



Artificial intelligence and job design: Insights from Job Demands–Resources theory

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ABSTRACT

Artificial intelligence (AI) is transforming work by reshaping how jobs are designed, experienced, and performed. This article reviews emerging evidence on the implications of AI adoption for job design from the perspective of Job Demands–Resources theory. We develop a conceptual framework that explains how AI adoption may alter the balance between job demands and job resources, and thereby influence both motivational and health-impairment processes. We further propose AI readiness resources (AI-R) – including personal resources, such as AI self-efficacy, and job resources, such as colleague support for AI – as important conditions that help explain when AI adoption is more likely to strengthen rather than undermine employee well-being and performance. Building on this framework, we formulate three guiding principles for future research. First, scholars should distinguish the level of AI adoption, namely top-down versus bottom-up adoption, from the type of AI use, namely automation versus augmentation, because these dimensions may have different job design implications. Second, researchers should differentiate AI-R resources at the personal and job levels, as they point to different mechanisms and intervention opportunities. Third, research should approach AI adoption as a dynamic process in which employee well-being, performance, and AI readiness may influence one another over time. The article concludes with an agenda for future research and practical directions for designing AI-enhanced jobs that are meaningful, motivating, and sustainable.

1. Introduction

Artificial intelligence (AI) has rapidly moved from research laboratories into the fabric of everyday work life. Large language models, such as ChatGPT and Claude, now assist with writing, coding, and creative work. At the same time, predictive algorithms shape hiring, scheduling, and performance evaluation, while AI-enabled automation takes over routine administrative tasks (Parker & Grote, 2022; Raisch & Krakowski, 2021). Across sectors, AI is changing how work is allocated, coordinated, and evaluated – with direct implications for the well-being and performance of employees and organizations at large (Y. Liu et al., 2026).

AI holds the potential to foster more engaging and human-centered work, but it may equally undermine trust, psychological health, and

sustainable employee functioning if its implications for job design are not carefully addressed (Demerouti, 2022; N. Jia et al., 2024; Wei et al., 2026). To clarify when and how AI adoption benefits workers and organizations, we need a theoretical framework that moves beyond the question of *where* AI can be adopted (e.g., in what tasks or job roles) to *how* this change impacts the content, organization, and experience of work (i.e., job design; Parker, 2014). Much of the current debate focuses on AI exposure: which jobs contain tasks that AI could perform or support (e.g., Burn-Murdoch & O'Connor, 2026; Eloundou et al., 2024; Felten et al., 2021; McElheran et al., 2024). Yet, how these predictions will unfold is not only a question of AI exposure but also of job design.

To address the latter question, the present article reviews emerging literature on the impact of AI on job design through the lens of Job Demands–Resources (JD–R) theory (Bakker, Demerouti, & Sanz-Vergel,

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2023; Demerouti & Bakker, 2023). Rooted in organizational psychology, JD-R theory conceptualizes AI adoption from a job design perspective, focusing on how technologies change the content and organization of tasks, relationships, and responsibilities (Parker, 2014). The theory posits that every job entails a dynamic interplay between demands – those aspects requiring sustained effort and associated with strain – and resources – those that facilitate goal attainment, foster development, and stimulate motivation (Demerouti et al., 2001). The balance between demands and resources determines whether work becomes a source of engagement or exhaustion.

Research on AI and job design is a moving target, as each AI advancement brings new technical possibilities for its use in the workplace (Stollberger et al., 2025). Prior reviews provided descriptive overviews of AI and job design (J. Jia et al., 2025), focused on specific types of job demands (e.g., cognitive job demands; Kulikowski, 2026), or specific types of workers (e.g., frontline service employees; Jooss et al., 2026). We aim to develop an explanatory conceptual framework guided by the two central processes in JD-R theory: the motivational process and the health-impairment process. The motivational process states that individuals in resource-rich environments have the energy and motivation to build and sustain their work engagement through proactive behaviors (e.g., job crafting; Tims et al., 2012). In contrast, job demands instigate a health-impairment process that, if left unaddressed, can undermine employee well-being and performance (Bakker & de Vries, 2021). We argue that AI adoption can impact both processes depending on how it is implemented (top-down vs. bottom-up) and used (automation vs. augmentation-focused; Raisch & Krakowski, 2021). By making this distinction, we aim to bring more clarity to the evolving impact of AI on job design, offering a guiding framework that could help in understanding why AI instigates motivational processes in some cases and health-impairment in others.

