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AI, Employee Productivity and Performance: An Integrated ISM–MICMAC and SEM Investigation of the Pathway from Organisational Investment to Individual Output

Deepak Ranjan Sahoo

dcdrsahoo@gmail.com

MIT Art, Design and Technology University

Vaishali Deepak Sahoo

Vishwakarma University

Ashwini Deshpande Joshi

MIT Art, Design and Technology University

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Abstract

Organisations have committed substantial capital to artificial intelligence in workforce management without a settled account of why productivity returns arrive so unevenly across employees working in the same firm under the same systems. This study approaches that problem in two stages. Twelve enabling and constraining factors are first extracted from the AI-HRM literature and ordered through interpretive structural modelling (ISM), with the resulting structure classified by driving and dependence power using MICMAC analysis. The hierarchy that emerges places top management commitment and digital leadership at the base and employee productivity and performance at the eighth and final level, with employee trust in AI and AI-related job insecurity occupying a reciprocal middle position that separates organisational investment from employee outcome. The mid-hierarchy portion of that structure is then specified as a measurement model and estimated on 412 employee responses from Indian knowledge-intensive firms using confirmatory factor analysis and structural equation modelling. The measurement model fits acceptably and every construct clears conventional reliability and discriminant validity thresholds. Human-AI task complementarity is the strongest proximal predictor of productivity and performance, followed at some distance by trust in AI and by job insecurity, which carries a negative sign. AI governance and reskilling investment have indirect effects, albeit small but reliable, that are passed on through the process of trust. However, job insecurity undermines the complementarity-performance relationship, although the interaction does not contribute much (under one percent) to the explained variance and should be avoided. The two phases imply that investment in artificial intelligence to boost productivity primarily is reshaping jobs and the context in which they exist.

Keywords: artificial intelligence; employee productivity; job performance; human resource management

1. Introduction

Investment in AI for human resource and workforce has surpassed the proof of its value. What is documented in the systematic reviews collected over the last four years (Chowdhury et al., 2023; Pan & Froese, 2023; Prikshat, Islam, et al., 2023; Dasaklis et al., 2026) is how widespread AI is in the field of recruitment screening, performance appraisal, workforce planning, learning delivery, and internal mobility, in companies of virtually all sizes. Those reviews can't yet provide a reliable idea of how those working on the project are affected. In a qualitative study spanning organizational levels, Khalil, Agarwal, Yaqub and Papa (2025) clearly articulated the issue that HR leaders feel they are improving efficiency while front-line employees do not. This difference further away from the system owner to system user grows larger. A similar disconnect between the enablers that managers nominate and what they can demonstrate in terms of productivity is found by Watts & Munir (2026). This problem has developed into two research streams which have remained distinct. The first is in relation to organisations and capabilities. It poses the question of what a firm needs to be ready for AI to do something useful, and it has formulated thoughtful frameworks of readiness and capability for AI (Tehrani et al., 2024; Chowdhury et al., 2023; Chang, Swift, & Shulga, 2026; Simón, Revilla, & Sáenz, 2024). The second is an employee focused and psychological. It questions

the fate of workers after the systems come, and it's recorded that trust can form, algorithmic aversion can develop, workers can become insecure about their roles, they can respond in deviant ways, and their well-being and commitment can suffer (Wu, Cheo, & Yuen, 2026; Nguyen, Ferm, & Ngo, 2026; Nayak, Budhwar, & Malik, 2025; Zheng et al., 2025; Chi, Wu, Chen, & Xu, 2026). The streams are productive. None of these factors alone account for the lack of evenness that drove this study; the first assumes that employees will or will not respond while the second assumes that organisational capability is a given backdrop.

Another methodology gap that should be mentioned is that. In the vast majority of quantitative research in this domain models involving multiple antecedents predicting an outcome are estimated. This type of model is useful for understanding magnitude, and is informative of the statistical reliability, but it speaks nothing about order. They cannot say whether governance must precede trust or whether the two can be built in parallel, and they cannot identify which factors a manager should move first when resources are constrained. Interpretive structural modelling was designed for exactly this question, and it has been applied to adoption problems in adjacent fields, yet it remains uncommon in AI-HRM research. Used alone, however, ISM has an equally serious weakness: the hierarchy it produces rests on expert judgement and carries no significance test, no effect size, and no measure of construct validity.

This study therefore uses both, in sequence, and treats the weakness of each as the reason for the other. Stage one applies ISM and MICMAC analysis to twelve factors distilled from the literature, producing a contextual hierarchy that orders those factors from foundational to dependent. Stage two takes the middle band of that hierarchy — the layers where organisational investment converts into employee response — specifies it as a latent variable model, and estimates it with confirmatory factor analysis and structural equation modelling on 412 employee responses. The ISM output constrains the SEM specification rather than merely preceding it; paths were drawn only where the reachability matrix indicated a direct relation between adjacent levels.

The empirical setting is the knowledge-intensive sector in India, that is, the information technology and IT-enabled services; the banking and financial services; and the technology-intensive manufacturing. It's recommended by three considerations. AI's entry into the Indian IT services sector is quite extensive, with 82% of respondents having first-hand experience with systems, as opposed to anticipated. This is important because a large part of the literature on job insecurity is based on anticipation rather than experience. The sector has young enough labor force to have been brought into the labour market at the same time as these technologies, meaning that there's less "displacement anxiety" caused by previous technological changes. In comparison, the EU has now introduced the AI Act as a compliance bottom line (Väyrynen, Holmström,

Sundberg, Hietala, & Lanamäki, 2026) and governance in this context is an optional organisational choice, which means that it can be seen to vary.

The contribution of this study to the literature of AI-HRM is in four aspects. First, it provides a "contextual" ranking of the factors that lie between AI investments and employee productivity, with the result being eight "steps up" from the bottom driver. Second, it highlights two variables that are linked and at the intersection of the hierarchy: employee trust in AI and employee AI job insecurity. These variables are introduced as a linked pair – as a condition – rather than two separate variables to be managed independently. Third, it estimates the magnitudes that ISM cannot measure, and it finds that a job design variable (human-AI task complementarity) is more important than the technology and governance variables in predicting performance. Fourth, it finds a statistically significant but modest moderation effect, and suggests that one should not draw the broader conclusions from the job-insecurity literature that one might wish based on this one effect.

2. Theoretical background

2.1 The productivity question in AI-enabled HRM

The AI-enabled HRM and productivity question is not a new one as it traces its roots back many years. When it comes to the gains from AI, the most obvious and readily quantifiable applications are in recruitment and selection, as the counterfactual is most evident and the gains easy to measure (Albert, 2019; Black & van Esch, 2020, 2021; Allal-Chérif, Aránega, & Sánchez, 2021). The number of applicants increases, screening time decreases and cost of hire decreases. The results of those studies have proven fairly consistent. The idea that efficiency at a transaction level equates to productivity at an employee level has not been slow to come through. The problem is that AI alters what work is and, not always, in a positive manner. Nayak, Budhwar and Malik (2025) report negative consequences of algorithmic HRM on stress, well-being and commitment for the hospitality industry. A similar dark side is found in specific features of algorithms, not in AI per se, as the researchers Zhou, Wang and Chen (2023) conclude. Cui, Wang, Cao and Zhu (2026) have found that while relying on AI can enhance creativity in certain situations, it can also detriment it in others. Ma and Su (2025) state that the intelligence is bound, thus becoming superficially competent and also deceptive, which is significant if it has to be used to evaluate performance. Conversely, the benefits of generative AI on employee creativity and performance in hotel marketing are highlighted by Wang and Zhang (2025) and a rise in organisational commitment after the introduction of AI in HRM practice has been documented by Mo, Liu, Chark, Zeng and Song (2025). There is no single direction to the literature and any model that predicts a consistently positive impact will be out of synch with it.

