

Is AI a double-edged sword? Navigating employee concerns in AI as an innovation

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Abstract

Purpose – This study aims to conceptualize artificial intelligence (AI) as a “double-edged sword” in organizational innovation by examining how AI simultaneously generates employee strain and developmental opportunities.

Design/methodology/approach – Adopting a theory-building and conceptual approach, this study integrates the Job Demands-Resources model, Conservation of Resources theory and the sociotechnical systems perspective. Drawing on an extensive interdisciplinary literature review, this study develops an integrated conceptual framework and a set of theoretical propositions to explain the mediating and moderating mechanisms through which AI influences employee outcomes.

Findings – AI-powered innovation increases demands on employees by reducing workload and uncertainty, but it also creates opportunities for learning, development and new work resources. Employee responses are shaped more by organizational practices such as leadership support, transparency, fairness and reskilling than by the technology itself.

Originality/value – This study proposes an integrated multilevel framework that combines Job Demands-Resources, Conservation of Resources and sociotechnical perspectives to explain the dual effects of AI in organizational settings. By framing employee concerns as rational, context-dependent responses rather than technological resistance, this study advances AI and work research and lays a foundation for future empirical studies on human-centered AI-driven innovation.

Keywords AI, Innovation management, Employee psychology, Job demands-resources, Sociotechnical systems

Paper type Conceptual paper

1. Introduction

The organizational consequences of AI adoption are no longer a matter of speculation. A substantial body of empirical research has established that AI simultaneously generates strain through algorithmic monitoring, role ambiguity and skill obsolescence and developmental opportunity through cognitive augmentation, task automation and learning enrichment (Yin *et al.*, 2024; Chuang *et al.*, 2025; Rahmi *et al.*, 2025; Zirar *et al.*, 2023). That AI produces both kinds of effects is well documented across sectors, including manufacturing, financial services, hospitality and knowledge-intensive industries (Haefner *et al.*, 2021; Sjödin *et al.*, 2023; Radic *et al.*, 2025). The key unresolved issue is not whether AI influences organizational outcomes, but why the same system generates markedly



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different effects across employees, job roles and organizations and how organizational design decisions shape employees' psychological responses (Berente *et al.*, 2021; von Krogh *et al.*, 2023).

Current research has begun to discuss, in greater depth, the impact of AI use on both stress-related and developmental outcomes among employees (Soulati *et al.*, 2024). Studies identify AI-related job demands, resource threats, skill losses and learning-related opportunities and benefits, but struggle to explain how these mechanisms are linked across different levels of analysis (Mo and Ouyang, 2025). Consequently, literature lacks a clear macro-micro translation mechanism that explains how organizational-level AI design choices translate into individual-level psychological assessments (Eggers and Kaplan, 2013).

The claim that technology can simultaneously function as both a demand and a resource should not be perceived as a new approach. The literature on AI-supported work environments highlights that digital technologies may enhance learning, autonomy and performance, while also contributing to stress under certain conditions (Jia *et al.*, 2025; Virgillito and Ledda, 2025). Therefore, the resulting theoretical challenge and complexity lie not in rephrasing the dual effects of AI, but in explaining how these effects manifest differently. This article contributes to the literature by drawing on multiple theoretical perspectives to examine whether AI enhances employees' skills while also increasing performance-related pressures.

This gap is not solely empirical; it also points to a structural limitation in the way existing theoretical perspectives have been applied to AI-enabled work. Research grounded in the Job Demands-Resources (JD-R) model has demonstrated that AI changes the configuration of job demands and available resources within work settings (Bakker and Demerouti, 2007; Demerouti *et al.*, 2001; Scholze and Hecker, 2023). However, these studies generally treat employee appraisal as an implicit mechanism, leaving unresolved why employees with similar structural conditions may respond to the same AI environment with markedly different levels of anxiety or adaptation (Chuang *et al.*, 2025; Radic *et al.*, 2025). Studies informed by Conservation of Resources (COR) theory have clarified how anticipated resource loss can stimulate defensive reactions to technological change (Hobfoll, 1989; Hobfoll *et al.*, 2018; Farkash *et al.*, 2022). Yet this perspective focuses primarily on individual-level processes and provides limited insight into how organizational structures shape the accessibility, stability and credibility of resources before individual appraisal takes place (Liao *et al.*, 2022). Sociotechnical research has further shown that AI can transform authority relations, task allocation and human-machine interdependence at the system level (Trist and Bamforth, 1951; Emery and Trist, 1960; Raisch and Krakowski, 2021). Nevertheless, this body of work rarely connects these structural transformations to the micro-level psychological processes through which employees interpret AI as either threatening or enabling (Brauner *et al.*, 2025; Ishowo-Oloko *et al.*, 2019).

As a result, the literature remains fragmented, with individual psychological processes and organizational structures often examined separately rather than as interrelated dimensions of AI-enabled work (Lesener *et al.*, 2019; Tummers and Bakker, 2021). Existing studies tend to explain employee responses to AI either through perceptual and motivational mechanisms that pay limited attention to organizational design (Babashahi *et al.*, 2024; Jing *et al.*, 2023) or through structural analyses that give insufficient consideration to individual psychological processes (Murire, 2024; Mossavar-Rahmani and Zohuri, 2024). Consequently, none of the perspectives fully resolves the central empirical question: why macro-level conditions surrounding AI implementation, such as governance structures, role design, transparency architecture and justice climate, systematically influence employees' micro-level appraisals in

ways that cannot be adequately captured by a single-level theoretical framework (von Krogh *et al.*, 2023; Berente *et al.*, 2021; Jia *et al.*, 2024).

This study directly addresses this puzzle by moving beyond a simple description of AI's dual effects. It develops an integrated conceptual framework that explains how macro-level sociotechnical conditions influence micro-level resource appraisal processes and how these appraisal processes subsequently generate the diverse employee outcomes observed across different AI adoption contexts (Raisch and Krakowski, 2021; Hobfoll *et al.*, 2018; Hakanen *et al.*, 2008). The framework integrates JD-R, COR and sociotechnical systems perspectives (Demerouti *et al.*, 2001; Hobfoll, 1989; Trist and Bamforth, 1951), not as complementary descriptions of the same phenomenon, but as theoretically distinct lenses whose combination resolves specific explanatory failures that each produces when applied alone. Its central organizing tension the conflict between productivity demands and skills discretion generated by AI implementation (Raisch and Krakowski, 2021; Arias-Pérez and Vélez-Jaramillo, 2022) provides a structural anchor that connects organizational design choices to individual psychological responses within a single, parsimonious explanatory logic.

This study contributes to the literature in three main ways. First, it conceptualizes employee responses to AI as appraisal processes shaped by organizational conditions rather than as solely individual attitudinal reactions (Hobfoll *et al.*, 2018; Liao *et al.*, 2022). In doing so, it shifts theoretical attention from identifying which employees respond negatively to AI toward understanding which organizational conditions increase or reduce the likelihood of negative appraisals (Berente *et al.*, 2021; Murire, 2024; von Krogh *et al.*, 2023). Second, this study identifies three key limitations in the existing AI, JD-R and COR studies: appraisal without sufficient consideration of organizational structure, structure without adequate attention to appraisal processes and system-level change without clear psychological translation. It further demonstrates that integrating these perspectives yields propositions that cannot be derived from any single framework alone (Lesener *et al.*, 2019; Hakanen *et al.*, 2008; Raisch and Krakowski, 2021). Third, this study develops five theoretically grounded propositions that explain nonlinear, paradoxical and threshold-dependent relationships between AI implementation conditions and employee outcomes (Yin *et al.*, 2024; Jia *et al.*, 2024; Huang and Rust, 2024). These propositions provide a more rigorous and empirically testable foundation for future research than many previous conceptual accounts (Truong and Papagiannidis, 2022; Haefner *et al.*, 2021).

2. Conceptual background

The conceptual background of this study is organized around a single analytical purpose: identifying where existing theoretical accounts of AI and employee outcomes break down and why those breakdowns point toward the need for an integrated multi-level framework. Rather than summarizing what is known about AI's effects on employees, a task already accomplished by several recent reviews, this section maps the specific points at which established findings become theoretically irreconcilable and traces those irreconcilabilities to the macro-micro gap that the integrated framework is designed to close.