It is unlikely that the impact of AI adoption is uniform, even when one considers how a given type of AI is implemented and used. In other words, there likely exist considerable individual and situational differences in the impact of AI adoption on JD-R processes. Building on the insights of our review, as well as ideas from research on technology adoption and readiness (cf. Parasuraman, 2000; Venkatesh et al., 2016), we propose that the impact of AI adoption on JD-R processes is contingent on what we call *AI-readiness resources* or shortly AI-R

resources. We further distinguish between AI-R job resources (e.g., organizational AI support; Quan et al., 2025) and AI-R personal resources (e.g., metacognitive skills; Sun et al., 2025). These resources constitute job and individual characteristics that enable employees to work effectively with AI, manage AI-related demands, and adapt to AI-induced changes in tasks, roles, and workflows, thereby supporting goal achievement, motivation, and development. Hence, we position AI-R resources as moderators that influence the extent to which AI-adoption instigates motivational and health-impairment processes.

Building on the most recent version of JD-R theory (Bakker & Demerouti, 2024; Bakker, Xanthopoulou, & Demerouti, 2023), we further propose that AI-R resources themselves are influenced by motivational and health-impairment processes (see Fig. 1). We propose a dynamic model explaining why some employees thrive whereas others fall behind as AI adoption increases. Employees in gain spirals, characterized by job resources, work engagement, and proactive behaviors, are more likely to develop AI-R personal resources, such as AI literacy, and to access AI-R job resources, such as developmental opportunities. By contrast, employees in loss spirals, characterized by high job demands, exhaustion, and self-undermining behaviors, may struggle to use or develop such resources. AI adoption may therefore create a cumulative advantage-disadvantage process: employees with strong job resources and AI readiness gain further autonomy, learning opportunities, and performance benefits, whereas those with fewer resources face increasing demands, reduced control, and declining well-being (cf., Hakonen et al., 2011). In doing so, we extend debates on AI-related inequality from the macro level (e.g., Karunakaran et al., 2025) to the micro level, explaining why workers may follow divergent trajectories even when their occupations are similarly exposed to AI.

We aim to make one principal theoretical contribution, supported by two further ones. Our central contribution is a dynamic model of AI readiness (Fig. 1) that explains why some employees thrive while others fall behind as AI adoption spreads. At its core is the concept of *AI-readiness (AI-R) resources* – job resources such as colleague support for AI and personal resources such as AI self-efficacy – which govern whether the adoption of a given AI tool feeds the motivational or the health-impairment process. Crucially, we do not treat these resources as static moderators. Building on the most recent version of JD-R theory, we propose that the two JD-R processes feed back onto AI-R resources:

