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EMPLOYEE ADAPTATION TO ARTIFICIAL INTELLIGENCE IN THE WORKPLACE: A PHENOMENOLOGICAL STUDY IN SOUTH SULAWESI COMPANIES

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Abstract

The rapid integration of Artificial Intelligence (AI) into organizational systems has transformed workplace dynamics, employee responsibilities, and patterns of human labor. Although AI implementation improves operational efficiency and productivity, it also creates psychological and professional challenges for employees adapting to technological change. This study aims to explore the lived experiences, emotional responses, and adaptation strategies of employees in South Sulawesi companies undergoing AI-driven digital transformation. This research employed a qualitative phenomenological approach. Data were collected through in-depth semi-structured interviews with 20 participants from the banking, manufacturing, retail, technology, and service sectors in South Sulawesi, Indonesia. Participants were selected using purposive sampling based on direct exposure to AI systems and a minimum of 1.5 years of work experience. The data were analyzed using thematic analysis to identify recurring patterns and meanings related to employee adaptation. The findings revealed six major themes: AI as a tool for improving efficiency and productivity, fear of job displacement and career uncertainty, the importance of continuous learning and digital skill development, the role of organizational support and leadership communication, the emergence of human–AI collaboration, and varied psychological responses to technological change. Employees who received organizational support and training demonstrated greater adaptability and confidence in responding to AI implementation. The study emphasizes the importance of human-centered change management strategies that prioritize psychological safety, transparent communication, and continuous digital training. This research contributes to the limited phenomenological literature on AI adaptation in Indonesia and provides practical implications for human resource management and organizational behavior in the era of digital transformation.

Keywords: *Artificial Intelligence, Employee Adaptation, Digital Transformation, Phenomenological Study, Organizational Change*

1. INTRODUCTION

The emergence of Artificial Intelligence (AI) as a dominant force in contemporary organizational management has catalyzed one of the most consequential technological shifts in modern labor history. AI technologies encompassing machine learning, natural language processing, robotics, and predictive analytics have permeated virtually every sector of the global economy, reshaping how work is conceived, structured, and executed (Davenport & Ronanki, 2022; Haenlein & Kaplan, 2021). The World Economic Forum's Future of Jobs Report (2023) projected that AI and automation would displace approximately 85 million jobs globally while simultaneously generating 97 million new roles by 2025, signaling both an era of profound disruption and unprecedented opportunity. The critical question facing organizations and human resource practitioners is not simply whether AI will transform work, but how employees will navigate, internalize, and adapt to this transformation.

Within the broader discourse on digital transformation, AI adoption presents uniquely complex challenges that extend beyond technical implementation. Unlike previous waves of technological change, such as the introduction of personal computers or enterprise resource planning systems, AI introduces a qualitatively different form of disruption because it encroaches upon cognitive and decision-making domains previously considered exclusively human (Brynjolfsson & McAfee, 2023). AI systems are now capable of performing tasks involving pattern recognition, language comprehension, data analysis, and even creative problem-solving, blurring the boundaries between human and machine competencies (Wilson & Daugherty, 2021). This encroachment generates not only practical challenges related to skill obsolescence but also profound psychological and existential anxieties among employees concerning their professional identities, job security, and future relevance in the workplace.

Research on employee adaptation to technological change has gained considerable momentum in organizational behavior and human resource management scholarship. However, the predominant focus has been on macro-level organizational outcomes, productivity gains, efficiency metrics, and return on investment, with comparatively limited attention to the micro-level phenomenological reality of employees experiencing this transformation from within (Huang & Rust, 2021). Understanding the subjective, lived experiences of employees who must adapt to AI-driven changes is not merely an academic exercise; it has direct implications for organizational policy, change management strategy, talent retention, and employee well-being. Employees who feel unsupported, underinformed, or threatened by AI implementation are more likely to resist technological adoption, experience burnout, disengage from organizational goals, or voluntarily exit the organization (Oreg et al., 2022; van der Voet & Vermeeren, 2020).

