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# Dynamics of Employee Adaptation, Anxiety, and Role Change Under AI Integration in Indonesia

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**ABSTRACT**

The rapid adoption of artificial intelligence (AI) is transforming Indonesian workplaces, reshaping employees' perceptions of work, identity, and job security. This study explores employees' experiences of AI integration, workplace anxiety, readiness for change, and evolving job roles. Guided by the Transactional Theory of Stress and Coping, the Job Demands–Resources model, Change Readiness Theory, Role Theory, and UTAUT, an interpretive phenomenological approach was employed. Eighteen semi-structured interviews were conducted with employees and HR practitioners from banking, manufacturing, and digital-service organizations in Indonesia. Data were triangulated through workplace observations and organizational documents and analyzed using thematic analysis. Five themes emerged: ambivalent perceptions of AI, anxieties over job displacement and surveillance, uneven readiness shaped by digital literacy and psychological safety, role shifts toward analytical and relational work, and the importance of transparent communication and learning culture. The findings demonstrate that successful AI adoption depends on technological implementation, organizational support, psychological safety, AI literacy, and participatory change management.

**Keywords:** Artificial Intelligence; Digital Transformation; Employee Adaptation; Job Anxiety; Role Transformation

## INTRODUCTION

The implementation of artificial intelligence (AI) in the workplace has moved from a peripheral technological experiment to mainstream work infrastructure in less than a decade. World Economic Forum projections estimate that AI and information processing will affect 86% of businesses by 2030, with roughly 85 million jobs displaced by automation and 97 million new roles created simultaneously (Soulami et al., 2024; Tursunbayeva & Renkema, 2023). In the Indonesian context, a PwC Indonesia (2024) survey shows that 76% of workers report an acceleration of workplace change, and 91% remain optimistic about facing it, the highest figure in the Asia-Pacific region. Beneath this optimism, however, lie everyday tensions: the need to master new tools rapidly, uncertainty about role boundaries, and concerns about job continuity.

Research over the past five years has mapped the psychological consequences of workplace AI, primarily through the construct of Smart Technology, AI, Robotics, and Algorithms (STARA) awareness developed by Brougham and Haar (2020). Quantitative studies consistently show that awareness of AI is positively associated with job insecurity (Lingmont & Alexiou, 2020), emotional exhaustion (Yam et al., 2023), and turnover intention (Kong et al., 2021), as well as reduced organizational commitment and career satisfaction. In parallel, technology-adoption research grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT) demonstrates that performance expectancy, effort expectancy, social influence, and facilitating conditions are strong predictors of AI acceptance (Kim et al., 2024; Venkatesh, 2022). Concurrently, human-resource-management scholarship documents a transformation of roles from routine work toward human–AI collaboration that demands analytical, relational, and ethical capabilities (Budhwar et al., 2022; Malik et al., 2023; Prikshat et al., 2023).

Despite the richness of quantitative evidence, four literature gaps motivate the present study. First, the dominant quantitative paradigm reduces psychological experience to scale scores and loses the nuanced meanings that employees attach to AI (Pereira et al., 2023; Soulami et al., 2024). Second, deep qualitative inquiry into employees' subjective experiences remains limited and fragmented (Bankins et al., 2024). Third, most studies examine anxiety, readiness, and role change in isolation, even though these dimensions co-evolve within recursive appraisal–coping cycles (Spătaru et al., 2024). Fourth, the Indonesian context, characterized by a collectivist work culture, strong hierarchical relations, and substantial gaps in digital literacy, remains underexplored, despite Indonesia being one of the world's largest users of generative AI (Wijayati et al., 2022).

This study addresses these gaps through three complementary contributions. Theoretically, it integrates five complementary frameworks: the Transactional Theory of Stress and Coping (Lazarus & Folkman, 1984), the Job Demands–Resources (JD-R) model (Bakker et al., 2023), Change Readiness Theory (Holt et al., 2007), Role Theory (Biddle, 1986), and UTAUT to explain adaptation as a layered process. Methodologically, it employs interpretive phenomenology to enable deep exploration of employees' meaning-making, an approach still rare in the AI-HRM literature. Contextually, it generates empirical insight from Indonesia, with direct implications for managers, human resource (HR) practitioners, and policy-makers in emerging economies undergoing similar transitions.

The research questions guiding the study are: (RQ1) How do Indonesian employees experience the integration of AI into their work? (RQ2) What forms and sources of anxiety arise from AI use? (RQ3) How do employees appraise their situation and prepare themselves to adapt? (RQ4) How do roles, tasks, and responsibilities change following

AI integration? (RQ5) Which organizational and individual factors shape adaptive success?.

## LITERATURE REVIEW

### Integration of AI in the Workplace

AI in the workplace refers to computational systems that perform tasks ordinarily requiring human intelligence, including natural language processing, pattern recognition, and autonomous decision-making (Vrontis et al., 2022). Unlike earlier mechanical automation, which targeted repetitive physical tasks, AI now reaches white-collar cognitive work such as credit analysis, recruitment screening, customer service, and legal documentation (Acemoglu & Restrepo, 2020; Frey & Osborne, 2017). The recent surge of generative AI built on large language models has further widened this exposure, even to creative occupations once considered safe (Jia et al., 2024).

AI adoption in Indonesia displays distinctive patterns. Wijayati et al. (2022) found that AI exerts a significant positive effect on employee performance and work engagement in the banking and services sectors, with change leadership emerging as an important moderator. Large-scale AI infrastructure investments from global partners and upskilling initiatives launched by the Ministry of Manpower have accelerated this trend. Nonetheless, the skills gap remains substantial: Indonesia is projected to face a shortage of nine million digitally skilled workers by 2030, and gender disparities in Science, Technology, Engineering, and Mathematics (STEM) constrain the talent pool. This context renders the experience of operational employees especially salient for in-depth study.

### AI-Related Job Anxiety: From Awareness to Subjective Experience

AI-related workplace anxiety has been studied primarily through the STARA-awareness construct. Brougham and Haar (2020) define this awareness as the extent to which employees anticipate that smart technologies will transform their work in the next decade. Subsequent quantitative work has linked it to specific psychological outcomes. Lingmont and Alexiou (2020) showed that STARA awareness is positively related to perceived job insecurity, with organizational culture acting as a moderator. Kong et al. (2021) found that AI awareness lowered career competencies and elevated burnout among hospitality workers. Liang et al. (2022) described a double-edged-sword effect: service employees with high AI awareness exhibited both innovative behavior and emotional exhaustion, depending on their cognitive appraisal of threat versus challenge.

Recent work has broadened the construct from a fear of replacement to a multidimensional concept. Yam et al. (2023) showed that the presence of blue-collar robots raised job insecurity and maladaptive behavior (e.g., minor sabotage and theft) even among workers whose jobs were not factually under immediate threat. Teng et al. (2024) traced how AI awareness mediates emotional exhaustion via work–family interference, while Walczok and Bipp (2025) call for distinguishing affective and cognitive components of AI-related job insecurity. Most of this evidence, however, derives from cross-sectional surveys, leaving the subjective meaning of anxiety and how it evolves over time largely opaque.