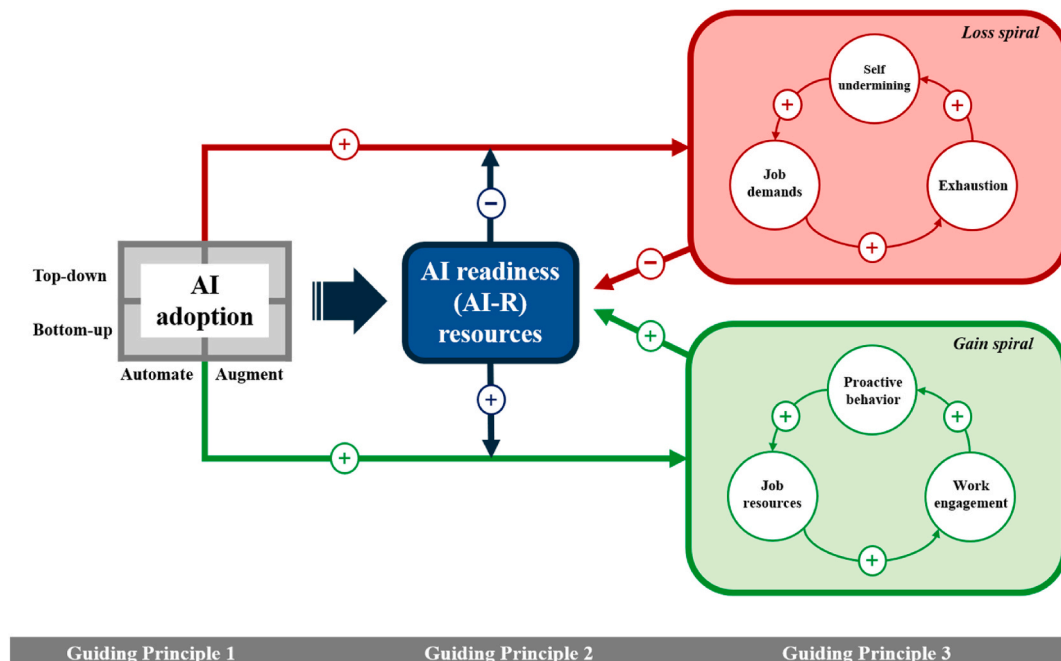


Fig. 1. A dynamic model of AI readiness (JD-R perspective).

employees in a gain spiral of job resources, work engagement, and proactive behavior develop and gain access to further AI-R resources, whereas those in a loss spiral of job demands, exhaustion, and self-undermining see these resources erode. As Fig. 1 shows, these recursive loops turn small initial differences into diverging trajectories – a cumulative advantage-disadvantage process that helps explain why workers in similarly AI-exposed occupations can nonetheless end up far apart. To our knowledge, this is the first model to treat AI readiness not as a stable trait but as an evolving resource influenced by the very work processes it helps set in motion, and we specify how its feedback loops can be tested in longitudinal research.

This dynamic model of AI readiness rests on a broader JD-R framework for organizing the fast-moving and still-fragmented evidence on how AI affects job design, well-being, and performance. Rather than drawing premature conclusions, we specify *when* AI is likely to activate motivational versus health-impairment processes, distinguishing the *level* of adoption (top-down vs. bottom-up) from the *type* of use (automation vs. augmentation). As the input side of Fig. 1 makes explicit, these two dimensions characterize the AI adoption that enters the model, and they yield testable propositions for future systematic reviews and meta-analyses – for example, whether the impact of adoption differs by its level or its type.

Finally, the model extends outward to practice and policy. By distinguishing AI-R job resources from AI-R *personal* resources, we identify two complementary levers for AI-readiness interventions – a distinction that will only grow in importance as tools evolve from generative to agentic AI. The framework can thus serve as a basis for theory-based intervention research on AI adoption and job design (Demerouti et al., 2025). Because structural, job-based resources can be addressed at the organizational and policy level, our model also offers a starting point for countering the inequalities that uneven AI readiness may otherwise entrench – an important contribution to practice and policy.

In what follows, we first introduce readers to the basics of JD-R theory, outlining its core propositions (Bakker, Demerouti, & Sanz-Vergel, 2023; Demerouti & Bakker, 2023). Subsequently, we present a narrative review of the impact of AI adoption on job design and introduce the concept of AI readiness resources. Finally, we develop a dynamic model that explains: (1) how AI adoption translates into motivational or health-impairment processes contingent on AI readiness resources, and (2) how these JD-R processes, in turn, influence AI readiness by influencing the extent to which employees make use of and develop AI readiness resources. Finally, we discuss the implications of this framework for future research and practical AI readiness interventions.

2. Job Demands–Resources theory

The Job Demands–Resources theory (Bakker, Demerouti, & Sanz-Vergel, 2023; Demerouti & Bakker, 2023) provides a powerful yet flexible lens for understanding how the design of work influences employees' motivation, well-being, and performance. Unlike classic job design models that assume a fixed set of motivating job characteristics (e.g., Hackman & Oldham, 1976), JD-R theory starts from the premise that *every job* – regardless of sector, organization, or level – can be understood in terms of its unique configuration of job demands and job resources.