In the Indonesian context, digital transformation has emerged as a national strategic priority, underscored by the government's Making Indonesia 4.0 roadmap and the Indonesia Digital Talent Scholarship program. Indonesia's rapidly expanding digital economy, projected to reach USD 360 billion by 2030 (Google, Temasek & Bain, 2022), has accelerated AI adoption across key industries, including banking and financial services, manufacturing, telecommunications, retail, and logistics. South Sulawesi, as one of Indonesia's major economic corridors outside Java, has witnessed a growing wave of digital transformation among both state-owned enterprises and private sector companies. The region's strategic industries, including agribusiness, mining, maritime logistics, and banking, have increasingly invested in AI-driven systems for process optimization, customer service enhancement, and operational efficiency. Yet, despite these organizational-level changes, limited scholarly attention has been directed toward understanding how employees in this region subjectively experience and adapt to these technological transformations.

The existing literature on AI in the workplace has revealed a complex and often contradictory landscape of employee responses. Studies conducted in Western and East Asian contexts have documented a spectrum of reactions ranging from enthusiasm and increased engagement (Vrontis et al., 2022) to anxiety, resistance, and psychological distress (Huang & Rust, 2021; Tschang & Almirall, 2021). Several factors have been identified as moderating these responses, including organizational communication quality, perceived support from management, access to training and reskilling opportunities, individual digital self-efficacy, and prior experience with technological change (Orlikowski & Scott, 2021; Smite et al., 2023). However, the vast majority of these studies have employed quantitative survey methodologies that, while offering breadth, necessarily sacrifice the depth of insight required to understand the nuanced, contextually embedded nature of employee adaptation experiences.

Phenomenological research offers a powerful methodological alternative for exploring the essence of employee lived experiences during AI adoption. By prioritizing the rich, first-person narratives of individuals navigating technological change, phenomenological inquiry can illuminate the specific meanings, emotions, and coping strategies that underpin adaptation processes, insights that are typically obscured by aggregate quantitative data (Smith et al., 2022; van Manen, 2021). Despite the recognized value of this approach, phenomenological studies of AI adaptation in Indonesian organizational contexts remain remarkably scarce, representing a significant gap in the regional and cross-cultural understanding of digital transformation.

This study addresses this gap by examining the lived experiences of employees in South Sulawesi companies that have implemented AI-based systems. The research is guided by the following overarching question: What are the phenomenological experiences of employees adapting to AI-driven transformations in South Sulawesi's organizational environments? Sub-questions explore: (1) What emotional and psychological responses do employees exhibit toward AI implementation? (2) What adaptation strategies do employees employ to navigate AI-driven changes? (3) How do organizational support mechanisms, including leadership communication and digital training, influence the adaptation process? (4) What implications do employee experiences have for human resource management practice and organizational change management?

The theoretical contributions of this study are threefold. First, it extends the Technology Acceptance Model (TAM) by incorporating phenomenological dimensions of perceived usefulness and ease of use, enriching this framework's applicability to complex, emotionally laden technology adoption scenarios. Second, it contributes to change management theory by providing empirical evidence of the role of leadership communication and organizational support in mediating employee adaptation. Third, it advances the understanding of employee resilience in the context of AI-driven organizational transformation. Practically, the findings provide actionable insights for HR managers, organizational leaders, and policymakers in South Sulawesi and the broader Indonesian context as they design and implement human-centered AI adoption strategies.

2. RESEARCH METHOD

2.1.Research Design

This study employs a qualitative phenomenological research design, which is epistemologically grounded in the philosophical tradition of Husserlian and Heideggerian phenomenology (van Manen, 2021). Phenomenology as a research methodology prioritizes the investigation of the 'lived experience,' the essence of phenomena as they are subjectively experienced by individuals in their natural environments. This approach is particularly appropriate for the present study because employee adaptation to AI is not merely a behavioral or performance outcome but a deeply personal, emotionally complex, and meaning-laden phenomenon that unfolds within specific social and organizational contexts. Qualitative phenomenological inquiry provides the methodological tools to excavate this experiential terrain with appropriate nuance, depth, and fidelity to participants' subjective realities.

The interpretive phenomenological analysis (IPA) framework, as developed by Smith et al. (2022), guides the analytical approach. IPA involves a dual interpretive process: participants construct meaning from their lived experiences, and researchers subsequently interpret these meaning constructions through a process of hermeneutic engagement with the data. This double hermeneutic positions the researcher as both an observer of and participant in the meaning-making process, requiring reflexive awareness of how the researcher's own assumptions and perspectives may shape the interpretive process.