A reasonable synthesis is that AI's effect on productivity is conditional, and that the conditions are organisational and psychological rather than technical. This is the position taken, in different vocabularies, by the AI capability framework of Chowdhury and colleagues (2023), by the socio-technical reading in Chowdhury, Budhwar, Dey, Joel-Edgar and Abadie (2022), and by Krotov's (2026) argument that firms pursuing automation without redesigning the surrounding organisation forgo most of the available benefit. Bastida, García, Taín and Araujo (2025) frame the same shift as a move from automation to augmentation. Simón, Revilla and Sáenz (2024) formalise it as a dynamic capability for human-AI teaming. The common claim is that the technology is a necessary but distinctly insufficient condition, and that what converts it into performance is a set of complementary organisational assets.

2.2 Theoretical anchoring

Three theoretical lenses inform the model developed here, and each carries a specific piece of the argument.

The AI capability view extends the concept of resources-based logic to the intelligence of systems and suggests that AI can create value only when combined with other hard-to-imitate resources – human skills and intangible organisational assets – (Chowdhury et al., 2023; Sandeep & Lavanya, 2026; Chin, Li, Caputo, & Marrone, 2025). This provides the foundation of the hierarchy: data infrastructure, analytics maturity, absorptive capacity, and leadership commitment to support these. It doesn't really tell us much about employees, however, except that they are a source of complementary skill that is presented in the capability literature.

Socio-technical systems theory is able to provide what the capability view lacks. The main concept of technical and social subsystems optimization is that intertwined optimisation of both is required, and optimisation of one will negatively impact the other (Chowdhury et al., 2022; Zirar, Ali & Islam, 2023). But in this context it means that the same AI deployment can have a positive or negative impact on productivity, depending on how the work role, decision rights and information flows are reconfigured around it. In the current model, the construct that represents the proposition is human-AI task complementarity.The construct in the current model that represents the proposition is human-AI task complementarity.

The job demands-resources framework takes into account the psychological trajectory. AI imposes requirements — level of surveillance, speed, lack of transparency in evaluation — and resources — decision support, offloading routine, feedback. Whether the net effect is engagement or strain depends on the balance, and on how employees appraise the system's intentions toward them. Trust in AI functions as a resource in this scheme and job insecurity as a demand, which is why the two appear together in the model

rather than separately (Wu et al., 2026; Zhou, Hu, Chen, & Luo, 2026; Yu, Kawasaki, Magni, Yu, & Munusamy, 2026; Kim & Lee, 2025).

This study's argument is not that AI investment fails to raise productivity. It is that the investment reaches productivity through a specific and fairly long chain, that the chain runs through job design and employee appraisal rather than around them, and that interventions placed at the wrong point in the chain will appear ineffective for reasons that have nothing to do with the quality of the technology.

2.3 Identifying the factor set

Factor identification proceeded in three steps. A structured reading of the AI-HRM literature published between 2017 and 2026 was used to compile candidate factors appearing in at least three independent studies as either an antecedent or a boundary condition of AI-related workforce outcomes. Candidates that were redundant at the conceptual level were merged; candidates that operated at the national or industry level rather than the firm level were dropped, since the unit of analysis here is the firm and its employees. The resulting twelve factors were then reviewed by the expert panel described in Section 4.2, which added no new factors and endorsed two mergers. Table 1 reports the final set with definitions and representative sources.

Two inclusion decisions deserve comment. AI-related job insecurity was retained as a distinct factor rather than folded into well-being, because the evidence indicates that it operates through a different appraisal process and is responsive to different interventions (Burhan, 2024; Nguyen et al., 2026). And algorithmic transparency was kept separate from AI governance, despite their obvious relation, because governance is a policy property of the organisation while transparency is a design property of the system, and firms with strong policies routinely deploy opaque systems (Chen, Han, Zhang, & Lu, 2025; Karami & Ghasemi, 2026).

Table 1. Factors influencing AI-enabled employee productivity and performance

Code	Factor	Working definition	Representative sources
F1	Top management commitment and digital leadership	Sustained sponsorship of AI in the workforce agenda by the senior team, and leadership behaviour that models rather than delegates its use.	Amjad & Shang (2026); Zhang, Wang & Hu (2027); Mahroof, Rafi & Ahmad (2025)
F2	AI governance, ethics and regulatory compliance	Documented policy on permissible uses of AI in employment decisions, accountability for outcomes, and mechanisms for contestation.	Prikshat, Patel, Varma & Ishizaka (2021); Varma, Dawkins & Chaudhuri (2023); Bar-Gil, Ron & Czerniak (2024); Hasani (2026)
F3	Data infrastructure and HR analytics maturity	Integration, quality and accessibility of workforce data, and the analytical capability built on it.	Huselid, Minbaeva, Edwards & Levenson (2025); Wang, Zhou, Sanders, Marler & Zou (2024); Arora, Chaudhary & Singh (2024)
F4	Organisational AI readiness and absorptive capacity	Technical, structural and cognitive preparedness to assimilate AI into existing HR and operational processes.	Tehrani, Ray, Roy, Gruner & Appio (2024); Chowdhury et al. (2023); Chang, Swift & Shulga (2026); Behera, Behera & Bala (2026)
F5	Reskilling and continuous learning investment	Provision, funding and reach of training that develops the competencies AI-augmented work requires.	Deepa, Sekar, Malik, Kumar & Attri (2024); Burhan (2024); Wang, Zhang, Ma et al. (2025); Axiak (2025)

Code	Factor	Working definition	Representative sources
F6	Algorithmic transparency and explainability	The degree to which system logic, inputs and recommendations are legible to the employees affected by them.	Chen, Han, Zhang & Lu (2025); Karami & Ghasemi (2026); Roumbanis (2025)
F7	Employee trust in AI systems	Willingness to rely on AI outputs in consequential work decisions, comprising both competence and intention components.	Wu, Cheo & Yuen (2026); Hu, Huang, Wong & Wan (2024); Xie et al. (2026)
F8	AI-related job insecurity	Perceived threat to the continuity, scope or status of one's role arising from AI deployment.	Nguyen, Ferm & Ngo (2026); Zhou, Hu, Chen & Luo (2026); Burhan (2024); Tao & Xu (2026)
F9	Human-AI task complementarity and job redesign	The extent to which the division of labour between employee and system is deliberately allocated by comparative advantage.	Krotov (2026); Simón, Revilla & Sáenz (2024); Bastida, García, Taín & Araujo (2025)
F10	Knowledge sharing and organisational learning	Circulation of task knowledge and practice among employees, and its absorption into organisational routines.	Malik, Silva, Budhwar & Srikanth (2021); Sundaresan & Zhang (2021); Hussain, Khan, Awad & Bansal (2026)
F11	Employee engagement and well-being	Affective and motivational state at work, including strain, and its persistence under AI-augmented conditions.	Alzeiby, Islam, Shaik & Yaqub (2025); Yu et al. (2026); Nayak, Budhwar & Malik (2025); Kim & Lee (2025)
F12	Employee productivity and performance	Task output, quality and efficiency attributable to the individual employee in the AI-augmented role.	Khalil, Agarwal, Yaqub & Papa (2025); Watts & Munir (2026); Seth et al. (2026); Ullah, Sun, Yalan & Ali (2026)

Note. Factors were retained where they appeared as an antecedent or boundary condition of AI-related workforce outcomes in at least three independent studies and operated at the firm or individual level.

