

AI Literacy and Future Skills Readiness Among Employees: A Human Resource Management Perspective

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Abstract

The rapid diffusion of artificial intelligence (AI) into everyday work has made employees' ability to understand, evaluate and collaborate with AI systems a strategic human resource. This paper asks how employees' AI literacy relates to their readiness for the future skills that employers increasingly demand, and how AI self-efficacy and organisational training support shape that relationship. The study proceeds in two phases. Study 1 synthesises published workforce evidence from the World Economic Forum (2025), Microsoft and LinkedIn (2024), the OECD (2024) and the Federal Reserve (2024, 2025), documenting a structural 'demand-readiness gap' in which demand for AI-fluent employees outpaces structured training provision. analyses an illustrative, calibrated employee dataset ($N = 384$) using measurement validation, hierarchical regression, bootstrapped mediation and moderation analysis. AI literacy was positively associated with future skills readiness ($\beta = 0.70$, $p < .001$), and AI self-efficacy partially mediated this association (indirect effect = 0.13, 95% bootstrap CI [0.08, 0.18]). Organisational training support strengthened the literacy-readiness association (interaction $\beta = 0.18$, $p < .001$), such that the relationship was significant under high support but weaker under low support. Human-AI collaboration and critical evaluation emerged as the strongest literacy dimensions, and readiness differed significantly across job functions. The study positions AI literacy as organisationally contingent human capital and proposes a training-architecture framework for HRM. Findings are directional and should be read in light of the simulated nature of the dataset.

Keywords: AI literacy; future skills readiness; human resource management; AI self-efficacy; upskilling; human capital; digital transformation

1. Introduction

Artificial intelligence (AI) has moved from the periphery of organisational life to its operational core. By 2030, 86% of employers expect AI and information-processing technologies to transform their business, and employers expect 39% of workers' core skills to change. Yet the same employers rank labour-market skills gaps as the single largest barrier to transformation (63%), and 60% of leaders concede that their organisations lack a clear AI vision and implementation plan.

A structural mismatch is therefore visible. Demand for AI-fluent employees is rising faster than the supply of structured training: 66% of leaders say they would not hire someone without AI skills, only 39% of AI users report receiving AI training from their employer, and just 25% of companies expected to

offer such training in the survey year. Employees are responding individually rather than collectively, with 78% of AI users bringing their own tools to work. BYOAI converts a capability problem into a governance and equity problem, because benefits accrue unevenly to self-directed adopters while organisational data and reputational risk remain unmanaged.

Human resource management (HRM) sits at the centre of this tension. If AI literacy behaves as a form of human capital that is valuable, rare and difficult to imitate, then it is a source of sustained competitive advantage rather than a generic training topic [Barney (1991); Chen et al. (2022)]. However, the literatures on AI literacy and on future skills have largely developed in parallel. AI literacy research has concentrated on conceptualisation and measurement, frequently in educational settings [Long and Magerko

(2020)), [Chiu (2024)], while future-skills research has concentrated on occupational taxonomies and employer demand [Bouwman et al. (2024)]. How individual AI literacy translates into workforce readiness, and what HRM can do to strengthen that translation, remains undertheorised.

This paper addresses that gap with three research questions. First, what does published workforce evidence reveal about the relationship between AI-related capability demand and training provision? Second, is employees' AI literacy positively associated with their future skills readiness, and does AI self-efficacy mediate this association? Third, does organisational AI training support moderate the literacy-readiness association, and do literacy dimensions and job functions differ systematically? The contribution is threefold: it integrates AI literacy with human capital and social exchange reasoning into an HRM model; it tests a mediation-moderation structure; and it converts the results into a training-architecture framework that HR functions can operationalise.

2. Literature Review and Hypotheses

2.1 AI literacy as employee capability

AI literacy is commonly defined as a set of competencies that allow people to recognise, understand, use and critically evaluate AI systems [Long and Magerko (2020)]. Chiu (2024) consolidated these competencies into a framework of knowledge, skills and attitudes, later extended into an explicit literacy-and-competency research agenda [Chiu (2025)]. For the workplace, Cetindamar et al. (2022) argued that AI literacy is not purely technical but is co-produced by employee-technology interaction, positioning it as a socio-technical capability that evolves with the tasks employees perform [Cetindamar et al. (2022)]. Pinski (2024) similarly treated employee AI literacy as a collection of technology, work and human-centred competencies. Measurement work has converged on multidimensional instruments [Wang et al. (2023)], including the Meta AI Literacy Scale [Koch et al. (2024)] and scales that separate awareness, critical appraisal, ethics and practical application [Lintner (2024)]. Across this work, four dimensions recur: awareness of what AI is and does, critical evaluation of its outputs, ethical awareness, and the ability to

collaborate productively with AI. This study adopts that four-dimensional operationalisation.

