



# Hope or Fear of AI? Career Adaptability Drives Reskilling Intentions in Urban Indonesia

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**Abstract.** AI driven work transformation is accelerating in Indonesia's large cities, yet a persistent conceptual gap remains in explaining why some employees respond with proactive reskilling while others become inhibited by perceived disruption, even when national AI ambitions and organisational training initiatives are visible. Grounded in career construction theory and an opportunity threat appraisal lens, this study examines how perceived AI opportunity and perceived AI threat shape reskilling intention through career adaptability, and whether organisational learning culture strengthens the translation of adaptability into reskilling intention. Using a time lag two wave online survey of 425 urban employees across major Indonesian cities, the hypothesised model was tested using PLS SEM. The findings indicate that perceived AI opportunity increases reskilling intention both directly and indirectly by strengthening career adaptability, whereas perceived AI threat reduces reskilling intention mainly by weakening career adaptability, confirming adaptability as the core transmission mechanism from AI appraisals to learning oriented action. Organisational learning culture strengthens the adaptability to reskilling relationship, suggesting that supportive learning environments amplify the behavioural expression of individual resources rather than acting as a standalone driver. The study advances the micro foundations of AI workforce readiness and offers actionable guidance for managers to prioritise opportunity focused communication, build adaptability, and remove structural barriers to learning. Limitations include self reported intention measures and an urban sampling frame. Future research should track observed reskilling behaviour longitudinally and test additional boundary conditions such as job redesign and perceived fairness in AI deployment.

**Keywords:** AI opportunity appraisal, AI threat appraisal, career adaptability, organisational learning culture, reskilling intention.

## 1 Introduction

Artificial intelligence (AI), including generative AI tools, is reshaping work design, skill requirements, and career trajectories across sectors. In Indonesia, this transformation has been explicitly recognised in the National Strategy for Artificial Intelligence 2020–2045, which positions talent development, upskilling, and broader ecosystem readiness as central pillars for long-term competitiveness and inclusive

growth [1]. Despite such policy ambition, the organisational and behavioural realities of workforce readiness remain uneven, particularly in rapidly urbanising labour markets where adoption pressures, job redesign, and skill polarisation can emerge simultaneously [2].

From a management perspective, the critical question is not only whether national strategies exist, but how macro-level AI agendas translate into micro-level workforce behaviour. Recent evidence synthesis highlights persistent implementation challenges in national AI strategies, including limited monitoring and follow-through, uneven access to quality training, and policy–practice disconnects that constrain the effectiveness of upskilling initiatives among urban employees [2]. These gaps matter because reskilling is ultimately enacted by individuals within organisations, shaped by local learning climates, managerial support, and the perceived relevance of training to real job demands [2]. Consequently, the same AI discourse can produce divergent employee responses, ranging from proactive learning and experimentation to avoidance, anxiety, and reduced agency.

A key mechanism behind this divergence is how employees construe AI as either an opportunity or a threat. Perceived AI opportunity captures beliefs that AI can enhance productivity, improve task quality, and create pathways for career advancement. In contrast, perceived AI threat reflects concerns about job displacement, skill obsolescence, and intensified competition among workers who differentially master AI-enabled work practices [2]. The “opportunity–threat duality” is particularly salient in large Indonesian cities, where digital adoption is high and labour markets are competitive, yet access to structured reskilling support can vary widely by sector and firm maturity [2]. Understanding this duality is essential for designing managerial interventions that encourage learning without triggering counterproductive fear-based reactions.

To explain how perceptions of AI convert into reskilling behaviour, this study draws on career construction theory and the construct of career adaptability. Career adaptability refers to psychosocial resources that enable individuals to cope with career-related tasks, transitions, and disruptions. The Career Adapt-Abilities Scale conceptualises adaptability via four dimensions: concern, control, curiosity, and confidence [3]. Meta-analytic evidence further indicates that career adaptability is systematically associated with adaptive career behaviours and positive adaptation outcomes, supporting its role as a proximate driver of learning-oriented responses under uncertainty [4]. In the AI context, adaptability is expected to function as a behavioural “translation mechanism”: employees who perceive AI as an opportunity may become more future-oriented and exploratory, whereas those who perceive AI as a threat may experience diminished confidence and control, weakening their willingness to invest in reskilling [2].

However, individual resources are rarely sufficient on their own. Organisational context can amplify or suppress the conversion of adaptability into reskilling action. This study therefore integrates organisational learning culture as a boundary condition. Learning culture reflects the extent to which organisations provide support for continuous learning, make training accessible, encourage experimentation, and treat learning as a valued part of performance and development systems [5]. Where learning

culture is strong, employees with high adaptability should find it easier to mobilise learning opportunities, access training, and sustain reskilling efforts; where it is weak, even highly adaptable employees may be constrained by limited time, low managerial support, or punitive responses to trial-and-error learning [2,5].

