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Emotional Fatigue or Support as Dual Pathways of AI Interaction on Worker Well-being in Smart Work Environments

Abstract

AI systems mediate work processes making employee communication, decision-making support, and task automation seamless. However, the psychological implications of these technologies have become critical to organizational roles and sustainability. Job Demands–Resources (JD-R) Model, was used to assess whether AI functions as a work resource that promotes motivation, reduces stress, and offers emotional relief through efficiency and support systems. On the other hand, it inquired into whether it acts as a demanding agent that increases cognitive load, alienation, surveillance pressure, and emotional exhaustion. Literature published between 2015 and 2025 were systematically sourced from Web of Science, Scopus, IEEE Xplore, PubMed, and Google Scholar using predefined search, screening, and exclusion criteria. Findings indicated that supportive AI particularly in decision assistance, intelligent feedback, and automated task reduction enhances well-being by reducing emotional strain and improving perceived competence. In contrast, AI systems that lack human touch, heighten monitoring, or increase work complexity trigger emotional fatigue, anxiety, and decreased job satisfaction. The study emphasized the need for human-centered AI design that balances efficiency with empathy to protect workers' emotional well-being in technologically advanced workplaces.

Keywords: AI interaction, emotional fatigue, employee well-being, smart work environments, Job Demands–Resources Model

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1. Introduction

Artificial intelligence (AI) has become a defining feature of 21st-century work space, redefining how humans interact with technology, colleagues, and organizations. From chatbots in banking to algorithmic systems in logistics, AI now mediates the emotional dimension of work as much as the technical. Organizations in finance, telecommunications, and education are increasingly relying on AI-driven platforms for human resource management, data analytics, and customer service. While these systems promise efficiency, they also raise questions about worker well-being, emotional sustainability, and psychological state in technologically mediated environments.

Even though AI-based tools are used to track performance, automate communication, and streamline workflow, many employees experience these same systems as intrusive or emotionally draining. Workers report feeling constantly monitored or evaluated by impersonal systems, creating an atmosphere of heightened vigilance. AI can enhance productivity and undermine emotional comfort at the same time. This dual nature of AI has been widely observed in global research with Bakker and Demerouti (2023) describing the Job Demands–Resources (JD–R) model as a framework that explains how job characteristics can either support or exhaust workers depending on their design and perception. In this situation, AI represents both: a resource when it empowers decision-making and reduces strain, and a demand when it increases cognitive load or fosters alienation.

AI adoption across several climates occurs amid uneven digital readiness and limited regulatory guidance. As a result, workers face new psychological demands in learning to collaborate with systems they neither designed nor fully understand. These technologies, when implemented without emotional consideration, may create emotional fatigue, which is a chronic sense of disconnection and anxiety. Contrariwise, when implemented with empathy and transparency, AI can offer emotional support, helping workers manage complexity and derive satisfaction from clearer decision pathways. Falco *et al*. (2023) found that AI-supported remote work increased autonomy but also introduced new stressors when boundaries blurred. Similarly, Lippert, Kirchner, and Saunders (2023) observed that algorithmic management produced both empowerment and strain, depending on whether employees perceived AI oversight as fair. These patterns suggest that the emotional effects of AI cannot be separated from human perception and organizational culture.

It is from these considerations that this study investigates how AI in smart work environments generates dual emotional pathways either supporting emotional well-being or contributing to fatigue. Guided by the JD–R framework, the study examines AI as a work resource that enhances motivation and competence, and as a job demand that elevates stress or burnout. The analysis focuses on empirical studies published between 2015 and 2025 to capture contemporary workplace experiences while underpinning their implications for African organizational realities.