3. Hypothesis development

The hypotheses below concern the mid-hierarchy portion of the ISM structure, which is the portion that can be measured with employee-reported data. The foundational levels — top management commitment and data infrastructure — are firm-level properties poorly assessed by individual respondents, and they are therefore represented in the SEM only through AI readiness and infrastructure, which employees do observe in their daily work. This is an intentional narrowing, which implies that not the whole ISM structure is tested by the SEM.

Organisational AI readiness – the usability of systems, the integration of data and technical support – influences the employee response in two ways. Where systems are stable and outputs are available when needed, employees have grounds for treating them as reliable, which is the cognitive component of trust (Wu et al., 2026; Hu, Huang, Wong, & Wan, 2024). Where systems are stable, employees can also allocate work between themselves and the system on the basis of comparative advantage rather than on the basis of what happens to be working that day, which is the practical content of complementarity (Krotov, 2026; Bastida et al., 2025).

H1. Organisational AI readiness and infrastructure is positively associated with employee trust in AI systems.

H2. Organisational AI readiness and infrastructure is positively associated with human-AI task complementarity.

AI governance and algorithmic transparency operate on a different mechanism. Their function is not to make the system work but to make its reasoning legible and its use accountable. The ethics literature in AI-HRM has converged on the view that procedural safeguards are what allow employees to accept algorithmic involvement in consequential decisions (Varma, Dawkins, & Chaudhuri, 2023; Prikshat, Patel, Varma, & Ishizaka, 2021; Bar-Gil, Ron, & Czerniak, 2024; Andrieux, Johnson, Sarabadani, & Slyke, 2024). Bennett and Martin (2026) make the organisational justice basis of this explicit. The same safeguards should reduce insecurity, since a documented and contestable process is harder to read as a prelude to displacement than an unexplained one.

H3. AI governance and algorithmic transparency is positively associated with employee trust in AI systems.

H4. AI governance and algorithmic transparency is negatively associated with AI-related job insecurity.

Reskilling and continuous learning investment carries the clearest signal available to employees about the firm's intentions. Deepa, Sekar, Malik, Kumar and Attri (2024) show that the competency demands on HR managers shift substantially under AI, and Burhan (2024) finds that skill development converts career insecurity into career adaptability rather than leaving it as strain. Training also has a direct effect on complementarity, since an employee who understands what a model can and cannot do allocates tasks better than one who does not (Wang, Zhang, Ma, et al., 2025; Axiak, 2025).

H5. Reskilling and continuous learning investment is positively associated with employee trust in AI systems.

H6. Reskilling and continuous learning investment is positively associated with human-AI task complementarity.

H7. Reskilling and continuous learning investment is negatively associated with AI-related job insecurity.

Trust is identified as a predictor of complementarity, not a predictor of performance in and of itself. The rationale for this is behavioural – those who don't trust the system do not use it and miss the complementarity benefit, and those who do use it excessively do not save time and miss the time saving. Both responses are documented (Chi et al., 2026; Xie et al., 2026).

H8. Employee trust in AI systems is positively associated with human-AI task complementarity.

The three proximal predictors then act on the outcome. Complementarity should carry the largest effect, because it is the variable that changes what the employee actually does. Trust should retain a smaller direct effect after complementarity is controlled, reflecting the reduction in monitoring cost and defensive

checking. Job insecurity should depress performance through attentional and motivational routes documented in the insecurity literature (Zhou et al., 2026; Nguyen et al., 2026).

H9a. Human-AI task complementarity is positively associated with employee productivity and performance.

H9b. Employee trust in AI systems is positively associated with employee productivity and performance.

H9c. AI-related job insecurity is negatively associated with employee productivity and performance.

Because governance and reskilling act on the outcome largely through the intermediate variables, indirect effects are predicted rather than direct ones.

H10a. Employee trust in AI systems mediates the relationship between AI governance and transparency and employee productivity and performance.

H10b. Employee trust in AI systems mediates the relationship between reskilling investment and employee productivity and performance.

Last but not least, insecurities are supposed to shape the complementary path and not just augment it. The risk of an employee reading AI as an enemy threat gives him/her motivation to not share the information that allows AI to be effective as a tool for delegation, which should level off the slope between complementarity and performance. In other words, there should be a larger productivity gain from a well-designed division of labour between employee and system for the secure employee than for the insecure one.

H11. AI-related job insecurity negatively moderates the relationship between human-AI task complementarity and employee productivity and performance.

4. Method

4.1 Design

The study uses a sequential mixed-method design in which a qualitative structuring stage precedes a quantitative estimation stage. The order matters. ISM was conducted first so that the structural model tested in stage two would be specified from an explicit and auditable set of expert judgements rather than from the authors' priors, and the reachability matrix produced in stage one was used to decide which paths would be estimated and which would be constrained to zero.

4.2 Stage one: interpretive structural modelling

Interpretive structural modelling converts pairwise judgements about directional influence into a levelled hierarchy. The procedure followed here is the standard one. A panel of experts judges, for each pair of factors, whether the first influences the second, the second the first, both, or neither, producing a structural self-interaction matrix coded V, A, X and O. That matrix is converted to a binary initial reachability matrix, checked for transitivity, and partitioned into levels by iteratively identifying factors whose reachability set equals the intersection of their reachability and antecedent sets. MICMAC analysis then classifies factors by driving and dependence power.

The panel consisted of 14 experts: six senior HR practitioners who work directly with HR systems that use AI in companies with over 2,000 employees, four HR technology consultants and four academics who are published in HRM or information systems. The mean number of years of relevant experience for the panel members was 13.4 years. Judgements were gathered one by one so as to not influence each other, and then combined into one, moderated session, with an initial agreement rate of 71.2% of 66 unique judgements, while the other 19 pairs were discussed to a point where they were able to reach agreement. Two pairs had to play another round. When the panel agreed that a relation existed but failed to agree on direction, the pair was coded X; this only happened once (for the trust-insecurity pair) and it was retained because the theoretical literature considers that pair to have a reciprocal relation.

4.3 Stage two: sample and procedure

Stage two used a cross-sectional employee survey administered in Indian knowledge-intensive firms across Pune, Bengaluru, Hyderabad and the National Capital Region. Eligibility required that the respondent use at least one AI-enabled system in their work at least weekly, and that the respondent not be a member of the HR function, since HR employees are system owners rather than system users and their appraisals differ systematically. The questionnaire was distributed to 640 employees through organisational contacts in eleven firms; 447 responses were returned and 412 were usable after removing 21 incomplete responses and 14 that failed one of the two attention checks. The effective response rate is 64.4%.

Non-response bias was assessed by comparing early and late respondents on all seven constructs; no comparison reached significance at the 5% level, which is consistent with, though not proof of, an absence of systematic non-response. Table 6 reports the sample profile.