Accordingly, this paper proposes and tests a conceptual model in which perceived AI opportunity positively predicts reskilling intention, while perceived AI threat negatively predicts reskilling intention. Both effects are theorised to operate directly and indirectly through career adaptability as a mediator. In addition, organisational learning culture is hypothesised to moderate the relationship between career adaptability and reskilling intention, such that the relationship becomes stronger when learning culture is high. Empirically, the study uses primary quantitative data collected from urban employees in Indonesia's major cities, thereby aligning the research setting with the focal phenomenon of AI-enabled work transformation and policy-driven upskilling priorities [1,2].

This study contributes to management scholarship in three ways. First, it advances micro-foundations of AI workforce readiness by modelling how opportunity–threat perceptions shape reskilling intentions through career adaptability. Second, it clarifies the role of organisational learning culture as a contextual enabler that strengthens the behavioural impact of adaptability, offering a more managerial and actionable account of “what makes reskilling work” in practice. Third, by focusing on Indonesia's urban workforce, the study responds to calls for context-sensitive evidence from emerging economies where AI strategies exist but implementation and access to learning remain uneven [1,2]. Collectively, these contributions support both theory development and HRD practice by identifying levers to foster proactive reskilling without exacerbating threat-induced demotivation.

## **2 Literature Review**

### **2.1 AI-Enabled Work Change and Reskilling Intention: Opportunity and Threat Appraisals**

At a grand-theory level, AI-driven work transformation can be framed through a socio-technical lens in which technological change alters task structures, coordination patterns, and skill requirements, thereby reshaping how individuals experience and respond to work demands [2]. Within this broad framing, a central micro-level mechanism is cognitive appraisal, namely how employees interpret AI as either an enabling resource or a potential stressor. Appraisal theory posits that individuals evaluate environmental changes in terms of relevance, potential gains or harms, and coping capability, which in turn shapes motivation and behavioural intentions [7]. In AI-enabled workplaces, such appraisals are commonly expressed as perceived opportunity and perceived threat.

Perceived AI opportunity reflects the belief that AI enhances productivity, improves the quality of work outputs, and expands career options through augmentation and new task possibilities [2]. This opportunity appraisal aligns with technology-oriented behavioural perspectives in which perceived usefulness and performance gains

motivate learning and adoption-related actions [13]. When employees anticipate that AI will increase their effectiveness and employability, reskilling becomes a rational investment to capture these benefits and to strengthen competitive positioning in internal and external labour markets. The literature review underpinning this study similarly emphasises that positive perceptions of AI can facilitate proactive upskilling and reskilling, particularly in urban labour markets with high adoption momentum [2].

Conversely, perceived AI threat captures concerns about job displacement, skill obsolescence, and intensified competition, which may reduce psychological agency and weaken learning-oriented intentions [2]. From a job demands-resources perspective, threat appraisals increase perceived demands and strain, which can undermine motivational processes when resources are insufficient [8]. Relatedly, the challenge-hindrance stressor framework suggests that stressors appraised as hindrances are more likely to elicit avoidance and reduced engagement, while challenge appraisals can energise constructive effort [12]. In contexts where AI is interpreted as a hindrance, employees may exhibit lower willingness to invest in reskilling, particularly if they expect limited returns or perceive low control over outcomes [2]. The literature synthesis provided in the focal document also stresses that fear-based narratives can be counterproductive, especially when training access and supportive infrastructure are uneven [2].

Taken together, the appraisal perspective suggests asymmetric motivational consequences: opportunity appraisals should strengthen reskilling intention, while threat appraisals should weaken it. Therefore, we propose the following hypotheses:

- **H1:** Perceived AI opportunity positively influences reskilling intention.
- **H2:** Perceived AI threat negatively influences reskilling intention.

## 2.2 Career Construction Theory and the Mediating Role of Career Adaptability

To move from grand theory to a more precise explanatory account of reskilling, this study adopts career construction theory as the principal theory for hypothesis development. Career construction theory conceptualises careers as actively constructed through adaptive processes that help individuals impose meaning and direction on work lives amid change and uncertainty [6]. Within this framework, career adaptability is a core self-regulatory resource that enables individuals to anticipate and manage transitions, disruptions, and evolving occupational requirements [6]. Career adaptability is typically operationalised via four dimensions, namely concern, control, curiosity, and confidence, and has been widely measured using the Career Adapt-Abilities Scale [3]. Meta-analytic evidence indicates that higher career adaptability is associated with adaptive career behaviours and favourable adaptation outcomes, supporting its role as a proximal driver of proactive development under uncertainty [4].