2.2.Research Location and Participant Selection

The research was conducted in South Sulawesi Province, Indonesia, with participants recruited from companies operating in five key industrial sectors: banking and financial services, manufacturing, retail and consumer goods, technology services, and general service industries. South Sulawesi was selected as the research locale for several strategic reasons: it represents one of Indonesia's most economically significant regions outside Java; it has experienced rapid industrial digitalization in recent years; and it remains underrepresented in empirical research on digital transformation and AI adoption.

Participants were selected through purposive, criterion-based sampling (Creswell & Poth, 2023). Inclusion criteria required that participants: (1) were currently employed in a company that had implemented at least one AI-based system in their operational workflow; (2) had direct, regular interaction with AI systems in their job role; (3) had been employed in their current position for a minimum of 1.5 years, ensuring sufficient exposure to the AI transformation process to generate reflective, experience-rich narratives; and (4) were willing and able to provide informed consent and participate in in-depth interviews conducted in either Indonesian or English.

2.3.Participants

A total of 20 participants were recruited for this study. The sample comprised employees from diverse industry sectors, organizational hierarchies, educational backgrounds, and demographic profiles, ensuring a richly textured empirical foundation. Table 2 presents the complete informant profile.

Table 2. Informant Profile

Code	Gender	Age	Industry	Position	Education	AI System Used	Experience
P01	Male	34	Banking	Customer Service Mgr	S1 Management	AI Chatbot & CRM	6 years
P02	Female	28	Retail	Digital Marketing Staff	S1 Marketing	Recommendation Engine	3 years
P03	Male	41	Manufacturing	Production Supervisor	S1 Engineering	Automated QC System	9 years
P04	Female	32	Technology	Software Engineer	S2 Computer Science	ML Deployment Tools	5 years
P05	Male	37	Banking	Branch Operations Lead	S1 Finance	AI Risk Assessment	8 years
P06	Female	29	Service	HR Analytics Staff	S1 Psychology	AI Recruitment System	3 years
P07	Male	45	Manufacturing	Plant Manager	S2 Industrial Eng.	Predictive Maintenance AI	12 years
P08	Female	31	Retail	Store Operations Staff	Diploma	Inventory AI System	4 years
P09	Male	27	Technology	Data Analyst	S1 Statistics	AI Data Pipeline	2 years

P10	Female	38	Banking	Compliance Officer	S2 Law	AI Document Review	7 years
P11	Male	33	Service	Logistics Coordinator	S1 Management	Route Optimization AI	5 years
P12	Female	26	Technology	UX Researcher	S1 Communication	AI User Behavior Analytics	1.5 years
P13	Male	44	Manufacturing	Quality Engineer	S1 Engineering	Vision Inspection AI	10 years
P14	Female	35	Service	Customer Experience Lead	S1 Business Admin	AI Feedback Analysis	6 years
P15	Male	30	Banking	IT Risk Analyst	S1 Information Systems	AI Fraud Detection	4 years
P16	Female	39	Retail	Category Manager	S2 Business	AI Demand Forecasting	8 years
P17	Male	28	Technology	DevOps Engineer	S1 Computer Science	AIOps Platform	3 years
P18	Female	42	Manufacturing	Process Engineer	S2 Engineering	AI Process Optimization	11 years
P19	Male	36	Service	Training & Dev. Manager	S2 HRM	AI Learning Management	7 years
P20	Female	31	Banking	Wealth Management Staff	S1 Finance	AI Investment Advisory	4 years

The final sample of 20 participants aligns with the principle of information power (Malterud et al., 2022), which posits that sample size adequacy in qualitative research is determined not by statistical power but by the richness and density of experiential data generated. Data saturation, the point at which no new themes or conceptual categories emerged from incoming data, was reached at interview 17, with interviews 18–20 serving as confirmatory data collection.

