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Abstract:

This study examines how AI adoption psychologically influences employee retention in the Indian IT sector through productivity, work culture, and communication, mediated by employee engagement. A structured survey was carried out with 410 IT sector workers in Karnataka, India. AI adoption was the independent variable, employee engagement as the mediator and retention the dependent variable. PLS-SEM was chosen for its suitability for predictive models and non-normal data; bootstrapped mediation (n = 5,000) and Necessary Condition Analysis (NCA) were used to differentiate sufficient and necessary antecedents of engagement. Productivity and communication significantly predict employee engagement; work culture does not. Engagement partially mediates the AI effect on retention; the serial pathway AI → Productivity → Engagement → Retention is dominant. NCA establishes productivity as both necessary and sufficient for engagement (d = 0.363), and work culture as a necessary-only hygiene condition (d = 0.260). Productivity is the primary pathway through which AI influences retention. Work culture acts as a hygiene floor; required, but not enough; communication adds to but does not dictate engagement. Grounded in Social Exchange Theory, the JD-R Model and Herzberg's Two-Factor Theory, the study offers practitioners actionable NCA-derived retention thresholds.

Keywords: Artificial Intelligence, Employee Engagement, Employee retention, PLS SEM, Necessary Condition Analysis, Indian IT Sector.

1. Introduction

In the global knowledge economy, Artificial Intelligence (AI) is changing the face of work at a pace that far exceeds organisations' ability to address its human impact. AI has the potential to transform 40 to 50 per cent of current work activities over the next decade, according to the McKinsey Global Institute (Brynjolfsson & McAfee, 2014), and the World Economic Forum identifies managing the workforce amid AI transformation as the most pressing people management challenge of this generation. This background lends itself to one of the most strategic questions in HRM research, namely, 'How will the adoption of AI affect the psychological experience of employees and whether this experience will contribute to engagement and retention?

The adoption of AI in HRM has transformed from a future prospect to a practical reality (Budhwar *et al*., 2023; Malik *et al*., 2023; Yue *et al*., 2024). There are at least three core values of AI: data analysis is used to provide insights that can be translated into actions for the workforce, personalised interactions with employees are scalable, and AI supports decision-making at all levels of the organisation (Kasubi *et al*., 2025; Bankins *et al*., 2024). It simplifies repetitive tasks, enhances communication and collaboration, and directly impacts retention results (Rožman *et al*., 2023b). AI tools can forecast employee satisfaction and engagement outcomes (Rana, 2023); HR can take proactive measures before employee disenchantment leads to attrition.

While AI in HRM has attracted considerable research interest, relatively few studies have examined its applications within specific HR functions, such as recruitment (Upadhyay & Khandelwal, 2019; Albassam, 2023), performance management (Varma et al., 2024), or the effect of AI on HR engagement and retention, by applying traditional HRM theories without incorporating AI as an antecedent (Pandita & Ray, 2018; Moore & Hanson, 2022). Most importantly, the three psychological mechanisms through which AI alters the work experience, productivity, work culture, and communication have never been modelled simultaneously in an empirical framework as antecedents of engagement and retention. As a result, organisations lack a clear foundation for prioritising AI investment decisions aimed at enhancing human capital outcomes. Research on AI-enabled human resource management has also examined how AI adoption reshapes HR practices and employees' experiences at work (Goswami *et al*., 2023; Kambur & Akar, 2022).

This study fills this gap with four contributions. First, it presents the first empirical model testing productivity, work culture, and communication as psychological mechanisms linking AI adoption to employee retention via engagement, a set of mechanisms that has not been tested together previously. Second, it brings together two methodological approaches, PLS-SEM and Necessary Condition Analysis (NCA), which have not been used in the same domain, as far as we know: PLS-SEM uncovers what contributes to engagement, and NCA uncovers what engagement cannot exist without, both with implications for managerial practices. Third, it offers the first empirical evidence for Herzberg's hygiene-motivator distinction in the context of AI adoption: NCA ceiling analysis shows that work culture is a floor condition, but not a driver, whereas productivity is both. Fourth, the NCA bottleneck table provides specific, operational scoring thresholds, offering HR practitioners a diagnostic, not merely a direction.

The research questions guiding the study are: Q1: Is the implementation of AI really having a significant impact on employee productivity, work culture, and communication? (Q2) What

impact does AI have on employee engagement and retention? The paper is divided into the following sections: Section 2 reviews the literature and states the hypotheses; Section 3 provides the theoretical perspective; Section 4 outlines the methodology; Section 5 explains the results of the measurements; Section 6 reports the results of the structure; Section 7 discusses the results; Section 8 presents implications for the study; Section 9 presents the conclusion of the study; and Section 10 presents the limitations and directions for future research of the study.

2. Literature Review

2.1 Artificial Intelligence and Employee Productivity

Employee productivity refers to the efficiency with which employees achieve work goals within a given period (Zhai et al., 2024). Artificial intelligence (AI) has the potential to automate routine tasks and support employees in performing complex activities, making productivity improvement an important organisational priority (Brynjolfsson & McAfee, 2014). AI can enhance human decision-making, task performance and human–machine interaction, potentially strengthening organisational competitiveness (Wang & Ding, 2024; Wang et al., 2024). Related research by Rajeswari and Venugopal (2024) found that employee engagement mediates the positive relationship between the hybrid work model and employee productivity among IT professionals, highlighting the role of engagement in the productivity process. From a Job Demands–Resources perspective, job resources can facilitate employee motivation and engagement by helping employees achieve work goals and manage job demands (Bakker & Demerouti, 2007). In AI-enabled work environments, applications such as AI-supported performance management, training and workload management may provide additional resources for employees, although their effects depend on how these technologies are implemented and experienced. Recent evidence from the Indian IT sector indicates that AI adoption positively influences employee task performance, with work engagement partially mediating this relationship (Arif & Nabi, 2026). Evidence on work arrangements and productivity also highlights the importance of work context in shaping employee productivity (Farooq & Sultana, 2022). In line with Conservation of Resources (COR) theory (Hobfoll, 1989; Hobfoll et al., 2018), employees who perceive AI as a resource rather than a threat to their existing resources may be better positioned to direct their cognitive resources towards task performance and engagement. This perspective provides a theoretical basis for examining employee productivity as a potential pathway linking AI adoption with employee engagement.

H1: There is a positive psychological effect of AI on the productivity of employees.