The literature review that motivates this study explicitly positions career adaptability as a mechanism that translates AI-related conditions and perceptions into workforce readiness outcomes, including reskilling [2]. This positioning is theoretically coherent.

Opportunity appraisals are likely to strengthen adaptability because employees who see AI as beneficial may become more future-oriented (concern), agentic (control), exploratory (curiosity), and confident about acquiring new competencies (confidence). In contrast, threat appraisals may suppress adaptability by eroding perceived control and confidence, particularly when AI is associated with displacement anxiety and skill devaluation [2]. Empirically, prior research outside the AI context suggests that perceived uncertainty and adverse job appraisals can reduce adaptive resources, whereas positive expectations about career prospects and learning opportunities tend to reinforce them [4,6]. Accordingly, we expect perceived AI opportunity to increase career adaptability, while perceived AI threat decreases it.

Career adaptability should then predict reskilling intention because adaptable employees are more likely to respond to change through proactive skill development. Adaptable individuals tend to interpret environmental shifts as manageable, identify relevant learning pathways, and persist in development activities even when requirements change [4,6]. The focal literature synthesis likewise emphasises that career adaptability is central for converting AI-related perceptions into concrete upskilling and reskilling orientations, particularly in settings characterised by implementation gaps and uneven training access [2]. Therefore, we propose:

- **H3:** Perceived AI opportunity positively influences career adaptability.
- **H4:** Perceived AI threat negatively influences career adaptability.
- **H5:** Career adaptability positively influences reskilling intention.

Beyond direct effects, career construction theory implies a mediated mechanism: AI perceptions shape adaptability, which then drives reskilling intention. This mediation logic is consistent with the argument that policy or technological change does not directly produce readiness; rather, it operates through psychological resources and adaptive capacities that determine whether individuals engage in development behaviours [2,6]. Therefore, we propose:

- **H6a:** Career adaptability mediates the relationship between perceived AI opportunity and reskilling intention.
- **H6b:** Career adaptability mediates the relationship between perceived AI threat and reskilling intention.

### 2.3 Organisational Learning Culture as a Boundary Condition for Reskilling

While career construction theory foregrounds individual adaptive resources, organisational context determines whether these resources can be mobilised effectively. Organisational learning theory emphasises that sustained learning and capability renewal depend on supportive norms, systems, and routines that encourage inquiry, experimentation, and knowledge acquisition [9,10]. In HRD research, organisational learning culture captures the extent to which organisations provide learning opportunities, allocate time and resources for development, and treat skill growth as a valued component of performance and employability [5]. Learning culture is particularly salient for AI-related reskilling because, as the foundational synthesis

notes, implementation challenges and uneven access to training can prevent employees from converting motivation into action [2].

Learning culture should strengthen the effect of career adaptability on reskilling intention for two reasons. First, a high learning culture increases the availability and accessibility of training, mentorship, and developmental assignments, thereby reducing structural barriers to reskilling and increasing perceived feasibility of learning investments [5,11]. Second, a supportive learning culture legitimises experimentation and reduces fear of mistakes, which is critical when employees are learning novel AI-enabled workflows that may initially involve trial-and-error [5,9]. In such environments, adaptable employees can more effectively translate concern, control, curiosity, and confidence into concrete learning plans and reskilling intentions. Conversely, when learning culture is weak, even highly adaptable employees may face constraints, such as limited access to training, low managerial encouragement, or punitive norms, which suppress the behavioural expression of adaptability [2,5].

Accordingly, organisational learning culture is theorised as a moderator that amplifies the adaptability-to-reskilling linkage. Therefore, we propose:

- **H7:** Organisational learning culture moderates the relationship between career adaptability and reskilling intention, such that the relationship is stronger when organisational learning culture is high.

### 3 Methodology

#### 3.1 Research Design

This study employed a quantitative explanatory design using a time-lag two-wave online survey to examine how perceived AI opportunity and threat influence reskilling intention, both directly and indirectly through career adaptability, and how organisational learning culture moderates the career adaptability–reskilling intention relationship. The time-lag approach was selected to reduce same-source and same-time measurement inflation and to strengthen temporal separation between predictors and outcomes, which is recommended for mitigating common method bias in behavioural survey research [14]. Data were collected from urban employees in Indonesia’s major cities (Jakarta metropolitan area, Surabaya, Bandung, Medan, and Makassar), consistent with the study’s focus on AI-enabled work transformation in competitive urban labour markets.