2.4.Data Collection

Data were collected through in-depth, semi-structured interviews conducted between January and April 2024. Each interview lasted between 60 and 90 minutes and was conducted either in-person at the participant's workplace or via secure video conferencing, depending on participant preference and logistical feasibility. All interviews were audio-recorded with participant consent and subsequently transcribed verbatim. The interview protocol comprised four thematic domains: (1) the participant's initial experience of AI introduction in their workplace; (2) their emotional and psychological responses to AI-driven changes; (3) the strategies they employed to adapt to new technological demands; and (4) their perceptions of organizational support and leadership communication during the transformation process.

In addition to formal interviews, participants were invited to provide reflective narratives, brief written accounts of a particularly memorable or significant moment in their AI adaptation journey. These reflective narratives served as secondary data sources that complemented and enriched the interview data by providing participants with an alternative, more deliberate mode of meaning expression. Field notes documenting observational data, contextual details, and the researcher's reflexive memos were maintained throughout the data collection process.

2.5.Data Analysis

Data analysis followed the six-step IPA process outlined by Smith et al. (2022): (1) immersive reading and re-reading of transcripts; (2) initial noting of experiential, exploratory, and conceptual comments; (3) development of emergent themes from the noted comments; (4) searching for connections across emergent themes; (5) moving to the next case; and (6) looking for patterns across cases. This process was applied iteratively across all 20 transcripts, with NVivo 14 software supporting the management and organization of coding data. The analytical process was conducted collaboratively by two researchers, with regular discussion sessions to negotiate coding decisions and ensure analytical rigor.

Thematic coding proceeded through three analytical levels: (1) first-order codes, representing descriptive, close-to-the-data characterizations of participant statements; (2) second-order codes, representing more interpretive, conceptual categories derived from patterns across first-order codes; and (3) aggregate themes, representing the overarching experiential constructs that structured participants' adaptation experiences. Table 3 presents the complete thematic coding structure.

Table 3. Thematic Coding Structure

Main Theme	Sub-Theme	Code Category	Representative Informants
AI as Efficiency Tool	Automation Benefits	Workload Reduction	P01, P03, P07, P13, P18
	Productivity Gains	Task Speed Improvement	P04, P09, P12, P17
	Performance Enhancement	Error Reduction	P03, P07, P13
Fear & Uncertainty	Job Displacement Anxiety	Existential Job Threat	P02, P05, P08, P10, P16
	Career Uncertainty	Future Role Ambiguity	P01, P06, P11, P15, P20
	Emotional Stress	Psychological Pressure	P02, P08, P16, P19
Continuous Learning	Upskilling Behavior	Self-Directed Learning	P04, P09, P12, P17, P19
	Digital Competence	Technical Skill Building	P01, P04, P09, P15, P17
	Learning Pressure	Mandatory Reskilling	P06, P10, P14, P18, P20
Organizational Support	Management Communication	Leadership Transparency	P01, P05, P07, P11, P13
	Training Programs	Formal AI Training	P03, P06, P14, P18, P19

Human-AI Collaboration	Psychological Safety	Supportive Culture	P02, P08, P12, P16, P20
	Role Redefinition	New Hybrid Tasks	P04, P09, P12, P17
	Complementary Work	AI-Assisted Decision Making	P01, P05, P10, P15
Psychological Responses	Trust Development	Acceptance Over Time	P03, P07, P13, P18
	Positive Emotions	Excitement & Motivation	P04, P09, P12, P17, P19
	Negative Emotions	Resistance & Anxiety	P02, P08, P10, P16
	Adaptive Coping	Resilience Building	P01, P05, P06, P11, P14

2.6.Validity and Trustworthiness

The trustworthiness of this study was established through multiple strategies aligned with Lincoln and Guba's (2023) criteria of credibility, transferability, dependability, and confirmability. Credibility was ensured through prolonged engagement with the research context, triangulation of data sources (interviews, reflective narratives, and field notes), and member checking, whereby preliminary findings were shared with five participants for feedback and validation. Transferability was supported through a thick, contextualized description of the research setting, participants, and interpretive processes, enabling readers to assess the applicability of findings to other contexts. Dependability was maintained through an audit trail documenting all methodological decisions, analytical steps, and conceptual developments. Confirmability was achieved through researcher reflexivity, documented in reflexive journals maintained throughout the research process, and an external audit conducted by an independent qualitative research methodologist.