### Change Readiness in the Context of AI Adoption

Change Readiness Theory defines readiness as a cognitive state encompassing the belief that change is needed, achievable, and beneficial (Höyng & Lau, 2023). In the AI context, readiness operates on three layers: competence (technical ability to use AI tools), mental disposition (openness to change and self-efficacy), and organizational support (adequate infrastructure and communication). Höyng and Lau (2023) developed the concept of intentional digital readiness, positioning intention as the bridge between belief and action, and found that job characteristics and leadership support significantly predict this readiness.

Recent empirical work shows that employee readiness for AI interaction is shaped by digital literacy, training access, and psychological safety. Zhang et al. (2025) demonstrated that co-skilling programs, in which employees and AI systems train each other, mitigate job insecurity and enhance adaptive readiness. Suseno et al. (2022) found that HR managers' beliefs about AI shape organizational readiness to adopt AI tools in core functions. A qualitative study in the Indonesian banking sector by Andika and Anindita (2023) emphasized the role of work engagement in fostering readiness, while Jewapatarakul and Ueasangkomsate (2024) showed that digital organizational culture correlates with transformation readiness in Southeast Asian SMEs.

**Work-Role Change: From Routine to Human–AI Collaboration**

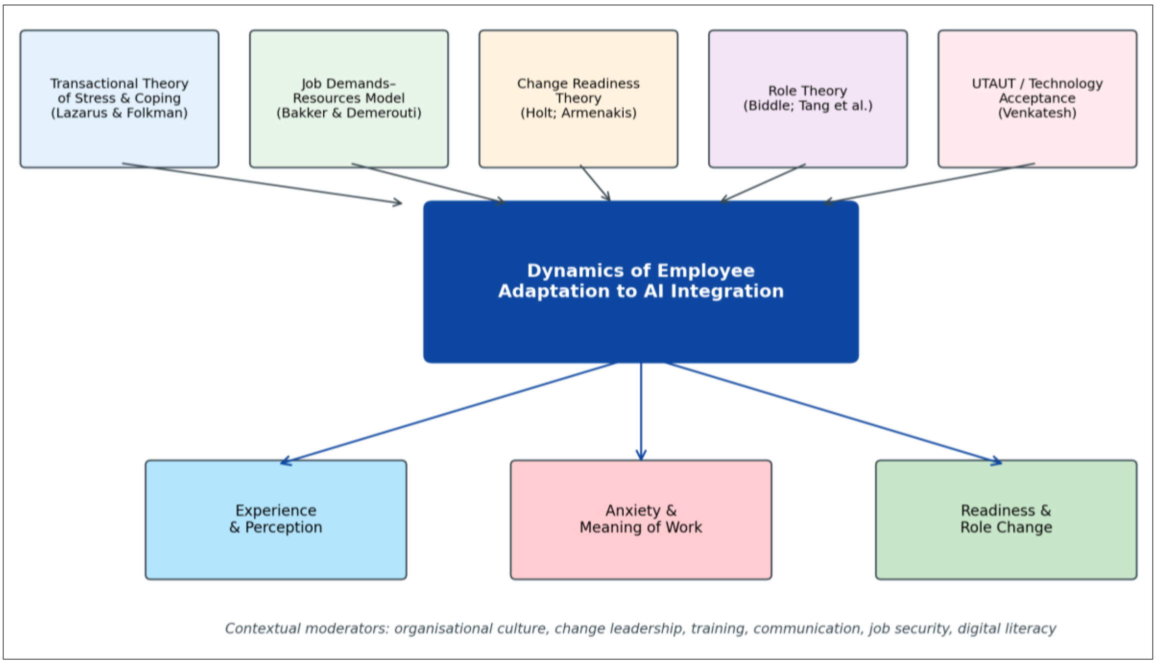
Role Theory offers a lens for understanding how expectations and responsibilities surrounding a job position shift when AI systems join the work team (Tang et al., 2022). As AI absorbs routine tasks- data entry, document classification, first-line customer responses- employees must renegotiate their roles: from operational executor to algorithm supervisor, from transaction processor to complex problem-solver, or from report writer to editor of AI output (Bankins et al., 2024; Parent-Rocheleau & Parker, 2022). This shift is frequently unaccompanied by formal changes to job descriptions, generating role ambiguity and expectation strain.

Current research describes three emerging role patterns. First, oversight roles, in which humans verify AI output, especially for high-stakes decisions such as credit assessment or medical diagnosis (Köchling & Wehner, 2023). Second, collaborative roles, in which AI acts as a partner that expands cognitive capacity, particularly in analytical and creative work (Arslan et al., 2022; Jia et al., 2024). Third, ethics and governance roles, in which employees interpret the ethical implications of AI output and safeguard accountability (Bankins, 2021; Tursunbayeva et al., 2022). Pereira et al. (2023) argue that successful role transition hinges on HRM strategies that weave technology together with continuous learning and job redesign.

**Integrated Theoretical Framework**

The present study integrates five theoretical perspectives to explain employee adaptation as a layered, dynamic process (see Figure 1). The Transactional Theory of Stress and Coping (Lazarus & Folkman, 1984) contributes the concepts of primary appraisal (whether AI is appraised as a threat, challenge, or opportunity) and secondary appraisal (whether the employee possesses resources to cope). The JD-R model (Ariawaty, 2026; Bakker et al., 2023) extends this perspective by highlighting how novel job demands (technical complexity, algorithmic monitoring) interact with resources (training, social support, autonomy) to yield engagement or exhaustion. Change Readiness Theory (Holt et al., 2007) positions cognitive beliefs as the precondition of adaptive action. Role Theory (Biddle, 1986) maps how role boundaries are renegotiated when non-human team members enter. UTAUT (Venkatesh, 2022) completes the picture by identifying proximal acceptance factors: performance expectancy, effort expectancy, social influence, and facilitating conditions (Alamanda et al., 2021; Kim et al., 2024; Venkatesh, 2022).

**Figure 1.** Conceptual Framework Integrating Five Theoretical Lenses to Explain the Dynamics of Employee Adaptation to AI in the Workplace




This integrated framework assumes that adaptation is not a single outcome but an iterative process: AI integration as a stimulus triggers appraisal; appraisal shapes coping strategies; those strategies materialize in action (learning, withdrawal, or resistance); and the outcomes of action feed back into subsequent appraisals. Organizational and individual contexts function as moderators that may strengthen or weaken every stage. An integrated lens is necessary because no single theory captures the complexity of employee experience from initial appraisal to consolidation of new roles.

**Research Novelty**

This study presents three main novelties. First, it departs from the dominant variable-oriented, cross-sectional approach in AI workplace research by adopting an interpretive phenomenological perspective that captures employees' lived experiences of AI-enabled organizational change. Rather than focusing primarily on statistical relationships among AI awareness, job insecurity, burnout, and turnover intention, it explores how employees make sense of and adapt to AI throughout the implementation process.