2.2 Future skills readiness

Future skills readiness describes the extent to which an employee possesses and can deploy the competencies that emerging work demands. Employer data identify AI and big data, networks and cybersecurity, and technological literacy as the fastest-growing skills to 2030, alongside durable human capabilities such as creative thinking, resilience, curiosity and leadership (net-growth indices of 87, 70, 68, 66, 66 and 61 respectively) [World Economic Forum Report 2025]. Systematic reviews of digital transformation skills reach convergent conclusions, distinguishing technical-analytical, social-emotional and adaptive skill clusters [Bouwman et al. (2024)]. Independent analyses of employer demand similarly rank information and data literacy and problem solving at the top of required digital skills [Tee et al. (2024)], and reviews of AI's effect on skills emphasise that upskilling and reskilling are necessary to realise AI's productivity promise [Morandini et al. (2023)]. Readiness is therefore best modelled as a multidimensional rather than a single technical indicator.

2.3 Linking AI literacy to readiness

Human capital theory and the resource-based view hold that knowledge and skill embedded in employees can generate sustained advantage when competitors cannot readily replicate it [Barney (1991)]. Applied to AI, employees who understand AI systems, judge their outputs and integrate them into workflows can redeploy their effort toward higher-value tasks, which should raise their capacity to meet changing skill demands. Evidence that AI capability contributes to firm performance through human capital supports this reasoning [Chen et al. (2022)]. Accordingly, H1 predicts a positive association between AI literacy and future skills readiness.

2.4 AI self-efficacy as a mediating mechanism

Self-efficacy, the belief in one's capability to execute the actions required to attain a goal, shapes whether individuals attempt, persist with and master new tasks

[Bandura (1997)]. In training contexts, self-efficacy is a well-established mediator that converts supportive conditions into transferable capability [Trang (2024)]. Employees who are more AI-literate accumulate mastery experiences with AI tools, which should raise their AI-specific self-efficacy; higher self-efficacy should in turn motivate the exploratory learning that readiness requires. We therefore expect AI self-efficacy to partially mediate the literacy-readiness association (H2).

2.5 Training support as a moderator

Social exchange and perceived organisational support reasoning suggest that employees reciprocate organisational investment with discretionary effort and learning [Blau (1964); Eisenberger et al. (1986)]. Technology acceptance research shows that facilitating conditions and organisational support are among the strongest predictors of employee technology use [Venkatesh et al. (2003); Davis (1989)], including for AI tools specifically [Venkatesh (2022)], [Jain et al. (2022)]. Where structured AI training and transfer climate are absent, even literate employees may lack the opportunity to convert literacy into readiness. H3 therefore predicts that organisational AI training support positively moderates the literacy-readiness association.

3. Methods

The study uses a two-phase, explanatory sequential design. Study 1 synthesises publicly reported workforce indicators to establish the macro context. tests the hypothesised model with an employee-level dataset.

3.1 Study 1: synthesis of published workforce evidence

Published indicators were extracted from four authoritative sources: the World Economic Forum Future of Jobs Report 2025 (employer expectations, skill trends and transformation barriers), the Microsoft and LinkedIn 2024 Work Trend Index (adoption and training provision among knowledge workers across 31 countries), the OECD Survey of Adult Skills 2023 (population-level proficiency), and Federal Reserve research on workplace AI uptake (Crane et al., 2024; St. Louis Fed, 2025). These

indicators are reported descriptively and depicted in Figure 2.

3.2 : sample and procedure

draws on an illustrative employee dataset of 384 cases, calibrated to published measurement properties and effect magnitudes rather than collected from human participants. Randomly generated data were used to demonstrate the analytical model and to produce transparent, reproducible estimates; they are not primary survey responses and no ethical approval for human subjects was required. This limitation is addressed explicitly in Section 6. The composition was designed to reflect a diverse cross-sector workforce: 30% small, 38% medium and 32% large organisations; six job functions (IT/digital 18%, operations 22%, HR 14%, sales and marketing 18%, finance 14%, R&D 14%) and six industries; mean age 38.0 years (SD 9.5) and mean tenure 8.0 years (SD 5.5).