Table 6. Sample profile (n = 412)

Characteristic	Category	n	%
Gender	Male	243	59.0
	Female	166	40.3
	Prefer not to state	3	0.7
Age	Under 30	148	35.9

Characteristic	Category	n	%
	30-39	171	41.5
	40-49	70	17.0
	50 and above	23	5.6
Sector	IT and IT-enabled services	157	38.1
	Banking and financial services	98	23.8
	Technology-intensive manufacturing	87	21.1
	Healthcare and other services	70	17.0
Role level	Individual contributor	198	48.1
	Team lead / supervisor	124	30.1
	Middle management	74	18.0
	Senior management	16	3.9
Organisational tenure	Under 3 years	134	32.5
	3-7 years	165	40.0
	Over 7 years	113	27.4
Frequency of AI use	Weekly	96	23.3
	Several times per week	171	41.5
	Daily	145	35.2

4.4 Measures and analytical procedure

All constructs were measured with multi-item reflective scales adapted from published instruments and rated on seven-point Likert scales anchored at strongly disagree and strongly agree. AI readiness and infrastructure (four items) was adapted from Tehrani et al. (2024) and Chang et al. (2026). AI governance and transparency (four items) draws on Prikshat et al. (2021) and Chen et al. (2025). Reskilling and skill development (four items) is adapted from Deepa et al. (2024). Trust in AI (four items) follows Wu et al. (2026). Human-AI task complementarity (four items) was developed for this study from the conceptual accounts in Krotov (2026) and Simón et al. (2024), since no established scale captures task-level division of labour between employee and system. AI-related job insecurity (four items) is adapted from Nguyen et al. (2026) and Zhou et al. (2026). Employee productivity and performance (five items) combines task performance and self-assessed productivity items in the manner of Khalil et al. (2025) and Seth et al. (2026).

Item wording was reviewed by three of the stage-one academic panellists and pilot-tested with 34 employees, whose responses are not included in the analytic sample. Two items were reworded after the pilot because respondents interpreted "the system explains its recommendations" as a question about their manager rather than about the software.

Analysis proceeded in the conventional two-step order. A seven-factor confirmatory factor analysis was estimated by maximum likelihood, and reliability, convergent validity and discriminant validity were assessed before any structural path was inspected. Common method variance was examined through

Harman's single-factor test and by comparing the fit of a one-factor model against the measurement model. The structural model was then estimated with the same estimator. Mediation was tested with bias-corrected bootstrap confidence intervals based on 5,000 resamples, and the moderation hypothesis was tested by hierarchical moderated regression on standardised composite scores, with simple slopes computed at one standard deviation either side of the mean. Fit was judged against the thresholds in common use: comparative and Tucker-Lewis indices at or above .95, RMSEA at or below .06, SRMR at or below .08, and a chi-square to degrees of freedom ratio below 3.

5. Stage one results: structural hierarchy

5.1 Structural self-interaction and reachability

The structural self-interaction matrix, which is generated by the panel, is shown in Table 2. The ordering convention for the factors (not a property of the data) resulted in the coding of 30 V's, 1 X, and 35 O's among the 66 different pairwise judgements; no A's were coded. It is noteworthy that there is a relatively high percentage of O codings. The panels with 12 factors can frequently generate matrices that are dense and have many pairs of factors connected together, and shallow hierarchies leave large clusters of linkages. This panel was conservative, whereby it only codes the relation when it is possible to name a mechanism, and the resulting hierarchy is correspondingly deep.

An additional 27 indirect links were added on to the 31 direct links by converting to a binary matrix and transitive closure. To obtain the final reachability matrix as shown in Table 3, the transitive entries have been added. The driving power varies from 12 (highest commitment of top management) to 1 (lowest commitment of lowest level). For dependence power it is the other way round; from 1 to 12.

Table 2. Structural self-interaction matrix (SSIM)

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12
F1	—	V	V	V	V	O	O	O	V	O	O	O
F2	—	—	O	O	O	V	V	V	O	O	O	O
F3	—	—	—	V	O	O	O	O	O	V	O	O
F4	—	—	—	—	V	O	O	O	V	V	O	O
F5	—	—	—	—	—	O	V	V	V	O	V	O
F6	—	—	—	—	—	—	V	V	O	O	V	O
F7	—	—	—	—	—	—	—	X	V	V	V	V
F8	—	—	—	—	—	—	—	—	O	O	V	V
F9	—	—	—	—	—	—	—	—	—	O	V	V
F10	—	—	—	—	—	—	—	—	—	—	V	V
F11	—	—	—	—	—	—	—	—	—	—	—	V
F12	—	—	—	—	—	—	—	—	—	—	—	—

Note. V = factor i influences factor j; A = factor j influences factor i; X = mutual influence; O = no relation. Cells on and below the diagonal are not evaluated.

Table 3. Final reachability matrix with driving and dependence power

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	DrP	DeP
F1	1	1	1	1	1	1*	1*	1*	1	1*	1*	1*	12	1
F2	0	1	0	0	0	1	1	1	1*	1*	1*	1*	8	2
F3	0	0	1	1	1*	0	1*	1*	1*	1	1*	1*	9	2
F4	0	0	0	1	1	0	1*	1*	1	1	1*	1*	8	3
F5	0	0	0	0	1	0	1	1	1	1*	1	1*	7	4
F6	0	0	0	0	0	1	1	1	1*	1*	1	1*	7	3
F7	0	0	0	0	0	0	1	1	1	1	1	1	6	8
F8	0	0	0	0	0	0	1	1	1*	1*	1	1	6	8
F9	0	0	0	0	0	0	0	0	1	0	1	1	3	9
F10	0	0	0	0	0	0	0	0	0	1	1	1	3	9
F11	0	0	0	0	0	0	0	0	0	0	1	1	2	11
F12	0	0	0	0	0	0	0	0	0	0	0	1	1	12
DeP	1	2	2	3	4	3	8	8	9	9	11	12		

Note. 1* denotes a link established by transitivity. DrP = driving power (row sum); DeP = dependence power (column sum). Transitive closure added 27 indirect links to the 31 direct links in the initial matrix.

5.2 Level partitioning and the ISM digraph

Eight iterations were needed to partition the levels and resulted in eight levels (Table 4, Figure 1). The level of hierarchy is a discovery. These 12 factors would have been likely to have been condensed into three or four levels, which suggests that the panel believed there was a long chain of causation as opposed to a series of parallel factors enabling a single result.

At the base is Top management commitment and digital leadership (level 8). It is the only factor with a driving power of 12 and a dependence power of 1, meaning nothing in the model influences it and it influences everything. Data infrastructure and HR analytics maturity sits alone at level seven, which places it as the single conduit through which leadership commitment reaches every downstream factor. This is a stronger claim than the literature usually makes, and it is worth registering some scepticism about it: the panel may have over-weighted infrastructure because five of its fourteen members work in technology-facing roles. The finding is consistent with Huselid, Minbaeva, Edwards and Levenson (2025) on workforce analytics and with Wang, Zhou, Sanders, Marler and Zou (2024) on the determinants of effective HR analytics implementation, but the structural isolation of the factor at its own level is likely sharper than a differently composed panel would produce.

AI governance and organisational AI readiness share level six, and reskilling and algorithmic transparency share level five. The pairing at level six is intuitive; the pairing at level five is less so, since reskilling is a human capital investment and transparency is a system design property. What they share in this structure is their position immediately before the trust-insecurity layer, and their common function of making the system interpretable to the person using it — one by improving the person, the other by improving the system.