Second, the study reconceptualizes STARA awareness as a dynamic adaptation process rather than a static psychological response. It demonstrates that employees continuously reappraise AI as organizational support, learning opportunities, and work experiences evolve, making AI-related anxiety, readiness, and role transformation interconnected over time.

Third, the study provides evidence from Indonesia, an emerging economy where rapid digital transformation, uneven digital capabilities, and collectivist workplace values shape AI implementation. By examining banking, manufacturing, and digital-service organizations, it broadens the empirical evidence beyond the predominantly Western contexts represented in existing research.

**Theoretical Contributions**

This study advances AI-at-work literature by integrating the Transactional Theory of Stress and Coping, the JD-R model, Change Readiness Theory, Role Theory, and UTAUT into a unified framework for explaining employee adaptation to AI.

The framework extends existing theory by showing that AI adoption is not solely a technology acceptance issue but also a psychological and organizational adaptation process. The Transactional Theory of Stress and Coping explains employees' cognitive appraisal of AI, while the JD-R model highlights how organizational resources shape coping and adaptation. Change Readiness Theory and Role Theory further explain how these appraisals translate into behavioral readiness, evolving work roles, and human–AI collaboration. UTAUT complements these perspectives by positioning technology acceptance within broader psychological and organizational contexts.

By linking these theories, the study offers a multi-level explanation connecting individual cognition, organizational resources, change readiness, role transformation, and technology acceptance. This integrated framework extends previous AI-at-work research by providing a more comprehensive explanation of employee adaptation than any single theoretical perspective alone.

## RESEARCH METHOD

### Research Approach and Design

The study adopts a qualitative approach with an interpretive phenomenological design. Phenomenology was chosen because the research questions focus on the meaning and structure of employees' experience rather than on the frequency or causal links between variables (Naeem et al., 2023). The interpretive (hermeneutic) variant from the Heideggerian tradition was deemed more appropriate than purely descriptive phenomenology because the researcher cannot fully bracket pre-understandings, and indeed the hermeneutic dialogue between text and interpreter is what makes meaning visible (Soulami et al., 2024). This design allows in-depth exploration of how employees understand, feel, and respond to AI integration in everyday work.

### Setting and Participant Selection

Fieldwork took place at three purposively selected Indonesian organizations: a national commercial bank (anonymized, hereafter Org-A), a multinational manufacturing firm in East Java (Org-B), and a digital-services company in Jakarta (Org-C). Inclusion criteria at the organizational level were (i) at least one AI-based tool implemented for twelve months, (ii) impact on a minimum of two job functions, and (iii) formal permission for access and interviewing. Identified AI implementations included customer-service chatbots, automated credit-scoring, machine-learning recruitment engines, predictive maintenance, and generative-AI writing assistants.

Participants were recruited through a combination of purposive and snowball sampling. The individual inclusion criteria were permanent employees who (i) were directly affected by AI in their daily work, (ii) had been employed for at least one year after the AI rollout, and (iii) provided written informed consent. Four informant groups were targeted to represent different hierarchical and functional positions: operational staff, administrative staff, line supervisors or managers, and HR practitioners. Data collection was stopped when no new themes emerged, which occurred at the fifteenth interview; three further interviews were conducted to confirm saturation, yielding a total of eighteen participants (see Table 1).

**Table 1.** Participant Characteristics (N = 18)

| Code | Sector / Organization | Role / Position | Age | Tenure | Experience with AI |
|---|---|---|---|---|---|
| P01 | Banking (Org-A) | Customer Service Officer | 27 | 4 years | Chatbot, automated KYC |
| P02 | Banking (Org-A) | Credit Analyst | 31 | 7 years | ML credit scoring |

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|---|---|---|---|---|---|
| P03 | Banking (Org-A) | Operations Supervisor | 38 | 13 years | Workflow automation, BI |
| P04 | Banking (Org-A) | HR Business Partner | 34 | 8 years | AI recruitment platform |
| P05 | Banking (Org-A) | Branch Manager | 41 | 15 years | Customer predictive analytics |
| P06 | Banking (Org-A) | Senior Teller | 29 | 6 years | Smart ATM, queue analytics |
| P07 | Manufacturing (Org-B) | Production-Line Operator | 35 | 11 years | Computer-vision QC |
| P08 | Manufacturing (Org-B) | Quality Control Inspector | 33 | 9 years | Predictive maintenance |
| P09 | Manufacturing (Org-B) | Production Supervisor | 42 | 16 years | AI scheduling, IoT |
| P10 | Manufacturing (Org-B) | HR Generalist | 30 | 6 years | HR analytics dashboard |
| P11 | Manufacturing (Org-B) | Maintenance Technician | 37 | 12 years | Predictive maintenance AI |
| P12 | Manufacturing (Org-B) | Production Administration Staff | 26 | 3 years | RPA + internal chatbot |
| P13 | Digital (Org-C) | Customer Support Specialist | 25 | 2 years | Generative AI co-pilot |
| P14 | Digital (Org-C) | Content Moderator | 28 | 4 years | AI moderation, NLP |
| P15 | Digital (Org-C) | Support Team Lead | 32 | 7 years | GenAI, sentiment analysis |
| P16 | Digital (Org-C) | Recruiter | 29 | 5 years | AI sourcing & screening |
| P17 | Digital (Org-C) | Marketing Analyst | 30 | 6 years | GenAI content tools |
| P18 | Digital (Org-C) | Junior Software Engineer | 24 | 2 years | AI code assistant |

Note: All names and identifying details have been anonymized in accordance with the ethics approval. Org-A, Org-B, and Org-C represent three different sectors selected to maximize variation in AI adaptation experiences.

## Data Collection

**Table 2.** Data Sources and Triangulation Strategy

| Data Source | Concrete Form | Volume | Analytic Purpose |
|---|---|---|---|
| In-depth interviews | Semi-structured, 60–90 min/session, five-block interview guide | 18 sessions, 23 hours of recording, ~512 transcript pages | Explore experience, meaning, anxiety, readiness, and perceptions of role change |
| Limited observation | Non-participant; observation of employee–AI interactions and team meetings | 24 hours of observation across the three organizations | Verify interview narratives against actual behavior; capture situational context |

| | | | |
|---|---|---|---|
| Document analysis | AI policies, SOPs, training materials, job descriptions, annual reports | 47 documents (1,124 pages) | Map the formal structure of change; cross-check participant claims about organizational support |
| Reflective field notes | Researcher memos, reflective journaling, weekly coding meetings | 63 memo entries, 14 meetings | Maintain reflexivity, manage bias, and document the audit trail |

Four data sources were used to enable robust triangulation (see Table 2). The primary source comprised semi-structured in-depth interviews lasting 60–90 minutes, conducted at participants' workplaces or via video conference where necessary. The interview guide was developed around the five research questions and pilot-tested with two employees outside the sample before use. Questions began with a general narrative prompt ("Tell me about your first experience with AI in your job"), moved on to anxiety and coping strategies, readiness, role change, and closed with reflection on organizational support. Interviews were conducted in Bahasa Indonesia and recorded with permission, transcribed verbatim, and verified through member checking; quotes used in this article were translated into English by the lead researcher and back-translated by an independent bilingual translator to preserve meaning.