Job demands are those aspects of the job that require sustained physical, emotional, or cognitive effort and are therefore associated with certain costs (Demerouti et al., 2001). These can include workload, emotionally demanding client interactions, complex problem-solving, or constraints imposed by rigid and inflexible AI systems. In contrast, job resources are physical, psychological, social, or organizational elements of the job that help achieve goals, reduce demands, or stimulate growth – such as autonomy, supportive leadership, skill variety, or access to well-designed digital tools. JD-R theory's first proposition is that demands and resources are context-dependent and must be studied

considering specific occupational realities (Bakker & Demerouti, 2024).

The second proposition of JD-R theory is that job demands and resources trigger two distinct psychological processes. Job demands, when they become excessive or chronic, deplete employees' energy and lead to strain – a dynamic known as the *health impairment process* (Demerouti et al., 2001; Schaufeli et al., 2009). For instance, a customer service agent continuously monitored by AI-driven performance systems may experience constant pressure to respond faster and maintain a positive tone during interactions with clients, leaving little room for recovery and eventually leading to fatigue or even burnout.

On the other hand, job resources drive motivation and engagement through the *motivational process*, especially when they satisfy basic psychological needs for autonomy, competence, and relatedness (Van den Broeck et al., 2008). A designer with creative freedom and regular feedback may feel energized and fulfilled – even on challenging days. Job resources motivate employees to reach work-related goals and facilitate persistence and performance (Kovjanec et al., 2013; Lesener et al., 2019).

Building on the distinction between the health impairment and motivational processes, the theory's third proposition introduces an important dynamic interaction: the interplay between job demands and job resources. Through the *buffering effect*, job resources can alleviate the unfavorable impact of high job demands on strain. For example, strong peer support can make a heavy workload or emotionally demanding interactions feel more manageable (Bakker et al., 2005; Lavoie-Tremblay et al., 2014). Conversely, through the *boosting effect*, job resources become especially potent in combination with demands, such as under pressure (e.g., Hakanen et al., 2005). A deadline may feel invigorating instead of overwhelming when paired with role clarity and recognition. Importantly, these dynamics do not just unfold over months or years. Daily diary studies (e.g., Breevaart & Bakker, 2018; Tadić et al., 2015) suggest that the synchrony between *daily* demands and resources is crucial. Namely, it is on these short time scales that well-being and performance often rise or fall.

JD-R theory also highlights the role of the individual. Propositions four and five bring personal resources into focus – positive self-beliefs such as optimism, resilience, and self-efficacy (Bakker, Xanthopoulou, & Demerouti, 2023). These resources not only help buffer the impact of demands (Bajaba et al., 2022) but also build a bridge to more job resources (Xanthopoulou et al., 2009). Employees who feel capable are more likely to seek feedback, connect with colleagues, and reframe stressors. For example, in a study among nurses, those high in optimism and self-efficacy experienced emotionally demanding shifts as more meaningful and engaging (Bakker & Sanz-Vergel, 2013), while others felt overwhelmed and drained.

The sixth proposition of JD-R theory emphasizes employee agency: individuals are not passive recipients of job design. Through job crafting, employees proactively modify their job demands and job resources to achieve a better fit between their work and their needs, abilities, and strengths (Tims & Bakker, 2010; Wrzesniewski & Dutton, 2001). A developer might reconfigure their day to include more coding and less admin, while a teacher may seek new learning materials to keep lessons fresh. Even small, daily acts of crafting – like asking for input, blocking time for focused work, or reframing a repetitive task – have been shown to enhance daily well-being and engagement (Demerouti & Bakker, 2024; Oprea et al., 2019; Petrou et al., 2012).