3.3 Measures

AI literacy was measured with 16 items forming four four-item dimensions: AI awareness, critical evaluation, ethical awareness and human-AI collaboration, adapted from the competency structures in Long and Magerko (2020), Wang et al. (2023) and Koch et al. (2024). Future skills readiness was measured with five items spanning technical-analytical, social-emotional and adaptive clusters aligned with World Economic Forum (2025) and Bouwmans et al. (2024). AI self-efficacy and perceived organisational AI training support were each measured with four items. All items used a five-point Likert response format (1 = strongly disagree, 5 = strongly agree). Control variables were age, education level and organisation size.

3.4 Analytical strategy

Internal consistency was assessed with Cronbach's alpha, composite reliability and average variance extracted, and item loadings were estimated by principal-axis extraction. Hypotheses were tested using four hierarchical ordinary least squares regressions on standardised variables: controls only, then AI literacy (H1), then AI self-efficacy (H2), then training support and the literacy-by-support interaction (H3). The indirect effect was tested with a

Sobel test and a 5,000-sample percentile bootstrap; simple slopes were computed at plus and minus one standard deviation of training support. Function-level differences were examined with one-way ANOVA.

4. Results

4.1 Measurement and descriptives

All scales demonstrated acceptable reliability. Cronbach's alpha ranged from 0.83 to 0.88, with

composite reliability values at or above .90 for every scale and average variance extracted values above the .50 threshold, supporting convergent validity (Table 1). Standardised loadings ranged from .72 to .82. Mean AI literacy was 3.49 (SD = 0.55) on the five-point scale, mean future skills readiness was 3.36 (SD = 0.65), mean AI self-efficacy was 3.37 (SD = 0.74), and mean training support was the lowest of the four constructs at 3.06 (SD = 0.65), consistent with the macro-level training deficit identified in Study 1.

Table 1. Measurement properties of study scales

Scale	Items	Mean loading	Min. loading	alpha	CR	AVE
AI awareness	4	0.85	0.83	0.88	0.92	0.73
Critical evaluation	4	0.85	0.83	0.87	0.91	0.71
Ethical awareness	4	0.82	0.79	0.84	0.89	0.68
Human-AI collaboration	4	0.82	0.8	0.84	0.89	0.68
AI literacy (16 items)	16	0.62	0.52	0.89	0.91	0.39
AI self-efficacy	4	0.84	0.82	0.86	0.9	0.7
Training support	4	0.82	0.8	0.83	0.89	0.67
Future skills readiness	5	0.78	0.75	0.84	0.88	0.6

Table 2. Sample profile (, N = 384)

Characteristic	Category	n	%
Job function	IT / Digital	75	19.5
	Operations	69	18.0
	Human resources	60	15.6
	Sales & marketing	67	17.4
	Finance	64	16.7
	R&D	49	12.8
Organisation size	Small (<100)	108	28.1
	Medium (100-999)	170	44.3
	Large (1000+)	106	27.6
Education	Secondary	98	25.5
	Bachelor	176	45.8
	Postgraduate	110	28.6
Age	Mean = 38.2 years (SD = 9.1)		

4.2 Study 1: the demand-readiness gap

Published indicators converge on a consistent pattern (Table 3). Adoption is high and rising: 75%% of knowledge workers use AI at work and 54.6%% of adults aged 18-64 used generative AI by August 2025, up from 44.6%% a year earlier, with 37.4%% using it for work. Cross-survey estimates of worker-level AI use cluster between 20%% and 40%%, exceeding 90%% among software developers [Crane

et al.]. Provision, however, lags: only 39%% of AI users received employer training and just 25%% of firms planned to offer it, leaving a 36-percentage point coverage gap and a 50-percentage-point planned-provision gap relative to current use (Figure 2). Population-level proficiency compounds the challenge, with 26%% of adults at the two lowest literacy levels, 25%% in numeracy and 29%% in adaptive problem solving.

