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Adoption of Artificial Intelligence and Employee Adaptive Performance Systematic Literature Review

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AI adoption; employee adaptive performance; human-AI collaboration; AI readiness; systematic literature review.

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Abstract

The adoption of artificial intelligence (AI) has transformed job demands and employee work practices. This systematic literature review examined theoretical frameworks, cognitive and behavioral mechanisms, and measurement approaches related to AI readiness and employee adaptive performance. Structured web-based searches conducted through October 13, 2026, identified English- and Indonesian-language journal articles published between 2015 and 2026. Of the 49 unique records identified, full-text retrieval was attempted for 17 reports, of which 11 were obtained and six remained inaccessible. Nine articles explicitly examined adaptive performance as an outcome, while two addressed the broader concept of adaptation. Publication details and outcome measures were reverified on October 14, 2026. The narrative synthesis identified associations between change appraisal, self-efficacy, exploratory behavior, work adjustment, and employee adaptation. The findings emphasized the importance of distinguishing AI readiness, awareness, literacy, and actual AI use as separate constructs. Positive, negative, and statistically nonsignificant associations were reported across different AI-related exposures and measurement instruments. Estimates that could not be reconciled with the original source tables were excluded from the interpretation of findings. The available evidence was insufficient to establish causal effects of AI adoption or identify a universally appropriate instrument for assessing AI readiness across occupational contexts. The review proposed a conceptual framework and a future research agenda for measuring technical and interpersonal dimensions of adaptive performance. Its findings were limited by the reliance on web-based searches, incomplete full-text access, AI-assisted screening and examination without independent human verification, and the predominance of nonexperimental study designs.

INTRODUCTION

Artificial intelligence (AI) has the potential to transform task allocation, access to information, and employee decision-making processes. These changes have made workplace adaptation an increasingly important concern in human resource development. Research on AI integration in infrastructure companies has demonstrated that improvements in operational efficiency are accompanied by task reconfiguration, evolving competency requirements, and psychological adjustments among employees (Oliveira et al., 2025; Bankins et al., 2024).

Therefore, organizational evaluations of AI adoption should consider how employees adapt to changing roles, responsibilities, and job demands.

Adaptive performance (AP) refers to employees' ability to adjust their behavior and work practices in response to changing job requirements and organizational conditions. Griffin et al. (2007) distinguished adaptive performance at the individual task, team, and organizational levels from proficiency in routine job performance. Variations in the conceptualization of adaptive performance are also evident in AI-related research. Do et al. (2025) examined reactivity, creativity, and interpersonal adaptability, whereas Rabbani et al. (2026) focused on creativity and reactivity. These differences highlight the importance of selecting measurement instruments that accurately capture the specific dimensions of workplace adaptation being investigated.

The relationship between AI adoption and employee adaptation also depends on the type of AI-related exposure examined. AI-driven human resource management (HRM) refers to the integration of AI technologies into HRM practices, whereas AI awareness concerns employees' perceptions of AI and its implications for their work. Li and Sun (2026) distinguished between challenge and hindrance appraisals, which were associated with different patterns of relationships with adaptive performance. Consequently, positive associations between AI awareness and adaptive performance should not be interpreted as direct evidence that more frequent AI use improves employee adaptability.

Previous literature reviews have examined AI-related changes in workforce skills and their implications for employees. Babashahi et al. (2024) investigated skill transformation across industries, while Jia et al. (2025) synthesized the consequences of AI adoption and the theoretical perspectives used to explain them. Building on these studies, the present review examined the relationships among different forms of AI exposure, employee adaptation processes, and the dimensions captured by adaptive performance measurement instruments. This approach sought to clarify why studies employing similar variable labels may report different findings. AI readiness introduces additional conceptual challenges because employees may possess technological knowledge, demonstrate confidence in using AI, or express readiness for organizational change without necessarily exhibiting corresponding improvements in adaptive performance. AI literacy instruments, such as the Metacognitive Awareness and AI Literacy Scale (MAILS), assess AI-related competencies and self-reported capabilities, whereas the Indonesian Adaptive Performance Scale (APS) measures workplace adaptability without requiring direct exposure to AI (Koch et al., 2024; Nasution & Wicaksono, 2025). Distinguishing these constructs is essential to maintaining conceptual clarity and preventing overlap between AI readiness as a potential predictor and adaptive performance as an outcome.

