUDY AND DATA COLLECTION PROCEDURE

Before the main survey, a pilot study involving 60 respondents was conducted to assess item clarity, wording, and the questionnaire's preliminary reliability. Minor modifications were made to improve clarity without altering the meaning of the original scales [23]. The main data collection was conducted in April and May 2026 using an online structured questionnaire distributed to employees in Indian IT organisations. Initially, 260 responses were collected. Following data screening to remove incomplete and inconsistent responses, 245 valid responses were retained for final analysis. The final sample size was considered adequate for PLS-SEM analysis, particularly for models involving mediation and moderation effects [21]. Participation was voluntary, and respondents were assured of confidentiality and anonymity to encourage unbiased responses.

4.4 MEASUREMENT INSTRUMENT

The questionnaire consisted of two sections. The first section collected demographic information, including gender, age, education, job position, work experience, and frequency of AI use. The second section measured the study constructs using previously validated scales. All items were assessed using a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree.

AI Adoption was measured using items adapted from prior studies informed by the Technology Acceptance Model (TAM) and the technology adoption literature [24], [25]. Work Engagement was measured using the Utrecht Work Engagement Scale (UWES-9) developed by Schaufeli et al. [9], which captures the dimensions of vigour, dedication, and absorption. Employee Task Performance was measured using items adapted from Williams and Anderson [16] to assess employees' effectiveness in performing formal job responsibilities. Digital Leadership was measured using established items assessing leaders' ability to facilitate digital transformation, support technological adaptation, and encourage workplace innovation.

4.5 DATA ANALYSIS TECHNIQUE

The study employed Partial Least Squares Structural Equation Modelling (PLS-SEM) using SmartPLS 4 for data analysis. PLS-SEM was selected because it is suitable for analysing complex models involving latent constructs, mediation, and moderation relationships simultaneously [21]. The analysis followed a two-stage approach.

First, the measurement model was assessed through Cronbach's alpha, composite reliability (CR), average variance extracted (AVE), and heterotrait–monotrait ratio (HTMT) to establish reliability and validity. Second, the structural model was evaluated using path coefficients, coefficient of determination (R^2), predictive relevance (Q^2), and bootstrapping procedures to test the proposed hypotheses.

4.6 ETHICAL CONSIDERATIONS

Ethical standards were maintained throughout the study. Respondents were informed about the academic purpose of the research, participation was voluntary, and confidentiality was assured. No personally identifiable information was collected, and responses were used solely for academic purposes.

5. RESULTS

5.1 RESPONDENT PROFILE

The demographic characteristics of the respondents are presented in Table.1. The final sample comprised 245 valid responses from employees working in the Indian IT sector. The sample consisted predominantly of male respondents (60.4%), whereas 39.6% were female. In terms of age distribution, the majority of respondents were in the 26–30 age group (33.5%), followed by the 31–35 age group (26.1%), indicating that most participants were early- and mid-career professionals. Regarding educational attainment, most respondents held a bachelor's degree (56.7%), followed by a master's degree or higher (38.4%), reflecting an educated workforce well-suited to AI-enabled workplaces.

With respect to organisational position, 49.8% of respondents occupied middle-level positions, followed by entry-level roles (34.7%) and managerial-level positions (15.5%). Regarding work experience, the majority reported 0–3 years (44.5%), followed by 4–7 years (34.7%) and more than 8 years (20.8%). Furthermore, most respondents reported frequent AI use (56.3%), indicating adequate exposure to AI-enabled technologies in the workplace. Overall, the demographic profile confirms the appropriateness of the sample for investigating AI adoption and employee outcomes within the Indian IT sector (Table.1).

5.2 MEASUREMENT MODEL ASSESSMENT

The measurement model was evaluated through indicator reliability, internal consistency reliability, convergent validity, discriminant validity, and multicollinearity assessment, following recommended PLS-SEM procedures [21]. The outer loadings of the indicators were first examined to assess indicator reliability. As shown in Table.1, all indicators demonstrated satisfactory loadings above the recommended threshold of 0.70, except one work engagement item (WE5 = 0.694), which was marginally below the threshold. However, this item was retained because outer loadings between 0.40 and 0.70 may be acceptable when construct reliability and convergent validity remain satisfactory [21].