2.1 Artificial intelligence as organizational innovation: What we know and where it stops

AI's capacity to reshape organizational processes, competitive dynamics and work design is well established in the innovation management literature (Gama and Magistretti, 2025). AI contributes to organizational innovation by accelerating R&D processes, supporting data-driven decision-making, and enabling the development of new products and services across manufacturing, financial services and knowledge-intensive sectors (Haefner *et al.*, 2021; Sjödin *et al.*, 2023). At the organizational level, AI also reshapes workflows by automating

routine activities and shifting human contributions toward tasks that require judgment, interpersonal interaction and creativity (Marion and Fixson, 2021; Raisch and Krakowski, 2021). These macro-level effects are documented with reasonable consistency across sectors and organizational types (Akinngbe, 2024).

What the innovation management literature does not adequately explain is how these macro-level restructuring processes translate into the heterogeneous employee responses observed empirically (Montobbio *et al.*, 2024). If AI systematically repositions employees toward higher-value cognitive work, then the literature predicts that employee outcomes should improve as AI adoption deepens. Yet empirical studies consistently find that AI adoption is associated with both increased engagement and increased anxiety, often within the same organizations and sometimes among the same employees across time. The innovation management literature, by focusing on organizational-level capability and competitive outcomes, lacks the theoretical vocabulary to explain this micro-level variation, and it is precisely this vocabulary that the integrated framework developed here provides. Although innovation management research discusses how artificial intelligence (AI) creates value at the organizational level, it struggles to explain how employees psychologically interpret AI-driven restructuring within organizations (Cantarello *et al.*, 2012; Zahra *et al.*, 2020; Chen *et al.*, 2023).

2.2 *Employee responses to artificial intelligence: the macro-micro translation problem*

At the employee level, the adoption of AI has been associated with a broad spectrum of responses, including technostress, perceptions of job insecurity, anxiety related to skill obsolescence, resistance to change, adaptation, creative engagement and motivation to learn (Vrontis *et al.*, 2022; Chuang *et al.*, 2025; Rahmi *et al.*, 2025). The consistency of this finding across studies that AI produces both positive and negative responses has led to repeated invocations of AI's dual nature in the literature. However, documenting this duality is not the same as explaining it. The theoretical challenge is not to establish that AI has heterogeneous effects but to specify the mechanisms through which macro-level organizational conditions produce micro-level appraisal divergence (Han *et al.*, 2023). The effort of employee-level research to explain anxiety, resistance and compliance is important. However, it treats organizational context as a moderating factor, rather than a structural condition that shapes assessment before individual responses emerge (Lumpkin and Dess, 2001).

This is precisely where current research reaches its limit. Studies examining technostress and digital strain tend to focus on individual-level predictors, such as technology anxiety, self-efficacy and prior digital experience, while treating organizational context as a control variable rather than a theoretically active mechanism. Studies examining organizational conditions, leadership, transparency and justice climate tend to treat them as moderators of already-established individual-level relationships rather than as structural forces that shape the appraisal landscape before individual responses form. The result is a persistent analytical separation between the level at which AI's organizational consequences unfold and the level at which employees experience them a separation that no existing single-framework account has successfully bridged (Makarius and Larson, 2017; Bentley *et al.*, 2022; Bradley *et al.*, 2024).

2.3 *The macro-micro gap as the central theoretical problem*

Across innovation management, employee psychology and organizational behavior, a common limitation remains: macro-level organizational conditions and micro-level employee responses are rarely integrated within a single theoretical explanation (Cowan *et al.*, 2022). Existing research identifies organizational AI practices, employee reactions and

contextual moderators, yet it does not explain how sociotechnical design features such as governance, role structures, transparency and justice shape employees' perceptions of resource gains, losses and role change (Felín *et al.*, 2015). Consequently, the key gap is not the absence of AI research but the lack of a mechanism linking organizational design to employee resource appraisal (Budhwar *et al.*, 2022).

This macro-micro translation problem is the central theoretical gap that motivates the integrated framework developed in this study. Addressing it requires not a broader synthesis of existing findings but a theoretically specific account of the mechanisms through which organizational structure enters individual psychology and through which individual psychology, aggregated across employees, generates the organizational-level outcomes that AI adoption is meant to produce. The following section develops that account by integrating JD-R, COR and sociotechnical systems perspectives around the core tension between productivity demands and skills discretion.

3. Theoretical foundations for the “Double-Edged sword” argument

Accepted as an innovation, AI in organizations can create tension regarding productivity expectations based on inputs and outputs and how skills should be assessed. Employees in organizations interpret this tension as a threat to resources, the direct or indirect acquisition of resources and a redefinition of roles within the organization (Malik *et al.*, 2022). Therefore, AI becomes a “double-edged sword” when considered in both micro and macro contexts.

The “double-edged sword” proposition that AI simultaneously creates anxiety and is a source of development does not seem adequately explained by a single theory. The most important reason for this is that AI-driven innovation changes job characteristics, reshapes valuable resources and reorganizes organizational structures and power relations. Therefore, the need arises to integrate three complementary perspectives to create a coherent chain of explanation leading to the propositions in Section 4. These are:

- (1) JD-R to explain how AI reshapes job demands and job resources and, thus, affects anxiety and employee motivation;
- (2) Resource-Power Relations Theory (COR) to explain why changes resulting from AI can be perceived as resource threats or resource gains and the different responses that arise; and
- (3) a socio-technical systems perspective to explain how organizational design and governance conditions shape human-machine interaction.

3.1 Job Demands-Resources (JD-R) perspective

The JD-R model is a widely used and flexible framework for explaining employees' work experiences and related outcomes (Demerouti *et al.*, 2001). It conceptualizes work environments through the balance between job demands physical, emotional and cognitive aspects requiring sustained effort and job resources, which support goal achievement, personal development and work meaningfulness (Bakker and Demerouti, 2007). The model functions through three interconnected processes. The health-impairment process explains how excessive job demands can result in stress and burnout. The motivational process emphasizes that job resources promote work engagement and other positive outcomes. The personal resources process further highlights the protective role of factors such as self-efficacy, resilience, optimism and learning orientation in buffering the effects of job demands (Hakanen *et al.*, 2008; Tummers and Bakker, 2021; Jing *et al.*, 2023). Collectively, these

processes offer a multidimensional framework for understanding employee responses within complex work environments.

The relevance of the JD-R model has become increasingly prominent as digitalization accelerates and AI becomes more integrated into work processes. The adoption of AI introduces new and intensified job demands, including algorithmic pressure, the need for continuous skill development, role ambiguity and data-driven performance monitoring, as well as technology-related stressors such as complexity, insecurity and overload (Chuang *et al.*, 2025; Scholze and Hecker, 2023; Rahmi *et al.*, 2025). At the same time, AI can provide important job resources by offering cognitive support, improving access to information, reducing errors and increasing task autonomy, which has led to its characterization as a “cognitive augmenting technology” (Zirar *et al.*, 2023; Babashahi *et al.*, 2024). This dual function creates more complex demand-resource configurations than those associated with traditional technologies, making the JD-R model a valuable, though not fully sufficient, framework for understanding how AI shapes employee experiences (Radic *et al.*, 2025).

According to the JD-R theory, AI can introduce both job demands and job resources. While AI-related job demands may contribute to strain, burnout and withdrawal, AI-related job resources can enhance motivation, learning, work engagement and performance (Pinho *et al.*, 2025). However, JD-R alone cannot be expected to explain why similar AI applications produce significantly different results among employees and organizations. Therefore, the importance of evaluation and resource dynamics, which are central to COR theory, becomes apparent, and it becomes necessary to delve into the foundations of the theory.