2.2 Psychological impact of AI and work culture

Organisational work culture refers to the shared norms, values, beliefs and assumptions that influence how employees react to change and new technologies (Murire, 2024). The implementation of AI requires a cultural mindset change: organisations that cultivate digital maturity, collaborative learning and psychological safety are more likely to achieve the performance gains of AI (Al Samman, 2024; Tariq *et al*., 2021). The fear and uncertainty surrounding AI's possible disruption of job markets and fears of skills obsolescence are a major psychological hurdle that can erode cultural bonds and engagement (Chen *et al*., 2025; Soulami *et al*., 2024). This technostress dynamic represents the two aspects of using AI: as a job resource that enhances capability, and as a job demand that creates adaptation pressure (Bakker & Demerouti, 2007; Hobfoll, 1989). By implementing structured training programs and upskilling initiatives, combined with managerial support, it is possible to mitigate such anxiety and

enhance the psychological readiness of employees working in environments where AI is becoming more common (Wang *et al*., 2024; Rožman *et al*., 2023a). The net resource gain of AI adoption holds even more significance because workplace stressors that strain psychological resources have a direct impact on employee performance and engagement (Rahman & Hossain, 2024).

H2: The psychological impact of AI has a significant positive effect on work culture.

2.3 Psychological Impact of Artificial Intelligence and Communication

AI is reshaping workplace communication, changing the way it is expressed, experienced, and delivered (Hohenstein *et al*., 2023). At scale, AI enables real-time, personalised communication, eliminating information gaps and improving perception of organisational support among employees (Florea & Croitoru, 2025). The speed and flexibility of AI interactions can strengthen employees' feelings of belonging to the organisation and to the company (Hohenstein *et al*., 2023; Yue *et al*., 2024), which directly influences their psychological engagement and motivation (Florea & Croitoru, 2025).

H3: The psychological effects of AI have a significant positive impact on communication.

2.4 Antecedents of Employee Engagement: AI-Driven Mechanisms

Employee engagement is affected by the organisation's environment in which they work

(Chowdhury *et al.,* 2023). AI-powered productivity environments provide tangible and immediate measures of success, which increase employees' feelings of accomplishment and, in turn, their work engagement (Rožman *et al*., 2023b; Xanthopoulou *et al*., 2009). The social exchange perspective (Saks, 2006) states that when employees receive job resources provided by AI, they give back by being more engaged, which involves a psychological commitment on their part and an investment on the part of the organisation in their capacity to perform. The JD-R model (Schaufeli & Taris, 2014) proposes that job resources, including better communication, cultural openness, and AI-driven productivity, reduce strain and enable the motivational process that results in engagement (Bakker & Demerouti, 2007). By improving response time, personalisation, and information availability, AI-driven communication tools boost employees' sense of organisational support, leading to greater engagement and loyalty as a result of the social exchange theory (Eisenberger *et al*., 1986; Rhoades & Eisenberger, 2002; Yue *et al*., 2024). Empirical studies in the Indian context confirm that HRM practices stimulate engagement through social exchange mechanisms, with work engagement mediating the relationship between HRM quality and employee outcomes (Iram *et al*., 2024).

H4: There is a significant positive relationship between employee productivity and employee engagement.

H5: Work culture has a significant positive effect on employee engagement.

H6: Communication has a significant positive effect on employee engagement.

2.5 Employee Engagement and Employee Retention

Long-term employee retention is a strategic human capital outcome that is significant (Ali et al., 2024). Employee engagement is a key factor that determines retention and has a strong negative relation with intention to leave both at the sectoral and national level (Chowdhury *et al*., 2023; Truss *et al*., 2013). The workers whose emotional attachment to the organisation was

lower had a significantly higher probability of leaving the organisation (Ismail *et al*., 2021). There is overwhelming empirical evidence that engagement is one of the strongest predictors of performance and retention, as highly engaged employees are found to have greater performance and lower voluntary turnover rates (Anitha, 2014; Saks, 2006; Garg *et al*., 2018; Sheoran *et al*., 2023). Talent management processes grounded in the concept of engagement programs have been proven to enhance organisational commitment and lower dysfunctional attrition (Pandita & Ray, 2018), while engagement-based retention strategies have been proven to stabilise human capital even in such an active work environment as the Indian IT industry (Ghosh *et al*., 2013). Similarly, Jindal and Shaikh (2021) found that talent retention mediates the relationship between talent identification, talent development, and succession planning, underscoring its importance in sustaining organisational continuity.

H7: Employee engagement has a significant positive effect on employee retention.

3. Theoretical Framework

This study builds on three complementary theories that together provide a psychologically viable explanation for the effect of AI on employee engagement and retention.

3.1 Social Exchange Theory

Social Exchange Theory (SET) suggests that the consequences of social actions are the result of a reciprocal exchange process in which people try to maximise return and minimise costs (Cropanzano & Mitchell, 2005). In the workplace, when employers use AI tools to alleviate cognitive strain, improve the speed and efficiency of tasks, and boost the quality of work, employees feel an implicit obligation to reciprocate through greater commitment, effort, and engagement to the employer (Saks, 2006). A positive feedback loop emerges when AI-driven HR practices enhance productivity and tailor employee experiences, fostering greater engagement and reducing the likelihood of turnover (Suengkamolpisut & Singhatong, 2025). Empirical studies have found that this exchange logic also applies to HRM practice: HRM fosters engagement via SET mechanisms and engagement has a mediating role in HRM's impact on employee outcomes (Iram *et al*., 2024). Therefore, SET serves as the theoretical lens for the AI-adoption–engagement–retention pathway that is core to this research.

3.2 Job Demands-Resources Model

The Job Demands-Resources (JD-R) model proposed by Bakker & Demerouti (2007) and Schaufeli & Taris (2014) categorises job demands as aspects of the job that require prolonged physical or mental exertion and job resources as those elements of the job that reduce job demands, support job performance, and enable personal growth. AI technologies are the tools that can be great job resources: they can automate repetitive tasks with high demands, offer real-time performance feedback, and create data-driven pathways to meaningful careers. AI reduces psychological pressure and establishes the motivational framework for long-term employee commitment through the provision of additional work resources. The JD-R model also suggests that resources mediate the relationship between demands and strains, which is particularly noticeable in the high-demand, high AI context examined in this study (IT sector).

3.3 Herzberg’s Two-Factor Theory

According to Herzberg's Two-Factor Theory (Herzberg *et al*., 1959), there are two sets of factors: one set is called hygiene factors, which, when absent, cause dissatisfaction and when present do not necessarily lead to performance satisfaction; and another set is called motivators, which motivate performance and lead to satisfaction. The framework offers a rich

understanding of the potential for varying engagement through different AI-enabled mechanisms. AI-driven productivity enhancements serve as motivators, delivering real, personal results, successful task completion, recognition of effort, and a sense of success that foster intrinsic motivation and engagement. Unlike motivation, on the other hand, work culture is a hygiene factor; if it doesn't work properly, then it will lead to disengagement, but if it works properly, beyond a point, it will not result in a proportional rise in motivation. The theoretical conclusion in the present work is just what the result of the NCA confirms empirically: This study provides the first empirical validation of the hygiene-motivator distinction within an AI adoption context, confirmed through NCA ceiling line analysis. The conceptual framework that combines these three theories is presented in Figure 1.