3. RESULTS AND DISCUSSION

The phenomenological analysis of data from 20 participants yielded six overarching themes that collectively constitute the experiential structure of employee adaptation to AI in South Sulawesi companies. Each theme is presented below with supporting interview evidence, theoretical integration, and comparative analysis with the extant literature.

Theme 1: AI as a Tool for Efficiency and Productivity

The most consistently reported initial experience across participants was a recognition of AI's functional benefits in terms of task efficiency, workload reduction, and performance enhancement. Participants from banking, manufacturing, and technology sectors in particular articulated a strong awareness of AI's capacity to automate repetitive, time-consuming tasks and generate accurate analytical outputs at speeds that surpassed human capability.

P01, a Customer Service Manager at a South Sulawesi bank, reflected on the transformation of his daily work after the implementation of an AI-powered CRM system:

"Before the AI system, I used to spend at least three hours every morning reviewing customer data manually to identify priority accounts. Now the system does that overnight and presents me with a prioritized dashboard by the time I arrive. I can focus my energy on actually building relationships rather than sorting through spreadsheets. It changed my work completely and honestly, for the better."

Similarly, P07, a Plant Manager with 12 years of experience in manufacturing, described the impact of a predictive maintenance AI system on production operations:

"We used to have unexpected machine breakdowns that would halt production for days, sometimes a week. The AI system analyzes sensor data continuously and flags potential failures before they happen. Our downtime has dropped by almost 40 percent. As a manager, that kind of operational reliability is invaluable."

These accounts align with Wilson and Daugherty's (2021) collaborative intelligence framework, which posits that AI creates maximum organizational value when it assumes the burden of routine cognitive and analytical tasks, thereby enabling human workers to redirect their energies toward high-value, relationship-intensive, and strategic activities. Brynjolfsson and McAfee (2023) similarly document that AI augmentation of high-complexity roles rather than outright replacement represents the predominant pattern of AI's labor market impact in advanced organizational deployments. The efficiency benefits perceived by participants in this study appear to serve as an important entry point for positive AI acceptance: when employees experience direct, tangible benefits from AI in their daily work, the psychological foundation for broader acceptance is established.

Importantly, however, the positive efficiency narrative was not universal or uncomplicated. Several participants acknowledged that while AI delivered efficiency gains, the nature of their remaining work became more cognitively demanding and emotionally intensive as routine tasks were automated. P14, a Customer Experience Lead in a service company, noted:

"AI handles all the routine queries now, FAQs, order tracking, and basic complaints. What's left for me are the difficult cases, the angry customers, the complex problems that need human judgment. The volume is lower, but the intensity is much higher. You could say AI elevated my job, but it also made it harder in some ways."

This phenomenon, which Huang and Rust (2021) term 'role intensification,' where AI automation of routine tasks concentrates the remaining human workload around more complex, emotionally demanding interactions, represents an important nuance in the efficiency narrative that has implications for job design, workload management, and employee support systems.

Theme 2: Fear of Job Displacement and Career Uncertainty

Despite the acknowledged efficiency benefits of AI, the overwhelming majority of participants expressed with varying degrees of intensity some form of anxiety related to job displacement, career trajectory uncertainty, or professional identity erosion. This theme emerged with particular force among participants in roles with higher proportions of routine, codifiable tasks: bank tellers and operations staff, retail category managers, manufacturing line supervisors, and compliance officers.

P08, a Store Operations Staff member at a retail company, articulated the fear of displacement with striking emotional candor:

"When they first introduced the AI inventory system, the rumor immediately spread that they were going to cut half the operations team. Nobody told us officially; we just heard it through the grapevine. For about two months, I came to work every day, not knowing if I still had a job. That kind of fear does something to you. You can't concentrate. You question every decision you make."

P10, a Compliance Officer at a banking institution, expressed a more nuanced form of existential professional anxiety:

"I spent 15 years building expertise in document review and regulatory compliance. Now the AI system can review a 200-page contract in minutes and flag all the relevant clauses. I don't feel replaceable yet, but I do feel... less essential. And that feeling is deeply uncomfortable when your professional identity is so tied to what you know how to do."