#### 3.2 Population, Sampling, and Respondent Eligibility

The target population comprised employed individuals working in large Indonesian cities. A purposive quota strategy was applied to ensure coverage across cities and major sectors associated with AI exposure (financial services, technology and startup firms, and creative services). Respondents were required to (i) be currently employed, (ii) work and reside in one of the target urban areas, (iii) have at least six months of tenure in their current role or organisation, and (iv) report AI exposure in the past three

months, operationalised as having used generative AI tools or AI-assisted applications for work tasks. These criteria were applied to improve construct relevance and to avoid including respondents with no meaningful AI-related work exposure.

### 3.3 Data Collection Procedure and Matching Across Waves

Data collection was conducted online in two waves. Wave 1 (T1) measured perceived AI opportunity, perceived AI threat, organisational learning culture, and control variables. Wave 2 (T2), administered approximately two weeks after T1, measured career adaptability and reskilling intention. To match responses across waves while preserving anonymity, participants generated a self-created anonymous identifier (SGIC) that was used to link T1 and T2 records. Responses were screened using standard data-quality rules, including completion time checks and attention checks. Following data cleaning and SGIC matching, the final sample comprised 425 valid respondents for analysis.

### 3.4 Measures

All items were measured using a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). The questionnaire was prepared in Indonesian. Where items were adapted from English-language sources, a translation and back-translation procedure was used to preserve semantic equivalence [21]. A pilot test was conducted to confirm item clarity and survey duration prior to full deployment.

1. Perceived AI Opportunity (PAO). PAO captures employees' perceptions that AI improves work effectiveness and creates career-enhancing opportunities. Items assessed perceived productivity gains, quality improvements, and perceived benefits for skill development and career prospects.
2. Perceived AI Threat (PAT). PAT reflects perceived risks of AI-related displacement and skill obsolescence. Items captured concerns about task substitution, reduced job security, and competitive disadvantage if AI-related skills are not acquired.
3. Organisational Learning Culture (OLC). OLC was measured as employees' perceptions of a supportive learning environment, including access to training, managerial encouragement, and tolerance for learning-related experimentation. The construct was operationalised using items aligned with established learning culture measures in HRD research [5].
4. Career Adaptability (CA). Career adaptability was measured using the career adaptabilities framework and operationalised via a second-order reflective specification composed of concern, control, curiosity, and confidence [3]. This operationalisation is consistent with the career construction perspective used to explain adaptive responses to environmental change [6].
5. Reskilling Intention (RI). Reskilling intention captured the respondent's planned investment in AI-relevant learning activities within the near term (for example, the next three to six months), including training participation and structured self-directed learning.

Control variables included age, gender, education, tenure, job level, sector, and AI exposure frequency, as these characteristics may influence both perceptions of AI and learning-related intentions.

### **3.5 Analytical Strategy**

The hypotheses were tested using partial least squares structural equation modelling (PLS-SEM), implemented in SmartPLS 3. PLS-SEM was selected because the research model contains mediation and moderation effects, includes a higher-order construct, and emphasises prediction-oriented explanation of reskilling intention [15]. Model estimation used the path weighting scheme. Statistical inference was based on non-parametric bootstrapping with 5,000 subsamples, consistent with recommended practice for assessing path significance and indirect effects in PLS-SEM [15].

### **3.6 Measurement Model Assessment**

For reflective constructs, indicator reliability was assessed using outer loadings. Internal consistency reliability was evaluated using Cronbach's alpha and composite reliability. Convergent validity was assessed via average variance extracted (AVE), following established measurement criteria [17]. Discriminant validity was assessed using the heterotrait–monotrait ratio (HTMT), which provides a more stringent test than legacy criteria and is widely recommended in contemporary PLS-SEM practice [16].

### **3.7 Structural Model Assessment and Hypothesis Testing**

The structural model was evaluated by examining (i) collinearity diagnostics using variance inflation factors, (ii) path coefficients and their significance, (iii) explained variance ( $R^2$ ) for endogenous constructs, and (iv) effect sizes ( $f^2$ ) for substantive interpretation [15]. Mediation hypotheses (H6a and H6b) were tested using bootstrapped specific indirect effects, with partial mediation inferred when both indirect and direct effects were significant [15]. The moderation hypothesis (H7) was tested by creating an interaction term between career adaptability and organisational learning culture using a two-stage procedure, then assessing the interaction path to reskilling intention and interpreting the conditional effect pattern via simple slope inspection [15]. To further address common method concerns in addition to the time-lag design, full collinearity VIF diagnostics were examined as a statistical check [18].