3.2 *Conservation of resources (COR) theory*

The COR theory offers a strong psychological perspective for understanding employee stress, adaptation and behavior through the dynamics of resource loss, gain and perceived threat (Hobfoll, 1989; Hobfoll *et al.*, 2018). The theory is based on the assumption that individuals seek to protect, preserve and enhance resources they value, including material, social and psychological resources. Accordingly, stress may arise from not only actual resource loss but also the anticipation of loss or from situations in which expected resource gains are not realized (Farkash *et al.*, 2022). Recent COR research also highlights that resource loss tends to have a stronger psychological impact than resource gain, and that resources operate within interconnected “resource caravans” influenced by organizational conditions that facilitate or restrict resource accumulation (Liao *et al.*, 2022).

AI-driven organizational change significantly alters these resource dynamics. Practices such as automation, algorithmic governance and data-driven performance systems can heighten perceptions of resource threat by affecting employees’ sense of competence, job security, autonomy and organizational status. In addition, reductions in predictability and control may increase uncertainty and encourage defensive reactions (Murire, 2024; Medlama *et al.*, 2025). However, under supportive organizational conditions, AI may also serve as an important source of resource gain by improving decision quality, reducing cognitive load and errors and strengthening strategic thinking and career capital through reskilling and upskilling initiatives (Huang and Rust, 2024; Berente *et al.*, 2021). As a result, employees may interpret AI as either a threat or an opportunity, depending on their existing resource levels and access to organizational support. This dynamic reflects the core logic of COR theory and complements the JD-R model in explaining why employee responses to AI differ across broader sociotechnical contexts.

3.3 Sociotechnical systems view

The Sociotechnical Systems Approach conceptualizes organizations as integrated systems in which technical components, such as technologies, algorithms and work processes, interact continuously with social components, including human behavior, cultural norms, interpersonal relationships and organizational values (Trist and Bamforth, 1951; Emery and Trist, 1960). A central principle of this approach is joint optimization, which argues that technological and social subsystems should be aligned simultaneously to achieve sustainable organizational outcomes. This perspective is particularly relevant for understanding employee concerns related to job insecurity and workplace surveillance.

From a managerial perspective, the degree of transparency and accountability in AI use, the extent to which employees are involved in organizational redesign and the maintenance of human oversight in high-risk decisions are critical factors shaping employees' perceptions and concerns (Hayes and Burrell, 2026). With the acceleration of digitalization, the sociotechnical perspective has regained prominence by emphasizing that AI affects not only operational processes but also organizational culture, power relations and identity structures (Raisch and Krakowski, 2021). The adoption of AI initiates sociotechnical restructuring by altering the division of labor, decision-making processes and role definitions, while algorithmic management increasingly mediates employee participation and redistributes authority between humans and machines (Ishowo-Oloko *et al.*, 2019).

These changes reshape job roles, blur professional boundaries and redefine employees' work identities as tasks are redistributed between humans and AI systems. In this context, human workers are expected to focus more on creative, relational and judgment-based activities, whereas AI systems increasingly perform routine, analytical and data-intensive tasks (Mossavar-Rahmani and Zohuri, 2024). At the same time, the growing reliance on algorithmic decision-making raises important concerns regarding ethics, fairness, transparency and trust, including issues such as algorithmic bias, limited accountability and reduced human oversight (von Krogh *et al.*, 2023). These tensions, often described as "sociotechnical contradictions," arise from conflicts between efficiency-oriented technical logics and the normative and cultural expectations embedded in social systems (Brauner *et al.*, 2025). Consequently, employee responses to AI, ranging from anxiety and resistance to trust and adaptation, should not be interpreted solely as individual reactions but rather as outcomes shaped by broader organizational, structural and cultural contexts. In this respect, the sociotechnical perspective complements the JD-R and COR frameworks by clarifying the organizational conditions through which AI-driven transformation occurs.

3.4 Need for an integrated theoretical lens

The rationale for theoretical integration in this study emerges not from a general appeal to complementarity but from the identification of specific and recurrent explanatory failures in the existing literature. A systematic reading of AI-JD-R research reveals that studies applying the JD-R model to AI contexts consistently demonstrate that AI-generated demands are associated with strain and that AI-generated resources are associated with engagement, yet they are unable to explain why employees in structurally comparable roles, exposed to the same AI systems, report markedly different levels of anxiety, adaptation or resistance.

This explanatory gap points to a missing appraisal layer: JD-R identifies what the work environment offers but does not theorize how employees cognitively evaluate those offerings in terms of what they stand to lose or gain. COR fills this gap at the individual level but introduces its own blind spot: by focusing on how individuals protect and accumulate resources, it underspecifies how organizational structures determine which resources are accessible, credible and stable in the first place. Sociotechnical research addresses

organizational structure, but its unit of analysis, the work system, rarely connects downward to the individual psychological processes through which structural changes become motivationally or emotionally consequential. The integrated framework proposed in this study is, therefore, not a synthesis of compatible theories but a response to three interlocking explanatory failures: structure without appraisal, appraisal without structure and system-level change without psychological translation. Identifying these failures through systematic literature mapping is what makes the integration theoretically necessary rather than merely convenient.

There is broad consensus that no single theoretical framework can fully capture the impact of AI-based innovation on employees. The JD-R model explains how AI-related job demands and resources influence outcomes such as motivation, burnout and performance. The COR theory extends this understanding by clarifying how perceptions of resource threat, loss and gain shape employees' psychological responses. Complementing these approaches, the sociotechnical systems perspective emphasizes that AI also transforms job design, organizational structures and human-machine interactions within specific technical, structural and cultural contexts. Taken together, these perspectives suggest that AI functions simultaneously as a job stressor, a mechanism for transforming resources and a force that reshapes organizational design (Lesener *et al.*, 2019). Therefore, employee reactions to AI cannot be adequately understood through individual-level psychological explanations alone.

By integrating the JD-R, COR and sociotechnical perspectives, this study develops a relational framework that explains how AI reshapes demand-resource dynamics, influences employees' perceptions of threat and opportunity and generates context-dependent responses shaped by organizational design and governance rather than solely by individual reactions. By synthesizing insights from these theoretical traditions, this study also helps organize the emerging research landscape on AI and employee outcomes by identifying the key mechanisms and contextual factors that account for the heterogeneous effects reported in prior studies.

What distinguishes this integrated approach from merely additive theory use is its capacity to reveal a dynamic that neither JD-R nor COR can expose independently. JD-R identifies what AI changes in the structure of work the configuration of demands and resources but it does not explain why objectively similar changes produce radically different responses across employees. COR addresses this gap by theorizing that the psychological weight of a demand depends on how it is appraised in terms of resource threat or gain; yet COR, operating primarily at the individual level, cannot account for how organizational design choices systematically shape those appraisals before they even reach the individual. When integrated, the two frameworks generate a new explanatory logic: the *demand-resource reconfiguration* that JD-R maps becomes psychologically consequential only through the *resource appraisal process* that COR describes, and both processes are structured and constrained by the sociotechnical architecture within which they unfold. In other words, the combination does not merely double the explanatory coverage; it produces a mechanism demand-triggered resource reappraisal within sociotechnical constraints that cannot be derived from either theory alone. This integrated mechanism explains a phenomenon that existing single-theory accounts cannot: why AI that increases demands for one employee simultaneously functions as a developmental resource for another, not because of individual differences alone, but because organizational conditions systematically filter how the same AI is experienced.

More specifically, the selection of these three frameworks is theoretically grounded in the multidimensional nature of AI-driven workplace transformation. The JD-R model explains how AI influences the balance between job demands and job resources, thereby affecting

employee well-being and work-related outcomes (Bakker and Demerouti, 2007; Demerouti *et al.*, 2001). The COR theory complements this explanation by focusing on how employees cognitively evaluate these changes as potential resource threats, losses or gains, which in turn shape their psychological responses to technological change (Hobfoll, 1989; Hobfoll *et al.*, 2018). As AI adoption also transforms the structural configuration of work systems, the sociotechnical perspective offers an important macro-level lens for understanding how organizational design, governance structures and patterns of human-machine interaction influence these demand-resource dynamics. (Raisch and Krakowski, 2021; Trist and Bamforth, 1951). Together, these frameworks offer a complementary and sequential explanation: JD-R explains how work characteristics change; COR explains how employees interpret these changes psychologically; and the sociotechnical perspective explains how organizational structures condition these processes.