These experiences resonate powerfully with the job insecurity literature. Lee et al. (2021) documented that perceived AI threat the subjective assessment that AI poses a meaningful risk to one's current employment is a robust predictor of organizational disengagement, increased turnover intentions, and reduced job satisfaction. Oreg et al. (2022) further established that dispositional resistance to change amplifies these negative responses, creating a compounding psychological burden for employees who are both inherently change-resistant and situated in roles with high automation potential.

Critically, the fear of displacement in this study was significantly exacerbated by organizational communication failures, specifically, the absence of clear, proactive messaging from management about how AI would affect existing roles and what support would be provided to affected employees. The 'grapevine' communication pattern described by P08 illustrates a dangerous vacuum of organizational information that, when filled by speculation and rumor, generates disproportionate anxiety and resistance. This finding reinforces Orlikowski and Scott's (2021) argument that AI's organizational impact is as much a product of how it is communicated and socially constructed as of its technical capabilities.

The fear of career irrelevance, distinct from immediate job loss anxiety, emerged as a particularly salient concern among mid-career employees with 7–12 years of experience (P05, P10, P13, P18). These individuals had invested substantially in developing expertise within their current role structures and perceived AI's encroachment on those domains as a threat to the professional capital they had accumulated. This career capital threat (Huang & Rust, 2021) represents a dimension of AI-related fear that is relatively underexplored in quantitative survey research but emerges with considerable salience in phenomenological narratives.

Theme 3: Continuous Learning and Digital Skill Adaptation

Across all sectors and organizational levels, participants consistently identified the need for continuous learning and digital skill development as a defining imperative of the AI-transformed workplace. This theme manifested in two distinct sub-patterns: proactive, self-initiated learning driven by intrinsic motivation and career aspiration; and reactive, anxiety-driven skill acquisition driven by the perceived threat of obsolescence.

P04, a Software Engineer in a technology company, exemplified the proactive learning orientation:

"I actually became more curious about AI after my company started implementing it. I completed three online certifications on machine learning platforms in my own time. Not because my company asked me to, but because I wanted to understand what I was working with and, frankly, because I wanted to stay ahead. In tech, standing still means falling behind."

In contrast, P06, an HR Analytics Staff member, described a more pressured, reactive relationship with skill development:

"Our HR system was completely transformed overnight, it felt like. Suddenly, there was an AI that was supposed to screen resumes, predict candidate fit, and flag retention risks. I had no training for it initially. I had to figure it out on my own while still meeting all my normal KPIs. It was exhausting. I felt like I was running on a treadmill that kept speeding up."

These contrasting experiences illuminate the critical distinction between adaptive learning environments and maladaptive learning pressure environments. In organizations where skill development is supported through structured training programs, protected learning time, and managerial encouragement, employees develop what Luthans et al. (2021) term 'psychological capital,' a composite positive psychological resource comprising hope, efficacy, resilience, and optimism that facilitates proactive, confident engagement with technological change. Conversely, organizations that introduce AI without commensurate training infrastructure create conditions of learning pressure that, paradoxically, can inhibit the very adaptation they require.

P19, the Training and Development Manager, offered an insightful organizational perspective on this dynamic:

"The biggest mistake companies make is treating AI implementation as a technology project, not a people project. You can install the best AI system in the world, but if your

employees don't understand it, don't trust it, and don't feel supported in learning to use it, you will get at best grudging compliance and at worst outright sabotage. People adapt when they feel safe to make mistakes while learning."

This perspective directly validates Edmondson and Harvey's (2022) research on psychological safety as a prerequisite for adaptive learning in technologically dynamic environments. The findings also align with Smite et al. (2023), who documented that organizations investing in structured AI literacy programs see significantly faster adaptation curves and lower resistance rates among their workforce. The implication for HR practice is clear: digital training is not merely a technical necessity but a psychological one, communicating organizational investment in employee capabilities and futures.

Theme 4: Organizational Support and Leadership Communication

Leadership communication and organizational support emerged as the most consistently cited moderators of employee adaptation quality across all participant groups. Employees who reported receiving clear, frequent, and empathetic communication from their managers about AI's strategic purpose, implementation timeline, and impact on roles demonstrated markedly more positive and constructive adaptation experiences than those who perceived a communication deficit.