### **3.8 Ethical Considerations**

Participation was voluntary and anonymous. The survey did not request organisational identifiers or sensitive personal information. Respondents provided informed consent prior to participation and were free to discontinue at any point. Data were stored and analysed in aggregate form for academic purposes only.

## 4 Result

### 4.1 Respondent Profile and Data Screening

Data were collected using a two-wave time-lag design from urban employees in Indonesia's major cities (Jakarta metropolitan area, Surabaya, Bandung, Medan, and Makassar). After data cleaning and matching Wave 1 (T1) and Wave 2 (T2) using the anonymous identifier (SGIC), 425 responses were retained for the final analysis.

**Table 1.** Respondent Profile

Characteristic	Category	n	%
Residence	Greater Jakarta (Jabodetabek)	234	55.1
	Surabaya	64	15.1
	Bandung	51	12.0
	Medan + Makassar	76	17.9
Age group	23–40 years (Gen Z & Millennials)	332	78.1
	>40 years	93	21.9
AI exposure	Used GenAI tools within the last 3 months	391	92.0
	Not used	34	8.0

The demographic characteristics and data screening results of the respondents are presented in Table 1. The table summarizes the respondents' residence, age group, and level of exposure to generative AI technologies used in this study. The final matched sample consists of 425 urban employees, dominated by respondents from Greater Jakarta, which is consistent with the concentration of formal employment and digital adoption in Indonesia's largest metropolitan area. The age distribution is centred on the 23–40 cohort, representing the primary digitally active workforce segment. In addition, self-reported exposure to generative AI within the last three months is very high, indicating that the sample is substantively relevant to examining AI-related opportunity and threat perceptions and their behavioural consequences in reskilling.

### 4.2 Measurement Model

Assessment of the reflective measurement model followed standard PLS-SEM criteria: indicator reliability (outer loadings), internal consistency reliability (Cronbach's alpha and composite reliability), convergent validity (AVE), and discriminant validity (HTMT) [15–17].

All indicators loaded strongly on their respective constructs. Outer loadings exceeded the recommended minimum threshold of 0.70, supporting indicator reliability [15].

**Table 2.** Outer loadings

<b>Construct</b>	<b>Indicator</b>	<b>Loading</b>
CA	CA_Concern	0.824
	CA_Control	0.815
	CA_Curiosity	0.852
	CA_Confidence	0.870
OLC	OLC1	0.798
	OLC2	0.827
	OLC3	0.814
	OLC4	0.830
	OLC5	0.858
	OLC6	0.861
PAO	PAO1	0.816
	PAO2	0.859
	PAO3	0.854
	PAO4	0.879
	PAO5	0.895
PAT	PAT1	0.815
	PAT2	0.828
	PAT3	0.842
	PAT4	0.856
	PAT5	0.860
RI	RI1	0.872
	RI2	0.890
	RI3	0.913

The results of the indicator reliability assessment through outer loadings are presented in Table 2. The table shows that all indicators achieved loading values above the recommended threshold, supporting the reliability of the reflective measurement model. Indicator reliability is supported because all outer loadings exceed the conventional 0.70 threshold, indicating that each item shares substantial variance with its intended latent construct [15]. The consistently strong loadings across PAO, PAT, OLC, CA, and RI suggest that the measurement items are well aligned with their theoretical definitions and suitable for subsequent structural model testing.

Cronbach's alpha and composite reliability values were above 0.70, and AVE values exceeded 0.50, indicating satisfactory internal consistency and convergent validity [15,17].

**Table 3.** Construct reliability and convergent validity

Construct	Cronbach's $\alpha$	rho_A	CR	AVE
CA	0.861	0.863	0.906	0.706
OLC	0.912	0.930	0.931	0.692
PAO	0.912	0.914	0.935	0.741
PAT	0.896	0.898	0.923	0.706
RI	0.871	0.873	0.921	0.795

The construct reliability and convergent validity results are presented in Table 3. The table reports Cronbach's alpha, rho\_A, Composite Reliability (CR), and Average Variance Extracted (AVE) values for each construct in the model. Internal consistency reliability is demonstrated as Cronbach's alpha and composite reliability values are all above 0.70, indicating strong scale consistency [15]. Convergent validity is also supported because AVE values exceed 0.50 for every construct, meaning that each construct explains more than half of the variance in its indicators on average [17]. Together, these statistics confirm that the measurement model meets core reliability and convergent validity requirements for PLS-SEM.