The second source consisted of limited non-participant observation (approximately twenty-four hours in total) of employee–AI interactions at the workplace, including dashboard use, internal-chatbot dialogues, and team meetings discussing AI output. The third source was document analysis — internal AI policies, training materials, job descriptions before and after AI deployment, and annual performance reports. The fourth source comprised reflective field notes from the researcher, which served to monitor bias and maintain an audit trail. Data collection ran from March to August 2025.

**Data Analysis**

Data were analyzed using Clarke and Braun's (2017) six-phase thematic analysis (Naeem et al., 2023) with the support of NVivo 14 (see Figure 2). Phase one was familiarization: the researcher re-listened to recordings, read the transcripts multiple times, and wrote initial notes. Phase two was initial coding: each transcript was coded line by line inductively, generating 412 raw codes. Phase three was searching for themes: related codes were grouped into 14 candidate themes. Phase four was reviewing: candidate themes were checked against the raw data and refined into five final themes. Phase five was defining and naming the themes, carried out through two peer-debriefing sessions with senior researchers. Phase six was the writing of the narrative report, with illustrative quotes from a diverse range of participants.

**Figure 2.** Six-Phase Thematic Analysis Workflow

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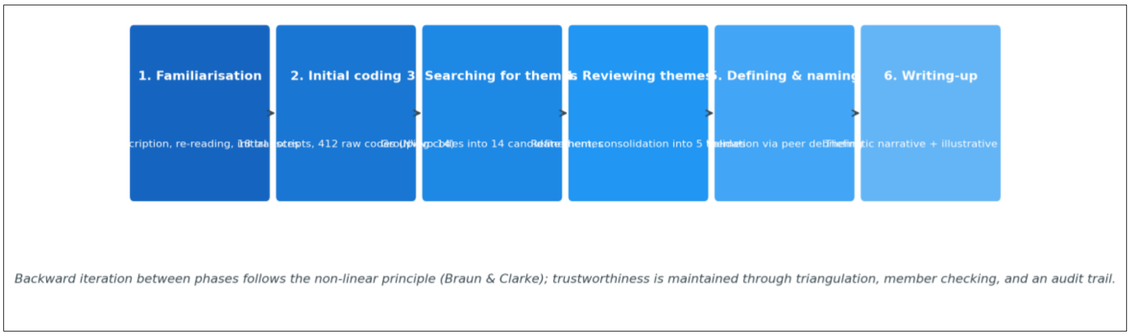


Source: Based on Clarke and Braun's (2017), Adapted Following Naeem et al. (2023)

**Trustworthiness**

The four Lincoln and Guba (1985) criteria were applied to ensure quality. Credibility was maintained through triangulation across four data sources, member checking with eight participants (44 per cent) who read and confirmed initial interpretations, and peer debriefing with two senior researchers who challenged interpretations. Transferability is supported by a thick description of the three organizational contexts and participant profiles, enabling readers to assess the relevance of the findings for other settings. Dependability was secured through a comprehensive audit trail covering memos, analytical-decision logs, and versioned coding. Confirmability was preserved through a researcher's reflective journal in which personal assumptions were recorded and checked against the data.

**Ethical Considerations**

The study received approval from the institutional ethics committee (protocol number masked). Participants received written information about the purpose, procedure, benefits, and risks, and signed an informed consent form. The right to withdraw without consequence was emphasized. Anonymity was maintained through participant codes, removal of specific identifying markers, and storage of raw data in an encrypted repository accessible only to the principal investigator. Because the topic of AI can elicit anxiety, the researcher monitored emotional responses during interviews and offered psychological support resources where appropriate.

## RESULTS

Thematic analysis produced five interrelated themes that describe the dynamics of employee adaptation to AI: (1) ambivalent first encounters; (2) layered anxieties; (3) uneven readiness; (4) role migration; and (5) organizational moderators. Table 3 summarizes these themes along with their sub-themes and illustrative quotes. The discussion connects each theme with the theoretical framework and recent literature. The final synthesis, presented as a model of adaptation dynamics in Figure 3, integrates the five themes into a single empirical framework.

**Table 3.** Themes, Sub-themes, and Illustrative Quotes

| Main Theme | | Sub-themes | Illustrative Quote |
|---|---|---|---|
| 1 | Ambivalent first encounters | a. Initial enthusiasm<br>b. Operational confusion<br>c. Lack of formal guidance | "At first I was enthusiastic because it was something new, but after two weeks I was confused — who was I supposed to ask when the output looked odd?" (P06, Senior Teller) |
| 2 | Layered anxieties | a. Fear of replacement<br>b. Fear of deskilling<br>c. Fear of algorithmic surveillance | "I can feel my skills slowly being unused. If AI does the credit analysis, in five years I'll just be the one who signs off." (P02, Credit Analyst) |

| | | | |
|---|---|---|---|
| 3 | Uneven readiness | a. Varying digital literacy<br>b. Unequal access to training<br>c. Self-efficacy differences | "AI training was only two hours online, and then we were expected to use it right away. For younger staff it may be easy; for someone my age it's very hard." (P11, Maintenance Technician) |
| 4 | Role migration | a. From execution to oversight<br>b. From routine to analytical work<br>c. Ethics and quality roles | "My job now isn't writing reports — it's checking whether AI is making things up. It's just as hard but it isn't recognized in the KPIs." (P14, Content Moderator) |
| 5 | Organizational moderators | a. Transparent communication<br>b. Psychological safety<br>c. Learning culture | "When my boss said clearly that AI is to help, not to replace, my motivation was different. But many colleagues only get information from WhatsApp groups — confusing and uncertain." (P15, Support Team Lead) |

Source: Thematic Analysis of Interview Data (2025)

Table 3 presents the five major themes that emerged from the thematic analysis, illustrating employees' lived experiences of AI integration in the workplace. Collectively, these themes depict employee adaptation as a dynamic and iterative process rather than a linear transition from acceptance to resistance. The findings indicate that employees continuously reassess AI as they gain experience, acquire new competencies, and negotiate changing work expectations. The first theme, ambivalent first encounters, captures employees' mixed initial reactions toward AI implementation. Most participants described their early experiences as a combination of curiosity and uncertainty. While AI was initially perceived as an innovative tool capable of improving efficiency, this enthusiasm quickly gave way to operational confusion due to limited guidance, unclear procedures, and insufficient technical support. These findings suggest that employees' primary appraisal of AI was neither wholly positive nor negative but remained contingent on the organizational environment in which implementation occurred. The second theme, layered anxieties, reveals that employees' concerns extended far beyond the fear of job replacement. Participants expressed anxiety about the gradual erosion of professional expertise, increasing dependence on automated systems, and continuous algorithmic monitoring of their performance. Rather than perceiving AI as an immediate threat to employment alone, employees described a broader sense of uncertainty regarding their long-term professional identity, autonomy, and future career relevance. These multiple forms of anxiety illustrate that AI-related stress develops through interconnected psychological concerns that evolve alongside technological adoption.