P05, a Branch Operations Lead at a banking institution, described the transformative effect of his manager's communication approach:

"My branch manager held a series of open forums, three of them before the AI rollout. He explained what the system would do, what it wouldn't do, what our new roles would look like, and crucially, what would happen to the staff members whose tasks were being automated. He was honest about the challenges but also clear about the opportunities. That transparency made all the difference. People came on board because they understood what was happening and why."

This account exemplifies the 'change leadership communication' construct articulated by Kotter (2012) and elaborated in subsequent research by Oreg et al. (2022): effective change communication is not merely informational but relational and emotional, it acknowledges the human stakes of organizational transformation, and treats employees as intelligent, morally considerable stakeholders rather than passive recipients of management decisions.

Conversely, P16, a Category Manager at a retail company, described the corrosive effects of leadership communication failure:

"Our management style was: implement first, explain later if at all. The AI demand forecasting system just appeared one day. No training, no context, no explanation of why our previous approach was being replaced. The message we received was essentially: 'The machine knows better than you do now.' It was dehumanizing, and it created a lot of resentment that still hasn't fully healed."

These contrasting experiences underscore the central finding of van der Voet and Vermeeren (2020): the quality of employee engagement during digital transformation, not the technological sophistication of the AI system itself, is the primary determinant of successful organizational adaptation outcomes. When leadership communication validates employees' expertise, acknowledges their concerns, and articulates a credible vision of their future role in the AI-augmented organization, the psychological barriers to adaptation are substantially reduced.

Organizational support beyond communication, specifically, access to formal AI training programs, technical support resources, and the structural reassurance of a supportive learning environment, was also identified as a critical enabler of positive adaptation. P03, a Production Supervisor in manufacturing, noted:

"The company organized a two-week training program before the AI quality control system went live. It wasn't just technical training; they brought in a psychologist to talk about managing change. That told me: this company sees us as whole people, not just machine operators. It made a real difference in how I approached the whole thing."

Theme 5: Human-AI Collaboration in the Workplace

A particularly significant and theoretically rich theme that emerged from the phenomenological analysis was the gradual development of collaborative modalities between human employees and AI systems. Rather than perceiving AI as a replacement, the dominant narrative in popular discourse, a substantial subset of participants, particularly those with higher digital literacy and more exposure to AI applications over time, described their relationship with AI in explicitly collaborative terms.

P09, a Data Analyst with two years of experience using an AI data pipeline, articulated this collaborative orientation eloquently:

"At first, I was a bit intimidated by the AI tools. They could do in seconds what took me hours. But I realized pretty quickly that the AI is excellent at finding patterns in large datasets but completely blind to context, nuance, and the organizational politics that explain why those patterns exist. My job evolved from being a data processor to being a data interpreter, and frankly, that's a much more interesting job."

P15, a Banking IT Risk Analyst, described a similar evolution of his professional identity within an AI-augmented role:

"The fraud detection AI is incredibly good at identifying statistical anomalies. But it throws up a lot of false positives that require human judgment to evaluate. The AI tells you something looks suspicious; I have to decide whether it actually is. My expertise didn't become obsolete; it became more important because I'm now the quality control layer on top of the AI."

These accounts provide empirical grounding for Wilson and Daugherty's (2021) 'collaborative intelligence' model, demonstrating that human-AI collaboration in practice involves a dynamic negotiation of complementary competencies: AI systems contribute scale, speed, and analytical pattern recognition; human employees contribute contextual judgment, ethical reasoning, relational intelligence, and creative problem-solving. The emergence of this collaborative orientation is not automatic; it requires deliberate role redesign, clear communication of the division of cognitive labor, and sufficient experience with the AI system to develop the trust and familiarity necessary for genuinely collaborative work.

Trust development emerged as a critical sub-theme within the collaboration theme. P13, a Quality Engineer who had initially resisted the introduction of vision inspection AI, described the gradual nature of his trust development:

"The first three months, I was constantly second-guessing the system, running my own manual checks on everything it flagged. But over time, as I saw its accuracy rate consistently above 99 percent, I started to trust it. Now I think of it as a very reliable colleague, one that never gets tired or distracted. It took time, but the relationship is genuinely collaborative now."