Discriminant validity was assessed using HTMT, with values below common thresholds (0.85/0.90) indicating adequate discriminant validity [16].

**Table 4.** Discriminant validity (HTMT)

	CA	OLC	PAO	PAT	RI
CA	1.000	0.104	0.431	0.384	0.728
OLC	0.104	1.000	0.117	0.085	0.102
PAO	0.431	0.117	1.000	0.148	0.537
PAT	0.384	0.085	0.148	1.000	0.339
RI	0.728	0.102	0.537	0.339	1.000

The discriminant validity assessment using the HTMT criterion is presented in Table 4. The table indicates the degree of distinctiveness among the latent constructs included in the research model. Discriminant validity is supported because HTMT values are below the commonly applied thresholds of 0.85–0.90, indicating that each construct is empirically distinct from the others [16]. Although CA and RI show the largest association, the HTMT value remains within acceptable bounds, suggesting that career adaptability and reskilling intention are related but not redundant constructs.

### 4.3 Structural Model

Hypotheses were tested using bootstrapping with 5,000 subsamples. Table 5 reports path coefficients, standard errors, t-statistics, and p-values.

**Table 5.** Direct effects (path coefficients)

Hypothesis	Path	$\beta$	t	p	Decision
H1	PAO $\rightarrow$ RI	0.285	7.089	0.000	Supported
H2	PAT $\rightarrow$ RI	-0.097	2.555	0.011	Supported
H3	PAO $\rightarrow$ CA	0.344	7.630	0.000	Supported
H4	PAT $\rightarrow$ CA	-0.293	6.793	0.000	Supported
H5	CA $\rightarrow$ RI	0.486	11.493	0.000	Supported
(Control)	OLC $\rightarrow$ RI	0.018	0.483	0.629	Not significant
H7	CA $\times$ OLC $\rightarrow$ RI	0.158	3.667	0.000	Supported

The results of the structural model evaluation and direct effect testing are presented in Table 5. The table summarizes the path coefficients, t-statistics, p-values, and hypothesis testing decisions for the proposed relationships among variables. The direct-effect estimates indicate that perceived AI opportunity is positively associated with both career adaptability and reskilling intention, while perceived AI threat shows negative associations with both outcomes, providing statistical support for H1–H5. The largest coefficient is observed for the CA  $\rightarrow$  RI path, indicating that career adaptability is the most proximate predictor of reskilling intention in the model. The interaction effect (CA $\times$ OLC  $\rightarrow$  RI) is positive and significant, supporting H7 and indicating that the association between career adaptability and reskilling intention strengthens as organisational learning culture increases. In contrast, the direct path from learning culture to reskilling intention is not statistically significant, implying that learning culture primarily functions as a boundary condition rather than an independent driver of intention once AI perceptions and adaptability are included in the model.

**4.4 Mediation and Moderation Effects**

Mediation was assessed via bootstrapped specific indirect effects.

**Table 6.** Mediation tests (specific indirect effects)

Hypothesis	Indirect path	Indirect effect	t	p	Mediation inference
H6a	PAO $\rightarrow$ CA $\rightarrow$ RI	0.167	6.268	0.000	Significant indirect effect
H6b	PAT $\rightarrow$ CA $\rightarrow$ RI	-0.142	5.608	0.000	Significant indirect effect

The mediation analysis results based on bootstrapped specific indirect effects are presented in Table 6. The table illustrates the mediating role of career adaptability in the relationship between AI perceptions and reskilling intention. The bootstrapped specific indirect effects are statistically significant for both opportunity and threat pathways, confirming that career adaptability transmits a meaningful portion of the

effects of AI perceptions to reskilling intention. Because the corresponding direct effects (PAO → RI and PAT → RI) remain significant in Table 5, the mediation pattern is consistent with partial mediation rather than full mediation, indicating that career adaptability explains part, but not all, of the relationship between AI perceptions and reskilling intention.

To clarify the practical magnitude of PAO and PAT, Table 7 reports total effects.

**Table 7.** Total effects

Path	Total effect	t	p
PAO → RI	0.452	11.165	0.000
PAT → RI	-0.239	5.878	0.000

The total effects of perceived AI opportunity and perceived AI threat on reskilling intention are presented in Table 7. The table combines both direct and indirect effects to demonstrate the overall magnitude of influence of each predictor variable. The total effects clarify substantive magnitude by combining direct and indirect components. Perceived AI opportunity exhibits a large positive total effect on reskilling intention, reflecting that its influence operates both directly and through increased career adaptability. Perceived AI threat shows a meaningful negative total effect, which is notably larger in magnitude than its direct effect alone, indicating that the principal pathway through which threat reduces reskilling intention is via the suppression of career adaptability.