Specifically, the outer loadings for AI adoption ranged from 0.762 to 0.803, for digital leadership from 0.727 to 0.822, for employee task performance from 0.805 to 0.831, and for work engagement from 0.694 to 0.788, thereby indicating acceptable indicator reliability (Table.2, Fig.3).

Table.1. Demographic Characteristics of Respondents (N = 245)

Variable	Category	Frequency (N)	Percentage (%)
Gender	Male	148	60.4
	Female	97	39.6
Age	20–25	34	13.9
	26–30	82	33.5
	31–35	64	26.1
	36–40	33	13.5
	40+	32	13.1
Education	High school/ Diploma	12	4.9
	Bachelor's	139	56.7
	Master's or above	94	38.4
Job Level	Entry level	85	34.7
	Middle level	122	49.8
	Managerial level	38	15.5
Work Experience	0–3 years	109	44.5
	4–7 years	85	34.7
	8+ years	51	20.8
AI Usage	Rarely use AI tools	30	12.2
	Occasionally use AI tools	77	31.4
	Frequently use AI tools	138	56.3

Source: Authors' compilation

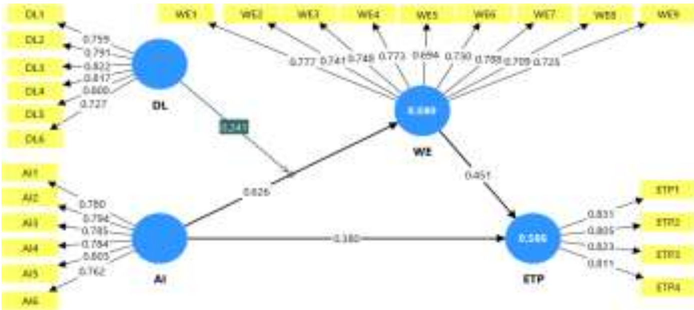


Fig.2. Measurement and Structural Model

Source: Authors' analysis using SmartPLS 4.0.

Internal consistency, reliability, and convergent validity were assessed using Cronbach's alpha (CA), composite reliability (CR), and average variance extracted (AVE). As reported in Table.2, Cronbach's alpha values ranged from 0.835 to 0.899, exceeding the recommended threshold of 0.70 while remaining below 0.95, indicating satisfactory internal consistency reliability [21], [26]. Similarly, the composite reliability values ranged from 0.890 to 0.917, exceeding the recommended cut-off of 0.70, thereby confirming construct reliability [21], [27].

Table.2. Measurement Model (result of the reliability and convergent validity)

Construct	Items	Outer Loading	VIF	Cronbach's alpha	Composite reliability (rho_c)	AVE
AI Adoption (AI)	AI1	0.780	1.897	0.875	0.906	0.616
	AI2	0.794	1.942			
	AI3	0.785	1.817			

	AI4	0.784	1.918			
	AI5	0.803	2.043			
	AI6	0.762	1.774			
Work engagement (WE)	WE1	0.777	2.002	0.899	0.917	0.552
	WE2	0.741	1.832			
	WE3	0.748	1.893			
	WE4	0.773	1.984			
	WE5	0.694	1.675			
	WE6	0.730	1.800			
	WE7	0.788	2.114			
	WE8	0.709	1.731			
	WE9	0.725	1.786			
Digital Leadership (DL)	DL1	0.759	1.813	0.877	0.907	0.619
	DL2	0.791	1.982			
	DL3	0.822	1.997			
	DL4	0.817	2.008			
	DL5	0.800	1.954			
	DL6	0.727	1.702			
Employee Task Performance (ETP)	ETP1	0.831	1.962	0.836	0.890	0.669
	ETP2	0.805	1.758			
	ETP3	0.823	1.772			
	ETP4	0.811	1.732			

Source: Author's own work

Further, all AVE values exceeded the threshold of 0.50, ranging from 0.552 to 0.669, suggesting adequate convergent validity and indicating that the latent constructs explained more than half of the variance in their indicators [28]. Therefore, the reliability and convergent validity of the measurement model were considered satisfactory (Table.1).