To operationalize this theoretical integration and clarify how these perspectives jointly explain AI-induced employee dynamics, this study develops an integrated conceptual structure summarized in Table 1. Table 1 was developed by combining the third stage of the literature review of the study. Each row in the table was evaluated in the context of layer, construct, theoretical grounding, role in model and blind spot addressed. Factors shaping Table 1 included demonstrating that AI increases productivity expectations and changes the on-demand use of employees' skills, how human-machine task assignment can be done and whether AI-driven change is interpreted as threatening or improving.

In addition, Table 1 is not derived from a previously published source; rather, it is an original integrative synthesis developed by the authors to map the layered architecture of the proposed framework. It distinguishes between the core theoretical tension driving the model, the appraisal mechanisms through which that tension produces employee outcomes, the interpretive process linking sociotechnical change to psychological responses and the enabling conditions that moderate these dynamics, reflecting the principle that a parsimonious model gains explanatory power not by reducing the number of constructs it considers, but by organizing them within a coherent and hierarchically structured causal logic.

In the proposed framework, all structures are not equally organized, but hierarchically. At the highest level, the key explanatory factor is the balance between the productivity demands stemming from AI and the authority to appreciate employee skills. This balance determines whether AI will initially be positioned and perceived as a threat or a resource-generating innovation. At the second level, perceived internal and external resource threats, resource acquisition and role redefinition function as primary mediating mechanisms that make the resulting tension psychologically meaningful. At the third level, transparency, fairness, leadership support, digital self-efficacy and reskilling opportunities function as factors that alter the strength or direction of these mechanisms. Therefore, the model has a sequential explanatory architectural structure.

This integrated approach reframes employee concerns not as isolated individual reactions but as responses systematically shaped by the tension between productivity demands and skills discretion, the core axis around which AI's double-edged nature unfolds. By organizing mediating appraisal processes and moderating enabling conditions relative to this central tension rather than treating them as parallel explanatory layers, the framework explains why the same AI system is experienced as a resource threat by some employees and a developmental opportunity by others: the critical variable is not technology itself, but whether organizational conditions allow skills discretion to expand alongside productivity demands or force employees to absorb one at the expense of the other.

Table 1. Core tension and contextual architecture of the integrated framework

Layer	Construct	Theoretical grounding	Role in model	Blind spot addressed
Core tension	Productivity demands and skills discretion	JD-R	The primary axis around which AI's double-edged nature unfolds	JD-R maps demand-resource configurations but cannot explain why identical demands produce divergent responses
Appraisal mechanism	Perceived resource threat	COR	Translates productivity pressure into strain when skills discretion narrows	COR explains appraisal but not how organizational design pre-structures what is available to be lost
Appraisal mechanism	Perceived resource gain	COR	Translates expanded skills discretion into motivation and well-being	COR gain dynamics rarely linked to structural work design choices in AI contexts
Interpretive process	Role redefinition	Sociotechnical	Determines whether shifting task boundaries are experienced as erosion or enrichment	Sociotechnical research maps structural change but rarely translates it into micro-level psychological processes
Enabling conditions	Transparency, justice, leadership support, digital self-efficacy and reskilling	JD-R + sociotechnical	Moderate the direction and intensity of appraisal processes; do not constitute them	Moderating conditions treated as isolated variables across studies; never organized relative to a core demand-discretion tension

Source(s): Authors' own work; each construct addresses a specific explanatory gap identified through systematic review of the AI, JD-R and COR studies

4. Proposed conceptual model

4.1 Rationale and structure of the model

The proposed conceptual model is organized around a core theoretical tension: the conflict between productivity demands and skills discretion generated by AI-based innovation. Productivity demands refer to the performance expectations, pace intensification, algorithmic monitoring and output accountability that AI systems introduce into work environments. Skills discretion refers to the degree to which employees retain meaningful control over the cognitive, relational and judgment-based dimensions of their work, the aspects that constitute professional identity and developmental opportunity. This tension is theoretically central because it captures the moment at which AI's double-edged nature becomes psychologically consequential: when productivity demands expand while skills discretion contracts, employees are most likely to interpret AI as a resource threat; when productivity demands are managed while skills discretion is preserved or expanded, the same AI is most likely to be experienced as a developmental resource. All other elements of the model, the mediating appraisal processes and the moderating organizational conditions, are organized relative to this core tension rather than treated as parallel and equivalent explanatory layers. This architecture reflects the principle that theoretical parsimony and explanatory depth are not in conflict: a focused model can account for a wider range of outcomes precisely because its causal logic is coherent rather than exhaustive.

4.2 Mediating mechanisms

Mediators explain the internal process through which AI-related conditions are translated into employee outcomes, whereas moderators specify the contextual and personal conditions under which these processes become stronger, weaker, more positive or more negative.

In the proposed framework, AI-based innovation is not assumed to influence employee outcomes directly; rather, its effects unfold through a set of underlying psychological and role-related processes that explain how employees interpret and internalize technological change. For this reason, the model conceptualizes perceived resource threat, perceived resource gain and role redefinition as mediating variables. These constructs are positioned as mediators because they represent the intervening mechanisms through which AI-related characteristics are translated into employee outcomes such as anxiety, resistance, adaptation, well-being and learning. In other words, they do not merely strengthen or weaken the relationship between AI and employee outcomes; instead, they describe the processes through which such effects emerge.

The first central mediator is perceived resource threat, which refers to employees' subjective appraisal that AI adoption may endanger valued resources such as competence, autonomy, status, job security, predictability and control. This construct is theoretically grounded in the COR theory, which argues that stress responses may arise from not only actual resource loss but also the anticipation or perceived threat of future loss (Hobfoll, 1989; Hobfoll *et al.*, 2018). In AI-enabled work contexts, factors such as intensified monitoring, accelerated work pace, digital complexity and uncertainty regarding future relevance do not necessarily lead directly to anxiety or resistance. Rather, these reactions are more likely to occur when employees interpret such conditions as threatening resources they consider valuable. Accordingly, perceived resource threat is best understood as a mediating mechanism because it explains how AI-related demands become psychologically consequential. Its role is, therefore, processual rather than conditional: it transmits the effect of AI-induced job demands onto negative employee outcomes such as stress, burnout, withdrawal and turnover intention (Farkash *et al.*, 2022; Liao *et al.*, 2022).

The second mediator is perceived resource gain, defined as employees' appraisal that AI adoption provides access to or strengthens valued resources such as cognitive support, learning opportunities, decision quality, task autonomy, employability and career capital. This construct also draws on the COR theory but captures the gain-oriented side of resource dynamics. Prior studies indicate that digital tools and AI-supported systems can enhance work quality and reduce cognitive burden when employees perceive these technologies as supportive rather than controlling (Berente *et al.*, 2021; Babashahi *et al.*, 2024). Accordingly, perceived resource gain is conceptualized as a mediating mechanism because positive outcomes are not produced solely by the existence of AI capabilities; instead, they emerge when employees interpret AI-related changes as enhancing their available resources. Through this mechanism, AI-related job resources are transformed into stronger work meaningfulness, adaptation, well-being and organizational learning. Thus, perceived resource gain explains the underlying positive pathway linking AI-enabled work redesign to developmental employee outcomes.

A third mediating mechanism is role redefinition, which refers to employees' interpretation of how AI changes the content, boundaries and value of their work roles. This construct is primarily grounded in the sociotechnical systems perspective, which holds that technological change reshapes task allocation, authority relationships and patterns of human-machine interdependence rather than simply modifying isolated job characteristics (Trist and Bamforth, 1951; Emery and Trist, 1960; Raisch and Krakowski, 2021). In AI-enabled work environments, employees may need to reassess whether their roles continue to be meaningful, whether their expertise remains valued and whether they are being directed toward higher-value analytical and relational activities or toward more passive forms of system monitoring. Role redefinition is conceptualized as a mediating mechanism because it reflects the interpretive process through which changes in the sociotechnical structure influence employee responses. This perspective helps explain why the same AI application may be perceived as empowering in one context but alienating in another: the key distinction lies in whether employees interpret role transformation as an enrichment or an erosion of their professional identity (Mossavar-Rahmani and Zohuri, 2024).