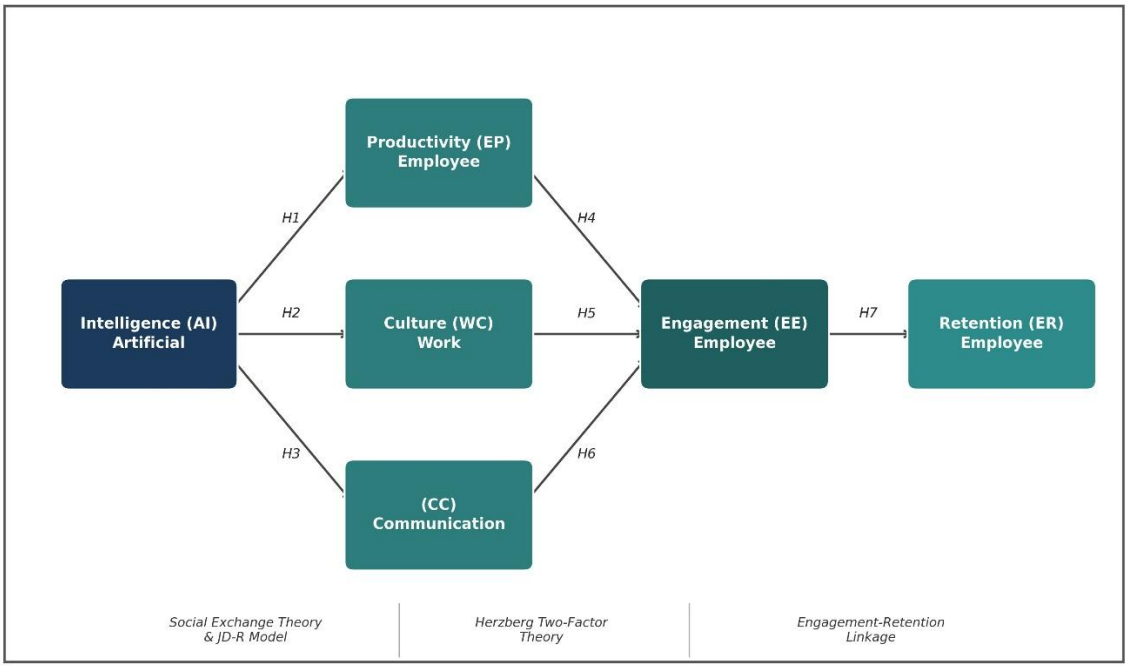


Figure 1: Conceptual Framework: Psychological Impact of AI on Employee Retention through Employee Engagement

Note: H1–H7 denote the seven hypothesised paths. Theoretical grounding: Social Exchange Theory (Cropanzano & Mitchell, 2005), JD-R Model (Bakker & Demerouti, 2007), Herzberg's Two-Factor Theory (Herzberg et al., 1959. Source: The Author

4. Methodology

The respondents were drawn from the IT industry in Karnataka, where the adoption of AI in everyday business and HR is well underway and commonplace. A convenience sampling technique was used, and the structured questionnaire used was Google Forms, which was sent to a selected number of 434 respondents. After removing 24 responses with missing or extreme values, the number of valid responses for analysis was 410. The survey items were adapted from Garg *et al*. (2018) and validated using a systematic literature review.

Data were collected using a structured questionnaire comprising 23 items organised into six constructs: artificial intelligence (four items), employee productivity (four items), work culture (three items), communication (four items), employee engagement (four items), and employee retention (four items). Employee-engagement items drew on the work-engagement literature, including the scale discussed by Garg et al. (2017). The questionnaire also collected demographic information relating to respondents' age, gender, educational qualification,

organisational position, and experience in the IT industry. Responses to the construct items were recorded on a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree).

The items operationalised different dimensions of respondents' experiences and perceptions of AI-enabled work, productivity, workplace culture, communication, engagement, and retention-related outcomes. The measurement items and their wording are provided in the supplementary questionnaire.

PLS-SEM was chosen over Covariance-Based SEM (CB-SEM) for three reasons. First, the research model is predictive rather than confirmatory in orientation. Second, the sample size, while adequate for PLS-SEM, is smaller than what CB-SEM typically requires for models of this complexity. Third, PLS-SEM performs more robustly with reflective-formative hybrid constructs (Hair *et al*., 2019). NCA was added as a complementary analytical technique: whereas PLS-SEM identifies sufficient conditions, what predicts high engagement, NCA identifies necessary conditions, what must be present for engagement to occur at all (Dul, 2016; Richter *et al*., 2020). This methodological combination has not previously been applied in the AI–HRM–retention domain.

The sample was also demographically young, as 53.6% of the respondents were below the age of 25 and 32.7% were between the ages of 25 and 34 years. The educational level was mainly undergraduate (48.2%) and postgraduate (45.5%). The respondents included entry level (53.6%), mid-level (22.7%) and senior level (14.5%). Organisational tenures were similar to the career-stage profile, with 53.6% having less than one year of experience. The overall demographic profile is given in Table 1.

Table 1: Demographic Profile of Respondents (N = 410)

Variable	Category	n	%	Variable	Category	n	%
Gender	Male	209	51.0	Position	Entry-level	220	53.6
	Female	197	48.0		Mid-level	93	22.7
	Third gender	4	1.0		Senior-level	59	14.5
Age	Under 25	220	53.6		Managerial	30	7.3
	25–34	134	32.7		Executive	7	1.8
	35–44	30	7.3	Experience	Less than 1 year	220	53.6
	45–54	19	4.6		1–3 years	86	20.9
	55 and above	7	1.8		4–6 years	48	11.8
Education	UG degree	198	48.2		7–10 years	41	10.0
	PG degree	186	45.5		> than 10 years	15	3.6
	Doctorate	26	6.3				

Source: Primary data collected via Google Forms (2024).

The items operationalised different dimensions of respondents' experiences and perceptions of AI-enabled work, productivity, workplace culture, communication, engagement, and retention-related outcomes. The measurement items and their wording are provided in the supplementary questionnaire and are represented in Table 2.