The fourth level is characterized by trust in AI among employees and job insecurity due to AI, which are connected with each other. This is the area of the hierarchy that hinges on. All that below is an organisational investment decision all that above is an employee behavioural response. The reciprocal coding implies that the two are not separable in terms of sequence, and it has a practical implication: a firm can't trust first and then deal with an issue of insecurity, or it can set up a level of insecurity and then build a level of trust that feeds the other. Human-AI complementarity and knowledge sharing is coupled with engagement and well-being at level two and productivity and performance at level one.

One aspect of the digraph runs against the common framing of this literature. Employee productivity and performance is separated from top management commitment by seven intervening levels. Firms that treat AI adoption as a decision with a proximate productivity payoff are, on this reading, mis-specifying the problem by a considerable margin.

Table 4. Level partitioning

Iteration / level	Factor(s)	Description
Level 1	F12	Employee productivity and performance
Level 2	F11	Employee engagement and well-being
Level 3	F9, F10	Human-AI task complementarity and job redesign; Knowledge sharing and organisational learning
Level 4	F7, F8	Employee trust in AI systems; AI-related job insecurity
Level 5	F5, F6	Reskilling and continuous learning investment; Algorithmic transparency and explainability
Level 6	F2, F4	AI governance, ethics and regulatory compliance; Organisational AI readiness and absorptive capacity
Level 7	F3	Data infrastructure and HR analytics maturity
Level 8	F1	Top management commitment and digital leadership

Note. Level 1 is the top of the hierarchy (most dependent); Level 8 is the base (most driving). Partitioning converged in eight iterations.

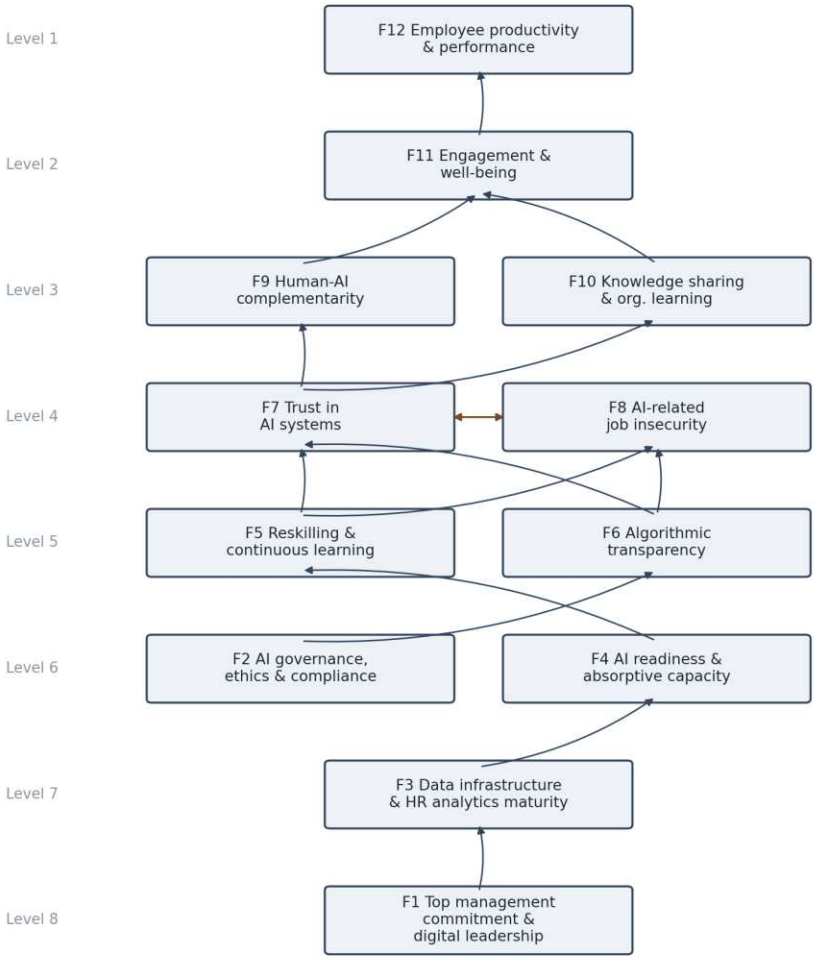


Figure 1. ISM digraph of factors influencing AI-enabled employee productivity and performance

Note. Arrows show direct relations between adjacent levels after removal of transitive links. The double-headed arrow between F7 and F8 denotes the reciprocal relation coded X in the SSIM.

5.3 MICMAC classification

MICMAC results appear in Table 5 and Figure 2. Six factors fall in the independent quadrant with high driving and low dependence power: leadership commitment, data infrastructure, AI readiness, AI governance, reskilling and algorithmic transparency. These are the levers. Six fall in the dependent quadrant: trust, insecurity, complementarity, knowledge sharing, engagement, and the outcome itself. No factor was classified as autonomous, which means the panel judged every factor in the set to be connected to the system rather than peripheral to it — a reassuring result for the factor identification procedure, though also a reminder that factors are unlikely to be nominated as autonomous by a panel that has just been asked to justify their inclusion.

Trust and insecurity are the interesting cases. Both have a driving power of 6 and a dependence power of 8, placing them exactly on the boundary of the linkage quadrant under the conventional midpoint cut. They are formally dependent but substantively act as linkage variables - they are highly influenced by the investment upstream, but have significant influence on the reaction downstream. The unstable variables in the MICMAC interpretation are the linkage variables meaning that changing their value affects the system. It's why they're appealing as interventions and an issue when they are reported, and that's why the SEM in stage two centres around them.

Table 5. MICMAC classification of factors

Code	Factor	Driving power	Dependence power	Quadrant
F1	Top management commitment and digital leadership	12	1	IV Independent
F2	AI governance, ethics and regulatory compliance	8	2	IV Independent
F3	Data infrastructure and HR analytics maturity	9	2	IV Independent
F4	Organisational AI readiness and absorptive capacity	8	3	IV Independent
F5	Reskilling and continuous learning investment	7	4	IV Independent
F6	Algorithmic transparency and explainability	7	3	IV Independent
F7	Employee trust in AI systems	6	8	II Dependent
F8	AI-related job insecurity	6	8	II Dependent
F9	Human-AI task complementarity and job redesign	3	9	II Dependent
F10	Knowledge sharing and organisational learning	3	9	II Dependent
F11	Employee engagement and well-being	2	11	II Dependent
F12	Employee productivity and performance	1	12	II Dependent

Note. Quadrants are defined by the conventional midpoint cut at 6 for a twelve-factor system. F7 and F8 sit exactly on the boundary between the dependent and linkage quadrants and are discussed as weak linkage variables in the text.