METHOD

Review Protocols and Limitations

The review followed an internally developed protocol established before the final study selection and synthesis, without external registration. An audit conducted on October 14, 2026, clarified the study selection process and restricted the use of estimates that were inconsistent with the source data. The eligibility criteria and number of studies included in the review remained unchanged. The PRISMA 2020 guidelines were used to guide reporting of the study selection process rather than to assess methodological quality (Page et al., 2021). The primary corpus comprised empirical journal articles published in English or Indonesian between 2015

and October 13, 2026. Foundational theoretical and measurement references published outside this period were used as supporting literature but were excluded from the bibliographic analysis. The search was restricted to publications from 2015 onward to emphasize contemporary research, although this restriction may have excluded relevant earlier evidence.

Aspects	Inclusion of the main corpus	Exclusion or separation
Publications	Empirical journal article 2015–October 13, 2026	Review/theory/instrument as support; proceedings/thesis not included
Language	English or Indonesian	Other languages outside the main scope
Population	Employee/worker in the context of employment	Students only or organizational outcomes only
Phenomenon	Exposure/perception/capabilities of AI or AI-related work integration	General digitalization without obvious AI components
Outcome	Explicit AP or mapable work customization	General performance or adoption intent only
Access	Full text available for appraisal	Abstracts only are recorded as not obtained
Measurement	Definitions and items/dimensions can be compared	Outcomes are more widely labeled and separated

The target population comprised employees and workers in occupational settings. Eligible studies examined AI-related exposure, perceptions of AI-induced job changes, AI-specific competencies, or AI integration into workplace processes. Studies addressing general digitalization or routine automation without an explicit AI component were excluded. Studies focusing exclusively on technology adoption intentions, general job performance, or organizational-level outcomes were not considered direct evidence of individual adaptive performance. Qualitative studies and studies employing broader measures of adaptation were retained when they provided identifiable evidence of adjustments in work practices. These studies were classified separately according to their analytical relevance, as presented in Table 1.

Table 1. Inclusion and exclusion criteria

Source: article extraction and reviewer analysis.

Sources of Information and Search Strategies

The initial search was conducted on October 13, 2026 via an AI-assisted web search service. Publisher pages, Crossref DOI records, PMCs, and institutional repositories were used to check the identity of the publication and obtain the full text; the search did not use Scopus or Web of Science direct exports. On October 14, 2026, identities, selected figures, and access to unobtained reports were re-examined as corpus audits, while the publication coverage end date remained October 13, 2026.

The five search groups include the AI–adaptive performance–adaptive relationship, cognitive mechanisms, behavior and collaboration, readiness and instruments, and complementary theory and search. The concept block combines the terms AI, adoption/use/awareness, adaptive performance, and employee. Short queries are used for results to be reviewed, and the terms theory and readiness are not required for all core queries because these requirements may exclude studies that use different mechanisms.

Complementary searches examine article references, publisher pages, and repositories; new candidates are listed according to their first discovery groups (17, 5, 7, 13, and 7). This number describes the search process performed, not a measure of the completeness of the literature.

Study Identification and Selection

The logs of the five search groups contained 208 web result entries, including copies of pages and results that were not bibliographic candidates. The curated registers contained 49 unique candidates; Figure 1 and Table 3 are started from the register because the number of web results is not equivalent to the number of article records in the database export. Deduplication was performed based on DOI or title match, and the repository copy was treated as a version of the same article. Of the 49 candidates, 26 were separated as supporting sources, five did not meet the publication type or outcome, and one could not confirm the identity of the publication. Full text was searched for 17 reports; six had not been obtained and eleven were checked and maintained in mapping. No reports were issued after a complete examination of inconsistencies in the maintained articles were addressed by limiting the use of certain claims or estimates (Table 2).

Table 2. Reconciliation of selection in the candidate register

Stages	Quantity	Basis for recording
Unique candidates in the register	49	Candidate identities are deduplicated based on DOIs or titles
Removed from the main corpus	32	26 supporters + 5 non-conforming + 1 identity not verified
Report searched for full text	17	49 − 32 = 17
Full text not yet obtained	6	17 − 6 = 11; recorded in the review access log
Full text checked	11	All reports obtained are checked
Removed after a complete inspection	0	Reporting issues are addressed at the claim and estimate levels
Articles in mapping and synthesis	11	9 named AP outcomes; 2 examined adaptation more broadly

Source: candidate register. The subcategories issued (26 supporters, 5 not in accordance with the type of publication/outcome, 1 identity not verified) are no longer added to a total of 32.