Discriminant validity was examined using both the heterotrait–monotrait ratio (HTMT) and the Fornell–Larcker criterion. As presented in Table.3, all HTMT values were below the conservative threshold of 0.85, with the highest value observed between employee task performance and work engagement (0.822), thereby establishing discriminant validity [29]. In addition, the Fornell–Larcker criterion indicated that the square root of AVE for each construct exceeded its corresponding inter-construct correlations (Table.4), further confirming adequate discriminant validity [28].

Table.3. Heterotrait-Monotrait (HTMT) Ratio

	AI	DL	ETP	WE	DL x AI
AI					
DL	0.211				
ETP	0.807	0.279			
WE	0.783	0.384	0.822		
DL x AI	0.107	0.098	0.138	0.291	

Table.4. Fornell-Larcker criterion (discriminant validity).

	AI	DL	ETP	WE
AI	0.785			
DL	0.191	0.787		
ETP	0.694	0.243	0.818	
WE	0.698	0.350	0.716	0.743

Potential multicollinearity was assessed using the variance inflation factor (VIF) values. As shown in Table.2, all VIF values ranged between 1.675 and 2.114, remaining substantially below the recommended threshold of 3.3 and indicating the absence of multicollinearity concerns [21], [30]. Collectively, these findings confirm that the measurement model demonstrated satisfactory reliability and validity, allowing further assessment of the structural relationships.

5.3 STRUCTURAL MODEL ASSESSMENT AND HYPOTHESIS TESTING

Following the establishment of measurement model adequacy, the structural model was evaluated through path coefficients, explanatory power (R^2), predictive relevance (Q^2), and bootstrapping procedures [21]. The explanatory power of the endogenous constructs was assessed using the coefficient of determination (R^2). As shown in Table.6, the model explained 59.0% of the variance in work engagement ($R^2 = 0.590$) and 58.6% of the variance in employee task performance ($R^2 = 0.586$). According to Chin [33], R^2 values around 0.50 indicate moderate explanatory power, suggesting that AI adoption and digital leadership substantially explain employee engagement and task performance in AI-enabled workplace settings (Fig.2).

Table.5. Hypotheses testing

Hypothesized path	β - value	Sample mean	SD	t-statistics	p-values	Supported
AI→ETP (H1)	0.380	0.379	0.066	5.782	< .001	Yes
AI→WE (H2)	0.626	0.627	0.039	16.111	< .001	Yes
WE→ETP (H3)	0.451	0.453	0.064	7.019	< .001	Yes
DLxAI→WE (H4)	0.241	0.237	0.038	6.411	< .001	Yes
AI→WE→ETP (H5)	0.282	0.285	0.045	6.231	< .001	Yes
DLxAI→WE→ ETP (H6)	0.108	0.107	0.020	5.370	< .001	Yes

Source: Author's own work

The model's predictive relevance was assessed using the Stone–Geisser Q^2 statistic, which evaluates its predictive capability [31], [32]. As reported in Table.6, the Q^2predict values for work engagement (0.576) and employee task performance (0.490) were substantially greater than zero, indicating adequate predictive relevance of the structural model [21]. Additionally, the corresponding RMSE and MAE values suggested acceptable predictive accuracy, indicating that the proposed model has meaningful predictive capability for explaining employee outcomes in digitally enabled environments.