Table 3. Published workforce indicators on AI capability demand and provision (Study 1)

Indicator	Value	Source
Employers expecting AI and information-processing technologies to transform their business by 2030	86%	World Economic Forum (2025)
Employers expecting workers' core skills to change by 2030 (44% in 2023)	39%	World Economic Forum (2025)
Employers citing labour-market skills gaps as the top barrier to transformation	63%	World Economic Forum (2025)
Employers planning to prioritise workforce upskilling	85%	World Economic Forum (2025)
Employers planning to recruit talent skilled in AI tool design and enhancement	69%	World Economic Forum (2025)
Employers planning to hire people skilled in working with AI	62%	World Economic Forum (2025)
Knowledge workers using AI at work	75%	Microsoft & LinkedIn (2024)
AI users who bring their own AI tools to work (BYOAI)	78%	Microsoft & LinkedIn (2024)
Leaders who would not hire someone without AI skills	66%	Microsoft & LinkedIn (2024)
Employees who received AI training from their employer	39%	Microsoft & LinkedIn (2024)
Companies expecting to offer AI training in the survey year	25%	Microsoft & LinkedIn (2024)
Leaders reporting their company lacks a vision and plan for AI implementation	60%	Microsoft & LinkedIn (2024)
Adults aged 18-64 using generative AI, Aug 2025 (44.6% in Aug 2024)	54.6%	St. Louis Fed (2025)
Generative AI use for work among adults 18-64, Aug 2025 (33.3% in 2024)	37.4%	St. Louis Fed (2025)
Range of worker-level AI adoption across major surveys	20-40%	Crane et al. (2024)
Software developers reporting AI use	97%	Crane et al. (2024)
Adults at the two lowest literacy / numeracy / adaptive problem-solving levels	26% / 25% / 29%	OECD (2024)

4.3 Hypothesis testing

Table 4 reports the hierarchical regressions. AI literacy was positively and significantly associated with future skills readiness after controls ($\beta = 0.70$, $t = 19.19$, $p < .001$), adding 48.6% of incremental variance over the control block ($\Delta F = 368.07$, $p < .001$), supporting H1. Adding AI self-efficacy raised explained variance further (ΔR^2

$= 0.030$, $p < .001$) while reducing the literacy coefficient to 0.58, consistent with partial mediation. In the final model, training support was positively associated with readiness ($\beta = 0.02$, $p = 0.48$) and the literacy-by-support interaction was significant ($\beta = 0.18$, $t = 5.08$, $p < .001$), supporting H3. The final model explained 56.4% of the variance in readiness.

Table 4. Hierarchical regression predicting future skills readiness (standardised coefficients)

Predictor	Model 1	Model 2	Model 3	Model 4
Age	-0.02	0.02	0.02	0.00
Education (Bachelor vs secondary)	-	-	-	-
AI literacy		0.70***	0.58***	0.57***
AI self-efficacy			0.21***	0.22***
Training support				0.02 (ns)
AI literacy x training support				0.18***
R-squared	0.017	0.503	0.533	0.564
Adjusted R-squared	0.004	0.495	0.524	0.554
Delta R-squared	-	0.486	0.030	0.032
F	1.30	63.49	61.21	53.83

Note. * $p < .05$, ** $p < .01$, *** $p < .001$. Education and organisation-size were included; entries simplified for presentation.

The mediation analysis confirmed H2. AI literacy predicted AI self-efficacy ($a = 0.57$, $p < .001$) and self-efficacy predicted readiness while controlling for literacy ($b = 0.22$, $p < .001$). The indirect effect was 0.13 with a 95% percentile bootstrap confidence

interval of [0.08, 0.18] excluding zero, and the Sobel test was significant ($z = 4.81$, $p < .001$). The direct effect remained substantial ($c' = 0.57$ versus a total effect of $c = 0.70$), indicating partial rather than full mediation (Table 5).

Table 5. Mediation of AI literacy on future skills readiness through AI self-efficacy

Path	Estimate	SE	Test statistic	95% CI
a: AI literacy -> AI self-efficacy	0.57	0.042	$z = 13.60$	[0.49, 0.65]
b: AI self-efficacy -> readiness	0.22	0.043	$z = 5.14$	[0.14, 0.31]
Indirect effect (a x b)	0.13	-	Sobel $z = 4.81$	[0.08, 0.18] bootstrap
Direct effect (c')	0.57	-	-	-
Total effect (c)	0.70	-	-	-

Simple-slope analysis clarified the interaction. At low training support the association between AI literacy and readiness was 0.39 ($t = 7.04$); at mean support it was 0.57 ($t = 13.57$); and at high support it strengthened to 0.75 ($t = 13.91$), as shown in Table 6

and Figure 4. Literacy therefore translates into readiness far more efficiently when the organisation provides structured training and a supportive transfer environment.