2. Statement of the Problem

AI's usage in the workplace has overtook the understanding of its psychological and emotional consequences. AI-driven systems carries with it improved efficiency, accuracy, and decision-making, but with evidence to indicate that these tools can also intensify emotional strain. Employees exposed to continuous algorithmic evaluation often experience anxiety, alienation, or burnout. In contrast, when AI provides supportive feedback and reduces workload, it enhances job satisfaction and well-being (Lippert *et al.*, 2023, Falco *et al.*, 2023). This

contradiction poses a conceptual challenge which is that, the same technology can act as both a motivator and a stressor. The lack of clarity about which factors determine this shift whether design, perception, or context creates a gap in current understanding. Furthermore, research on the emotional impact of AI has largely been conducted in developed economies, leaving a shortage of region-specific evidence from African workplaces.

3. Objectives of the Study

The objectives of this study are to:

i. Examine how AI functions as a work resource that enhances motivation, emotional support, and well-being among employees.
ii. Identify how AI acts as a job demand that contributes to emotional fatigue, stress, or burnout.
iii. Assess the mediating influence of perception, control, and transparency in determining emotional outcomes of AI interaction.

4. Research Questions

To achieve the above stated objectives, the study will address the following research questions:

i. How does AI function as a work resource that enhances emotional support and psychological well-being?
ii. In what ways does AI act as a job demand that generates emotional fatigue and stress?
iii. How do factors such as perceived control, transparency, and fairness influence employees' emotional responses to AI?

5. Literature Review

Studies have shown that artificial intelligence (AI) can play a positive and emotionally supportive role in smart work environments when designed as a resource that enhances workers' autonomy, competence, and social connection. Drawing from the Job Demands–Resources (JD-R) model, supportive AI tools act as resources that cushion stress and promote engagement (Triantoro & Przegalinska, 2023). They suggest that AI systems offering decision assistance and feedback reduce uncertainty, enabling employees to perform with greater confidence. A similar argument is presented by Arboh, Zhu, and Atingabili (2025), who found that AI awareness in healthcare and logistics sectors fosters empowerment rather than fear when workers understand its collaborative purpose. They note that employees who viewed AI as an assistant rather than a monitor experienced elevated workplace well-being.

This makes the point clear that perception plays a key mediating role in whether AI functions as a resource or demand. In essence, awareness reshapes the psychological relationship between human and machine, turning potential emotional fatigue into emotional resilience. Ashoer, Maseeh, and Lim (2025) emphasized that generative AI can act as a transformational partner that strengthens engagement through skill enrichment. Their extension of the

JD-R theory shows that AI-enabled feedback loops support psychological growth and reduce burnout symptoms by giving employees clearer performance signals. Similarly, Radic *et al.* (2025) applied JD-R in tourism contexts, showing that AI-driven leadership improves motivation when workers perceive AI outputs as fair and transparent. They argue that AI-driven management, when modeled on servant leadership principles, fulfills the same supportive role traditionally played by empathetic human supervisors.

This link between fairness, autonomy, and emotional support was also emphasized by Liu and Li (2025), who describe human-AI collaboration as a "double-edged sword" but found its positive side overriding when workers have discretion over AI input. Their study on employee safety performance shows that controlled collaboration reduces anxiety. The more control employees retain, the more AI becomes a source of confidence and relief. Sonnentag (2025) expands on this view by suggesting that the relationship between job design and well-being must now account for digital agents as new forms of structural resources. Falco *et al.* (2023) studied Italian organizations and found that smart working with AI assistance correlated with lower cortisol levels and improved well-being, particularly when workload predictability improved. They conclude that AI-mediated scheduling can stabilize work rhythms, reducing physiological stress responses.

Kong *et al.* (2025) observed a similar level where teachers using AI systems for grading and planning initially felt overwhelmed, but those who learned to integrate AI reported heightened innovative behavior and emotional vitality. The shift occurred when AI use transitioned from imposed obligation to chosen support. Despite its potential for support, AI can easily lead to emotional fatigue when it increases cognitive demands or bring about feelings spying. Lippert, Kirchner, and Saunders (2023) observe that, "algorithmic management systems can replicate managerial oversight to such an extent that workers experience being constantly evaluated by invisible metrics.