Table 2: Construct Measurement and Item Allocation

Construct	Construct abbreviation	Number of items	Item identifiers
Artificial Intelligence	AI	4	AI1–AI4
Employee Productivity	EP	4	EP1–EP4
Work Culture	WC	3	WC1–WC3
Communication	CC	4	CC1–CC4
Employee Engagement	EE	4	EE1–EE4
Employee Retention	ER	4	ER1–ER4

5. Measurement Model

5.1 Reliability and Convergent Validity

SmartPLS 4 was used to assess reliability and convergent validity. All constructs exceeded the 0.70 threshold for both Cronbach's alpha (Cronbach, 1951) and composite reliability. This is evidenced by the average variance extracted (AVE) values being greater than 0.50 across all constructs (Hair *et al*., 2019). All the standardised factor loadings were significant ($p < 0.001$). Full results are presented in Table 3.

Table3: Measurement Model: Reliability and Convergent Validity

Construct	Items	Loading Range	Cronbach's α	CR	AVE	p-value
Artificial Intelligence (AI)	4	0.793–0.868	0.865	0.908	0.713	< 0.001
Employee Productivity (EP)	4	0.814–0.879	0.857	0.905	0.704	< 0.001
Work Culture (WC)	3	0.787–0.900	0.828	0.897	0.744	< 0.001
Communication (CC)	4	0.813–0.889	0.882	0.919	0.739	< 0.001
Employee Engagement (EE)	4	0.741–0.835	0.783	0.864	0.615	< 0.001
Employee Retention (ER)	4	0.791–0.873	0.864	0.909	0.715	< 0.001

Note: CR = composite reliability; AVE = average variance extracted. Minimum thresholds: α > 0.70, CR > 0.70, AVE > 0.50.

5.2 Discriminant Validity, Fornell-Lacker Criterion

The Fornell-Lacker criterion stipulates that the square root of the AVEs must be larger than the correlations of each construct with the other (Hair *et al*., 2019). Table 4 demonstrates that this criterion is met for all construct pairs.

Table 4: Discriminant Validity — Fornell-Lacker Criterion (Diagonal = √AVE)

Construct	AI	EP	WC	CC	EE	ER
AI	**0.844**					
EP	0.476	**0.839**				
WC	0.607	0.647	**0.862**			
CC	0.424	0.594	0.704	**0.860**		
EE	0.412	0.767	0.621	0.634	**0.784**	
ER	0.440	0.661	0.766	0.679	0.734	**0.846**

Note: Diagonal values (bold) = square root of AVE. Off-diagonal values = inter-construct correlations

5.3 Discriminant Validity, HTMT Criterion

The Heterotrait-Monotrait Ratio of Correlations (HTMT) represented in Table 5 was computed as a more stringent test of discriminant validity (Hair *et al*., 2019). Most construct pairs meet the conservative criterion of 0.85. Two pairs are above the liberal threshold of 0.90, namely Employee Productivity–Employee Engagement (HTMT = 0.940) and Work Culture–Employee Retention (HTMT = 0.921). There is one such pair, Employee Engagement-Employee Retention (HTMT = 0.896), that falls between the conservative (0.85) and liberal (0.90) thresholds. These "borderline" values are recognised as a limitation of the study. They can be theoretically predicted due to the high conceptual similarity among productivity, engagement, and retention in AI-intensive work contexts, where task performance is directly linked to emotional commitment. The Fornell-Lacker criterion is met for all pairs, thus establishing discriminant validity for constructs.

Table 5: Discriminant Validity: HTMT Matrix (Threshold: < 0.85 Conservative, < 0.90 Liberal)

Construct	AI	EP	WC	CC	EE	ER
AI	—					
EP	0.561	—				
WC	0.715	0.773	—			

CC	0.486	0.684	0.829	—		
EE	0.508	0.940*	0.781	0.762	—	
ER	0.523	0.773	0.921*	0.781	0.896†	—

*Note: * Exceeds 0.90 liberal threshold (discriminant validity concern); † Between 0.85 and 0.90 (borderline). Values below the diagonal only*

5.4 Common Method Bias Assessment

Given that all data were collected through the same self-report instrument at a single time point, common method bias (CMB) was evaluated using Harman's single-factor test (Podsakoff *et al*., 2003). The 23 scale items were entered into a one-factor exploratory factor analysis. The first factor accounted for 48.1% of the variance, less than the 50% cutoff used to define problematic CMB. These findings indicate that CMB is not likely to compromise the results, although the cross-sectional design from a single source is noted as a limitation. Future research is encouraged to use multi-source data collection and/or designs with temporal lags.

6. Structural Model and Results

6.1 Path Coefficients

PLS-SEM path coefficients were estimated using SmartPLS 4 with 5,000 bootstrapping sub-samples and are presented in Table 6 and Figure 2. Full results are given in Table 5. H1 (AI → EP: $\beta = 0.493$, $t = 5.406$, $p < 0.001$), H2 (AI → WC: $\beta = 0.619$, $t = 7.632$, $p < 0.001$), and H3 (AI → CC: $\beta = 0.494$, $t = 4.686$, $p < 0.001$) are all supported, confirming AI's significant influence across all three psychological mechanisms. H4 (EP → EE: $\beta = 0.559$, $t = 6.984$, $p < 0.001$) is supported, confirming productivity as the dominant driver of engagement. H5 (WC → EE: $\beta = 0.086$, $t = 0.933$, $p = 0.353$) is not supported, while H6 (CC → EE: $\beta = 0.203$, $t = 2.644$, $p = 0.010$) is supported. H7 (EE → ER: $\beta = 0.760$, $t = 10.817$, $p < 0.001$) is strongly supported. The three predictors collectively explain 64.1% of the variance in employee engagement ($R^2 = 0.641$); employee engagement explains 53.9% of the variance in retention ($R^2 = 0.539$).

Table 6: Path Coefficients — Structural Model Results

H	Path	β	SE	t-value	p-value	Decision
H1	AI → Employee Productivity	0.493	0.091	5.406	< 0.001	Supported
H2	AI → Work Culture	0.619	0.081	7.632	< 0.001	Supported
H3	AI → Communication	0.494	0.105	4.686	< 0.001	Supported
H4	Employee Productivity → Employee Engagement	0.559	0.080	6.984	< 0.001	Supported
H5	Work Culture → Employee Engagement	0.086	0.092	0.933	0.353	Not Supported
H6	Communication → Employee Engagement	0.203	0.077	2.644	0.010	Supported
H7	Employee Engagement → Employee Retention	0.760	0.070	10.817	< 0.001	Supported

Note: β = standardised path coefficient; SE = standard error. R^2(EE) = 0.641; R^2(ER) = 0.539.