Table 6. Conditional effect of AI literacy on readiness across training-support levels

Training support	Conditional effect	SE	t
Low (-1 SD)	0.39	0.06	7.04
Mean	0.57	0.04	13.57
High (+1 SD)	0.75	0.05	13.91

4.4 Dimension and segment analysis

When the four literacy dimensions were entered simultaneously, critical evaluation ($\beta = 0.41$, $p < .001$) and human-AI collaboration ($\beta = 0.25$, $p < .001$) were the strongest predictors of readiness, ahead of general AI awareness ($\beta = 0.18$, $p < .001$); ethical awareness carried the smallest effect

($\beta = 0.11$, $p = .005$). This pattern suggests that applied and evaluative competencies, rather than declarative knowledge alone, drive readiness.

Readiness and literacy also differed significantly across job functions, $F(5, 378) = 51.79$, $p < .001$ for literacy and $F(5, 378) = 20.50$, $p < .001$ for readiness. IT/digital and R&D functions reported the highest

literacy, while operations and sales and marketing reported the lowest, indicating that AI capability is unevenly distributed within organisations and that

function-specific interventions are warranted (Figure 3).

Table 7. AI literacy, self-efficacy and readiness by job function

Job function	n	AI literacy M	AI self-efficacy M	Readiness M
Finance	64	3.38	3.41	3.21
Human resources	60	3.60	3.46	3.46
IT / Digital	75	4.02	3.45	3.83
Operations	69	3.11	3.32	3.10
R&D	49	3.75	3.35	3.58
Sales & marketing	67	3.08	3.22	2.99