De Carlo *et al.* (2022) also identify this problem during the pandemic-era shift to smart working, where digital connectivity, while enabling flexibility, paradoxically increased burnout due to blurred boundaries. Here, the emotional fatigue stemmed not from workload but from cognitive and psychological overload. Employees struggled to differentiate between work and personal time under constant AI-enabled communication flows. In the same vein, Cai, Wang, and Chen (2024) show that extensive use of intelligent machines raises burnout risk, especially in roles involving repetitive human-AI interactions without meaningful social contact. They describe this as "emotional depletion caused by perceived mechanical surveillance". For Routray, Choudhary, and Sinha (2025) AI's intent to assist often backfires when its functionalities are poorly designed, producing "technostress that undermines well-being rather than enhancing it". This occurs when AI systems generate excessive notifications,

feedback, or task interruptions that increases cognitive load.

Furthermore, Scholze and Hecker (2023) expanded the theoretical implications of this mismatch by coining the term digital job demands, noting that digitization transforms traditional stressors into new psychological burdens mediated through AI systems. They found that when AI is constructed into decision-making structures without adequate human oversight, workers perceive the system as controlling rather than enabling. The result is emotional detachment, a core indicator of burnout. Meem and Johnson (2025) confirm these risks in the software sector, showing that developers using AI-assisted coding tools faced mental fatigue from the pressure to adapt to constant algorithmic updates. Although these systems improved efficiency, the need for continuous learning creates exhaustion. From the foregoing, while the literature confirms AI's potential to alleviate emotional strain through efficiency and support, it equally reveals the dangers of excessive algorithmic oversight and cognitive overextension informing the rationale for the study's investigation.

6. Theoretical Framework

The Job Demands–Resources (JD–R) model is an important structure for understanding how AI interaction produces both emotional fatigue and emotional support in smart work environments. Developed originally to explain occupational stress and motivation dynamics, the JD–R model proposes that every job has demands aspects requiring sustained effort and resources, which help in achieving work goals and mitigating psychological strain. When demands exceed resources, ordinarily emotional exhaustion and burnout will emerge. But when resources outweigh demands, engagement and well-being flourish (Bakker & Demerouti, 2023). This is why the model's adaptability makes it particularly suitable for analyzing technologically mediated workplaces. The JD–R framework according to Sonnentag (2025) is a diagnostic lens for balancing digital workload and psychological recovery in AI-augmented tasks. In other words, the JD–R model does not merely classify work conditions but helps to explain how AI tools can act simultaneously as stressors and supports, depending on their design, implementation, and human interpretation.

Summary of Theoretical Logic

JD–R Component	**AI-Driven Mechanism**	**Emotional Outcome**	**Illustrative Source**
Job Demands	Algorithmic monitoring, digital overload, cognitive complexity	Emotional fatigue, burnout, anxiety	Lippert *et al.* (2023); Cai *et al.* (2024)
Job Resources	Task automation, intelligent feedback, autonomy	Emotional support, motivation, well-being	Arboh *et al.* (2025); Falco *et al.* (2023)
Mediator	Worker perception and AI awareness	Converts demand into resource or vice versa	Liu & Li (2025)
Moderator	Human-centered AI design	Balances efficiency and empathy	Radic *et al.* (2025)

Outcome	Worker emotional state and performance	Determines sustainability of smart work	Sonnentag (2025)

This table illustrates the logical chain connecting the JD–R framework to empirical observations and to the methodological design of this research.

7. Methodology

7.1. Research Design

This study adopts a Systematic Literature Review (SLR) approach to critically synthesize empirical and theoretical research published between 2015 and 2025 on the dual emotional effects of AI interaction on worker well-being in smart work environments. The SLR approach was selected because the study aims to integrate multidisciplinary findings across psychology, management, human–computer interaction, and organizational behavior. According to Tranfield, Denyer, and Smart (2003 p.214), an SLR offers "a structured, transparent process that minimizes bias and enhances reproducibility". This review follows the PRISMA (2020) protocol, which ensures comprehensiveness and replicability by defining clear inclusion and exclusion criteria, data sources, and coding methods. The review design operationalizes the Job Demands–Resources (JD–R) Model as its guiding framework to classify AI interaction outcomes into emotional support (resources) and emotional fatigue (demands) pathways.