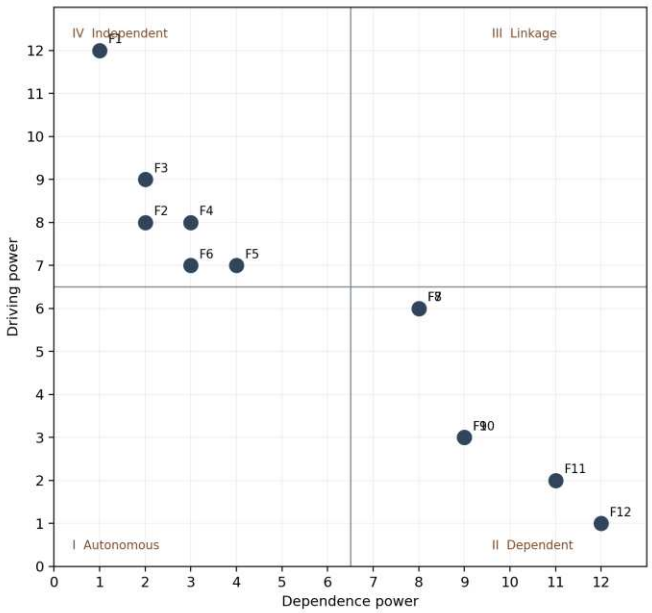


Figure 2. MICMAC driving power–dependence power diagram

6. Stage two results: measurement and structural models

6.1 Measurement model

The measurement model has a good fit with seven factors. This ratio of chi-square to degrees of freedom is 1.79 with 356 degrees of freedom. The comparative fit index is .957, and the Tucker-Lewis index .951, values both higher than the conventional benchmark of .95, while RMSEA is .044 and SRMR .049, which are both comfortably below their ceilings. The chi-square statistic is significant at $p < .001$ which is expected for this sample size and not used as evidence against the model.

Standardised loadings, reliabilities and average variance extracted are reported in table 7. None of the 29 loadings is not significant at the 1% level and none of the loadings is lower than .669. There is only one loading that was below .70 and it was quite a way below, so no item was dropped. The composite reliabilities of these factors vary from .847 for reskilling to .888 for the outcome, and Cronbach's alpha correlates well with composite reliability. All constructs have average variance extracted greater than .50.

Discriminant validity was assessed two ways and is reported in Table 8. Under the Fornell-Larcker criterion, the square root of average variance extracted for each construct exceeds its correlation with every other construct; the tightest case is trust and complementarity, where .792 and .773 are compared against a correlation of .633. Heterotrait-monotrait ratios, which are the more demanding test, range from .206 to .629 and are therefore well under the conservative .85 threshold. Neither test raises a concern.

Common method variance was examined in two ways. Harman's single-factor test yields a first factor accounting for 34.65% of variance, below the 50% rule of thumb. More informative is the fit comparison: a one-factor model returns a comparative fit index of .563 and an RMSEA of .135, which is a catastrophic deterioration from the seven-factor model. This does not eliminate the possibility of method effects — no post hoc test does, and the design is single-source and cross-sectional — but it makes a single dominant method factor implausible.

Table 7. Measurement model: items, standardised loadings, reliability and convergent validity

Item	Indicator	λ	α / CR	AVE
AIR1	The AI systems I use at work are available and reliable when I need them.	0.779		
AIR2	Workforce data in this organisation is well integrated across systems.	0.856		
AIR3	Technical support for the AI tools I use is adequate.	0.681		
AIR4	The AI tools I use fit the way my work is actually organised.	0.746	0.851 / 0.851	0.590
AGT1	This organisation has clear rules about how AI may be used in decisions affecting employees.	0.860		
AGT2	I can find out why an AI system produced a particular recommendation about my work.	0.778		
AGT3	There is a way to challenge an AI-supported decision that affects me.	0.787		
AGT4	Someone is accountable when an AI system in HR gets something wrong.	0.669	0.855 / 0.858	0.603

Item	Indicator	λ	α / CR	AVE
RSD1	This organisation invests in developing the skills I need to work with AI.	0.808		
RSD2	I have had adequate training on the AI tools used in my role.	0.744		
RSD3	Learning opportunities here keep pace with changes in the technology.	0.731		
RSD4	I am confident I can acquire the skills my role will require in three years.	0.764	0.846 / 0.847	0.581
TAI1	I am willing to rely on the outputs of the AI systems I use.	0.822		
TAI2	The AI systems in my work are competent at what they are used for.	0.794		
TAI3	I believe these systems are used with employees' interests in mind.	0.829		
TAI4	I would act on an AI recommendation in an important work decision.	0.717	0.870 / 0.870	0.627
HAC1	The tasks handled by AI in my role are the ones AI handles well.	0.782		
HAC2	I retain the parts of my work that require judgement.	0.783		
HAC3	The division of work between me and the system is deliberate rather than accidental.	0.775		
HAC4	AI in my role frees time for work that makes better use of my skills.	0.752	0.854 / 0.856	0.598
JIS1	I am concerned that AI will reduce the scope of my role.	0.811		
JIS2	AI could make parts of my job unnecessary within a few years.	0.776		
JIS3	I worry about my job security because of AI at work.	0.799		
JIS4	AI threatens the standing of roles like mine in this organisation.	0.707	0.854 / 0.857	0.600
EPP1	I complete my assigned work to the standard expected of my role.	0.810		
EPP2	The quality of my output has improved over the past year.	0.807		
EPP3	I get more done in a working day than I did before AI was introduced.	0.822		
EPP4	I meet deadlines consistently.	0.717		
EPP5	My overall work performance is strong.	0.755	0.887 / 0.888	0.613

Note. n = 412. All loadings significant at $p < .001$. λ = standardised factor loading; α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted. Model fit: $\chi^2(356) = 636.76$, $\chi^2/df = 1.79$, CFI = .957, TLI = .951, GFI = .908, AGFI = .895, RMSEA = .044, SRMR = .049.

Table 8. Discriminant validity: Fornell–Larcker criterion and HTMT ratios

	AIR	AGT	RSD	TAI	HAC	JIS	EPP
AIR	0.768	0.539	0.566	0.523	0.606	0.213	0.505
AGT	0.567	0.777	0.509	0.545	0.367	0.372	0.414
RSD	0.563	0.510	0.762	0.560	0.548	0.387	0.510
TAI	0.528	0.543	0.560	0.792	0.629	0.252	0.544
HAC	0.598	0.360	0.545	0.633	0.773	0.206	0.620
JIS	-0.219	-0.354	-0.375	-0.233	-0.201	0.775	0.291
EPP	0.510	0.417	0.515	0.554	0.618	-0.286	0.783

Note. Values on the diagonal (bold in the source model) are the square root of AVE. Below the diagonal: latent construct correlations from the CFA. Above the diagonal: heterotrait–monotrait ratios, reported as absolute values. AIR = AI readiness and infrastructure; AGT = AI governance and transparency; RSD = reskilling and skill development; TAI = trust in AI; HAC = human–AI task complementarity; JIS = AI-related job insecurity; EPP = employee productivity and performance.

Table 9. Descriptive statistics and construct correlations

	M	SD	AIR	AGT	RSD	TAI	HAC	JIS	EPP
AIR	4.603	1.010	1.000						
AGT	4.583	1.013	0.463	1.000					
RSD	4.571	1.010	0.483	0.434	1.000				
TAI	4.609	1.060	0.453	0.470	0.483	1.000			

	M	SD	AIR	AGT	RSD	TAI	HAC	JIS	EPP
HAC	4.541	1.062	0.519	0.316	0.468	0.546	1.000		
JIS	4.561	1.009	-0.184	-0.320	-0.330	-0.220	-0.179	1.000	
EPP	4.570	1.015	0.441	0.363	0.444	0.482	0.544	-0.255	1.000

Note. n = 412. Composite scores on seven-point scales. All correlations of absolute magnitude above .10 are significant at $p < .05$.

6.2 Structural model

Structural estimates appear in Table 10 and are drawn in Figure 3. The structural model fits comparably to the measurement model (chi-square 650.47 on 362 degrees of freedom, CFI .956, TLI .950, RMSEA .044, SRMR .051), and the small increase in chi-square across six additional degrees of freedom indicates that constraining the non-hypothesised paths to zero costs little in fit.