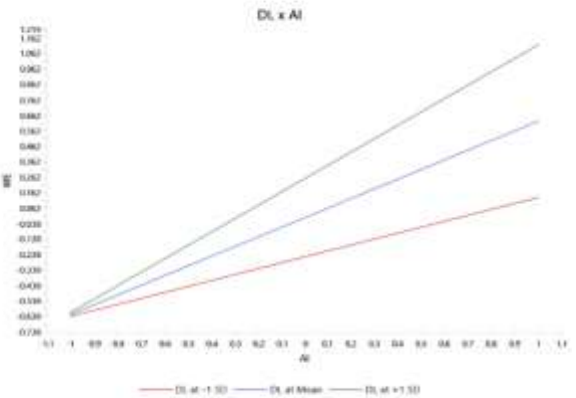
Table.6. Explanatory Power (R^2) and Predictive Relevance (Q^2) of the Structural Model

	R-square	R-square adjusted	Q² predict
ETP	0.586	0.583	0.490
WE	0.590	0.585	0.576

The structural relationships and hypothesis testing results are presented in Table.5. The findings revealed that AI adoption had a positive and significant effect on employee task performance ($\beta = 0.380$, $t = 5.782$, $p < .001$), thereby supporting H1. This finding suggests that greater utilisation of AI technologies contributes to higher employee effectiveness in performing assigned tasks.

Similarly, AI adoption positively influenced work engagement ($\beta = 0.626$, $t = 16.111$, $p < .001$), supporting H2. The substantial coefficient indicates that employees who perceive AI technologies as supportive and useful are more likely to exhibit higher levels of vigour, dedication, and absorption in their work.

Furthermore, work engagement significantly influenced employee task performance ($\beta = 0.451$, $t = 7.019$, $p < .001$), thereby supporting H3. This result indicates that employees who are psychologically engaged in their work tend to demonstrate superior task performance. Additionally, digital leadership positively affected work engagement ($\beta = 0.253$, $t = 5.729$, $p < .001$), suggesting that leaders who encourage digital transformation and technological readiness play an important role in enhancing employees' motivational states (Table.5).



s

Fig.3. Moderating Effect of Digital Leadership on the Relationship Between AI Adoption and Work Engagement

Source: Authors' analysis using SmartPLS 4.0

5.4 MEDIATION AND MODERATION ANALYSIS

The mediating role of work engagement in the relationship between AI adoption and employee task performance was examined through bootstrapping procedures. As shown in Table.5, the indirect effect of AI adoption on employee task performance through work engagement was positive and statistically significant ($\beta = 0.282$, $t = 6.231$, $p < .001$), thereby supporting H4. Since both the direct effect (AI → ETP) and indirect effect (AI → WE → ETP) remained statistically significant, the findings indicate partial mediation [21], [34]. This suggests that AI adoption improves employee task performance both directly and indirectly through enhanced work engagement.

The moderating role of digital leadership was examined using the interaction term (Digital Leadership × AI Adoption) to predict work engagement. As presented in Table.5, the interaction effect was positive and statistically significant ($\beta = 0.241$, $t = 6.411$, $p < .001$), thereby supporting H5. This finding suggests that digital leadership strengthens the positive influence of AI adoption on work engagement, implying that employees benefit more from AI technologies when supported by digitally competent leaders.

To further interpret the moderation effect, a simple slope analysis was conducted, and the results are illustrated in Fig.3. The slope analysis revealed that the positive relationship between AI adoption and work engagement was stronger under high digital leadership (+1 SD, $\beta = 0.866$) than under mean digital leadership ($\beta = 0.626$) or low digital leadership (−1 SD, $\beta = 0.385$). As depicted in Fig.3, employees working under highly digital leaders experienced substantially greater work engagement from AI adoption than employees working under less digitally supportive leaders. These findings further substantiate the strengthening role of digital leadership in AI-enabled workplaces.

Table.7. Conditional Direct and Indirect Effects of AI Adoption at Different Levels of Digital Leadership

Level of Digital Leadership	Conditional Direct Effect (AI → WE) β	Conditional Indirect Effect (AI→WE→ETP) β
Low (−1 SD)	0.385	0.174
Mean	0.626	0.282
High (+1 SD)	0.866	0.390

Source: Author's own work

Finally, the moderated mediation effect was assessed through conditional indirect effect analysis. The results reported in Table.7 demonstrated that the indirect effect of AI adoption on employee task performance through work engagement was strongest at high levels of digital leadership (+1 SD, $\beta = 0.390$), followed by mean levels ($\beta = 0.282$) and low levels (−1 SD, $\beta = 0.174$). Moreover, the specific indirect effect of the interaction term (DL × AI → WE → ETP) was statistically significant ($\beta = 0.108$, $t = 5.370$, $p < .001$), thereby supporting H6. These findings indicate that digital leadership not only strengthens the direct relationship between AI adoption and work engagement but also amplifies the indirect effect of AI adoption on employee task performance through work engagement (Table.7 and Fig.3).