The structural model was assessed for collinearity, explanatory power, effect sizes, predictive relevance, and model fit. The inner VIF values ranged from 1.271 to 2.010, indicating no serious collinearity concerns. The model explained 50.8% of the variance in employee engagement ($R^2 = 0.508$); adjusted ($R^2 = 0.504$) and 55.6% of the variance in employee retention ($R^2 = 0.556$); adjusted ($R^2 = 0.555$). Effect-size assessment indicated medium effects for AI → employee productivity ($f^2 = 0.325$) and AI → communication ($f^2 = 0.320$), and large effects for AI → work culture ($f^2 = 0.587$), employee productivity → employee engagement ($f^2 = 0.492$), and employee engagement → employee retention ($f^2 = 1.255$). The effect of communication on employee engagement was small ($f^2 = 0.052$), whereas the effect of work culture on employee engagement was negligible ($f^2 = 0.008$). The positive (Q^2) values for

employee engagement (0.489) and employee retention (0.553) indicated predictive relevance under the assessment procedure used. The SRMR value of 0.050 was below the commonly applied threshold of 0.08, indicating acceptable approximate model fit.

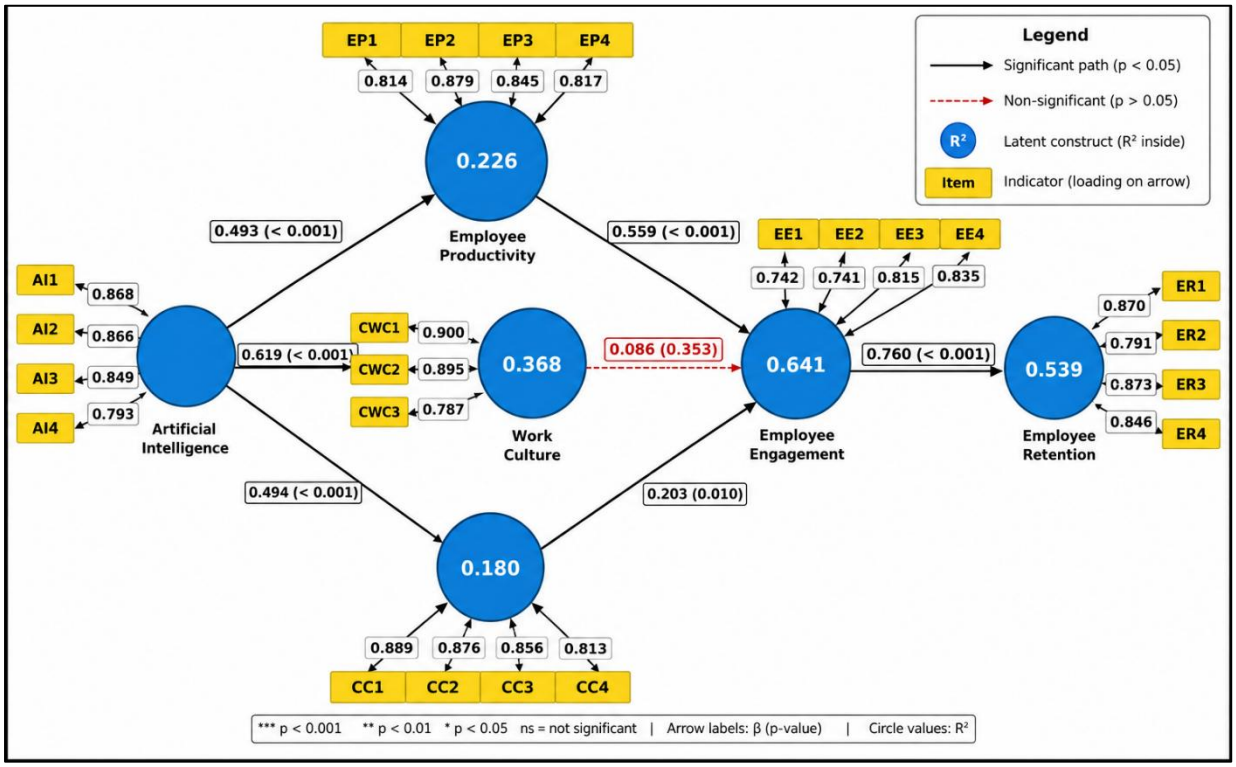


Figure 2: Structural Equation Model (PLS-SEM): Standardised Path Coefficients

*Note: Values on arrows are standardised path coefficients (β). R² values are shown inside the dependent variable boxes. Dashed arrow (H5) indicates a non-significant path. *** p < 0.001; ** p < 0.01; ns = not significant. AI = Artificial Intelligence; EP = Employee Productivity; WC = Work Culture; CC = Communication; EE = Employee Engagement; ER = Employee Retention. Source: The Author*

6.2 Mediation Analysis

Bootstrapped mediation analysis was conducted with 5,000 re-samples to test whether employee engagement mediates the AI–retention relationship (Hair *et al.*, 2019). Table 7 reports specific indirect effects, the total indirect effect, and the direct effect. The total indirect effect of AI on retention via engagement is significant (IE = 0.284, 95% CI [0.088, 0.488]). The partial mediation of AI by engagement is also supported by the significant correlation of AI with retention (β = 0.173, p = 0.025) while controlling for engagement.

It is interesting to note that the indirect effect through work culture (IE = 0.358) is slightly higher than the indirect effect through productivity (IE = 0.349) at the construct level. This is because AI has a greater direct effect on work culture (β = 0.619) compared to productivity (β = 0.493). The direct path from WC to EE, however, is not significant (β = 0.086, p = 0.353) and suggests that an increase in cultural conditions is not necessarily associated with increased engagement in this sample in the direct path from WC to EE. As for the confirmed serial mediation path, productivity is the predominant psychological pathway (AI → Productivity → Engagement → Retention: IE = 0.243, 95% CI [0.096, 0.395]).

Table 7: Mediation Analysis — Bootstrapped Indirect Effects (5,000 Re-samples)

Mediation Path	IE	95% CI Lower	95% CI Upper	Sig.	Mediation Type
AI → EP → EE (specific indirect)	0.349	0.154	0.533	Yes	—
AI → WC → EE (specific indirect)	0.358	0.205	0.527	Yes	—
AI → CC → EE (specific indirect)	0.233	0.106	0.361	Yes	—
→ EE → ER (total indirect via EE)	0.284	0.088	0.488	Yes	Partial mediation
AI → EP → EE → ER (serial indirect)	0.243	0.096	0.395	Yes	Partial mediation
Direct: AI → ER | EE (controlling EE)	0.173	—	—	0.025	Residual direct effect

Note: IE = indirect effect; CI = confidence interval (bias-corrected bootstrap, 5,000 sub-samples); Sig. = CI excludes zero (or p < 0.05 for direct). Partial mediation is confirmed when the direct effect remains significant. EP = Employee Productivity; WC = Work Culture; CC = Communication; EE = Employee Engagement; ER = Employee Retention

6.3 Necessary Condition Analysis

NCA was employed together with PLS-SEM to highlight the necessary constructs, rather than sufficient, conditions for employee engagement and retention (Dul, 2016; Richter *et al*., 2020). The Ceiling Envelopment-Free Disposal Hull (CE-FDH) method was used to determine the highest value of the outcome given each level of a predictor. The effect size (d) is the ratio of the area above the ceiling line to the total scope and can be considered as small (<0.10), medium (0.10–0.30), or large (> 0.30) (Dul, 2016). The effect size and permutation p-value are presented in Table 8.