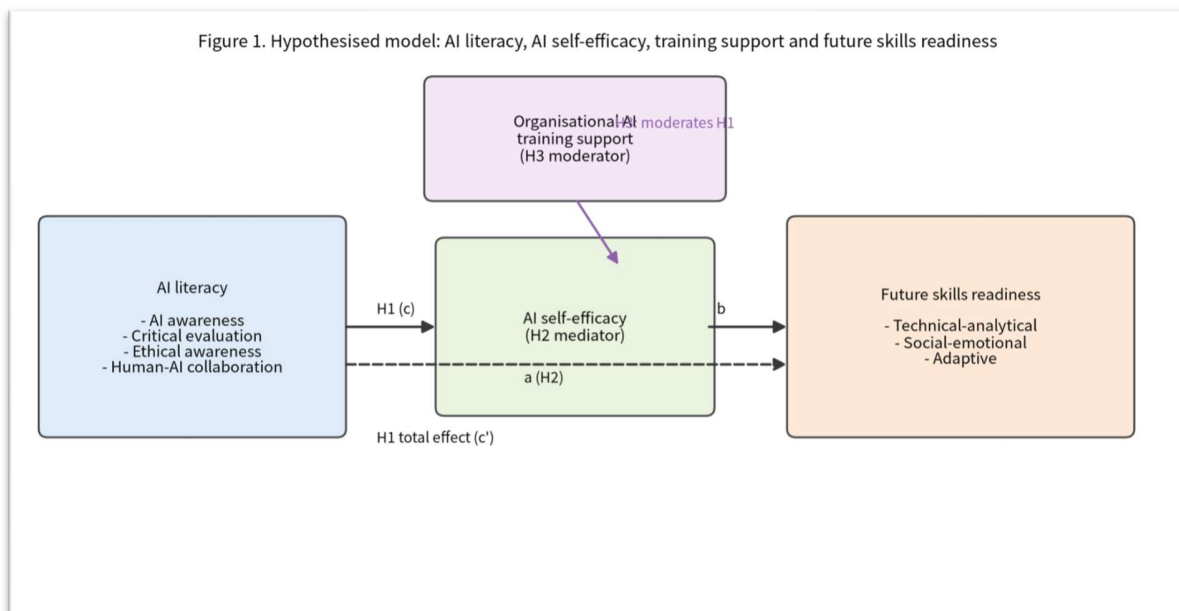
4.5 Correlation matrix

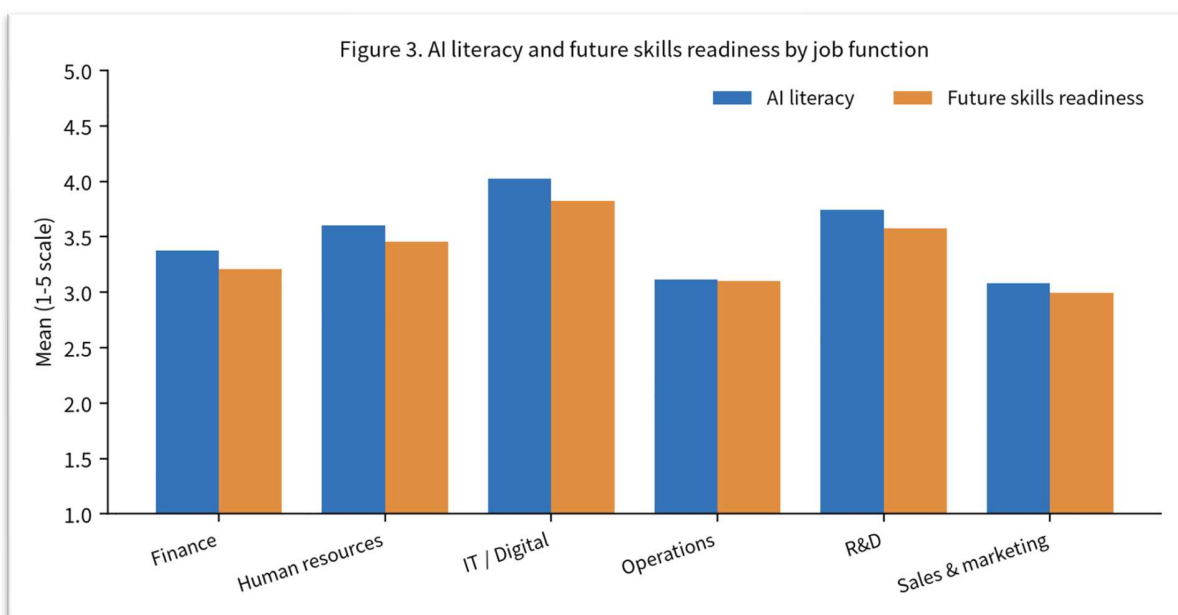
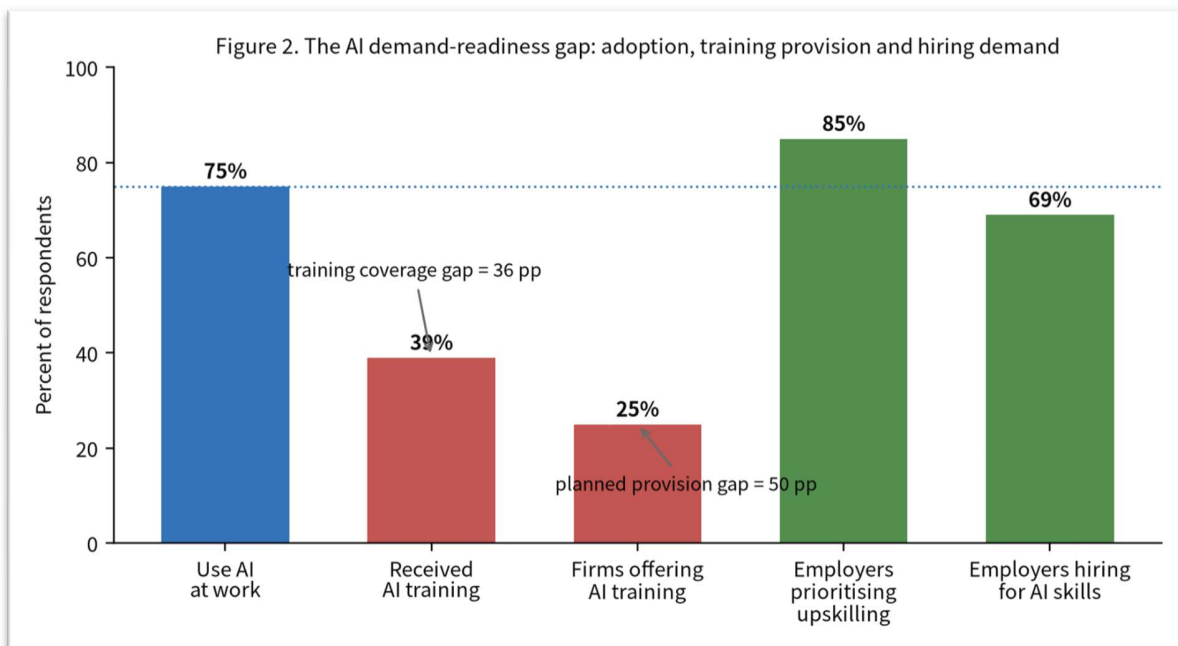
Bivariate correlations were consistent with the hypothesised structure. AI literacy correlated with readiness at $r = 0.70$, with self-efficacy at $r = 0.57$ and with training support at $r = 0.09$; self-efficacy