The third theme, uneven readiness, demonstrates that employees possessed substantially different capacities to adapt to AI. Readiness was influenced not only by digital literacy but also by previous technological experience, confidence in learning new systems, and equitable access to organizational training. Participants consistently reported that short, standardized training programs failed to accommodate differences in age, experience, and learning needs. Consequently, employees with stronger digital competencies adapted more rapidly, whereas others experienced prolonged uncertainty and reduced confidence. These findings indicate that readiness is both an individual capability and an organizational outcome shaped by learning opportunities and psychological support.

The fourth theme, role migration, illustrates how AI reshaped the nature of employees' work rather than simply replacing existing jobs. Participants described moving from routine operational tasks toward responsibilities involving verification, interpretation, quality assurance, ethical judgment, and decision oversight. Although these new responsibilities demanded higher-order cognitive and interpersonal skills, many employees perceived that organizational performance systems had not evolved to recognize these emerging forms of work. This mismatch generated role ambiguity and reinforced perceptions that AI had altered job expectations without corresponding changes in formal role definitions or evaluation criteria.

The final theme, organizational moderators, demonstrates that organizational practices significantly influenced employees' adaptation to AI. Transparent communication regarding the purpose of AI, supportive leadership, psychological safety, and opportunities for continuous learning reduced uncertainty and strengthened employee engagement. Conversely, inconsistent messages, informal communication channels, and limited opportunities for dialogue amplified workplace anxiety and encouraged speculation about AI's long-term consequences. These findings suggest that organizational context shapes how employees interpret technological change and determines whether AI is perceived primarily as a developmental opportunity or as a source of occupational insecurity.

Taken together, the five themes form an interconnected process of employee adaptation. Initial perceptions of AI influenced subsequent emotional responses, which in turn affected employees' readiness to learn and their ability to redefine professional roles. Organizational support operated throughout this process by either reinforcing employees' adaptive capacities or intensifying existing anxieties. This thematic structure aligns with the integrated theoretical framework adopted in the study, demonstrating that employee adaptation to AI results from the interaction between cognitive appraisal, organizational resources, readiness for change, evolving role expectations, and technology acceptance. Rather than representing independent phenomena, the themes collectively explain how Indonesian employees negotiate the transition toward human–AI collaboration within rapidly changing organizational environments.

**Theme 1: Ambivalent First Encounters with AI**

The first theme captures the ambivalence that consistently surfaced as participants recalled their early experiences with workplace AI. Enthusiasm for novel technology mingled with operational confusion and a sense of being left without direction. Several participants received AI tools without formal announcement — new software simply appeared on their computers, or familiar procedures were replaced without explanation. This ambiguity produced a primary-appraisal stage (Lazarus & Folkman, 1984) that oscillated between threat, challenge, and opportunity over short intervals.

> "At first I was enthusiastic because it was something new, but after two weeks I was confused — who was I supposed to ask when the output looked odd? There was no manual, and my supervisor was learning along with me." (P06, Senior Teller)

Some participants, particularly from Org-C (digital services), made sense of these first encounters as opportunities for career development and displayed a challenge appraisal. Conversely, more senior participants in Org-A and Org-B were more inclined toward a threat appraisal: AI was perceived as a subtle signal that their accumulated knowledge was approaching obsolescence. This pattern aligns with the double-edged-sword effect identified by Liang et al. (2022): among employees who interpreted AI as a challenge, creativity rose; among those who interpreted it as a threat, strain intensified. The original contribution of the present study is to show that this interpretation is not a stable individual trait but shifts in response to the concrete experiences of the first weeks of implementation.

**Theme 2: Layered Anxieties about Replacement, Deskilling, and Algorithmic Surveillance**

The second theme broadens AI-related anxiety from a simple fear of replacement into a three-layered construct. The first layer is replacement anxiety — a general fear of losing one's job. This layer surfaced most often among participants with mid-range tenure (5–10 years), who felt caught between being too expensive to retain and too out-of-date to promote. This is consistent with the quantitative findings of Lingmont and Alexiou (2020) and Yam et al. (2023) on the association between STARA awareness and job insecurity.

> "The fresh graduates are not the ones who are afraid — they know AI is their new skill. The ones who are afraid are people like me with 7–10 years of tenure: rotation is difficult, retirement is still far away, and any new certification means starting over." (P02, Credit Analyst)

The second layer is deskilling anxiety — the worry that the very skills that have anchored one's professional identity will be degraded as AI takes over the tasks that exercised them. Several participants, especially credit analysts and content moderators, reported that they no longer performed the "thinking" parts of the job but merely verified AI output. Tang et al. (2022) describe this phenomenon as a shift from producer to verifier that can erode self-efficacy. Our findings reinforce this pattern and add a temporal dimension: deskilling anxiety is anticipatory, peaking in the fourth to eighth months after the AI rollout, when the tool has matured enough to be relied upon.

> "I can feel my skills slowly being unused. If AI does the credit analysis, in five years I will just be the one who signs off. That is more frightening than being laid off outright." (P02, Credit Analyst)

The third layer, the most underexplored in earlier literature, is algorithmic-surveillance anxiety — the worry that AI not only takes over tasks but also monitors performance at a granular level. Several participants at Org-C reported that AI-derived metrics (response time, interaction sentiment, escalation counts) created continuous performance pressure that felt qualitatively different from human supervision. Parent-Rocheleau and Parker (2022) flagged this dimension in their work on algorithmic management, and our study confirms its resonance in actual lived experience.

> "Before, my boss did not see me take a five-minute break. Now the dashboard records everything. It is not that AI replaces me — AI watches me for the boss." (P13, Customer Support Specialist)

**Theme 3: Uneven Readiness**

The third theme highlights that employees' readiness to adapt to AI is not a single, uniform organizational outcome but a distribution stratified along lines of age, position, and access to training. Three sub-themes crystallized: variation in digital literacy, unequal training access, and a range of self-efficacy. Variation in digital literacy was most pronounced in Org-B (manufacturing), where senior operators with secondary-school backgrounds had to use predictive-maintenance dashboards originally designed for engineers. This is consistent with the digital-literacy-gap framework reported by Trenerry et al. (2021) for digital transformation across organizational levels.

> "AI training was only two hours online, and then we were expected to use it right away. For younger staff, it may be easy; for someone my age, it is very hard. Without the colleague next to me helping out, I would not be able to do it." (P11, Maintenance Technician)

Unequal training access emerged most clearly from the document analysis: in Org-A and Org-B, AI training relied on the same module package for all employees, so a production-line operator received the same level of technical detail as an analyst. In Org-C, by contrast, training was layered by role, and participants from this digital sector consistently reported higher readiness. This pattern aligns with the co-skilling recommendations of Zhang et al. (2025): reskilling programs are most effective when designed for the specific role context rather than as one-size-fits-all packages.