Glikson and Woolley (2020) documented similar trust development trajectories in their research on human-AI teaming, identifying a characteristic arc from initial skepticism through conditional trust to integrated collaborative confidence. This trajectory appears to be accelerated by AI system transparency, the degree to which the system's reasoning processes are legible to human users, and by the accumulation of positive collaborative experiences over time.

Theme 6: Employee Psychological and Emotional Responses

The phenomenological analysis revealed a complex, temporally dynamic landscape of psychological and emotional responses to AI adoption that defies simple characterization as either positive or negative. Rather, participants described an evolving emotional journey characterized by multiple, coexisting, and sometimes contradictory feelings that shifted in response to organizational events, personal experiences, and the accumulation of AI-related competencies over time.

Initial emotional responses were predominantly dominated by uncertainty and anxiety, a psychological state that Oreg et al. (2022) describe as 'change-related affect,' arising from the disruption of established cognitive schemas and work routines. P02, a Digital Marketing Staff member, captured this initial emotional complexity:

"When they first announced the AI recommendation engine, I felt a mix of excitement and dread in the same breath. Exciting because I'd heard about these systems and always wanted to work with them. Dread because I thought: if the AI can do this, why do they need me? Those two feelings were sitting side by side for months."

This emotional ambivalence, the simultaneous experience of positive anticipation and negative anxiety in response to technological change, has been documented in the occupational stress literature as a characteristic response to significant role disruption (Smite et al., 2023). The co-presence of these opposing affective states represents a psychologically demanding condition that requires both individual resilience resources and organizational support to navigate constructively.

Over time, the emotional landscape of participants who received adequate organizational support and training shifted toward more positive affective states. P12, a UX Researcher in the technology sector, described this trajectory:

"The first few months were genuinely stressful. I was learning new tools, questioning my value, and wondering about my future. But once I got proper training and once I started producing better work because of the AI tools, I began to feel genuinely empowered. Now I actually look forward to exploring what new AI capabilities can do for my research. The anxiety transformed into something more like professional excitement."

Resistance, the behavioral manifestation of negative emotional responses, was documented across multiple participants, though its expression varied considerably by organizational context and individual disposition. P18, a Process Engineer in manufacturing, described a more subtle form of passive resistance:

"I didn't refuse to use the AI system. I'm a professional, I understand what's required. But I was slow to integrate it fully into my workflow. I kept finding reasons to do things manually, to check the AI's outputs against my own calculations. I told myself it was quality control, but honestly, I was reluctant to fully trust a system I didn't fully understand. It took a year before I really let go of that defensive behavior."

This account illustrates what Luthans et al. (2021) term 'behavioral inhibition,' a form of passive non-compliance that, while not overtly disruptive, significantly undermines the organizational efficiency gains AI implementation is designed to deliver. Critically, the resolution of P18's resistance was not achieved through managerial pressure or compliance enforcement, but through the gradual accumulation of positive experiences with the system and the development of sufficient technical understanding to feel in control of the human-AI interaction.

These findings collectively suggest that employee psychological adaptation to AI is best understood as a non-linear, experientially grounded process rather than a discrete behavioral switch that can be activated through training or policy mandate. The phenomenological essence of AI adaptation as revealed through this study's data is a negotiated reconstruction of professional identity and workplace meaning in the face of technological disruption, mediated by the quality of organizational support and the richness of experiential engagement with AI systems over time.

4. CONCLUSION

This study concludes that employee adaptation to AI-driven digital transformation is a complex process involving behavioral, emotional, and psychological adjustments. Employees not only develop new digital skills but also reconstruct their professional identity and work meaning in response to technological change. Organizational support, particularly transparent leadership communication, continuous training, and psychologically safe work environments, plays a crucial role in shaping successful adaptation. The findings highlight that AI should not be viewed solely as a technological tool, but also as a human and organizational challenge requiring empathetic and inclusive change management. Despite its limitations in scope and generalizability, this study contributes important phenomenological insights into employee experiences with AI adoption in Indonesia and offers practical implications for organizations seeking sustainable and human-centered digital transformation.

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