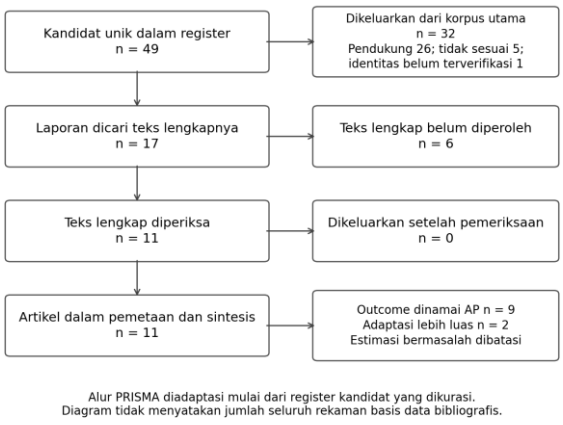


Figure 1. Selection flow in candidate register with PRISMA adaptation

Extraction, Quality Assessment, and Synthesis Strategy

Extraction records the identity of the publication, context state, sector, sample size, design, type of AI exposure, theory, mechanism, moderator, outcome, instrument, outcome, and location of evidence in the article. The context state is not derived from the author's affiliation, the ambiguity of the information is recorded as unreported, and the article becomes a unit of bibliographic calculation. The quality assessment uses the Mixed Methods Appraisal Tool (MMAT) 2018 domain as a narrative examination framework according to the study design (Hong et al., 2018), without total scores, quality ratings, or certainty of evidence that has not been supported by specific procedures.

Source search, selection, extraction, and examination are conducted with the help of AI; verification by independent human reviewers is not yet available, so quality assessments are preliminary and re-examinations are not considered an agreement between reviewers. In audits, claims in the abstract are compared with methods, tables, and appendices; if the meanings or figures cannot be reconciled, the estimates are not used as the basis for the review. The existence of a publication in the publisher or a DOI record confirms the identity of the source, but does not prove the validity of the respondent's data.

Bibliographic analysis used frequency and percentage with eleven article denominators, while content analysis used deductive coding from RQ and theme development through reading mechanisms and outcomes. Types of exposure were differentiated between AI practice/use, awareness, readiness, capability, and governance; explicit adaptive performance outcomes were separated from composite adaptations or qualitative findings. Meta-analyses were not performed because exposures, outcomes, and statistical models differed between publications, and regression coefficients, correlations, and descriptive outcomes were not combined as a single effect measure. Narrative sensitivity analysis examined whether themes could still be sustained after C11 descriptive results, C09 and C15 mediation estimates, and C04 mediation magnitude and C04 moderation direction were excluded from the basis of conclusions. Mediation in observational data was not treated as causal evidence.

RESULTS AND DISCUSSION

Study Bibliographic Profile

Table 3 summarizes eleven articles for which the full text is examined. Two articles are published in 2025 and nine in 2026; this distribution shows a corpus concentrated on the most recent publications, but does not prove the growth of the entire field as web-based searches and limited access can affect its composition.

Table 3. Characteristics of the synthesised article

ID and author	Context	Sample	Design	Display or focus
C01 Li and Sun 2026	China; Manufacturing	369	Three-wave survey	AI challenge and hindrance awareness
C03 Hasanein et al. 2026	Egypt; five-star hotels	372	Cross-cutting survey	AI awareness
C04 Do et al. 2025	United States; cross-organization	274 (+ separate validation samples)	Three-wave survey	AI-driven HRM 12-grain, two-dimensional
C09 Rabbani et al. 2026	Pakistan; information technology	202	Cross-cutting survey	AI instructional prescriptiveness

ID and author	Context	Sample	Design	Display or focus
C10 Shao 2026	Not clearly reported; cross-sector	527 surveys; 36 interviews	Mixed method	Organizational support and learning climate in the context of AI use
C11 Sunarto et al. 2026	Indonesia; Digital Companies	120	Cross-cutting survey	Uses and quality of human–AI collaboration
C12 Salama and Khairy 2026	Egypt; five-star hotels	406	Cross-cutting survey	AI and robotics awareness
C13 Peemanee et al. 2026	Thailand; private sector across jobs	387	Cross-cutting survey	Perceived value, inevitability, acceptance readiness, adaptive preparedness
C15 Wirjawan et al. 2026	Indonesia; E-commerce	285	Cross-cutting survey	Algorithmic fairness and AI anxiety
C16 Oliveira et al. 2025	Portugal; road infrastructure	10 interviews and company documents	Qualitative case studies	Integration of AI and automation in workflows
C18 Tomy et al. 2026	Not clearly reported; technology organizations	426	Cross-cutting survey	Human–AI collaboration capability and emotional intelligence

Source: full-text article. N is the number reported by the author; interview participants C10 are part of the survey sample.