Table 8: NCA Effect Sizes — CE-FDH and CR-FDH Methods

Path	CE-FDH (d)	CR-FDH (d)	Permutation p	Interpretation	Necessity Role
AI → EP	0.250	0.190	0.010	Medium	Necessary condition
AI → WC	0.365	0.298	< 0.001	Large	Necessary condition
AI → CC	0.363	0.291	< 0.001	Large	Necessary condition
EP → EE	0.363	0.310	< 0.001	Large	Necessary & Sufficient
WC → EE	0.260	0.185	0.002	Medium	Necessary only (hygiene)
CC → EE	0.000	0.000	> 0.050	None	Not necessary
EE → ER	0.297	0.241	< 0.001	Medium	Necessary condition

Note: d = NCA effect size. CE-FDH = Ceiling Envelopment-Free Disposal Hull; CR-FDH = Ceiling Regression-Free Disposal Hull. Effect size benchmarks: small < 0.10, medium 0.10–0.30, large > 0.30 (Dul, 2016). Permutation p-values based on 1,000 random permutations.

Employee productivity (CE-FDH d = 0.363) is identified as both a necessary and sufficient condition for engagement, reflecting a large effect consistent with PLS-SEM findings. In the case of Work Culture (CE-FDH d = 0.260), a threshold level of AI-enabled cultural readiness is also necessary, but not sufficient for engagement to take place: beyond that level, engagement gains do not increase. The AI–communication SEM path does not show any necessary condition effect (d = 0.000), implying that, although the communication path is statistically significant, AI-enhanced communication is not seen as a prerequisite for engagement. There is a medium effect in which employee engagement is necessary for employee retention (CE-FDH d = 0.297), which is evident from Figures 3 and 4.

Table 9: NCA Bottleneck Analysis — Minimum Predictor Levels Required (Percentile)

Percentile	EE Value	Min EP Required	Min WC Required	ER Value	Min EE for ER
0%	1.00	1.00	1.00	1.00	1.00
10%	2.75	2.25	1.67	2.75	1.75
20%	3.25	2.25	2.33	3.30	1.75
30%	3.50	2.25	2.33	3.50	1.75
40%	3.75	2.75	2.33	3.75	1.75
50%	4.00	2.75	2.33	4.00	3.25
60%	4.00	2.75	2.33	4.25	3.25
70%	4.25	2.75	2.33	4.50	3.25

80%	4.50	2.75	2.33	4.75	3.25
90%	5.00	4.75	2.33	5.00	3.50
100%	5.00	4.75	2.33	5.00	3.50

Note: Values are composite Likert scores (1–5 scale). 'Min EP/WC Required' = minimum predictor level needed for the outcome to reach the corresponding percentile, derived from the CE-FDH ceiling line. EE = Employee Engagement; EP = Employee Productivity; WC = Work Culture; ER = Employee Retention.

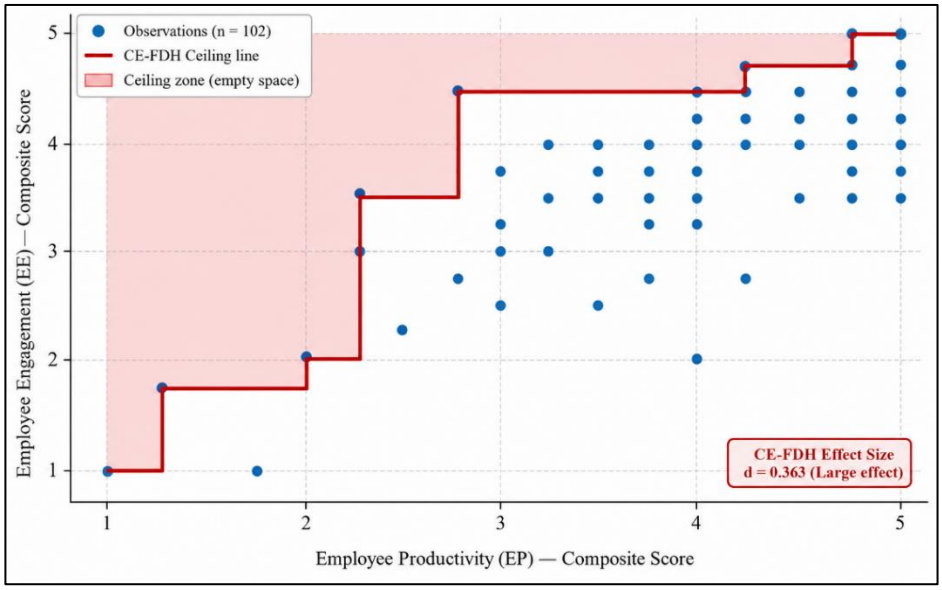


Figure 3: NCA: CE-FDH Ceiling Line: Employee Productivity on Employee Engagement

Note: Each dot represents one respondent. The red staircase line is the CE-FDH ceiling. The shaded area above the ceiling (empty space) represents the necessity effect. CE-FDH effect size d = 0.363 (large). This indicates that a minimum level of AI-enabled employee productivity is a necessary condition for achieving high employee engagement. EP = Employee Productivity composite score (Likert 1–5); EE = Employee Engagement composite score (Likert 1–5). Source: The Author

Table 9 is a bottleneck analysis of the minimum level of predictors required at each percentile of the engagement and retention curve. To achieve 90th percentile productivity, employees should get at least 4.75 points in productivity and 2.33 points in work culture. To achieve the 90th percentile of retention, employee engagement should be 3.5 or greater. These thresholds directly impact the design and operation of HR analytics platforms' productivity benchmarking.