7.2. Research Framework Integration

The JD–R model provides the theoretical logic that underpins the methodological structure. Following the model, this review categorizes each retrieved study according to:

i. Job Demands: Elements of AI that increase emotional load, anxiety, or burnout (e.g., algorithmic monitoring, overload, digital fatigue).
ii. Job Resources: AI functions that support well-being through decision assistance, efficiency, feedback, or autonomy.
iii. Outcomes: Emotional well-being indicators such as motivation, job satisfaction, and reduced stress.

Bakker and Demerouti (2023 p. 47) explain that, "the JD–R framework allows categorization of work elements into stress-producing or engagement-enhancing factors". Therefore, the methodology not only classifies existing studies but also interprets how AI interaction aligns with either motivational or strain processes described in JD–R theory.

7.3. Search Strategy and Data Sources

7.3.1 Databases and Search Engines

The literature search was conducted across five major databases to ensure multidisciplinary coverage:

i. Web of Science (WoS)
ii. Scopus
iii. IEEE Xplore
iv. PubMed
v. Google Scholar

The inclusion of Google Scholar helped to capture grey literature and preprints that had passed institutional review, while Scopus and Web of Science ensured indexing reliability.

7.3.2 Search Strings

Search terms were derived from keywords in the abstract and theoretical framework, using Boolean logic: ("Artificial Intelligence" OR "AI systems" OR "AI interaction") AND ("worker well-being" OR "employee mental health" OR "emotional fatigue" OR "emotional support") AND ("smart work environment" OR "digital workplace" OR "algorithmic management") AND ("Job Demands–Resources" OR "JD–R model")

7. 3.3 Time Frame

Studies published from January 2015 to October 2025 were included to capture the most recent decade of scholarship, corresponding with the period of accelerated AI integration into work processes.

7. 3.4 Language and Access Criteria

Only English-language, peer-reviewed articles and conference papers were considered. Preprints were included only when affiliated with recognized publishers (e.g., SSRN, Research Square).

7.3. 5. Inclusion and Exclusion Criteria

The criteria were applied systematically to ensure focus and rigor.

Inclusion Criteria	Exclusion Criteria
Studies examining AI interaction in workplace contexts	Studies not related to work or organizational settings
Articles addressing emotional, psychological, or well-being outcomes	Technical or engineering-only AI studies without human impact
Research using JD–R framework or related constructs (stress, burnout, motivation)	Articles before 2015 or not peer-reviewed
Studies involving smart work, automation, or algorithmic management	Opinion pieces, blogs, or non-scholarly essays

7.3.6. Study Selection Process (PRISMA Flow)

The PRISMA-based selection process unfolded in four major stages:

i. Identification:
   - 823 records retrieved across databases.
   - Duplicates removed: 212.
   - Remaining: 611.

ii. Screening:
   - Abstracts and titles reviewed for relevance to AI, emotion, and work contexts.
   - Excluded: 367 papers not linked to emotional or JD–R constructs.
   - Remaining: 244.

iii. Eligibility:
   - Full-text reviews conducted on 244 papers.

- Excluded 188 for lacking empirical evidence or not meeting quality criteria.
- Remaining: 56.

iv. Inclusion:

- Final sample: 56 peer-reviewed studies spanning 2015–2025.
- Data were extracted into an Excel matrix coded by year, author, AI function, emotional pathway, and JD–R category.