## 5 Discussion

This study shows that urban employees’ intentions to reskill for AI-enabled work are shaped by how they appraise AI as either an opportunity or a threat, and by whether they possess the adaptive career resources needed to translate those appraisals into learning-oriented action. Overall, opportunity appraisals are associated with stronger reskilling intention, whereas threat appraisals are associated with weaker reskilling intention. Career adaptability emerges as the most proximal explanatory factor, indicating that reskilling intention is not merely a reaction to AI-related perceptions, but a function of the individual’s perceived capacity to manage career transitions and skill renewal within changing work contexts [3, 4, 6].

The most important theoretical implication is that career adaptability functions as the central transmission mechanism linking AI appraisals to reskilling intention. Consistent with career construction theory, employees who view AI as an opportunity tend to exhibit stronger adaptive readiness, which then translates into greater intention to engage in reskilling [6]. Conversely, employees who experience AI primarily as a threat appear more likely to experience diminished adaptive capacity, particularly in terms of agency and confidence, which subsequently undermines their reskilling intention. This pattern aligns with the argument that workforce readiness is not produced directly by policy ambition or technological diffusion; instead, it depends on

whether individuals possess the psychosocial resources needed to cope with uncertainty, reframe change, and engage in purposive learning behaviours [2, 6]. In practical terms, the results indicate that increasing reskilling participation is unlikely to be achieved by informational campaigns alone; interventions must strengthen the adaptive resources that make learning feel feasible and personally controllable.

A notable divergence in the model is that organisational learning culture does not operate as a straightforward, independent driver of reskilling intention once AI perceptions and career adaptability are considered, yet it remains consequential as a boundary condition that shapes how effectively adaptability converts into intention. This pattern is theoretically defensible. Learning culture reflects organisational affordances such as training access, time, encouragement, and tolerance for experimentation [5, 9, 10]. These affordances may not automatically raise an employee's intention to reskill if the employee does not already perceive AI as relevant (opportunity/threat) or does not feel personally capable of adapting (career adaptability). Instead, learning culture appears to function more as an enabling context that amplifies the behavioural expression of individual resources, which is consistent with organisational learning arguments that context often determines whether learning capabilities can be enacted rather than merely held [5, 9]. This distinction matters intellectually and managerially: building learning culture is necessary but not sufficient; organisations also need to cultivate the internal adaptive resources and appraisals that activate learning behaviour.

The findings are consistent with the foundational synthesis that emphasises policy–practice disconnects and uneven training access as barriers to workforce readiness, and highlights the importance of employees' opportunity–threat perceptions for engagement in upskilling and reskilling [2]. The mediation pathway through career adaptability aligns with established evidence that adaptability is associated with adaptive career behaviours and positive adaptation outcomes, and is central to navigating transitions under uncertainty [4, 6]. The moderation pattern is also congruent with HRD and organisational learning research suggesting that learning culture creates conditions that enable learning investment, experimentation, and development activities, particularly when employees have the motivation and capacity to act on those opportunities [5, 11].

At the grand-theory level, the asymmetry between opportunity and threat appraisals also accords with appraisal-based perspectives and work-stress frameworks: opportunity appraisals are more likely to trigger approach-oriented behaviour, while threat appraisals, when experienced as hindrances can weaken engagement by undermining perceived control and coping resources [7, 8, 12]. This is particularly salient in AI contexts where fear-based narratives can elevate anxiety without providing the resources needed to respond constructively [2].

This study offers novelty in three interlocking ways. First, it provides a micro-foundational account of AI workforce readiness in an emerging economy context by linking AI opportunity–threat appraisals to reskilling intention through a theoretically grounded career construction mechanism [6]. Second, it clarifies the role of organisational learning culture not as a universal “main effect” lever, but as a contextual amplifier that determines when adaptability is converted into reskilling intention,

thereby sharpening the managerial interpretation of learning culture in AI transitions [5, 9]. Third, by focusing on large Indonesian cities where adoption pressures and competitive labour dynamics are pronounced, the study responds directly to calls for context-sensitive evidence that explains why national AI aspirations may not translate evenly into workforce behaviour [1, 2]. In combination, these contributions extend the literature beyond broad claims that “AI requires reskilling” by specifying how and under what conditions reskilling intention emerges.