6. DISCUSSION

The present study examined how AI adoption influences employee task performance through work engagement under varying levels of digital leadership in the Indian IT sector. Overall, the findings provide substantial support for the proposed model and reinforce the assumptions of the Job Demands–Resources (JD-R) theory, which posits that workplace resources enhance employee motivation and performance [10]. The model demonstrated satisfactory explanatory and predictive capability, with moderate explanatory power for work engagement and employee task performance and positive predictive relevance values, suggesting that the proposed framework effectively explains employee outcomes in AI-enabled work environments [21], [33], [34].

The findings indicate that employees become more psychologically engaged in their work when AI technologies are perceived as supportive workplace resources. AI-enabled systems may reduce repetitive tasks, improve efficiency, and facilitate decision-making, thereby enabling employees to focus on more meaningful and productive work activities. From a JD-R perspective, such technological support may function as a job resource, enhancing employees' motivational energy and psychological investment in work [10]. This finding is consistent with Korzynski et al. [4], who reported that AI-supported systems strengthen work engagement by improving workplace productivity and knowledge management. Likewise, Liu and Li [7] found that employees tend to experience greater engagement when AI is viewed as facilitating rather than replacing human work. The present study extends these findings by confirming the motivational role of AI adoption within the Indian IT sector, where employees frequently interact with digitally intensive systems.

The findings further suggest that employees with higher levels of work engagement are more likely to exhibit stronger task performance. Employees who are psychologically immersed in their work tend to invest greater cognitive, emotional, and behavioural effort in accomplishing organisational goals, thereby improving their effectiveness in performing assigned responsibilities [9]. This interpretation aligns with the motivational assumptions of JD-R theory, in which engaged employees are more likely to convert available workplace resources into productive outcomes [10]. The result is also consistent with Vuong [8], who reported that AI-related workplace resources contribute to performance through enhanced work engagement.

The study also shows that AI adoption directly contributes to employee task performance, suggesting that intelligent technologies enhance employee effectiveness through greater efficiency, improved information accessibility, and reduced manual effort. Employees working in AI-enabled environments may perform tasks more effectively because AI systems support faster decision-making and reduce time spent on routine activities. Similar conclusions have been reported by Nguyen et al. [5] and Prentice et al. [6], who found that AI technologies positively influence workplace performance. However, the simultaneous presence of both direct and indirect effects suggests that AI effectiveness extends beyond technological functionality and is partly dependent on employees' motivational engagement.

The mediating role of work engagement further demonstrates that the effectiveness of AI adoption is partly explained through employees' psychological involvement in work. Employees who perceive AI technologies as useful and supportive may become more enthusiastic and absorbed in their work, thereby enhancing performance outcomes. This finding supports prior evidence emphasising motivational mechanisms in AI-enabled work settings [4], [8]. Moreover, the finding extends prior literature by identifying work engagement as an important explanatory mechanism linking AI adoption to employee task performance in the Indian IT context.

An important contribution of this study concerns the role of digital leadership in strengthening employees' responses to AI adoption. The findings suggest that the motivational benefits of AI become stronger when employees operate under digitally supportive leaders.

Leaders who encourage digital readiness, reduce uncertainty, and support employees during technological change may increase employees' confidence in using AI systems, thereby strengthening engagement with work [11], [12]. As illustrated in Fig.3, the positive influence of AI adoption on work engagement became substantially stronger under high levels of digital leadership, indicating that leadership quality shapes how employees perceive and utilise AI-enabled technologies.