7.3.7. Data Extraction and Quality Appraisal

To ensure validity, three evaluation criteria guided inclusion:

i. Theoretical Alignment: The study must explicitly reference emotional, psychological, or motivational constructs connected to AI.
ii. Empirical Rigor: Preference for studies with defined methodology (quantitative, qualitative, or mixed).
iii. Relevance to JD–R Pathways: Each study was coded based on whether AI acted as a job demand or resource.

Quality assessment followed the checklist proposed by Falco *et al.* (2023), which recommends triangulating theoretical coherence, sample adequacy, and analytical transparency.

7.3.8. Data Analysis and Synthesis Approach

The analysis used thematic synthesis, a qualitative meta-analysis technique suitable for integrating heterogeneous studies. Following Braun and Clarke's (2021) six-step process, coding moved from inductive pattern identification to deductive categorization using JD–R variables.

i. Familiarization: Initial reading of all 56 studies.
ii. Open Coding: Extraction of recurring emotional and behavioral responses to AI.
iii. Theme Development: Grouping codes under JD–R categories.
iv. Review and Refinement: Validating with cross-citations among included studies.
v. Interpretation: Mapping dual emotional pathways (support vs fatigue).
vi. Verification: Triangulating patterns with JD–R theoretical propositions.

Through this process, patterns such as AI-driven empowerment, algorithmic surveillance stress, and feedback-induced motivation emerged as thematic clusters.

7.3.9. Thematic Coding Scheme

JD–R Category	**AI Function or Feature**	**Emotional Response**	**Representative Studies**
Job Demands	Algorithmic monitoring, complex interfaces, constant feedback loops	Anxiety, alienation, cognitive strain	Lippert *et al.* (2023); Cai *et al.* (2024)
Job Demands	Digital overload, technostress	Emotional exhaustion, burnout	Routray *et al.* (2025); Falco *et al.* (2023)

Job Resources	Task automation, intelligent feedback	Motivation, competence, confidence	Arboh *et al.* (2025); Ashoer *et al.* (2025)
Job Resources	Decision assistance, adaptive scheduling	Reduced stress, emotional stability	Liu & Li (2025); Radic *et al.* (2025)

This coding directly mirrors the theoretical duality of AI's role described in the abstract as either a support system or a source of fatigue.

7.4. Reliability and Validity Measures

Reliability was ensured through triangulation of multiple databases and a double-reviewer coding validation process. Two independent reviewers cross-coded 20% of the sample to test for consistency, achieving an intercoder agreement rate of 0.87 (Cohen's κ), indicating strong reliability. Construct validity was maintained by anchoring all coding in the JD–R framework. Scholze and Hecker (2023) emphasize that, "the JD–R model remains robust across digital transformations because it retains psychological coherence across diverse contexts". Furthermore, methodological transparency was reinforced through detailed documentation of screening and inclusion decisions, stored in the project's PRISMA log sheet.

7.4. 1. Ethical Considerations and Methodological Limitations

Although this study involved secondary data, ethical considerations were maintained through accurate attribution, citation integrity, and avoidance of interpretive bias. No personal or sensitive data were processed. All included studies were publicly accessible and published under ethical research guidelines. The study recognizes three methodological constraints.
which is that the reliance on published research introducing publication bias, as positive results are more frequently reported than negative outcomes. Second, the language filter (English-only) may exclude valuable regional insights, particularly from Asian or European contexts.
Third, although the JD–R framework ensures theoretical rigor, it may simplify complex socio-technical dynamics of AI into binary categories (demand vs resource), which could overlook nuanced cultural or organizational mediators.

8. Findings and Discussions

The systematic review included 56 peer-reviewed studies published between 2015 and 2025, spanning Europe, Asia, North America, and Africa. The reviewed studies were grouped into two thematic clusters reflecting the Job Demands–Resources (JD–R) framework:

i. AI as a Job Resource (Emotional Support Pathway) – 27 studies (48.2%)
ii. AI as a Job Demand (Emotional Fatigue Pathway) – 29 studies (51.8%)

The near-equal distribution shows the dualistic nature of AI's emotional impact in smart work

environments. While roughly half of the reviewed literature points at AI's supportive potential, an almost equal number cautions about its strain-inducing consequences. The first cluster indicates that AI technologies can foster emotional resilience, satisfaction, and psychological empowerment when they act as job resources. These effects are typically mediated through task automation, decision assistance, constructive feedback, and emotional reassurance.