The Egyptian and Indonesian contexts appear in two articles each; China, the United States, Pakistan, Thailand, and Portugal each on one article, while two articles do not describe the data collection countries decisively enough to be coded. The concentration of the hotel sector in the two studies is worth noting because the demands of their services and technologies can differ from manufacturing or knowledge jobs. The possibility of population overlap cannot be ascertained, so the sample size of the entire article is not summed as the number of unique individuals. Eleven articles were published in eleven different journals, one article each (9.09% per journal), and the journal index status was not used as a substitute for design checks, measurements, and reporting of results.

In terms of design, seven articles used cross-cutting surveys, two three-wave surveys, one mixed method, and one qualitative case study. Li and Sun (2026) and Do et al. (2025) measured variables at different times, but both used self-reports and did not randomize. Nine articles named adaptive performance outcomes, but the labels did not mean that all instruments measured the same content: two hotel studies primarily assessed adaptation approaches to customers, a descriptive study by Sunarto et al. (2026) mixed efficiency, collaboration, and adaptation perception, and Peemanee et al. (2026) used composite adaptations that included changes in work, human–AI compatibility, and trust. Oliveira et al. (2025) examined changes in roles and practices qualitatively; the last two studies were separated as evidence of broader adaptation.

Theoretical Framework in the Relationship between AI and Adaptation (RQ1)

The theoretical framework describes the different parts of AI's relationship to adaptation (Table 5). The COR highlights the resources that are acquired or threatened as jobs

change; JD-R places learning support and technological demands in the context of work; SDT directs attention to opportunities to explore and maintain autonomy; social cognitive theory and social learning explain ability beliefs; TAM and UTAUT discuss acceptance; and AMO and Feeling Economy are used to read governance and changes in the composition of tasks. The names and functions of the theory are noted as stated in the article.

Table 4. Explanatory theory and function

Theory	Article	Explanatory focus
Conservation of Resources (COR)	C01; C12	Gain or loss of resources when jobs change
Job Demands–Resources (JD-R)	C03; C10	Job demands and support to cope with change
Self-Determination Theory (SDT)	C04; C09	Exploration, autonomy, and AI instruction design
Social Cognitive Theory	C12	Digital capability confidence and adaptive behavior
Social Learning Theory	C10	Learning and confidence building of AI-related abilities
Technology Acceptance Model (TAM) and UTAUT	C13	Perception of acceptance and readiness to face AI
Ability–Motivation–Opportunity (AMO)	C15	Capabilities, motivations, and opportunities in AI governance models
Feeling Economy	C16	Changes in the composition of tasks and the need for emotional interaction
Not stated as the basis of the model	C11; C18	Theories were not added based on the reviewer's estimates

Source: the theoretical foundation stated in the article. UTAUT = Unified Theory of Acceptance and Use of Technology.

COR and JD-R are useful when AI change poses skill needs and pressures as well as opportunities; the appraisal differences in Li and Sun (2026) help explain why awareness can be positively or negatively related to adaptation, without assuming that technology is always a resource. SDT helps formulate conjectures about how AI design supports or limits employee actions, but the empirical support needs to be read carefully: mediation and moderation reporting in Do et al. (2025) is not fully aligned, while mediation in Rabbani et al. (2026) is not supported and the estimates are problematic. Both studies provide constructs for further testing, not evidence that the entire SDT pathway has been confirmed. TAM helps understand acceptance, but acceptance has not yet described the ability to adjust tasks when systems change or go wrong; in Peemanee et al. (2026), composite outcomes simultaneously mix compatibility and trust. Task–Technology Fit is not found as an explicit main theory in eleven articles, and it is confined to this corpus.

Cognitive and Behavioral Mechanisms (RQ2)

Findings on the adaptation process are grouped into assessment of change, confidence in ability and exploration, work adjustments, and readiness in the context of governance. Table 5 distinguishes the position of constructs and their empirical support limits; construct frequency indicates research attention, not magnitude of effect.