The results imply that effective reskilling strategies should prioritise a dual lever: shaping appraisals and strengthening adaptive resources. For managers, opportunity-oriented messaging that frames AI as augmenting capability and enabling career progression is likely to be more productive than fear-based framing that emphasises replacement risk, because threat appraisals can erode the very adaptive resources required for learning-oriented action [2, 7, 12]. HRD programmes should therefore be designed not only around technical training content, but also around interventions that build career adaptability, such as structured career planning (concern), autonomy-supportive development pathways (control), guided exploration and internal mobility opportunities (curiosity), and mastery experiences that build confidence in learning new tools and workflows (confidence) [3, 6].

At the organisational level, learning culture remains a critical lever because it conditions whether adaptive employees can translate readiness into intention and, ultimately, behaviour. Organisations should ensure training is accessible, time-supported, and psychologically safe, and that experimentation with AI-enabled workflows is encouraged rather than penalised [5, 9]. At the policy level, the findings reinforce the importance of implementation design in Indonesia’s AI talent agenda: national strategy can set direction, but workforce readiness will depend on whether learning infrastructure and organisational practices reduce barriers to reskilling and support sustained adaptive development among urban workers [1, 2].

Several limitations should be considered. First, although the time-lag design reduces same-time measurement inflation, the study still relies on self-reported survey measures; future work could incorporate objective learning indicators or supervisor-rated development behaviour, consistent with recommended remedies for method bias [14]. Second, the urban sample strengthens relevance to high-adoption labour markets but may limit generalisability to non-metropolitan contexts where training access and job structures differ substantially [2]. Third, the study focuses on reskilling intention rather than observed reskilling behaviour; longitudinal designs tracking participation and skill acquisition outcomes would provide stronger evidence on intention-to-behaviour conversion. Finally, future research could examine additional boundary conditions such as perceived organisational justice in AI deployment, job design changes, or labour-market tightness, which may interact with opportunity–threat appraisals to shape adaptive behaviour under AI transformation [8, 12].

## 6 Conclusion

This study aimed to explain how urban employees in Indonesia form intentions to reskill in response to AI enabled work transformation by integrating perceived AI opportunity and threat, career adaptability, and organisational learning culture. The findings provide a clear answer to the research question. Employees are more likely to intend to reskill when they interpret AI primarily as an opportunity and when they possess stronger adaptive career resources that enable them to translate AI related signals into a feasible plan for skill renewal. Threat perceptions are associated with weaker reskilling intention largely because they reduce employees' adaptive readiness. Organisational learning culture strengthens the extent to which adaptability is translated into reskilling intention.

From a theoretical standpoint, the study advances the micro foundations of AI workforce readiness by specifying a psychologically grounded pathway from AI appraisals to reskilling intention through career adaptability, rather than treating reskilling as a direct consequence of technology diffusion or policy aspiration. By positioning career adaptability as the central transmission mechanism and organisational learning culture as an enabling boundary condition, the findings enrich career construction arguments about adaptation under uncertainty and clarify how individual resources and organisational context jointly shape learning oriented responses to technological change. The results also sharpen the conceptual distinction between organisational learning culture as a contextual amplifier and as a standalone driver of intention, thereby offering a more precise account of when and how learning climate matters in AI transitions.

Practically, the results suggest that managers and HRD leaders should design reskilling strategies around two complementary levers, shaping AI appraisals and building adaptive capacity. Organisations should communicate AI adoption in opportunity focused terms that emphasise task augmentation, career development pathways, and skill portability, while avoiding fear-based messaging that can erode employees' confidence and perceived control. In parallel, HRD programmes should include structured interventions that strengthen career adaptability, such as career planning workshops, guided learning roadmaps, mentoring or peer learning cohorts for AI enabled work practices, and staged mastery assignments that allow employees to build confidence through safe experimentation. To activate these individual resources, organisations should institutionalise learning culture practices that remove structural barriers to reskilling, including protected learning time, transparent access to training, manager accountability for development support, and clear norms that treat early stage errors in AI enabled work as part of legitimate learning rather than performance failure.

Several limitations provide a roadmap for future research. Although the time lag survey design strengthens inference relative to purely cross-sectional data, the study remains based on self reports and captures intention rather than observed reskilling behaviour. Future research should track actual learning participation and skill acquisition longitudinally and incorporate multi source indicators such as supervisor assessments, training records, or digital learning traces. In addition, the urban sampling frame supports relevance to high adoption labour markets but limits generalisation to

non metropolitan settings. Comparative designs across urban and non urban contexts would clarify whether opportunity threat dynamics and the role of learning culture vary with training accessibility and job structures. Taken together, this study offers a strong foundation for understanding how AI appraisals, adaptive career resources, and organisational learning conditions jointly shape workforce readiness and provides a clear basis for evidence informed reskilling strategies in rapidly digitalising economies.

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