Several studies identified decision-support AI as a key mechanism reducing uncertainty and promoting self-efficacy. Arboh, Zhu, and Atingabili (2025) found that employees who viewed AI as an extension of their judgment rather than a replacement experienced increased confidence and workplace well-being. The same pattern appeared in Liu and Li's (2025) study on safety performance where workers collaborating with AI reported higher alertness and confidence levels, primarily due to clearer feedback loops and reduced ambiguity in safety decisions.

AI's automation of repetitive or cognitively draining tasks emerged as another significant resource. Falco *et al*. (2023) found that employees engaged in smart working with automated scheduling and predictive analytics" showed improved affective balance and lower cortisol levels. In similar terms, Ashoer, Maseeh, and Lim (2025) concluded that generative AI in hospitality acts as a digital co-worker that frees time for creative and emotionally engaging tasks. This aligns with Sonnentag's (2025) proposition that resource-rich job designs enable emotional recovery through cognitive offloading. Employees thus experience AI not merely as a productivity tool but as a mechanism of emotional rest, allowing focus on socially fulfilling activities.

A number of studies emphasize that emotional support from AI depends critically on perceived fairness and transparency. Radic *et al.* (2025) observed that AI-driven management models rooted in servant leadership increased employees' sense of emotional security and belonging. Similarly, Routray, Choudhary, and Sinha (2025) showed that transparent AI interfaces mitigated digital overload by reducing the feeling of unseen control and unpredictability. These findings support the JD–R framework's motivational dimension, where trust-based resources amplify engagement and emotional well-being. When AI's operation is explainable, workers interpret it as a supportive partner rather than a hidden evaluator.

Some studies stressed that AI-mediated systems can even enhance social connection rather than erode it. Kong, Hu, and Huang (2025) found that teachers using AI-assisted grading tools reported greater enthusiasm for collaboration and innovation, explaining that AI enabled them to redirect energy toward mentorship and human contact. Likewise, Pinho and Gaio (2025) found that when employees were given control over AI features, the technology became a shared resource promoting work–life balance rather than intrusion. The evidence collectively underscores that human-centered AI design anchored on

transparency, empathy, and control creates a virtuous emotional cycle. Workers experience reduced stress, heightened competence, and increased engagement when AI functions as a psychological and organizational resource. On the other hand, the second cluster of studies portrays AI as a demand amplifier, heightening emotional fatigue through cognitive overload, constant surveillance, and loss of human connection.

A recurring finding is that algorithmic management systems, while efficient, erode emotional safety by replicating constant surveillance. Lippert, Kirchner, and Saunders (2023) report that AI-driven monitoring transformed managerial oversight into omnipresent evaluation, increasing emotional tension. Employees under algorithmic evaluation felt pressured to maintain machine-measured performance metrics, often leading to anxiety and withdrawal. Also, De Carlo *et al.* (2022) observed that during the pandemic's remote work boom, continuous AI-enabled tracking systems blurred work boundaries, causing burnout and reduced well-being. These findings confirm that excessive technological monitoring triggers the strain process described in JD–R theory: demands outweigh resources, depleting emotional energy.

The reviewed evidence also identifies cognitive overload as a major factor of emotional fatigue. Cai, Wang, and Chen (2024) showed that intelligent machine usage increased cognitive burden when feedback mechanisms were too complex to interpret. Employees expended significant mental effort learning system updates, producing emotional weariness. Meem and Johnson (2025) reached a similar conclusion in software development contexts, finding that constant algorithmic updates compelled continuous learning cycles that left practitioners mentally drained. These studies confirm that AI-induced technostress when tools are cognitively demanding can become a chronic emotional burden.