Table 5. Constructed under review and limits of empirical support

Groups	Article	Roles in models	Support and limitations
Perception of challenges and obstacles	C01	Challenge Exposure	Different directions; not frequency of use
Eustress and task crafting	C03	Mediator	Indirect lines are reported; outcomes are mainly adjustments to customers
Exploration and trust	C04	Mediators and moderators	Explorations correlate with AP; mediation and moderation claims are limited due to different reporting
Autonomy and dependency	C09	Proposed mediators	Mediation is not supported; literacy is also not moderated
AI self-efficacy	C10	Support context mediators	Indirect effects are supported; abstract/table claims are different
DSE, crafting, resilience	C12	Mediators and moderators	Mediation reported; customer-related outcomes; negative crafting moderation
Acceptance readiness/preparedness	C13	Predictors	Composite outcome; overlap should be checked
Trust and readiness	C15	Serial mediator	AP-related readiness; serial mediation estimates are not used
Adaptation of practices and emotions	C16	Qualitative themes	Explain the context; without estimating the AP effect
Collaboration and adaptation	C11	Descriptive dimension	Perception figures are not used because the percentage base and results table are unclear
AI collaboration and support capabilities	C18	Cross-level predictors and moderators	positive pages; cluster and finite scale details

Source: full-text article. DSE = digital self-efficacy; AISE = AI self-efficacy. Both are belief in ability, not objective measures of performance.

The assessment of change helps explain why the response to AI is different. Li and Sun (2026) report a positive association for the perception of challenge and a negative relationship for the perception of resistance. Hasanein et al. (2026) examine eustress as an explanatory pathway, but the awareness item in the appendix contains the concern of the job being replaced by AI, and a similar item is used by Salama and Khairy (2026). The positive results in both studies therefore cannot be interpreted that the better the AI knowledge, the higher the adaptation; the comparison should follow the content of the measurement, not the name of the variable alone.

Confidence in ability is related to readiness to try new ways of working. Digital self-efficacy in Salama and Khairy (2026) and AI self-efficacy in Shao (2026) were placed as statistical mediators, and in Do et al. (2025) exploration was positively correlated with adaptive

performance. These findings provide a basis for discussing learning and trying, but self-efficacy remains a belief, not a performance outcome; Shao also did not estimate the effect of increasing frequency of AI use. Crafting is a form of action closer to job change: Li and Sun (2026) included cognitive, relational, and task crafting, while two hotel studies focused on task crafting the similarity of labels did not erase the difference in scope, and adjustments in relationships with colleagues or superiors need to be noted separately so that changes in task boundaries are not thought to explain all interpersonal adaptability.

Wirjawan et al. (2026) propose the relationship between algorithmic fairness, trustworthiness, AI readiness, and adaptive performance. The readiness–performance relationship in the path table can be read as an association, but serial mediation estimates are not used because they do not match their forming coefficients; cross-cutting surveys also do not show the sequence of changes in confidence and readiness, and the similarity of the content of readiness and adaptation items needs to be checked before the model is used as the basis for the intervention.

Boundary Conditions and Inconsistent Results

Trust, mindfulness, resilience, and literacy were tested as conditions that can alter relationships in different models. The direction of belief moderation in Do et al. (2025) has not been established from misaligned reporting; Salama and Khairy (2026) reported a resilience interaction on the awareness–crafting pathway in a negative direction, while Rabbani et al. (2026) found no significant literacy moderation. These findings do not support the notion that one individual characteristic always strengthens adaptation in the entire AI context. Cognitive dependency is a proposed mechanism, but the indirect relationship through that construct has not been supported in Rabbani et al. (2026); the nonsignificant findings are not evidence that mechanisms never existed, but a theoretical discussion of dependency should also not be used to state that the study proves a decline in long-term adaptive ability.

A qualitative study by Oliveira et al. (2025) shows that changes in workflows can maintain or alter the need for emotional interaction, thus expanding the interpretation of adaptation beyond technical mastery; since the technologies examined include AI and other forms of automation, the specific contributions of each system cannot be separated. Sunarto et al. (2026) descriptively map the perception of human–AI collaboration, but the percentage basis of contributions in the abstract is inconsistent with the use of AI and the average cannot be reconciled with the frequency table, so the perception figures are not used to infer performance improvements. Tomy et al. (2026) report the association of collaboration capabilities and AI support through hierarchical models, but the number of clusters and item sources is not detailed enough to examine the accuracy of the model thoroughly. Usable individual outcome information is summarized in Table 6; The coefficients come from different models and instruments so they are not combined into a single measure of effect.