All eleven hypothesised paths are supported in the predicted direction. Trust in AI is predicted by reskilling investment ($\beta = .312$, $p < .001$), AI governance and transparency ($\beta = .263$, $p < .001$) and AI readiness ($\beta = .205$, $p = .002$), with the three together explaining 34.5% of its variance; H1, H3 and H5 are supported. Complementarity is predicted most strongly by trust ($\beta = .377$, $p < .001$), then by AI readiness ($\beta = .298$, $p < .001$) and reskilling ($\beta = .166$, $p = .009$), with 41.1% of variance explained; H2, H6 and H8 are supported. Job insecurity is reduced by reskilling ($\beta = -.260$, $p < .001$) and by governance and transparency ($\beta = -.219$, $p < .001$), supporting H4 and H7, though the two together account for only 14.7% of its variance — the great majority of what drives AI-related insecurity in this sample lies outside the model.

On the outcome, complementarity carries much the largest effect ($\beta = .372$, $p < .001$), followed by trust ($\beta = .210$, $p = .001$), AI readiness ($\beta = .152$, $p = .013$) and job insecurity ($\beta = -.128$, $p = .007$), together explaining 37.7% of variance in productivity and performance. H9a, H9b and H9c are supported. The ordering is the substantive result of stage two. A job design variable outperforms both the technology variable and the psychological trust variable, and it does so by a factor of roughly two over the next-largest predictor.

It is worth being clear about what this ordering does not establish. The design is cross-sectional and the outcome is self-reported, so the estimate of the complementarity path is vulnerable both to reverse causality — high performers may be better at organising their work around a system — and to a common-source inflation that the Harman test cannot rule out at the level of individual paths. The relative ordering of the coefficients is more defensible than their absolute magnitudes, because a common-source bias affecting all self-reports equally would shift the coefficients together rather than reorder them.

Table 10. Structural path estimates and hypothesis outcomes

H	Predictor	Outcome	b	SE	β	z	p	Decision
H1	AI readiness & infrastructure	Trust in AI	0.224	0.072	0.205	3.13	0.002	Supported
H3	AI governance & transparency	Trust in AI	0.257	0.061	0.263	4.25	<0.001	Supported

H	Predictor	Outcome	b	SE	β	z	p	Decision
H5	Reskilling & skill development	Trust in AI	0.327	0.067	0.312	4.88	<0.001	Supported
H2	AI readiness & infrastructure	Human-AI complementarity	0.305	0.064	0.298	4.77	<0.001	Supported
H6	Reskilling & skill development	Human-AI complementarity	0.162	0.062	0.166	2.61	0.009	Supported
H8	Trust in AI	Human-AI complementarity	0.353	0.059	0.377	6.01	<0.001	Supported
H4	AI governance & transparency	AI job insecurity	-0.196	0.058	-0.219	-3.38	<0.001	Supported
H7	Reskilling & skill development	AI job insecurity	-0.249	0.063	-0.260	-3.93	<0.001	Supported
H9a	Human-AI complementarity	Productivity & performance	0.383	0.073	0.372	5.25	<0.001	Supported
H9b	Trust in AI	Productivity & performance	0.202	0.061	0.210	3.29	0.001	Supported
H9c	AI job insecurity	Productivity & performance	-0.135	0.049	-0.128	-2.72	0.007	Supported
--	AI readiness & infrastructure	Productivity & performance	0.160	0.064	0.152	2.48	0.013	Not hypothesised

Note. n = 412. b = unstandardised estimate; β = standardised estimate. Model fit: $\chi^2(362) = 650.47$, $\chi^2/df = 1.80$, CFI = .956, TLI = .950, RMSEA = .044, SRMR = .051. R^2 = .345 (trust in AI), .411 (human–AI complementarity), .147 (AI job insecurity), .377 (employee productivity and performance).

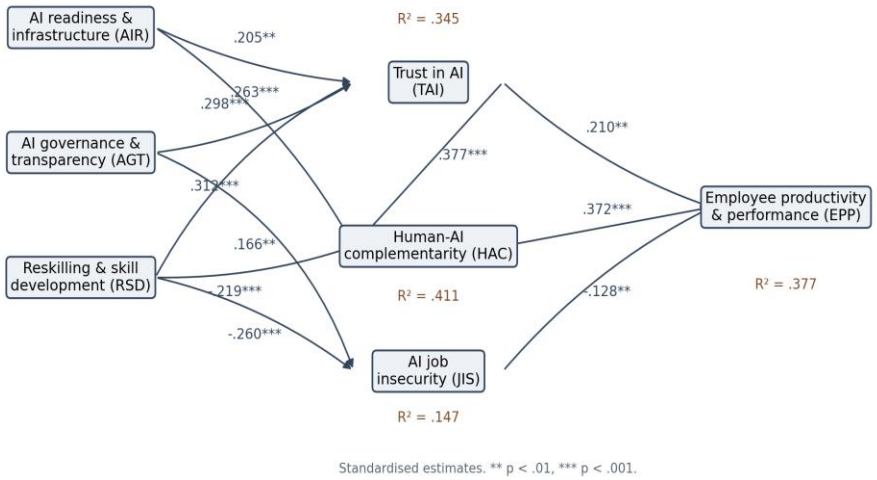


Figure 3. Estimated structural model with standardised path coefficients

6.3 Mediation and moderation

Bootstrap results for the two mediation hypotheses are in Table 11. The indirect effect of AI governance and transparency on productivity through trust is .053, with a bias-corrected 95% confidence interval of [.025, .088] that excludes zero, supporting H10a. The indirect effect of reskilling through trust is .056, with an interval of [.027, .090], supporting H10b. Both are reliable and both are small. Governance and reskilling therefore reach performance through trust, but the trust channel transmits only about a fifth of what reskilling contributes to the system overall once its effects on complementarity and insecurity are also counted. Reporting the trust pathway as the mechanism by which governance improves performance would substantially overstate it.

Moderated regression results are in Table 12 and the simple slopes in Figure 4. The interaction between complementarity and job insecurity is negative and significant (b = −.081, t = −2.10, p = .037), supporting H11 in direction. The change in explained variance attributable to the interaction is .0067. That is two-

thirds of one percent, and it is the weakest result in the paper. Simple slopes give .409 for employees one standard deviation below the insecurity mean and .246 for those one standard deviation above, so the practical reading is that complementarity pays off for insecure employees too, just less. The finding does not support the stronger claim, which appears in parts of the practitioner literature, that job insecurity nullifies the benefits of AI-enabled job redesign. On this evidence it attenuates them by about 40%, from a base that remains the largest effect in the model.

Table 11. Bias-corrected bootstrap tests of indirect effects

H	Indirect path	Effect	SE	95% CI
H10a	AI governance and transparency → trust in AI → productivity and performance	0.053	0.016	[0.025, 0.088]
H10b	Reskilling and skill development → trust in AI → productivity and performance	0.056	0.016	[0.027, 0.090]

Note. Standardised effects, 5,000 bootstrap resamples. Confidence intervals excluding zero indicate a reliable indirect effect.