The conditional indirect effect findings further indicate that digital leadership strengthens the indirect effect of AI adoption on employee task performance through work engagement. This suggests that leadership support amplifies the extent to which technological resources are translated into motivational and performance-related outcomes. Therefore, the benefits of AI adoption appear to be maximised when organisations combine technological implementation with strong digital leadership capabilities. This finding extends prior research by positioning digital leadership as an important contextual boundary condition in AI-enabled workplaces [5], [12].

Thus, the study makes several contributions. Theoretically, it extends JD-R theory by conceptualising AI adoption as a technological job resource that enhances employee motivation and task performance [10]. The findings also establish work engagement as an important psychological mechanism linking AI adoption with performance outcomes while highlighting digital leadership as a critical contextual factor that strengthens these relationships. Practically, the findings suggest that organisations should complement AI investments with leadership development initiatives that foster digital readiness and employee confidence in technological systems to maximise performance outcomes.

7. IMPLICATIONS OF THE STUDY

7.1 THEORETICAL IMPLICATIONS

This study offers several important theoretical contributions. First, it extends the Job Demands-Resources Model by conceptualising AI adoption as a technological job resource that enhances employee motivation and performance. While prior JD-R studies have primarily emphasised organisational and interpersonal resources, the present findings demonstrate that AI-enabled technologies can also function as motivational resources in digitally transformed workplaces. Second, the study advances the AI and employee outcomes literature by identifying work engagement as a key psychological mechanism linking AI adoption and employee task performance. Third, the study highlights digital leadership as an important contextual boundary condition, demonstrating that the effectiveness of AI adoption depends on leadership support in facilitating employee adaptation to technological change.

7.2 MANAGERIAL IMPLICATIONS

The findings provide several practical implications for managers and organisations, particularly within the Indian IT sector.

First, organisations should avoid viewing AI solely as a productivity-enhancing technology and instead recognise its potential to improve employee engagement and task performance. Managers should therefore ensure that AI tools are implemented in ways that support employees' daily work activities and reduce unnecessary workload.

Second, organisations should invest in digital leadership development, as digitally competent leaders can strengthen employees' confidence in AI systems and facilitate smoother technology adoption.

Finally, firms should complement AI implementation with employee training and engagement initiatives to help employees view AI as a supportive resource rather than a threat, thereby maximising the performance benefits of digital transformation.

8. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

Despite its contributions, this study has several limitations. First, the study employed a cross-sectional research design, which limits the ability to establish causal relationships among the study variables. Future studies may adopt longitudinal designs to better examine how AI adoption influences employee outcomes over time. Second, the study focused exclusively on employees in the Indian IT sector, which may limit the generalizability of the findings to other industries and geographical contexts. Future research may replicate the model across different sectors and countries to enhance external validity. Third, the study examined work engagement as the mediating mechanism and digital leadership as the moderating factor; however, future studies may incorporate additional mediators and moderators, such as employee digital competence, trust in AI, technological readiness, or organisational support, to provide a more comprehensive understanding of AI-enabled employee outcomes. Finally, future research may compare different forms of AI technologies to examine whether their effects on employee performance vary across workplace settings.

9. CONCLUSION

This study examined the influence of AI adoption on employee task performance through work engagement and the moderating role of digital leadership among employees in the Indian IT sector. The findings demonstrate that AI adoption positively affects employee task performance, both directly and indirectly through enhanced work engagement. Moreover, digital leadership strengthens the positive effects of AI adoption, highlighting the importance of supportive leadership in digitally transformed workplaces. The study contributes to the growing literature on AI-enabled work environments by extending the Job Demands-Resources Model and positioning AI adoption as a technological job resource that enhances employee motivation and performance. Overall, the findings suggest that organisations are more likely to realise the performance benefits of AI when technological adoption is accompanied by strong digital leadership and efforts to foster employee engagement.

REFERENCES

[1] E. Brynjolfsson and A. McAfee, "*Machine, Platform, Crowd: Harnessing our Digital Future*", W.W. Norton and Company, 2017.