Table 6. Individual results used and restricted

Id. at 1	Relationships or outcomes	Information used	Source boundaries and locations
C01	Challenge/hindrance awareness → AP	β = 0.364 and −0.187; p < 0.01. Indirect path crafting 0.163 [0.079; 0.246] and −0.094 [−0.154; −0.035]	Table 3 Model 4 and the mediation narrative; the coefficient before the mediator differs from the immediate effect after the mediator
C03	Awareness → AP; task crafting as a mediator	β direct 0.40; f² 0.276. Indirect crafting 0.090; CI [0.019; 0.161]	Table 5–6; CI 95%; Outcome adjustment to customer
C04	Exploration and AP	r = 0.35; p < 0.001	Correlations, not mediation evidence; mediation and moderation estimates are not used
C09	Prescriptiveness → AP; Moderation literacy	β direct −0.195; p = 0.050. Interaction β −0.052; p = 0.511	p is directly rounded at 0.050; mediation is not used because the estimates are inconsistent
C10	AI self-efficacy → AP; AISE → support → AP	β AISE 0.613; p < 0.001. Indirect support 0.194; CI [0.132; 0.267]	Tables 5–6; the direct line of support is insignificant
C11	Perception of collaboration and adaptation	Mean and percentage of contributions not used	Results and Tables 2–3 are irreconcilable; descriptive surveys show no change in performance
C12	Awareness → AP; DSE and crafting as a mediator	direct β 0.36; p < 0.01. Indirect DSE 0.132 [0.070; 0.195]; crafting 0.150 [0.087; 0.212]	Table 6–7; CI 95%; Adjustment outcomes to customers
C13	Acceptance readiness and preparedness → composite adaptation	β 0.233 and 0.424; p < 0.001; adjusted R² 0.767	Hierarchical regression; outcome is not pure AP
C15	Readiness → AP	β = 0,394; p < 0.001	Associations in cross-cut surveys; serial estimates Table 4 is not used
C16	Changes in practices and interaction needs	Not applicable to effect coefficients	Qualitative findings; not converted into effect figures
C18	Human–AI collaboration capabilities → AP	γ = 0,43; p < 0.001; R² AP 0.59	Test table HLM; cluster number and scale are not detailed; statistics are not recalculated from primary data

Source: table and narrative of the article. β/γ = model coefficient; r = correlation; R² = proportion of the variance described; CI = 95% confidence interval.

AI Readiness and Adaptive Performance Measurement (RQ3)

Comparison of instruments shows the need to examine the content of constructs before choosing a measuring tool (Table 7). Awareness is an assessment of the implications of AI; literacy is related to knowledge or competence; self-efficacy is a belief in ability; and readiness describes readiness to face technology, while adaptive performance requires indicators of adjustment to changing demands. Similarity or correlation between constructs is not enough to state that they all measure the same digital readiness.

Table 7. Comparison of readiness and adaptation measurements

Source	Instrument or dimension	Reported evidence	Interpretation limits
C01	AP Griffin; reported 9 items	Alpha AP 0.835	Details 3+3+5 do not match the sum of 9

Source	Instrument or dimension	Reported evidence	Interpretation limits
C04	AP 8 items; reactivity, creativity, interpersonal	Alpha 0.88; Three-factor CFA	The short version is not the same throughout APS
C09	AP 7 items; creativity and reactivity	Alpha 0.897	Limited interpersonal coverage
C03; C12	AP 10 butir Hartline–Ferrell	Reported measurement model	Items assess the variation of approaches to customers; not the entire AP dimension
C10	AP 10 grains; AISE 12 grains	Alpha AP 0.926; AISE 0.941	Less detailed sourcing and refining of scale
C13	Readiness/preparedness 5 each; composite adaptation 15	Alpha adaptation 0.94	Fit/trust in outcomes is different from AP
C15	Readiness 5; AP 6; Likert 1–5	Loading and HTMT reported	Potential overlap of learning and adjustment skills
Koch et al. 2024	MAILS 34; abbreviated version 10	Literacy development and validation	Self-assessment; short version still requires advanced validation; not AP scale
Augustiya et al. 2026	KOMPAS-AI: Likert readiness and SJT adaptability	311 workers; omega 0.933 and 0.855	Validation in one context; predictive validity of work performance needs to be tested
Nasution and Wicaksono 2025	APS Indonesia five factors	322 workers; CFA and reliability	Not testing AI exposure or adoption effects
C11	Four dimensions; Likert 1–5	Content validation is called	Content mixes efficiency and adaptation; inconsistent descriptive results
C18	Multi-indicator AP; Likert 1–5	Alpha AP 0.85; CR 0.89	Item source and cluster number are not detailed

Sources: articles and supporting instruments. AP = adaptive performance; alpha/omega = internal reliability; CFA = confirmatory factor analysis; CR = composite reliability; HTMT = discriminant validity check; SJT = situational assessment test.