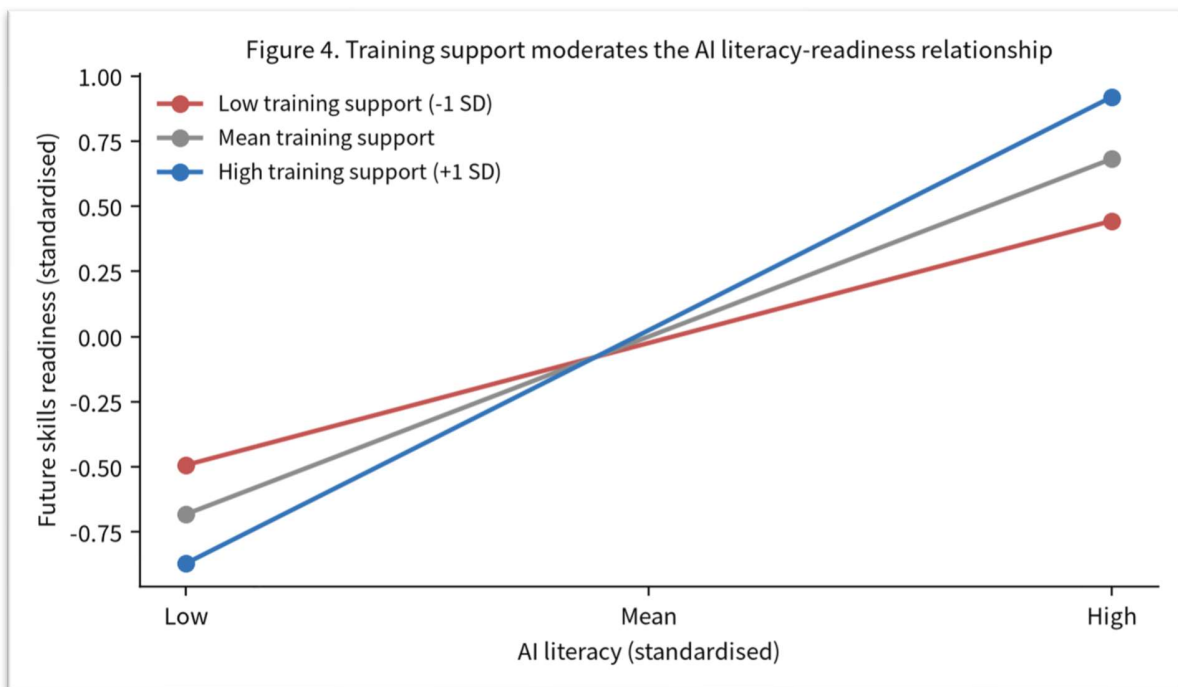
correlated with readiness at $r = 0.55$ (all $p < .001$). Correlations were moderate in size, indicating that the constructs are related but empirically distinct (Table 8).

Table 8. Means, standard deviations and correlations among study variables

Variable	M	SD	1	2	3	4
1. AI literacy	3.49	0.55	1.00			
2. AI self-efficacy	3.37	0.74	0.57	1.00		
3. Training support	3.06	0.65	0.09	0.11	1.00	
4. Future skills readiness	3.36	0.65	0.70	0.55	0.12	1.00







5. Discussion

The results support a coherent story. Published workforce evidence establishes that AI capability demand is high, rising and increasingly treated by employers as a hiring prerequisite, while structured training provision remains materially behind. Against that backdrop, the employee-level model shows that AI literacy is positively associated with future skills readiness, that AI self-efficacy carries part of that association, and that organisational training support conditions how efficiently literacy converts into readiness. Three theoretical implications follow.