Self-efficacy range proved a strong predictor of the coping strategies adopted. Participants with high self-efficacy tended to choose problem-focused coping: taking initiative to learn independently, asking colleagues, or exploring new features. Conversely, participants with low self-efficacy gravitated toward emotion-focused coping: avoiding particular AI tools, blaming inadequate training, or relying on younger colleagues to act as bridges. This two-track pattern echoes the core assumption of the Transactional Theory of Stress and Coping (Spătaru et al., 2024) about the role of psychological resources in shaping secondary appraisal.

**Theme 4: Role Migration from Routine Execution to Analytical and Oversight Work**
The fourth theme shows that work roles have shifted substantially since AI was integrated, even though those shifts have rarely been formalized in job descriptions. Three sub-themes were identified: a shift from execution to oversight, from routine to analytical work, and the emergence of ethics and quality roles. The execution-to-oversight shift was clearest for credit analysts, content moderators, and recruiters — roles in which most daily tasks were taken over by AI, leaving the employee in a verifier function. Köchling and Wehner (2023) call this "human-in-the-loop oversight" and stress its complexity: it requires technical knowledge (understanding the model's logic), domain knowledge (recognizing when AI is wrong), and ethical judgement (deciding when to override).

> "My job now is not writing reports — it is checking whether AI is making things up. It is just as hard, but it is not recognized in the KPIs. I feel like an emergency brake, not an analyst." (P14, Content Moderator)

The routine-to-analytical shift was reported mainly by junior participants at Org-C, who said that their routine administrative tasks had shrunk, leaving room for analytical and developmental work. This pattern aligns with the human–AI complementarity framework described by Jia et al. (2024), in which AI can release human cognitive capacity. However, this benefit is unevenly distributed. Senior participants at Org-A and Org-B reported the opposite experience: they continued to handle the complex and ambiguous administrative cases (the difficult exceptions AI could not handle), even as formal appreciation for this work declined because it was seen as the "residue" of automation.
Ethics and quality roles emerged as a new category that has yet to be institutionalized. Participants who detected biased, inaccurate, or ethically problematic AI output often felt obliged to act, but had no formal channel to report and follow up. This places the burden of ethical governance on operational employees without adequate structural support — a pattern Bankins (2021) also warned about in the framework of ethical AI in HRM.

**Theme 5: Organizational Moderators — Communication, Psychological Safety, and Learning Culture**

The fifth theme shows that adaptive success depends not only on individual factors but is strongly shaped by three organizational moderators: the quality of communication, psychological safety, and a learning culture. Transparent communication about the purpose, scope, and implications of AI determines whether employees interpret the technology as a threat or as a tool. At Org-A, an early town hall led by the director and followed by a written FAQ successfully dampened rumors; at Org-B, by contrast, information often flowed through informal WhatsApp groups, allowing inaccuracies to spread and amplify anxiety.

> "When my boss said clearly that AI is to help, not to replace, my motivation was different. But many colleagues only get information from WhatsApp groups — confusing and uncertain — and they end up anxious before anything else." (P15, Support Team Lead)

Psychological safety emerged as a moderator that determines employees' willingness to ask, experiment, or report AI errors. In teams where supervisors explicitly normalized mistakes as part of the learning process, participants reported greater confidence in trying new features. In teams with a culture of punishing mistakes, employees were more likely to hide their confusion and to develop informal workarounds that could impede full adoption. These findings echo the psychological safety construct as a key facilitator of technology adoption (Bakker et al., 2023; Demerouti & Bakker, 2023).

A continuous learning culture, distinct from formal training events, proved to be the organizational resource that most consistently predicted constructive adaptation. Org-C provided weekly learning hours, communities of practice, and access to external courses; participants from this sector reported the smoothest role transition. This pattern accords with the thesis of Pereira et al. (2023) that successful AI-HRM hinges on learning strategies embedded in everyday work practice rather than on one-off training events.

**Table 4.** Enablers and Barriers of Employee Adaptation to AI

| Level | Enabling Factors (Resources) | Hindering Factors (Demands) |
|---|---|---|
| Individual | • Adequate digital literacy<br>• High self-efficacy<br>• Openness to change<br>• Prior cross-functional experience<br>• Internal social learning network | • Older age without targeted training<br>• Professional identity anchored in tasks now automated<br>• Low self-efficacy<br>• Unrealistic task expectations |
| Team | • Supervisor who communicates AI vision clearly<br>• Knowledge-sharing norms<br>• Tolerance for mistakes during learning<br>• Adaptive task rotation | • Supervisor who applies tight KPI pressure<br>• A culture that blames mistakes<br>• Unequal distribution of training access |
| Organizational | • Transparent top-down communication<br>• Layered, role-fit training programs<br>• Written no-layoff commitment related to AI<br>• Communities of practice and learning hours | • AI implementation without an aligned HR plan<br>• Neglect of job-description redesign<br>• Ambiguous leadership messages<br>• No formal channel to escalate AI issues |

| | | |
|---|---|---|
| | • AI ethics and governance policy | |
| AI System | • User-friendly and explainable interface<br>• Easy override mechanism<br>• Timely feedback to the user | • Black-box output without explanation<br>• Fluctuating accuracy<br>• Complex interface without onboarding<br>• Micro algorithmic surveillance with no clear purpose |

Source: Synthesis of Empirical Findings (2025)

Table 4 demonstrates that employee adaptation to AI is a multilevel process shaped by the dynamic interaction between enabling resources and hindering demands operating simultaneously at the individual, team, organizational, and technological levels. Rather than functioning independently, these factors reinforce one another, creating either adaptive or maladaptive pathways during AI implementation.

At the individual level, employees with stronger digital literacy, higher self-efficacy, openness to change, and prior cross-functional experience were more likely to perceive AI as a learning opportunity rather than a threat. Conversely, employees whose professional identities were strongly tied to routine tasks reported greater anxiety about job displacement and reduced confidence in their ability to adapt. These findings suggest that personal resources influence employees' cognitive appraisal of AI and determine whether technological change is interpreted as a challenge or a source of stress.

The team environment further shaped these individual responses. Supervisors who clearly communicated the purpose of AI implementation, encouraged knowledge sharing, and tolerated mistakes during the learning process strengthened employees' confidence and willingness to experiment with AI tools. In contrast, excessive performance pressure, unequal access to training, and blame-oriented cultures intensified uncertainty and discouraged learning behaviors. This finding indicates that team-level resources either amplify or weaken employees' individual coping capacities.

Organizational conditions emerged as the most influential contextual factors. Transparent communication, structured AI training, explicit employment-security commitments, communities of practice, and clear AI governance policies created an environment in which employees perceived AI implementation as predictable and manageable. Conversely, organizations that introduced AI without aligning human resource strategies, redesigning job roles, or providing consistent leadership communication generated ambiguity regarding future career prospects. Under such conditions, employees experienced heightened role uncertainty and greater resistance to organizational change.