Do et al. (2025) used eight adaptive performance items that contained interpersonal adaptability, while Rabbani et al. (2026) used seven items focused on creativity and reactivity. In both hotel studies, the ten items referred to Hartline and Ferrell asked for variations in approaches to customers relevant to service adaptation, but did not represent all technical, team, and organizational adjustments; high internal reliability did not erase the coverage differences. Li and Sun (2026) reported a nine-item scale with details of subdimensions 3, 3, and 5; the review noted the discrepancies and did not select substitute numbers.

The supporting instruments provide measurement options with different limits. MAILS assesses AI-related psychological literacy and competence through self-reports (Koch et al., 2024); KOMPAS-AI combines the psychological readiness scale with a situational assessment test of AI adaptability in Indonesian workers (Augustiya et al., 2026); and APS Indonesia tests the structure of five adaptive performance factors without requiring AI exposure (Nasution & Wicaksono, 2025). None of them is automatically the best measure of readiness for all jobs; selection needs to follow measurement objectives and evidence of validity in the context to be used.

Reporting Quality and Conceptual Framework

Table 8 summarizes the issue of sources and their use decisions. Self-reports, nonprobability sampling, and limitations of instrument explanations limit many findings; measurements at different times provide sequence information but have not eliminated confounding or bias due to respondent loss, and diagnostics such as VIF and single-factor tests are insufficient to ensure the absence of method bias.

Table 8. Reporting issues and decisions on their use

Id. at 1	Source audit findings	Usage in synthesis
C01	Self-report survey; 687 initial responses to 369; total bullet count and AP subdimensional details are inconsistent.	The direction of the relationship and the crafting path are discussed; the number of grains is not considered definitive.
C03	Convenience sampling and self-reports; awareness of job replacement concerns; outcomes focus on adjusting approaches to customers.	The findings were limited to threat perception and customer service adjustments.
C04	Self-report surveys; 500 initial responses to 274; narratives and Table 4 differ regarding interactions, mediation intervals, and conditional effects of trust.	The exploration–AP association is maintained; the amount of mediation and direction of moderation is not used.
C09	Very small correlations are marked significantly; indirect effect numbers are inconsistent with product coefficients; the language of the results/abstracts is different.	Direct paths are treated as results at threshold limits; mediation estimates are not used.
C10	The abstract states significant direct effects whereas the table does not; the source of the instrument is less detailed; it does not test adoption as a primary predictor.	Tables 5–6 form the basis of the results; claims of significant direct effects in the abstract are not followed.
C11	The basis of the percentage of contribution is inconsistent; the average of Table 2 cannot be reconciled with the frequency of Table 3; the content of the instrument mixes efficiency, collaboration, and adaptation.	The identity, design, and content of the instrument are mapped; the mean and percentage of contribution are not used.
C12	Nonprobability samples and self-reports; awareness of concerns; customer-focused outcomes; moderation of the crafting path in a negative direction.	Mediation is discussed in the context of the service; the negative direction of crafting moderation is maintained.
C13	Simple random and convenience labels are inconsistent; readiness and adaptation have the potential to overlap; trust/fit is not pure AP.	The findings were placed as composite adaptations; not equated with pure AP scores.
C15	Cross-cutting surveys and self-reports; high R^2 AP; readiness/AP content potentially overlapping; Table 4 serial estimates do not match Table 3 line products.	The readiness–AP relationship is discussed as an association; serial estimates are not used.
C16	One company, purposive selection, AI and RPA technologies mixed; generalizations limited.	The theme of changing work practices is retained; it is not expressed as an AI effect in itself.
C18	The number of organizational clusters and geographic locations is unclear; the source of the item is less detailed; the capability predictor may overlap with the AP.	The results of HLM are recorded as source findings; the accuracy of the model is not stated to have been verified.

Source: examination of text, tables, and article appendices on October 14, 2026. The decision applies to specific claims, not the endorsement of primary data.

After the disaligned estimates were excluded from the basis of the conclusions, the relationship between change assessment and crafting was still reported in C01, C03, and C12, and self-efficacy persisted in C10 and C12. The exploration in C04 can be discussed as an

association, but the amount of mediation and the direction of its moderation have not yet been established. Support for readiness is more limited because C13 outcomes of composite adaptation and C15 serial mediation cannot be reconciled. This examination supports construct mapping, rather than the conclusion that AI adoption generally improves or decreases adaptive performance.