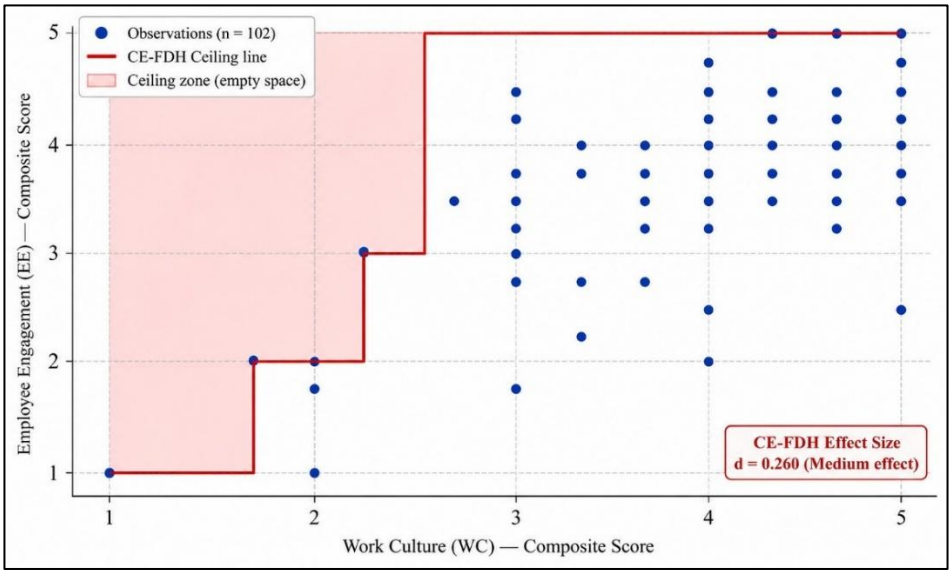


Figure 4: NCA: CE-FDH Ceiling Line: Work Culture on Employee Engagement

Note: Each dot represents one respondent. The red staircase line is the CE-FDH ceiling. CE-FDH effect size d = 0.260 (medium). This confirms that work culture functions as a necessary condition: a minimum level of AI-enabled work culture is required for engagement, but higher culture scores do not proportionally increase engagement beyond this threshold. WC = Work Culture composite score (Likert 1–5); EE = Employee Engagement composite score (Likert 1–5). Source: The Author

7. Discussion

The results indicate that the impact of AI on employee engagement is not always straightforward or consistent, but rather manifests in various psychological mechanisms that are specific to the question being addressed, whether it is the question of 'what makes people engaged' or 'what is the minimum necessary for employees to be engaged'. The distinction revealed by the combined use of PLS-SEM and NCA is the main theoretical contribution of the study.

The strongest link between AI and employee engagement is employee productivity ($\beta = 0.559$, $p < 0.001$; NCA $d = 0.363$, a large effect). In theory, it is consistent with SET: If employees believe that AI provides genuine productivity gains, then they are willing to engage (Cropanzano & Mitchell, 2005). From a Two-Factor Theory perspective (Herzberg *et al*., 1959), productivity improvements function as motivators, producing tangible, individually experienced outcomes- task completion, performance recognition, sense of efficacy that stimulate intrinsic motivation. The NCA result further supports this interpretation, which holds that productivity is not just a predictive indicator of engagement, but a prerequisite. High engagement cannot be achieved without a sufficient baseline of productivity (Anitha, 2014).

For PLS-SEM, work culture (H5) is not a significant direct predictor of engagement in PLS-SEM ($\beta = 0.086$, $p = 0.353$), yet NCA identifies it as a necessary condition with a medium effect ($d = 0.260$). This is the most theoretically intricate finding of this study. According to the Two-Factor model (Herzberg *et al*., 1959), the work culture is a hygiene factor, and once it is not present or is not working properly, it leads to disengagement; once it is present, however, above a certain threshold, it does not linearly increase motivation. The bottleneck analysis confirms this: a score for work culture of 2.33 is the floor level for work culture across almost all engagement percentiles – beyond that threshold, there is no incremental return in engagement. An important boundary condition is the skew of the sample toward entry-level employees (aged 25 or less), which was 53.6% of the sample. As theorised in COR theory (Hobfoll, 1989), early career IT professionals are heavily driven by immediate, productivity-related motives: task mastery, output visibility, and speed of acquisition of skills. Cultural dynamics, however, have a longer time scale, and become more important as employees develop a sense of organisational identity and commit to their careers. This is indicative of a career stage moderation hypothesis that needs to be explored longitudinally.

It should be noted that the specific indirect effect through work culture ($IE = 0.358$) marginally outpaces the effect through productivity ($IE = 0.349$) at the construct level, due to the stronger direct effect of AI on work culture ($\beta = 0.619$). However, since the WC → EE path is non-significant, productivity remains the dominant channel in the confirmed serial mediation pathway. Communication (H6) is a statistically significant predictor of engagement in PLS-SEM ($\beta = 0.203$, $p = 0.010$), but NCA shows no necessary condition effect ($d = 0.000$), indicating that AI-enhanced communication improves engagement when present but does not constitute a prerequisite for it to occur. In contexts that require AI-mediated communication, AI-enhanced communication tools can serve as contextual infrastructure without being a motivation factor for engagement, aligning with evidence that factors such as familiarity with

AI tools moderate the relationship between AI adoption and work passion (Chen *et al*., 2025). In the context of JD-R, the use of AI-powered communication technologies can be seen as a job resource, helping to eliminate information asymmetry and speed up response times, while for workers in digitally saturated environments, these resources can be viewed as essential and not as motivational extras, following Herzberg's hygiene logic (Herzberg *et al*., 1959).

Moreover, employee engagement is a strong predictor of employee retention (H7: $\beta = 0.760$, $p < 0.001$, $R^2 = 0.539$), which is a well-established fact in the literature on employee engagement and retention (Chowdhury *et al*., 2023; Anitha, 2014; Ali *et al*., 2024). Bootstrapped mediation confirms partial mediation of AI's effect on retention by engagement (IE = 0.284, 95% CI [0.088, 0.488]; direct effect $\beta = 0.173$, $p = 0.025$). The partial mediation suggests that, in addition to the psychological mechanism of engagement, there are direct pathways that link AI and retention, such as efficiency gains that lead to a greater structural embeddedness and less option to search for alternatives to the workplace (Ghosh *et al*., 2013). The serial mediation pathway from AI investment to productivity to engagement to retention (IE = 0.243, 95% CI [0.096, 0.395]) makes productivity the most important psychological pathway from AI investment to long-term talent retention.