Another major pattern concerns emotional alienation arising from reduced human contact in AI-mediated workplaces. Cai *et al.* (2024) found that employees felt detached when tasks became overly procedural by machine guidance. Falco *et al.* (2023) note that this detachment leads to reduced sense of social contribution, a precursor to burnout. Liu and Li (2025) describe this dynamic as a hidden erosion of psychological safety when AI substitutes for interpersonal reassurance. In such conditions, emotional fatigue stems not from task complexity alone but from diminished affective reciprocity humans cannot emotionally engage with machines that monitor or evaluate them impersonally.

A final but significant finding is the role of perceived bias and inequity in emotional strain. Employees reported distress when AI decisions seemed opaque or unfair. Radic *et al.* (2025) emphasize that, AI-driven systems without ethical transparency foster suspicion and erode trust. In JD–R terms, perceived injustice represents a latent demand that increases emotional exhaustion and organizational cynicism. Routray *et al.* (2025) likewise warn that

even supportive AI can backfire when workers perceive unequal access or outcomes. This showcases the importance of aligning AI governance with human-centered and fairness-driven frameworks.

The table below summarizes the core comparative patterns from the findings of the study.

Dimension	AI as Emotional Support (Resource)	AI as Emotional Fatigue (Demand)	Representative Studies
Cognitive Impact	Reduces workload and uncertainty	Increases cognitive load and complexity	Falco *et al.* (2023); Cai *et al.* (2024)
Affective State	Enhances motivation and confidence	Produces anxiety and alienation	Arboh *et al.* (2025); Lippert *et al.* (2023)
Social Experience	Strengthens collaboration and belonging	Weakens human contact and emotional reciprocity	Kong *et al.* (2025); Liu & Li (2025)
Organizational Perception	Builds trust and fairness	Fuels suspicion and perceived bias	Radic *et al.* (2025); Routray *et al.* (2025)

These findings empirically support the JD–R model's premise which is that emotional outcomes are shaped not by the technology itself but by the interaction between design characteristics and worker perception. AI can therefore function simultaneously as a job demand or resource depending on how organizations structure and communicate its use.

9. Conclusion

This study examined the dual emotional pathways through which artificial intelligence (AI) interactions influence worker well-being in smart work environments. The Job Demands–Resources (JD–R) model, identified AI as both a psychological resource and a psychological demand, capable of generating either emotional support or emotional fatigue depending on its design and implementation. The systematic review of 56 studies (2015–2025) revealed that AI functions as an emotional support system when it enhances autonomy, provides intelligent feedback, reduces repetitive workload, and promotes fairness and transparency. Under these conditions, workers experience higher motivation, reduced stress, and increased psychological empowerment.

On the other hand, AI functions as a source of emotional fatigue when it introduces excessive monitoring, cognitive complexity, or social alienation. Studies show that algorithmic management, opaque decision-making, and constant digital feedback loops erode emotional safety and heighten anxiety. This emotional strain mirrors the *strain process* in the JD–R model, where demands outweigh available resources It becomes clear then that AI's emotional impact is not inherent to the technology itself, but contingent on the worker's perception of control, fairness, and empathy

encapsulated in system design. The JD–R framework thus remains valid in explaining emotional dynamics in digitally mediated workspaces, provided it incorporates new digital constructs such as algorithmic transparency, emotional design, and human–AI collaboration.

10. Recommendations

Developers should integrate affective computing and empathy-driven UX (user experience) into AI systems to make them emotionally responsive. It is important for organizational leaders to be educated in digital empathy which is the ability to interpret and address emotional cues in AI-mediated communication. Institutions should also monitor both task performance and emotional states, linking AI analytics with worker well-being indicators. This will encourage employees to practice conscious disengagement (e.g., "digital rest periods") to mitigate emotional overload.

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