Overall, these mediating variables explain the internal processes through which AI-based innovation shapes employee outcomes. Perceived resource threat accounts for the strain pathway; perceived resource gain explains the developmental pathway; and role redefinition connects these resource dynamics to broader sociotechnical changes in the organization. Their inclusion as mediators is, therefore, theoretically justified because each variable captures an explanatory mechanism linking AI-related inputs to employee-level consequences rather than a contextual condition that merely alters the strength of those relationships.

4.3 Moderating conditions

The five moderating variables in this model, organizational transparency, AI-related organizational justice, digital self-efficacy, leadership support and reskilling opportunities, are not treated as an undifferentiated list of contextual factors. Rather, they are organized according to their proximity to the core tension between productivity demands and skills discretion. Transparency and organizational justice primarily operate at the institutional level by shaping employees' perceptions of whether the productivity-discretion tradeoff is legitimate and predictable. Leadership support and reskilling opportunities function at the relational and developmental levels, influencing whether employees receive the guidance and capabilities needed to navigate this tradeoff effectively. Digital self-efficacy, in contrast, operates at the individual level and influences how confident employees feel about engaging

with AI-driven changes to task structures. This layered organization prevents the model from appearing as a catalogue of potentially relevant variables and instead positions each moderator as performing a distinct function within the same explanatory logic: all five conditions determine the degree to which the productivity demands–skills discretion tension activates resource threat versus resource gain appraisals.

While mediating variables explain how AI-based innovation produces employee outcomes, the model also requires a set of moderating variables to explain why these effects vary across employees and organizational contexts. In this study, organizational transparency, AI-related organizational justice, digital self-efficacy, leadership support and reskilling opportunities are conceptualized as moderators because they do not constitute the core psychological process through which AI affects employees. Rather, they shape the strength, direction, and interpretive context of the relationships between AI-induced demands/resources, mediating mechanisms and employee outcomes. Their role is, therefore, conditional rather than processual.

The first moderator is organizational transparency, which refers to the extent to which organizations clearly communicate the purpose, logic, scope, data sources and potential consequences of AI-based systems and decisions. Transparency is particularly significant in AI-enabled workplaces because opaque systems can increase uncertainty, speculation and perceptions of diminished control, whereas transparent systems enhance predictability and strengthen the perceived legitimacy of organizational change (Ishowo-Oloko *et al.*, 2019; von Krogh *et al.*, 2023). Transparency is conceptualized as a moderator rather than a mediator because it does not directly constitute the internal process through which AI leads to anxiety or adaptation. Instead, it influences the strength and direction of employees' responses to AI-related changes. Instead, it changes how strongly AI-related demands are interpreted as threatening and how strongly AI-related resources are interpreted as beneficial. For instance, algorithmic monitoring may provoke substantially greater resource threat when the criteria and logic of the system are unclear, but its negative effect may be attenuated when employees understand how and why decisions are made. Thus, transparency conditions the effect of AI on employee appraisals rather than constituting the appraisal process itself.

A second and conceptually distinct moderator is AI-related organizational justice, which refers to employees' perception that AI-supported decisions, procedures and outcomes are fair. In the context of AI, justice may include distributive justice (fairness of outcomes), procedural justice (fairness of decision rules and processes) and interactional or informational justice (respectful treatment and adequate explanation regarding AI-based decisions). This distinction is important because organizational justice and transparency represent related but distinct constructs. Transparency refers to the visibility and clarity of information, whereas organizational justice concerns employees' normative evaluations of fairness and legitimacy. An AI system may be highly transparent yet still be perceived as unfair if its outcomes are biased, its procedures disproportionately disadvantage certain employees or employees have limited opportunities to participate in system design and appeal processes. Organizational justice is, therefore, positioned as a moderator because it influences whether employees interpret AI-based changes as legitimate or threatening. In this way, it can strengthen or weaken the relationships between AI-related conditions and outcomes such as perceived resource threat, trust, resistance and adaptation. Prior research on organizational justice and digital governance indicates that fairness perceptions play a crucial role in determining employees' acceptance of managerial systems, particularly when technologies affect evaluation, promotion, or task allocation (Berente *et al.*, 2021; von Krogh *et al.*, 2023). Therefore, AI-related organizational justice should be treated as a distinct

contextual condition that modifies employees' interpretations of AI rather than as a merged component of transparency.

The third moderator is digital self-efficacy, defined as employees' belief in their capability to understand, use and adapt to digital and AI-enabled systems. Drawing on JD-R and broader self-efficacy literature, digital self-efficacy functions as a personal resource that affects how employees appraise technological change (Hakanen *et al.*, 2008; Babashahi *et al.*, 2024). Employees with high digital self-efficacy are more likely to interpret AI implementation as a challenge that can be managed and potentially leveraged for development, whereas those with lower self-efficacy are more likely to perceive the same system as threatening and uncontrollable. Digital self-efficacy is, therefore, conceptualized as a moderator because it changes the strength of the relationship between AI characteristics and the mediating appraisals of resource threat and resource gain. It is not itself the mediating process; rather, it influences how likely employees are to enter one process or the other.

The fourth moderator is leadership support, which refers to the extent to which leaders provide direction, emotional reassurance, opportunities for participation and ethical guidance throughout AI-related transformation processes. Leadership support plays a critical role in AI-enabled change because leaders help employees interpret organizational transformation, shape perceptions of its meaning and provide resources that reduce uncertainty and enhance trust (Tummers and Bakker, 2021; Radic *et al.*, 2025). It is conceptualized as a moderator rather than a direct mechanism because supportive leadership does not itself represent employees' internal appraisal of resource threat or gain. Instead, it influences whether AI-driven changes are perceived as manageable, legitimate and oriented toward development. For instance, employees may evaluate the same AI system more positively when leaders clearly communicate its purpose, encourage participation and emphasize human-AI augmentation rather than workforce displacement.

The fifth moderator is reskilling opportunities, defined as the extent to which organizations provide accessible, credible and future-oriented learning opportunities that enable employees to adapt to AI-driven changes in work requirements. Reskilling is particularly significant in AI contexts because perceptions of employability and future relevance influence whether employees interpret technological change as a threat or an opportunity (Murire, 2024; Zirar *et al.*, 2023). It is positioned as a moderator because it alters the relationship between AI implementation conditions and employee appraisal processes. When employees have access to meaningful reskilling opportunities, AI-related transformation is less likely to trigger perceptions of resource threat and more likely to facilitate perceptions of resource gain. Conversely, in the absence of such opportunities, even potentially beneficial AI systems may trigger insecurity and defensive reactions.

Overall, these variables are positioned as moderators because they define the contextual and personal conditions under which AI-induced demands and resources are interpreted. Unlike the mediators, they do not explain the internal transmission mechanism between AI and employee outcomes; instead, they explain variation in the strength and direction of those mechanisms across settings and individuals. This distinction is theoretically important because it preserves conceptual clarity: mediators describe how effects occur, whereas moderators explain when, for whom and under what organizational conditions those effects become stronger or weaker.

4.4 Theoretical propositions (P1–P5)

The following propositions are derived from three theories identified in the previous review. First, the JD-R model proposes that AI-related resources can foster employee motivation, whereas the COR theory emphasizes that resources acquire psychological value through

employees' perceptions of their availability and significance. In contrast, the sociotechnical perspective highlights transparency, fairness and reskilling as enabling conditions for successful AI integration; however, these same conditions may produce paradoxical effects when they expose system complexity, reveal capability gaps or highlight perceived organizational injustices. Therefore, the propositions expand upon rather than summarize the literature. The propositions are ordered according to the theoretical priority of the framework established. *P1* presents, with justification, the nonlinear impact of AI application intensity on employee well-being. *P2* details the central demand-appreciation mechanism. *P3–P5* define the most important boundary conditions determining whether AI-induced change is a threat or a benefit.