Table 12. Moderated regression predicting employee productivity and performance

Predictor	b	SE	t	p	Comment
Human–AI complementarity	0.328	0.050	6.55	<0.001	Main effect
AI job insecurity	-0.124	0.040	-3.09	0.002	Main effect
Trust in AI	0.202	0.048	4.19	<0.001	Control
AI readiness and infrastructure	0.152	0.047	3.24	0.001	Control
Complementarity × job insecurity	-0.081	0.039	-2.10	0.037	H11 supported
R^2	0.384				ΔR^2 for interaction = .0067
Simple slope at −1 SD insecurity	0.409				Low insecurity
Simple slope at +1 SD insecurity	0.246				High insecurity

Note. n = 412. All variables standardised prior to forming the product term. The interaction is statistically reliable but adds less than one percent to explained variance.

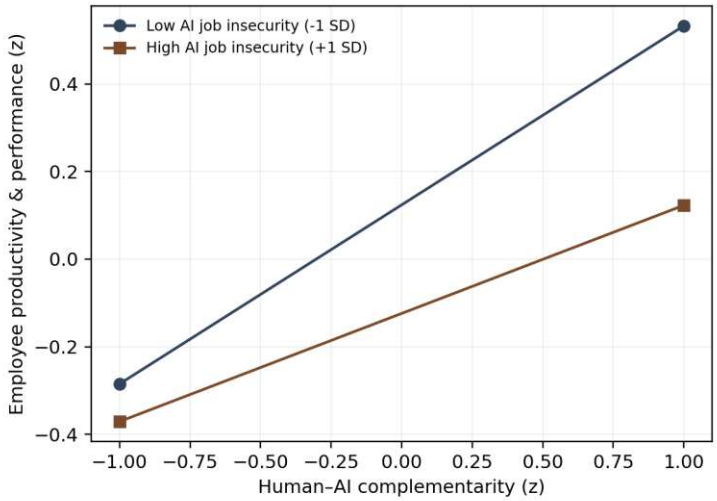


Figure 4. Simple slopes for human–AI complementarity at high and low AI job insecurity

7. Discussion

Two findings from this study sit awkwardly with how the AI-HRM literature usually frames its subject, and they are worth taking separately.

The first is the level of hierarchy in the ISM. There are seven levels between top managers' commitment and employee productivity. The research community regularly models leadership commitment (or even AI readiness) as a direct antecedent of workforce outcomes, and the practitioner literature regularly promises productivity as a near-term return on the investment in AI. There is no support for either here in the structure. The hierarchy, on the other hand, implies that leadership commitment is real, but remote, and that its impact is fully mediated: in infrastructure, in governance and readiness, in skills and transparency, in trust-insecurity, and in job design and outcomes. If the middle is broken, then the top of that chain can be done well and there is nothing at the bottom. This is consistent with what Khalil et al. (2025) call the AI-productivity paradox and it provides a structural explanation of this paradox: a long, mediated chain looks like the AI-productivity paradox if only its endpoints are measured.

The second is the structural model featuring dominance of human-AI task complementarity. This construct is a job design variable. It asks whether the division of labour between employee and system is sensible — whether the system handles what it handles well and the employee retains what requires judgement. It is not a technology variable, and it is not a training variable, though both feed it. Its coefficient of .372 exceeds the next-largest predictor by roughly a factor of two, and it also serves as the route through which trust, readiness and reskilling reach the outcome. The practical implication is uncomfortable for the way many firms organise AI programmes, since job redesign typically sits with line managers while AI deployment sits with technology and HR functions, and the variable that matters most is therefore owned by the group least involved in the decision.

The trust-insecurity pairing deserves separate comment because the two methods converge on it. ISM placed the two at the same level with a reciprocal link, and MICMAC placed both exactly on the linkage boundary. The SEM then found that trust operates largely through complementarity rather than directly on performance, while insecurity operates both directly and as a moderator. These are different roles for what the literature often treats as two poles of a single attitude. Trust appears to be enabling: it permits the employee to reorganise work around the system. Insecurity appears to be constraining: it does not prevent that reorganisation but it taxes the return on it. Interventions aimed at raising trust and interventions aimed at lowering insecurity are, on this evidence, doing different work and should not be substituted for one another.

The insecurity findings also complicate the more alarming readings of the displacement literature. Governance and reskilling together explain under 15% of variance in AI-related job insecurity. Whatever

is generating that insecurity in this sample is mostly not the firm's AI policy, its training provision, or the transparency of its systems. Labour market conditions, media coverage, occupational identity and personal career stage are the obvious candidates, and none was measured here. Firms should probably expect a lower return on internal reassurance efforts than the HR literature implies, because most of the variance they would need to move is not theirs to move.

Where the results align with existing work, they do so unremarkably. The positive governance-trust and reskilling-trust paths are consistent with the ethics and competency literatures (Varma et al., 2023; Deepa et al., 2024; Bennett & Martin, 2026). The negative direct effect of insecurity on performance replicates Nguyen et al. (2026) and Zhou et al. (2026) in a different national setting. The finding that AI readiness matters but matters less than job design is broadly the position argued conceptually by Krotov (2026) and by Bastida et al. (2025), now with an estimate attached.

8. Implications

The sequence of the items in the ISM hierarchy are more useful for managers than the coefficients, since they reflect sequence instead of importance. There's no reason to invest in the transparency of the algorithms before the data infrastructure is stable; this will only result in employees having to learn to trust the system again from a reliability standpoint. Pre-established reskilling programmes usually are viewed as preparation for displacement, while they are not thought of as investments. The hierarchy implies the sequence: infrastructure, then governance and readiness, then reskilling and transparency, and, finally, the layer of the trust and insecurity which must be addressed before a real effort at job redesign can be made. The second comes in the context of measurement. Companies that assess AI programs based on productivity are receiving an eighth level of the productivity chain - which doesn't provide any information, nor does it provide early warning of which segment of the chain has broken. The trust and insecurity are at the hinge and are easily measured in a pulse survey but would give a leading indicator to the one the productivity measures. Third, and most directly actionable: the largest effect is the complementarity effect and it is a job design feature so responsibility should be made explicit not implicit. This was true of the eleven firms sampled here, where no one could be said to be the owner of the question, which tasks should be included in the system and which not. That isn't a technology gap, rather that is a governance gap. So, modestly, the results say for policy. That transparency, apart from governance, is effective at reducing insecurity is consistent with the disclosure requirements being proposed for the European AI Act framework (Väyrynen et al., 2026; Lim & Lee, 2026), but the minimal variation found in insecurity indicates that regulation to help calm workers' nerves through firm-level disclosure will only signal a fraction of what makes them feel insecure.

9. Conclusion

Investing in AI is positively associated with employee productivity, and this is the key takeaway from the study. In the ISM hierarchy, there are eight steps between leadership commitment and performance, and a mutually reinforcing connection exists between employee trust and AI-related job insecurity, splitting organisational investments from employee reactions. Under the assumption that the intermediate level of the hierarchy is modelled as a latent variable model, the biggest proximal predictor of performance is human-AI task complementarity, which is approximately twice the size of the next biggest effect, and the pathway by which readiness, reskilling and trust gets to the outcome. The practical reading is that the firms enhance their productivity by redesigning their work around the system and not by installing the system. The importance of trust and governance is that it allows the redesign; the importance of infrastructure is that it makes the redesign possible; the importance of job insecurity is that it puts pressure on the return, but not as heavy as the fear of that literature would evoke. There is a reliable but modest trust channel for a fifth of explained variance, and the moderating effect of insecurity contributes little (under 1 percent of variance). Both are real. They do not have the significance attached to them by the present discussion, and to assert such is more to the point than to defend an overreaching claim that they do not prove.

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