Finally, the characteristics of the AI system itself directly influenced employees' willingness to collaborate with the technology. Explainable interfaces, opportunities for human override, and timely feedback increased trust and facilitated technology acceptance. By contrast, opaque algorithms, inconsistent system performance, intrusive algorithmic monitoring, and overly complex interfaces undermined employees' confidence and reinforced perceptions that AI functioned as a mechanism of surveillance rather than support.

Taken together, these findings demonstrate that successful AI adaptation depends on the alignment of resources across multiple organizational levels. Individual readiness alone is insufficient when team support, organizational policies, or AI system design fail

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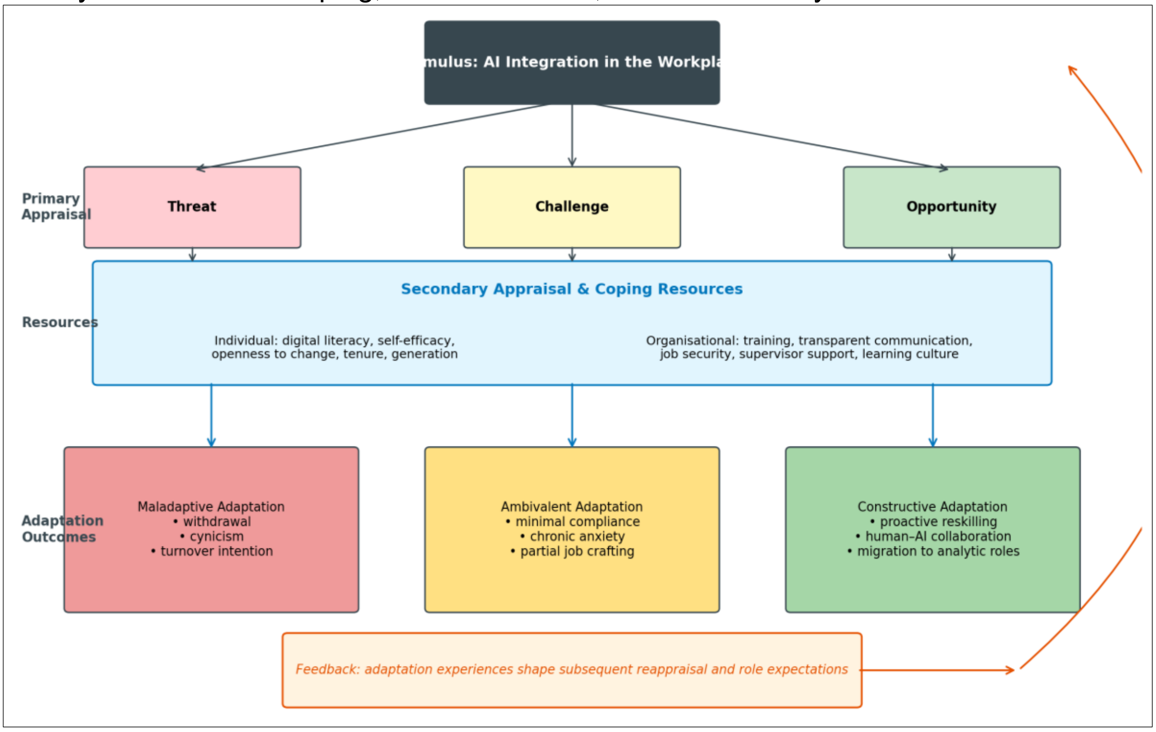
to provide an enabling environment. Likewise, sophisticated AI technologies cannot generate positive outcomes without complementary investments in communication, learning, leadership, and role redesign. Employee adaptation, therefore, emerges from the interaction between personal capabilities, social support, organizational practices, and technological characteristics, highlighting the need for an integrated approach to managing AI-enabled workplace transformation.

**Synthesis: A Model of Employee Adaptation Dynamics to AI**

**Figure 3.** An Empirical Model of Employee Adaptation Dynamics to AI, Synthesized from Findings Across Three Indonesian Organizations and Integrating the Transactional Theory of Stress and Coping, the JD-R model, and Role Theory




Synthesis of the five themes yielded an empirical model presented in Figure 3. The model positions AI integration as a stimulus that triggers a cycle of appraisal and coping. Primary appraisal categorizes the stimulus as a threat, challenge, or opportunity, influenced by the initial narratives that employees receive. Secondary appraisal and coping strategies are determined by the interaction of individual resources (digital literacy, self-efficacy, openness) and organizational resources (training, communication, psychological safety, supervisor support, learning culture). Adaptation outcomes cluster into three patterns: maladaptive (withdrawal, cynicism, turnover intention), ambivalent (minimal compliance, chronic anxiety, partial job crafting), and constructive (proactive reskilling, human–AI collaboration, migration to analytical roles). Crucially, the model emphasizes feedback: adaptation outcomes shape subsequent reappraisal and role expectations, framing adaptation as an iterative ongoing process rather than a one-off transition.

## DISCUSSION

**Linking Findings to the Literature**

The findings extend the growing literature on AI in the workplace by demonstrating that employee adaptation is a dynamic, multilevel process shaped by the interaction between individual cognition, organizational context, and technological characteristics. Rather than portraying AI adoption as a straightforward process of technology acceptance, this study reveals that employees continuously reinterpret AI as they accumulate experience, acquire new competencies, and renegotiate their professional roles. This dynamic perspective complements the predominantly cross-sectional evidence reported in previous AI-at-work research.

First, the findings indicate that AI-related anxiety is multidimensional rather than a single psychological construct. Participants described three interconnected forms of anxiety: fear of job replacement, fear of professional deskilling, and concern over algorithmic surveillance. Whereas existing STARA-awareness research has primarily conceptualized AI anxiety as anticipation of technological displacement (Brougham & Haar, 2020), the present findings demonstrate that employees also fear the gradual erosion of professional expertise and the increasing visibility of their performance through AI-enabled monitoring. These dimensions support Walczok and Bipp's (2025) argument that AI-related job insecurity should be differentiated into multiple psychological components and further suggest that the sources of anxiety evolve throughout the implementation process rather than remaining static.

Second, the study advances Change Readiness Theory by showing that readiness is not merely an individual psychological disposition but a socially and organizationally constructed capability. Although employees differed in digital literacy, self-efficacy, and openness to change, these individual characteristics alone did not explain successful adaptation. Readiness was strongly influenced by equitable access to training, leadership support, opportunities for learning, and psychological safety. Consequently, employees with similar technological abilities experienced substantially different levels of readiness depending on the organizational environment. This finding extends Höyng and Lau's (2023) conceptualization by positioning readiness as the outcome of interactions between personal capabilities and organizational resources rather than solely cognitive beliefs.

Third, the findings reveal that AI implementation transforms work roles long before organizations formally redesign job structures. Participants increasingly shifted from routine operational work toward responsibilities involving oversight, interpretation, ethical judgment, and quality assurance. However, these new responsibilities were rarely reflected in formal job descriptions, performance indicators, or promotion criteria. This mismatch created role ambiguity and increased cognitive workload despite improvements in operational efficiency. Consistent with Role Theory (Tang et al., 2022), employees continuously renegotiated professional identities as AI assumed routine functions, while Bankins (2021) similarly argues that AI introduces emerging governance responsibilities that organizations have yet to institutionalize.