To increase the testability and theoretical contribution of the proposed model, the following propositions move beyond documenting AI's dual effects to specifying the conditions under which established relationships reverse, intensify nonlinearly or produce outcomes that contradict prevailing assumptions in the JD-R and COR studies:

- P1.* Artificial intelligence-enabled job resources, such as cognitive support, decision assistance and task automation function as motivational resources only up to a threshold level of implementation intensity. Beyond this threshold, the same resources generate novel and compounding job demands, including the need for continuous algorithmic oversight, meta-cognitive monitoring of artificial intelligence outputs and accountability for artificial intelligence-assisted decisions whose logic employees cannot fully interrogate. Consequently, the association between artificial intelligence-enabled resource provision and employee well-being may follow a nonlinear, inverted U-shaped pattern. While initial access to artificial intelligence-related resources can enhance well-being and work engagement, excessive or accelerated artificial intelligence integration may transform these benefits into new forms of job demands that extend beyond the assumptions of traditional Job Demands-Resources configurations (Demerouti *et al.*, 2001; Rahmi *et al.*, 2025).
- P2.* Organizational attempts to protect employee skill discretion during artificial intelligence adoption through job enrichment, increased autonomy and broader role responsibilities may paradoxically heighten perceptions of resource threat among employees with low digital self-efficacy. When the expansion of discretionary decision-making exceeds employees' perceived ability to effectively manage these responsibilities within artificial intelligence-mediated work environments, autonomy may be interpreted not as a valuable resource but as an additional burden of accountability. This proposition challenges the conventional assumption that skill discretion consistently reduces artificial intelligence-related strain by identifying an important boundary condition: discretion contributes to resource gain only when it is accompanied by credible and timely reskilling investments that align expanded role expectations with employees' perceived competence (Hakanen *et al.*, 2008; Berente *et al.*, 2021).
- P3.* Organizational transparency regarding artificial intelligence-based decision-making systems reduces resource threat perceptions among employees with moderate-to-high digital self-efficacy, consistent with prior governance research. However, for employees with low digital self-efficacy, high transparency paradoxically intensifies resource threat by making the algorithmic complexity of artificial intelligence systems more visible and, therefore, more cognitively overwhelming. This nonlinear moderating effect suggests that transparency should not be viewed as an inherently

protective organizational practice; rather, it represents a double-edged mechanism whose psychological impact depends on employees' existing ability to process, evaluate and assign meaning to the information provided (Hobfoll *et al.*, 2018; Farkash *et al.*, 2022).

- P4. Reskilling opportunities moderate the relationship between artificial intelligence-induced productivity demands and resource threat perceptions, but only when employees perceive those opportunities as credible that is, as genuinely aligned with the skill requirements of their evolving roles rather than as generic digital literacy programs disconnected from their actual task environment. Below this credibility threshold, the provision of reskilling opportunities may paradoxically strengthen resource threat by signaling to employees that their current competencies are inadequate while failing to provide a convincing pathway to competence restoration. This proposition identifies reskilling credibility, rather than reskilling availability, as the theoretically critical moderating variable and challenges studies that operationalize reskilling as a binary organizational offering (Liao *et al.*, 2022; Babashahi *et al.*, 2024).
- P5. Perceptions of organizational justice in artificial intelligence-enabled contexts, including the fairness of artificial intelligence-based evaluation, task allocation and performance monitoring processes, have asymmetric effects on employee resource appraisals. Perceived unfairness in artificial intelligence-driven systems triggers resource threat responses that are substantially stronger than the resource gain effects generated by comparable levels of perceived fairness. This asymmetry aligns with the Conservation of Resources theory's central assumption that resource loss carries greater psychological significance than resource gain and may become even more pronounced in artificial intelligence contexts, where algorithmic decisions are often perceived as more consequential and less open to challenge than decisions made by human managers. Therefore, organizations cannot effectively address artificial intelligence-related injustice solely through enhanced transparency or leadership support. The psychological strain arising from perceived unfairness follows a distinct and stronger pathway than the motivational effects associated with perceived fairness (Tummers and Bakker, 2021; von Krogh *et al.*, 2023; Murire, 2024).

4.5 Illustrative application of the conceptual framework

Consider a medium-sized bank that introduces an AI-based decision support system for credit assessment. The system generates risk evaluations by analyzing historical repayment patterns, customer financial behavior and macroeconomic indicators and integrates these outputs into internal decision-making and performance evaluation processes. Within the proposed framework, such an AI implementation can simultaneously function as a source of both job demands and job resources. On the one hand, employees may face heightened monitoring pressure, uncertainty regarding their roles and concerns about the future value of their expertise, particularly when algorithmic recommendations begin to influence performance judgments or constrain discretionary decision-making. These conditions may activate the strain pathway described by the JD-R model and may lead to anxiety or resistance through perceived resource threat, especially when employees anticipate potential losses in autonomy, competence or professional status (Demerouti *et al.*, 2001; Hobfoll *et al.*, 2018).

On the other hand, the same AI system may serve as a resource-enhancing mechanism by providing cognitive assistance, accelerating information processing and improving analytical capabilities. Such benefits are more likely to emerge when employees interpret AI as a tool that augments their expertise rather than as a technology that replaces their contribution (Babashahi *et al.*, 2024; Berente *et al.*, 2021). From a sociotechnical perspective, the central issue is, therefore, not simply whether an AI system is introduced, but how the organization restructures work around this technology. When the bank redesigns roles toward more interpretive, advisory and judgment-oriented activities while ensuring transparency regarding the generation and application of algorithmic outputs, role redefinition may facilitate employee adaptation and learning rather than generate feelings of alienation (Trist and Bamforth, 1951; Emery and Trist, 1960; Raisch and Krakowski, 2021). In this sense, the example helps clarify the distinction between mediating and moderating mechanisms in the model: perceived resource threat, perceived resource gain and role redefinition explain the processes through which AI affects employee outcomes, whereas transparency, leadership support, digital self-efficacy, organizational justice and reskilling opportunities shape the extent to which these processes become more negative or more positive. Thus, the illustrative scenario does not serve as empirical validation; rather, it demonstrates how the model can be analytically interpreted in a plausible organizational context.

4.6 Conceptual diagram

AI-based organizational transformation reshapes the employee experience at the psychological, behavioral and structural levels by creating a much more complex matrix of demands and resources than traditional business systems. In this context, the developed conceptual model theoretically demonstrates that AI can simultaneously function as both a stressor that triggers negative reactions such as anxiety and resistance and a resource that strengthens adaptation and well-being by providing skill development, cognitive support and task autonomy. By integrating JD-R, COR and sociotechnical systems approaches, it proposes a multi-layered and contextually sensitive explanatory framework that examines the effects of AI on intra-organizational power dynamics, role identities and decision-making processes. The proposed model is presented in Figure 1.

To ensure consistency between the visual representation and the theoretical framework, each proposition is placed directly into the causal path it governs in Figure 1: *P1* is positioned in the AI application intensity–resource transformation linkage, capturing the nonlinear relationship between AI resource provision and employee well-being; *P2* is positioned in the productivity demands–skill appreciation fundamental tension arrow, illustrating the appreciation paradox under low digital self-efficacy; *P3* appears in the transparency moderating path, linking organizational conditions to perceived resource threat, reflecting the transparency reversal effect; *P4* is positioned in the reskilling–resource evaluation moderating arrow, marking the reliability threshold where reskilling paradoxically increases the threat; and *P5* is positioned in the organizational justice–resource evaluation path, indicating the asymmetric loss-superiority effect of perceived AI-related injustice. This interwoven structure allows readers to trace each proposition directly through the causal architecture of the model without referring to the text.