Figure 2 presents a conceptual framework for advanced research, which links AI contexts, cognitive responses, adaptive behaviors, and proposed measures of technical and interpersonal outcomes. The dotted line indicates the relationship that needs to be tested, not a confirmed model; organizational readiness and support may have different positions according to the definition and design of the study, and is not designated as a mandatory mediator or moderator.

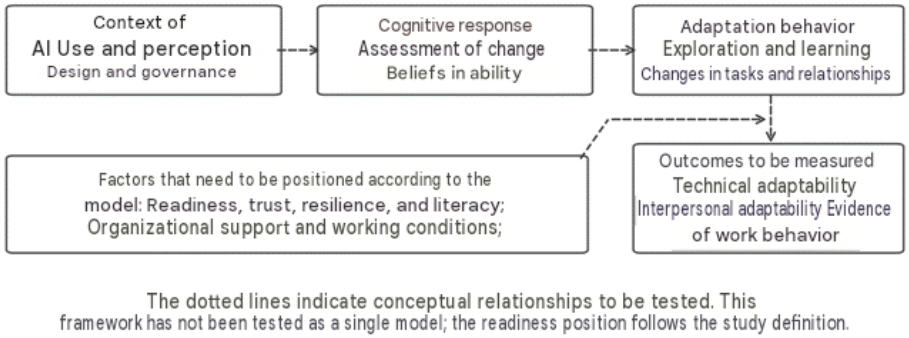


Figure 2. Conceptual framework for advanced research

CONCLUSION

The 11 articles examined provided different theoretical perspectives on employee adaptation in the context of artificial intelligence (AI) adoption. Resource-based theories, psychological needs theories, learning theories, technology acceptance models, and task-related changes explained different aspects of the relationship between AI adoption and employee adaptation. Change appraisal, self-efficacy, exploratory behavior, and job crafting emerged as relevant mechanisms, although the strength of empirical support and reporting quality varied across studies. Instruments measuring AI readiness and adaptive performance also differed in their conceptual dimensions and measurement content. Consequently, findings could not be considered directly comparable solely because the studies employed similar variable labels.

The review contributed to the literature by distinguishing among AI adoption and integration, employee adaptation processes, and adaptive performance outcomes. This distinction helped prevent the assumption that behavioral intentions to use AI or perceived technological competence necessarily demonstrated adaptive performance. The proposed integrative framework also incorporated interpersonal adaptability, a dimension that may be overlooked when measurement instruments focus primarily on creativity or technical responses to workplace changes. However, these contributions were conceptual and should be interpreted in light of the review's search limitations and the methodological quality of the available evidence.

Organizations could use these findings to develop more targeted approaches to evaluating employee adaptation to AI. Training programs should connect AI-related competencies with actual changes in job tasks, opportunities for practical experimentation,

and support mechanisms for addressing AI-generated errors. Evaluation criteria should incorporate observable adaptive behaviors and decision-making quality rather than relying exclusively on increased AI usage as an indicator of successful adaptation.

Human resource managers should also consider variations in employees' change appraisals and the conditions under which work is designed and performed. Learning support, transparent AI usage policies, and opportunities for human judgment represented potential organizational interventions requiring further empirical evaluation. In service-oriented and collaborative work environments, assessments should also consider coordination, interpersonal adaptability, and interactions with customers and colleagues. These implications were derived from the literature synthesis, and their effectiveness had not been established through intervention studies conducted as part of this review.

Human-in-the-loop (HITL) approaches could be considered to preserve human oversight and decision-making authority when AI-generated recommendations were inconsistent with task requirements or contextual conditions. Organizations could also provide opportunities for job crafting and reskilling to support employees in adapting to AI-related workflow changes. The effectiveness of these strategies should be evaluated using indicators of adaptive behavior and decision-making quality, as the reviewed evidence did not directly establish their effectiveness as organizational interventions.

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CONFLICT OF INTEREST

The authors state that there is no conflict of interest in this study. The author also does not have commercial, financial, or other relationships with certain parties that have the potential to affect the conduct of the research, interpretation of the results, or presentation of the findings in this manuscript.

AUTHOR CONTRIBUTIONS

All authors contribute in a balanced and equal manner in the completion of this manuscript. These contributions include the preparation of research ideas and frameworks, data analysis, to the writing and improvement of the manuscript, so that there is no division of dominant roles among the authors.

GENERATIVE AI STATEMENT

In the preparation of this manuscript, the author uses the help of Artificial Intelligence (AI) to a limited extent, which is only to improve grammar and check the accuracy of language use. AI is not used to generate ideas, analyze data, or compile research findings. All content and substance of the manuscript remain the responsibility of the author.

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