Fourth, organizational conditions emerged as critical moderators of employee adaptation. Transparent communication reduced uncertainty by clarifying organizational intentions, psychological safety encouraged experimentation without fear of punishment, and learning-oriented cultures enabled employees to transform initial anxiety into adaptive behavior. These findings support previous arguments that HR plays a central role in facilitating AI implementation (Charlwood & Guenole, 2022; Pereira et al., 2023) while identifying the specific mechanisms through which this influence operates. Communication shapes employees' primary appraisal of AI, psychological safety strengthens coping resources, and continuous learning expands adaptive capacity throughout organizational change.

The Indonesian context further enriches the international literature by demonstrating that AI adaptation is embedded within collectivist organizational cultures. Participants consistently attached considerable importance to messages communicated by direct supervisors and senior leaders, reflecting the influence of hierarchical relationships on employees' interpretations of organizational change. Unlike evidence from many Western settings, where individual autonomy often dominates technology adoption decisions, employees in this study relied heavily on organizational guidance and social reassurance when evaluating AI implementation. This finding suggests that cultural context influences not only technology acceptance but also stress appraisal, coping strategies, and readiness for change during digital transformation.

**Theoretical Contributions**

The present study contributes to theory by integrating the Transactional Theory of Stress and Coping, the JD-R model, Change Readiness Theory, Role Theory, and the UTAUT into a coherent framework explaining employee adaptation to AI. Rather than examining psychological appraisal, organizational resources, readiness, work-role transformation, and technology acceptance as separate processes, the findings demonstrate that these mechanisms operate sequentially and recursively throughout AI implementation.

Specifically, employees first cognitively appraise AI as either a threat or an opportunity (Transactional Theory of Stress and Coping). This appraisal is subsequently strengthened or weakened by available job resources such as training, leadership support, autonomy, and psychological safety (JD-R model). Organizational support then shapes employees' readiness to embrace technological change (Change Readiness Theory), enabling them to reconstruct work identities and responsibilities as AI increasingly performs routine tasks (Role Theory). Finally, employees' willingness to collaborate with AI depends on their perceptions of AI usefulness, usability, social influence, and facilitating conditions (UTAUT). The integration of these perspectives provides a dynamic explanation of AI adaptation that bridges psychological, organizational, and technological dimensions.

Accordingly, this study proposes that employee adaptation to AI should be conceptualized as an ongoing process of appraisal, resource mobilization, readiness formation, role renegotiation, and technology acceptance rather than as a single-stage response to technological implementation. This integrated perspective extends existing AI-at-work research by explaining not only whether employees accept AI but also how and why their perceptions, behaviors, and professional identities evolve throughout organizational transformation.

## CONCLUSION

This phenomenological study of eighteen employees across three sectors in Indonesia produced five themes describing the dynamics of adaptation to AI integration. First, the initial encounter with AI is ambivalent and can shift rapidly between threat, challenge, and opportunity appraisals during the first weeks of implementation. Second, AI-related anxiety is three-layered: fear of replacement, fear of deskilling, and fear of algorithmic surveillance. Third, readiness is unevenly distributed along lines of age, position, and access to training. Fourth, work roles have migrated from routine execution to analytical work, AI-output verification, and ethical governance, often without formal updating of job descriptions. Fifth, adaptive success depends on organizational moderators, especially transparent communication, psychological safety, and a continuous learning culture.

The study makes three theoretical contributions. First, it extends the STARA-awareness construct by showing that AI-related anxiety is multidimensional and dynamic rather than a stable trait. The three-layered framework (replacement, deskilling, surveillance) lays the groundwork for developing more sensitive quantitative instruments. Second, the study enriches Change Readiness Theory by adding a distributive-justice perspective:

readiness is the product of organizational architecture, not merely an individual attribute. Third, the study operationalizes the integration of five theories (Transactional Stress, JD-R, Change Readiness, Role Theory, UTAUT) through an empirical model that frames adaptation as an iterative cycle of appraisal–coping–action–feedback.

For managers and HR practitioners, the findings underline five concrete recommendations. First, develop a transparent, consistent, and multi-channel communication strategy before, during, and after AI implementation. The message must explicitly distinguish augmentation from replacement and include a medium-term workforce plan. Second, design layered, role-appropriate AI-literacy programs rather than a single module for everyone. Operators with technical backgrounds differ from analysts, and both differ from supervisors. Third, formally update job descriptions, KPIs, and career pathways to recognize the verification, ethics, and analytical work that have emerged. Without formal recognition, this new workload remains invisible and undervalued. Fourth, build psychological safety through norms of mistake tolerance and safe channels to report AI issues. Fifth, draft a written no-layoff commitment tied to AI for a defined period, since formal certainty carries more weight than verbal promises.

For policy-makers, especially in Indonesia, the study suggests three policy directions. First, national upskilling programs should target not only recent graduates but also mid-career and senior employees who are most vulnerable to deskilling. Second, a regulatory framework on algorithmic management, including the rights of employees to know which AI metrics monitor them and to contest AI-based decisions, should be considered, following the trajectory of the EU AI Act and similar initiatives. Third, tripartite dialogue among government, employer associations, and workers' unions should be institutionalized to navigate the AI transition fairly, as recently urged by the International Labour Organization (ILO, 2025).

AI integration in the workplace is not a single technological event but a continuous socio-psychological process that reshapes the meaning of work, professional identity, and the structure of roles. Indonesian employees navigate this process with a mix of enthusiasm, anxiety, and diverse coping strategies, the outcomes of which depend heavily on the architecture of organizational support. Listening to their experiences in depth, as this phenomenological study has sought to do, is an essential step toward designing AI transitions that are more humane, just, and sustainable.

## LIMITATION

The study has four limitations that deserve acknowledgement. First, the sample size of 18 participants, although sufficient for saturation, is confined to three organizations and three sectors; naturalistic generalization must be made with care. Second, participants are employees still working at the time of the interview; the voices of those who have left or have been dismissed because of AI are not represented. Third, the cross-cultural perspective is limited to the Indonesian context; comparison with other Southeast Asian countries or with developed economies would enrich understanding. Fourth, the phenomenological design captures experience at a single point in time; the temporal dynamics of adaptation should be explored through longitudinal follow-up studies. Four directions for future research are proposed. First, longitudinal studies that follow employees for 24–36 months after AI implementation would capture the temporal dynamics of appraisal–coping identified in our model. Second, mixed-methods research that measures three-layered anxiety with a new quantitative instrument and tests the organizational moderators using structural equation modelling would validate the model across a broader population. Third, cross-country comparative research in Southeast Asia would clarify the role of collectivist work culture and labor-market structures in shaping responses to AI. Fourth, participatory research that involves employees in redesigning roles and AI governance could yield grounded practical recommendations more likely to be adopted.

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