8. Managerial Implications

Given that AI-driven productivity is the dominant driver of engagement ($\beta = 0.559$, NCA d = 0.363) and the serial path AI → Productivity → Engagement → Retention is confirmed, organisations should prioritise AI tools that deliver immediate, tangible productivity gains for employees. The implementation of real-time performance alerts, artificial intelligence-supported decision-making tools, predictive analytics and task automation should be adopted to empower employees to shift their focus from mundane jobs to more impactful work. These are the engagement drivers for entry-level IT professionals, and push notifications, chatbots, and augmented-reality interfaces can reduce cognitive friction and accelerate decision-making. While these thresholds are derived from the Indian IT context, the underlying logic is to prioritise productivity-generating AI tools, ensure minimum cultural readiness, and monitor engagement as a retention-leading indicator, which applies to any knowledge-economy organisation undergoing AI-driven workforce transformation

However, because work culture is not a performance motivator, but a floor hygiene condition, managers must foster a culture in which AI integration is part of a culture of psychological safety, learning agility and openness to change. For engagement to become reality, the minimum cultural threshold (composite score ≈ 2.33 on a 5-point scale) must be met, and organisations with scores below this threshold need to ensure that they have cultural readiness programmes in place before implementing productivity-oriented AI tools.

Since employee engagement explains 53.9% of the variance in retention, it should be treated as a leading indicator of retention risk. The reduction in productivity and disengagement can escalate into attrition, but AI-powered dashboards can help monitor individual productivity patterns to alert to early signs of trouble, such as rebalancing workloads or engaging in mentoring and developmental discussions. Pulse surveys and stay interviews can also be used to identify those at risk of leaving the organisation, and high-potential talent should be engaged through tailored development plans, intentional signalling of career progression, and AI-powered performance recognition.

The NCA bottleneck analysis shows that for maximum employee engagement (100th percentile), the HR analytics platform needs to have an employee productivity score of at least 4.75 on a 5-point scale, which has direct implications for HR analytics platform design. In an AI monitoring system, organisations should establish thresholds for operational productivity as early warning indicators for HR intervention.

9. Conclusion

The study validates that the adoption of AI has a profound psychological impact on employee engagement and retention in the Indian IT industry, primarily through its influence on employee productivity. The psychological chain AI → Productivity → Engagement → Retention is the main one, and engagement partially buffers the relationship between AI and retention, as shown by bootstrapped mediation.

The work culture is a hygiene factor for engagement (NCA $d = 0.260$) rather than a motivational factor: it does not motivate; it prevents motivation when missing; and it cannot motivate beyond a certain level. Communication is a statistically significant predictor of the SEM ($\beta = 0.203$, $p = 0.010$); it does not show a necessary-condition effect ($d = 0.000$) and therefore serves as a predictor of engagement outcomes without gating them. The three AI mechanisms together explain 64.1% of the variance in employee engagement.

This study, based on Social Exchange Theory, JD-R Model, and Herzberg's Two-Factor Theory, takes a novel methodological approach using PLS-SEM, NCA, and bootstrapped mediation to provide distinctions between what must be present for engagement and what merely predicts it, providing richer guidance than either method alone. To benefit from AI for long-term employee retention, organisations seeking to harness AI for sustained talent retention should invest in tools that deliver immediately felt productivity gains, while ensuring minimum cultural readiness conditions are met, and AI literacy is cultivated across managerial levels.

Although grounded in the Indian IT context, the psychological mechanisms identified here- productivity as both necessary and sufficient, work culture as a hygiene floor, and communication as an enhancer rather than a prerequisite- are theoretically generalisable to any knowledge-economy setting where AI adoption is reshaping the employment relationship.

10. Future research and limitations

This study carries six limitations that collectively define a clear agenda for future research. Firstly, the sample is limited to the IT industry in Karnataka, and the results are not generally applicable geographically or by sector. Future research should replicate this framework in other sectors (such as manufacturing, healthcare, financial services, and public administration) and in other national contexts in order to determine if the productivity-dominant engagement pathway is sector-specific or more general.

Secondly, due to the cross-sectional nature, it is not possible to make causal inferences. A longitudinal study over time would significantly enhance causal inferences, especially those related to the increased role of work culture in improving hygiene as AI becomes more deeply integrated into organisational practice.

Third, the results from one source alone with self-reported outcome measures can be contaminated by common method variance. Although Harman's single-factor test suggests that CMB was not a significant concern (48.1% < 50%), it would be beneficial for future research to use multi-source designs that include both employee self-ratings and supervisor or third-

party ratings of an employee, or include objective productivity measures from an AI monitoring system (Podsakoff et. al., 2003).

Fourth, because the sample was demographically skewed towards newer employees, 53.6% had less than one year of tenure in the organisation. This profile might be the reason why work culture is not a good driver of engagement. Further research should explore the trajectories of the relative impact of AI productivity, work culture and communication as engagement drivers across different career levels, possibly in the form of stratified replication studies.

Fifth, the AI construct does not specifically refer to generative AI or large language model tools, which are qualitatively distinct uses of AI that have increased in number since 2023. New measurement tools need to capture generative AI experiences and their individual psychological effects more accurately.

Sixth, borderline HTMT values for two pairs of constructs (EP–EE: 0.940; WC–ER: 0.921) indicate a measurement limitation. More detailed scales that better differentiate between productivity behaviours and engagement states are needed in future studies.

Declarations

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Ethics Approval and Consent to Participate

The Research Committee of Xavier Institute of Management & Entrepreneurship (XIME), Bangalore, reviewed the study documentation and determined the study to be a minimal-risk, non-interventional, questionnaire-based research study. The study was conducted in accordance with the ethical principles of the Declaration of Helsinki, as applicable to questionnaire-based research involving human participants. Participation was voluntary, and informed consent was obtained electronically from all respondents before participation. Respondents' anonymity and confidentiality were maintained throughout the study.

Consent for Publication

Not applicable. This manuscript does not contain personally identifiable information about any individual participant.

Competing Interests

The authors declare that they have no competing interests.

Data Availability

The data supporting the findings of this study are available from the corresponding author upon reasonable request. The data are not publicly available due to privacy considerations relating to survey respondents.

Code Availability

Code used for data analysis and figure generation is available from the corresponding author upon reasonable request.

Author Contributions

S. K.: Conceptualisation, research design, data collection, data cleaning and revision.

C. J. A.C.: Research design, data analysis and interpretation, manuscript preparation and critical revision.

I. P.: Review of Literature, Gap analysis, framing of Research Questions and manuscript review.

S. P.: Framing Hypothesis and selection of Statistical analysis tools, and critical review of the manuscript.

R. D.: Findings and Discussion and final manuscript review.

C. S.: Review of Literature, Critical review of the manuscript.

All authors read and approved the final version of the manuscript and agree to be accountable for their contributions.

Use of AI-Assisted Technologies

Claude (Anthropic) was used as an AI-assisted tool for structural organisation of the manuscript, generation of Python code for analysis, statistical figure production, and conversion of references to APA 7th edition citation style. The authors reviewed the outputs and take full responsibility for the accuracy, integrity, and final content of the manuscript

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