The conceptual model proposed in this study offers a holistic and integrative framework that conceptualizes AI-based innovation as not merely a technical change process but also a socio-psychological and organizational transformation. The model predicts that the use of AI is most likely to produce negative employee outcomes when productivity demands increase faster than skill proficiency and most likely to produce positive outcomes when skill proficiency expands along with or before productivity demands. Addressing the increasingly

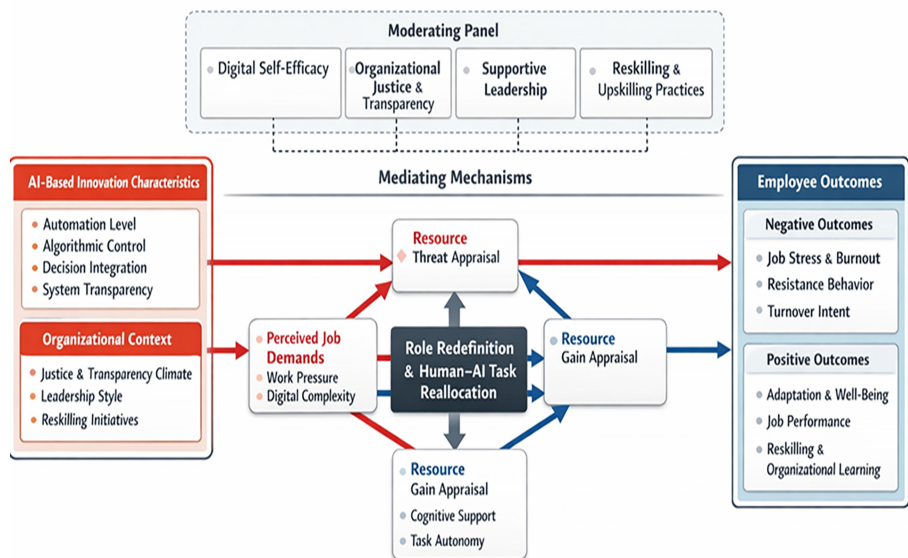


Figure 1. Artificial intelligence as a double-edged sword conceptual model
Source: Authors' own work

emphasized “double-edged sword” nature of AI, the model explains how AI simultaneously generates negative outcomes such as anxiety, resistance, burnout and turnover through heightened job demands, algorithmic surveillance, skill erosion and status threats, while also fostering positive outcomes including well-being, performance, adaptation, reskilling and organizational learning by enhancing cognitive support, error reduction, task autonomy and learning cycles. Drawing on the JD-R framework, the model captures both disruptive and motivational processes embedded in the demand-resource balance; through COR theory, it explicates resource loss and gain cycles; and from a sociotechnical systems perspective, it incorporates human-machine task allocation, decision architecture, organizational justice and shifting power relations. As shown in the conceptual diagram, AI characteristics and organizational context variables feed into employees’ perceived job demands and resource evaluations, which operate through the mediating mechanisms of resource threat and resource acquisition and are further conditioned by moderating factors such as fairness, transparency, leadership support, digital self-efficacy and reskilling strategies. These processes jointly produce differentiated employee outcomes, demonstrating that the effects of AI-driven innovation are dynamic, context-dependent and non-deterministic. Accordingly, the model integrates fragmented explanations in the literature and provides a robust, multi-level framework showing that employee responses to AI are shaped not by technology alone, but by the interaction of perceptual processes, organizational context, resource dynamics and sociotechnical architecture.

5. Theoretical implications

This study reconceptualizes employee anxiety toward AI as a contextually embedded response influenced by job design, resource conditions, leadership practices and

sociotechnical factors rather than as a simple form of technological resistance. By combining JD-R, COR and sociotechnical perspectives, this study positions AI as a dynamic organizational force that simultaneously transforms job demands, resource configurations and work structures. The findings indicate that employee responses are shaped less by the presence of AI itself and more by perceptions of fairness, transparency, autonomy and opportunities for reskilling, highlighting the importance of adopting multi-level and dynamic perspectives in future AI research.

5.1 Contributions to artificial intelligence and work psychology literature

More broadly, this study contributes to the AI and employee outcomes literature by addressing the theoretical fragmentation evident in existing research. Prior studies have often examined specific mechanisms in isolation, including technostress, algorithmic management, digital self-efficacy and AI-enabled creativity, which have contributed to mixed and sometimes contradictory empirical findings. By framing AI as a sociotechnical resource that simultaneously triggers demand-related strain mechanisms and resource-based motivational processes, this study integrates these perspectives into a unified framework that provides a more comprehensive explanation of divergent employee outcomes. In doing so, this study contributes to a more coherent theoretical understanding of AI-enabled work by demonstrating that the “double-edged sword” nature of AI is not a paradox but an inherent property of technological innovation operating within complex organizational systems.

5.2 Theoretical extensions to Job Demands-Resources and Conservation of Resources

This study extends the JD-R framework by conceptualizing AI as a source of qualitatively novel job demands such as algorithmic monitoring, accelerated work pace and role ambiguity and distinct job resources, including cognitive support and task automation, whose motivational or strain-related effects depend on their configuration and interpretation within the work system. At the same time, it advances the COR theory by demonstrating that AI adoption activates simultaneous trajectories of resource loss and gain, with employee responses driven less by the technology itself than by anticipated changes in valued resources such as job security, competence, status and career capital. By integrating JD-R and COR, this study clarifies that AI-related demands become psychologically consequential when they are appraised as resource threats, whereas AI-related resources generate sustainable benefits when embedded in supportive organizational investment and learning contexts.

Beyond extending each theory individually, this study demonstrates that integrating JD-R and COR yields a theoretically distinct contribution that neither framework alone can produce. JD-R, applied in isolation, predicts that high demands lead to strain and strong resources lead to motivation, but it treats appraisal as implicit and offers limited purchase on why the same demand produces divergent reactions across employees facing identical technological conditions (Li et al., 2025). COR, applied alone, explains the appraisal logic of resource loss and gain but lacks a structural vocabulary for describing how work design determines what is available to be lost or gained in the first place. Their integration resolves this mutual limitation by establishing that AI-induced demands become psychologically consequential *only when they activate resource threat appraisals*, and that AI-induced resources generate sustainable motivational benefits *only when they are embedded in organizational conditions that make resource gain credible and accessible*. This conditional, recursive logic, in which structural work characteristics and psychological resource evaluations are mutually constitutive, represents this study’s core theoretical advance and offers a more precise explanation of AI’s double-edged nature than prior single-framework accounts.

5.3 *Implications for multi-level theory*

The findings demonstrate that employee concerns regarding AI are inherently multi-level phenomena that emerge from the interaction between individual interpretations and organizational conditions. At the individual level, factors such as autonomy, perceived competence and uncertainty influence psychological responses, whereas organizational-level factors, including leadership communication, justice and transparency climates and reskilling infrastructures, shape how these perceptions develop and are managed. From a sociotechnical perspective, AI adoption further transforms power relations and role boundaries, generating reciprocal interactions between organizational design choices and employee responses. These dynamics indicate that approaches that focus exclusively on individual attitudes offer an incomplete explanation of AI-related outcomes and highlight the importance of multi-level research designs that connect employee experiences to broader AI governance structures.

5.4 *Practical and managerial implications*

To understand the managerial problem arising from the perception of AI as a “double-edged sword” by this study, the proposed theoretical framework should be understood not as a general perspective toward human-centered or transparent change, but as a process of establishing a conditional decision-making logic for AI applications in organizations. The JD-R/COR/sociotechnical model theories, addressed holistically by the study, argue that managers need to diagnose whether AI simultaneously increases productivity demands and preserves or expands skill appreciation. For instance, when AI implementation increases productivity expectations while diminishing employees’ perceptions of their skill value within the organization, AI is more likely to be perceived as a resource threat, potentially resulting in anxiety, resistance and withdrawal behaviors. Conversely, when higher productivity demands are accompanied by meaningful role enrichment, effective reskilling opportunities and participatory job redesign, employees are more likely to perceive AI as a resource-enhancing opportunity that facilitates adaptation, learning and engagement. Therefore, the framework’s contribution lies in identifying the specific conditions under which the same AI system becomes either threatening or beneficial to employees. These managerial implications create if-then scenarios to understand why the theories are taken together to explain the “double edge” approach. Several scenarios can be derived, as shown in the table. [Table 2](#) shows the scenarios with theoretical logic.