[2] Y.K. Dwivedi, N. Kshetri, E.L. Hughes, A. Slade, A. Jeyaraj and D. Buhalis, "So What if ChatGPT Wrote it? Multidisciplinary Perspectives on Opportunities, Challenges and Implications of Generative Conversational AI for Research, Practice and Policy", *International Journal of Information Management*, Vol. 71, pp. 102642-102657, 2023.

[3] M.H. Jarrahi, "Artificial Intelligence and the Future of Work: Human-AI Symbiosis in Organizational Decision Making", *Business Horizons*, Vol. 61, No. 4, pp. 577-586, 2018.

[4] P. Korzynski, O. Protsiuk, A. Tursunbayeva, A. Papa and D. De Cremer, "Enhancing Productivity and Work Engagement: The Mediating Role of Intrinsic Motivation toward Generative AI Knowledge Management", *Journal of Knowledge Management*, Vol. 23, No. 2, pp. 1-17, 2026.

[5] P.T. Nguyen, P.Q.T. Nguyen and M.T. Nguyen, "Artificial Intelligence, Transformational Leadership, and Job Performance: Mediating Role of Job Engagement and Moderating Role of Work Passion", *Journal of Applied Data Sciences*, Vol. 45, No. 2, pp. 1-19, 2026.

[6] C. Prentice, I.A. Wong and Z.C. Lin, "Artificial Intelligence as a Boundary-Crossing Object for Employee Engagement and Performance", *Journal of Retailing and Consumer Services*, Vol. 73, pp. 103359-103376, 2023.

[7] X. Liu and Y. Li, "Examining the Double-Edged Sword Effect of AI Usage on Work Engagement: The Moderating Role of Core Task Characteristics Substitution", *Behavioral Sciences*, Vol. 34, No. 2, pp. 1-13, 2025.

[8] B.N. Vuong, "The Impact of Generative Artificial Intelligence usage on Job Performance through Job Crafting and Work Engagement: Does Digital Competence Matter?", *Computers in Human Behavior*, Vol. 56, No. 3, pp. 23-38, 2026.

[9] W.B. Schaufeli, M. Salanova, V. Gonzalez-Roma and A.B. Bakker, "The Measurement of Work Engagement with a Short Questionnaire: A Cross-National Study", *Educational and Psychological Measurement*, Vol. 66, No. 4, pp. 701-716, 2006.

[10] A.B. Bakker and E. Demerouti, "Job Demands-Resources Theory: Taking Stock and Looking Forward", *Journal of Occupational Health Psychology*, Vol. 22, No. 3, pp. 273-285, 2017.

[11] A. Radic, S. Singh, N. Singh, A. Ariza-Montes, G. Calder and H. Han, "The Good Shepherd: Linking Artificial Intelligence-Driven Servant Leadership (SEL) and Job Demands-Resources (JD-R) Theory in Tourism and Hospitality", *Journal of Hospitality and Tourism Insights*, Vol. 34, No. 2, pp. 1-14, 2025.

[12] G. Gayathiri, G. Prabu, S.K. Sindu Bharathi, R. Prabhavathy and A. Prabu, "Digital Leadership and AI Performance Assessment Impact on Organisational Performance: Role of Empowerment and Engagement", *Knowledge and Performance Management*, Vol. 56, No. 3, pp. 1-19, 2026.

[13] A.B. Bakker and E. Demerouti, "The Job Demands-Resources Model: State of the Art", *Journal of Managerial Psychology*, Vol. 22, No. 3, pp. 309-328, 2007.

[14] E. Demerouti, A.B. Bakker, F. Nachreiner and W.B. Schaufeli, "The Job Demands-Resources Model of Burnout", *Journal of Applied Psychology*, Vol. 86, No. 3, pp. 499-512, 2001.

[15] W.B. Schaufeli and T.W. Taris, "A Critical Review of the Job Demands-Resources Model: Implications for Improving Work and Health", *Proceedings of International Conference on Bridging Occupational, Organizational and Public Health*, pp. 43-68, 2014.