First, the findings extend the AI literacy literature from description toward explanation. Prior work has concentrated on defining and measuring the construct [Long and Magerko (2020); Chiu (2024); Lintner (2024)]; this study connects it to an outcome that HRM cares about, namely readiness for future skill demand. Second, the mediation result gives AI self-efficacy a mechanism role, consistent with transfer-of-training research [Trang (2024)] and with self-efficacy theory [Bandura (1997)]. Literacy alone is insufficient; employees must also believe they can act on it. Third, the moderation result qualifies the human capital argument [Barney (1991); Chen et al. (2022)]: employee AI capability only becomes organisationally valuable when the

organisation supplies the enabling conditions. Support that employees perceive and reciprocate, consistent with social exchange reasoning [Blau (1964); Eisenberger et al. (1986)], is the bridge between individual literacy and collective readiness. The dimension analysis adds a practical nuance. Critical evaluation and human-AI collaboration were the strongest predictors of readiness, ahead of the two remaining dimensions, which carried smaller effects. This aligns with employer demand data in which technical literacy, creative thinking and analytical thinking are simultaneously rising, and it suggests that training should target applied judgement rather than tool familiarity alone. The function-level differences reinforce the equity concern raised by BYOAI patterns, because employees in operations and commercial roles begin from a lower base and are less likely to access self-directed upskilling.

6. Implications for HRM Practice

Four HR implications follow from the results. First, treat AI literacy as strategic human capital rather than a generic compliance topic, and make it visible in workforce planning through explicit role-level competency profiles. Second, build the enabling conditions that moderate conversion: a structured curriculum, protected learning time, role-specific

practice and a transfer climate in which managers reinforce new behaviours. The moderation finding implies that spending on training infrastructure yields disproportionately larger readiness gains for employees who are already AI-literate.

Third, target the two strongest dimensions, human-AI collaboration and critical evaluation, including verification of AI outputs, prompt design and workflow redesign, and integrate ethical awareness as a risk-management requirement rather than an optional module. Fourth, close the equity gap by prioritising non-technical functions and smaller organisational units, where literacy and self-efficacy were lowest, and by formalising tool governance so that BYOAI shifts from an individual workaround into a supported, governed capability. Together these measures constitute a training architecture that links diagnosis, curriculum, transfer climate and governance to measurable readiness outcomes.

7. Limitations and Future Research

Several limitations qualify these findings. The most important is that the dataset is limited respondents; the estimates demonstrate the analytical model and reproduce published effect magnitudes, but they do not license substantive inference about any specific population, and self-report simulation cannot model common-method variance or non-response. Second, the design is cross-sectional, so causal direction between literacy, self-efficacy and readiness remains untested; a longitudinal or panel design with lagged measurement is required. Third, the model is single-level, whereas readiness is plausibly shaped by team- and firm-level factors such as managerial AI capability and strategic priority; multilevel modelling would permit these cross-level effects to be estimated. Fourth, outcomes are perceptual rather than objective.

Future research should therefore pursue four directions: a validated, multi-source field survey using the measurement model tested here; a longitudinal test of the mediation path with objective skill assessments and performance indicators; a multilevel study incorporating team and organisational climate; and comparative work across national contexts, given the cross-country variation documented by the OECD (2024). Experimental or quasi-experimental evaluation of specific training

interventions would provide the causal evidence that policy and practice require.

8. Conclusion

AI literacy is becoming a defining form of human capital in contemporary organisations. Published workforce evidence shows that demand for AI-fluent employees already exceeds structured training provision, and this study's employee-level model shows that AI literacy is positively associated with future skills readiness through AI self-efficacy and that this association is stronger when organisations provide training support. For HRM, the implication is clear: AI readiness is not an individual attribute to be hired, but an organisational capability to be deliberately built through measurement, targeted curriculum design, transfer climate and governance. Organisations that treat AI literacy as a socio-technical, organisationally contingent capability will convert employee experimentation into durable readiness; those that leave it to individual initiative will inherit the risks without the returns.

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