Standard change management frameworks treat AI adoption primarily as an implementation challenge: communicate the change clearly, train employees and secure leadership buy-in. While these steps are not wrong, they share a common limitation that they assume that employee responses to AI are driven by information deficits and skill gaps that can be corrected through targeted interventions. The integrated JD-R–COR–sociotechnical framework developed in this study challenges this assumption and generates a qualitatively different set of managerial implications. What distinguishes this framework from a standard checklist is its insistence that employee responses to AI are not communication problems to be resolved but resource appraisal processes to be structured and that the organizational conditions shaping those appraisals must be designed before AI implementation begins, not retrofitted after resistance emerges.

Standard change management approaches monitor employee reactions following AI implementation and intervene when resistance appears. The productivity demands–skills discretion tension at the core of this framework implies a different managerial logic: the ratio between expanding performance expectations and preserved discretionary judgment must be assessed before deployment. A manager applying this framework would map, for each

Table 2. The integrated Job Demands-Resources/ Conservation of Resources/sociotechnical framework and managerial if-then scenarios

"If" managers observe that	"Then", they should	Theoretical logic
AI increases output pressure but reduces discretion in organizations	Redesign roles before rollout	JD-R demand intensification + COR resource threat
Transparency increases confusion in organizations	Use "interpretive" scaffolding	Transparency moderated by digital "self-efficacy" Soru 11
Training is perceived as "generic" and not "role-specific"	Redesign reskilling around future tasks	COR resource-gain credibility
Employees contest AI decisions	Create appeal and human review mechanisms	COR loss asymmetry + organizational justice
AI automates routine tasks but expands judgment work in organizations	Reinforce role enrichment and career pathways	JD-R motivational pathway + sociotechnical role redefinition

Source(s): Authors' own work

affected role, whether AI is likely to expand productivity demands without proportionally preserving or enriching skills discretion and would treat an unfavorable ratio not as a communication failure to be addressed through messaging but as a structural design problem requiring role redesign before rollout. This is not a diagnostic step available within standard change management, which lacks a construct for tracking the demand-discretion balance as a predictor of appraisal outcomes.

The transparency inversion proposition (*P3*) implies that communicating AI system logic does not uniformly reduce anxiety. A manager working with this framework would segment employees by not only role or seniority but also digital self-efficacy level and would calibrate disclosure accordingly: high-efficacy employees benefit from detailed algorithmic transparency, whereas low-efficacy employees require interpretive scaffolding that is, organizational intermediaries such as team leaders or AI liaisons who translate system logic into role-relevant terms before employees are exposed to it directly. Standard change management prescribes transparency as a uniform good; this framework prescribes transparency as a contingent intervention whose design must account for employees' existing capacity to process what is disclosed.

The reskilling credibility threshold proposition (*P4*) implies that employees evaluate reskilling not by its availability but by its alignment with the actual skill demands of their AI-altered roles. A manager applying this framework would assess whether reskilling offerings are perceived as role-specific and forward-looking, or as generic digital literacy programs that signal competence inadequacy without providing a credible restoration pathway. When reskilling lacks credibility, its provision paradoxically intensifies resource threat rather than attenuating it an effect invisible to standard change management frameworks that operationalize reskilling as a binary intervention. The practical implication is that reskilling design requires prior role mapping: managers must first specify what skills the AI-altered role will actually demand, then construct learning pathways backward from that specification rather than forward from available training catalogues.

The organizational justice asymmetry proposition (*P5*) implies that the psychological damage caused by perceived AI-related unfairness cannot be neutralized by equivalent levels of perceived fairness. A manager using a standard engagement survey who observes moderate fairness scores may conclude that the organizational climate is acceptable; this framework predicts that even moderate perceptions of injustice in AI-based evaluation systems generate resource-threat responses whose intensity is disproportionate to what

fairness scores alone would suggest. The practical implication is that managers should monitor injustice signals employee contestation of AI-based evaluations, informal appeals and expressions of algorithmic distrust as leading indicators of resource threat escalation and treat them as structurally consequential rather than as individual grievances to be resolved case by case.

Perhaps, the most fundamental distinction between this framework and standard change management is its sequencing logic. Change management frameworks typically deploy AI capabilities first and build organizational support structures in parallel or in response to emerging problems. The integrated framework implies the opposite sequence: organizational transparency architecture, justice-preserving evaluation design, leadership framing capacity, reskilling credibility and digital self-efficacy development must reach sufficient levels before AI capability expansion occurs, because these conditions determine whether productivity demands and skills discretion are experienced as complementary or antagonistic from the first moment of exposure. Once resource threat appraisals are activated at scale, the moderating conditions lose much of their buffering capacity, a prediction grounded in COR theory's loss spiral logic and absent from standard change management thinking.

5.5 Policy implications

At the policy level, the model highlights a growing mismatch between the rapid diffusion of AI in workplaces and the slower pace of institutional adaptation. Employee anxiety frequently arises before actual job displacement occurs, driven by concerns regarding skill obsolescence, algorithmic monitoring and reduced control over work processes. This highlights the need for preventive and enabling policy approaches that extend beyond conventional employment protection mechanisms. Accordingly, policy frameworks should address algorithmic transparency rights, establish clearer guidelines for AI-based evaluation and task allocation and promote coordinated reskilling ecosystems involving governments, educational institutions and organizations (Jia *et al.*, 2024; Yin *et al.*, 2024). Ensuring a fair distribution of AI-related benefits and risks also requires transition-oriented policies, including portable skill certifications, lifelong learning mechanisms and employee-centered AI governance indicators. Such approaches are critical for ensuring that AI-driven innovation contributes to sustainable workforce development rather than undermining long-term employability.

5.6 Directions for future research

The proposed model opens several important directions for future research. First, longitudinal designs are needed to capture how employees' perceptions of AI evolve, as resource threat and gain processes are inherently dynamic and cannot be adequately examined through cross-sectional studies. Second, future studies should move toward multi-level research designs that connect individual-level resources, such as digital self-efficacy and learning orientation, with organizational-level conditions, including justice climate, leadership communication and algorithmic transparency. Third, further research should examine employee heterogeneity by considering differences across occupations, skill levels and career stages to better explain why AI is perceived as an empowering resource by some employees while being experienced as a threat by others. Moreover, configurational and mixed-method approaches that combine qualitative examinations of role redefinition with quantitative techniques such as fsQCA may provide deeper insights into the complex combinations of demands, resources and contextual factors that generate diverse employee outcomes. Finally, future studies should explicitly incorporate ethical and power-related dimensions of AI, examine issues of surveillance, control, accountability and trust and

integrating ethical AI frameworks with JD-R and COR perspectives to deepen both theoretical and practical understanding.

6. Conclusion

The managerial contribution of this study is that the integrated framework identifies when applications might work, when they might fail and even when they might create undesirable negative effects. If injustice related to AI arises within the organization or is perceived by employees, then managers should intervene directly. The combined approach of the JD-R/COR/sociotechnical model also explains how the dual nature of AI is transformed into actionable managerial judgment. Also, the main contribution of this article is not in claiming that AI has both positive and negative consequences. The fundamental contribution lies in theorizing the macro-micro translation mechanism by which sociotechnical design choices related to AI have psychological consequences for employees.

Finally, this study conceptualizes AI as a “double-edged sword” by demonstrating that AI simultaneously introduces new job demands and psychological strain, creates opportunities for resource gain that support performance and well-being and functions as a sociotechnical design element that reshapes roles, power relations and human-machine task allocation. Rather than interpreting employee concerns about AI as mere resistance to technological change, this study conceptualizes them as rational and context-sensitive responses emerging from perceived resource threats, changing role expectations and uncertainty shaped by organizational design decisions. By integrating the JD-R, COR and sociotechnical systems perspectives, the proposed framework explains why AI adoption can generate different employee outcomes across organizational contexts. It highlights that transparency, fairness, supportive leadership and credible reskilling opportunities play a critical role in shifting AI from a perceived source of threat toward a mechanism for employee development. Although the framework is conceptual, it provides a theoretically grounded basis for future empirical studies examining its mediating and moderating mechanisms across industries and over time. In doing so, it offers insights into how organizations can pursue AI-driven innovation while maintaining employee well-being, trust and sustainable performance.

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