[16] L.J. Williams and S.E. Anderson, "Job Satisfaction and Organizational Commitment as Predictors of Organizational Citizenship and In-Role Behaviors", *Journal of Management*, Vol. 17, No. 3, pp. 601-617, 1991.

[17] A. Manresa, A. Sammour, M. Mas-Machuca, W. Chen and D. Botchie, "Humanizing GenAI at Work: Bridging the Gap between Technological Innovation and Employee Engagement", *Journal of Managerial Psychology*, Vol. 23, No. 2, pp. 1-23, 2024.

[18] F. Marimon, M. Mas-Machuca and A. Akhmedova, "Trusting in Generative AI: Catalyst for Employee Performance and Engagement in the Workplace", *International Journal of Human-Computer Interaction*, Vol. 41, No. 11, pp. 7076-7091, 2025.

[19] Khan, A. N., K. Shahzad, and N. A. Khan, "AI in the workplace: Driving employee performance through enhanced knowledge sharing and work engagement", *International Journal of Human-Computer Interaction*, Vol. 41, No. 17, pp. 10699-10712, 2024.

[20] F. Su, W. Liu, K. Xiong and Q. Zeng, "How and When Artificial Intelligence usage Facilitates Task Performance", *Proceedings of International Conference on Social Behavior and Personality*, pp. 1-9, 2024.

[21] J.F. Hair, G.T.M. Hult, C.M. Ringle and M. Sarstedt, "*A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*", Sage Publications, 2022.

[22] I. Etikan, S.A. Musa and R.S. Alkassim, "Comparison of Convenience Sampling and Purposive Sampling", *American Journal of Theoretical and Applied Statistics*, Vol. 5, No. 1, pp. 1-4, 2016.

[23] U. Sekaran and R. Bougie, "*Research Methods for Business: A Skill-Building Approach*", Wiley, 2019.

[24] F.D. Davis, "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology", *MIS Quarterly*, Vol. 13, No. 3, pp. 319-340, 1989.

[25] V. Venkatesh, M.G. Morris, G.B. Davis and F.D. Davis, "User Acceptance of Information Technology: Toward a Unified View", *MIS Quarterly*, Vol. 27, No. 3, pp. 425-478, 2003.

[26] J.C. Nunnally and I.H. Bernstein, "*Psychometric Theory*", McGraw-Hill, 1994.

[27] R.P. Bagozzi and Y. Yi, "On the Evaluation of Structural Equation Models", *Journal of the Academy of Marketing Science*, Vol. 16, No. 1, pp. 74-94, 1988.

[28] C. Fornell and D.F. Larcker, "Evaluating Structural Equation Models with Unobservable Variables and Measurement Error", *Journal of Marketing Research*, Vol. 18, No. 1, pp. 39-50, 1981.

[29] J. Henseler, C.M. Ringle and M. Sarstedt, "A New Criterion for Assessing Discriminant Validity in Variance-Based Structural Equation Modeling", *Journal of the Academy of Marketing Science*, Vol. 43, No. 1, pp. 115-135, 2015.

[30] N. Kock, "Common Method Bias in PLS-SEM: A Full Collinearity Assessment Approach", *International Journal of e-Collaboration*, Vol. 11, No. 4, pp. 1-10, 2015.

[31] S. Geisser, "A Predictive Approach to the Random Effect Model", *Biometrika*, Vol. 61, No. 1, pp. 101-107, 1974.

[32] M. Stone, "Cross-Validatory Choice and Assessment of Statistical Predictions", *Journal of the Royal Statistical Society: Series B*, Vol. 36, No. 2, pp. 111-147, 1974.

[33] W.W. Chin, "The Partial Least Squares Approach to Structural Equation Modeling", *Proceedings of International Conference on Modern Methods for Business Research*, pp. 295-336, 1998.

[34] X. Zhao, J. G. Lynch and Q. Chen, "Reconsidering Baron and Kenny: Myths and Truths about Mediation Analysis", *Journal of Consumer Research*, Vol. 37, No. 2, pp. 197-206, 2010.