Finally, Proposition 7 draws attention to a critical risk: self-undermining. When job demands remain high and recovery is insufficient, strain may accumulate and gradually become chronic, increasing the likelihood of maladaptive feedback loops (Bakker & de Vries, 2021). Under such conditions, employees do not simply suffer from high demands; they may also, often unintentionally, contribute to the persistence of those demands. Exhausted or distracted employees may miss deadlines, communicate less clearly, make avoidable mistakes, or withdraw from colleagues precisely when support is most needed (Bakker & Wang, 2020). These behaviors can make work even more

demanding and further reduce access to resources, thereby deepening the loss spiral rather than breaking it (Bakker & de Vries, 2021). For example, an employee under intense pressure may avoid asking for help, leading to errors that increase their workload and stress in the long run. Indeed, in a daily diary study, Roczniowska and Bakker (2021) found that nurses who started their workday depleted were less likely to proactively craft their job to increase resources and more likely to show self-undermining behaviors, ultimately leading to impaired daily performance.

Taken together, JD-R theory provides a dynamic, empirically grounded framework for understanding how job conditions, personal resources, and daily behaviors interact. It explains not only why some employees thrive while others struggle, but also how individuals, teams, and organizations can actively design for well-being and performance. This design orientation is particularly consequential in AI-infused workplaces, where technologies continuously reconfigure tasks, redistribute responsibilities, and recalibrate the balance between demands and resources.

3. Artificial intelligence and job design

Having outlined the core propositions of JD-R theory, we now examine how artificial intelligence is reshaping contemporary job design. We begin by analyzing how AI adoption reconfigures job demands and job resources. Next, we introduce the automation–augmentation framework (cf. Raisch & Krakowski, 2021) as a conceptual lens to differentiate how AI is deployed and experienced in organizations. We then consider the moderating role of AI-R resources at both job and personal levels. Finally, we develop a dynamic model of AI adoption and AI readiness. For each section, we conclude by proposing guiding recommendations to advance theoretically rigorous research on AI, JD-R processes, and job design more broadly. Fig. 1 presents our conceptual model of how AI reshapes job design and, in turn, influences employee functioning.

We conducted an initial Web of Science search in December 2025 for articles explicitly referring to both AI and JD-R theory, which yielded 90 records. Because relevant research on AI and work does not always explicitly invoke JD-R theory, we supplemented this search by screening the reference lists of influential reviews on AI in organizational behavior (e.g., Bankins et al., 2024), conducting forward citation searches, and performing additional keyword searches for studies relevant to the JD-R framework. The resulting literature was synthesized narratively, using JD-R theory as the organizing framework.

3.1. Impact of AI adoption on job demands and resources

In drawing initial conclusions on how AI adoption impacts job demands and job resources, it is important to keep the level of adoption in mind. By level of adoption, we mean whether AI is implemented by employees on their own discretion (bottom-up; Fong et al., 2025) rather than mandated by management or embedded in algorithmic systems (top-down; Parent-Rochelleau & Parker, 2022). In the case of bottom-up adoption, employees have more control over how and when they use AI to complete their work activities.

When AI is implemented top-down, it can vary in how directional the influence is between the technology and the employee. At one end, AI becomes part of a more bilateral work process, where employees actively engage with an AI system and the output is determined through iterative input, judgement, and adjustment. For instance, a financial analyst may be required to work with an AI agent to generate, test, and refine an analysis, making human–AI interaction an explicit element of the job's task execution. Similarly, contexts in which manufacturing employees (Goštautaitė et al., 2024) or warehouse workers (Berkers et al., 2023) coordinate their actions with intelligent robots reflect top-down adoption where influence is comparatively more reciprocal because employees must continuously respond to (and sometimes correct) the

system.

At the other end, top-down adoption can be largely unilateral, in that AI influences the parameters of work without inviting meaningful interaction – employees mainly experience its consequences rather than collaborating with it. Here, AI is embedded in organizational infrastructures that allocate work, optimize schedules, or set performance targets, with employees primarily on the receiving end and not necessarily aware that AI is driving these decisions (Röttgen et al., 2024). For example, in healthcare or retail, AI-enabled forecasting and optimization tools may determine staffing levels, shift timing, workload distribution, and productivity expectations, influencing pace and autonomy even when frontline employees never “use” AI directly in carrying out core tasks.

In what follows, we review how AI adoption changes job demands and job resources considering existing research. We identify four pathways through which AI alters the JD-R system: it can increase or decrease job demands, and it can increase or decrease job resources (cf. Wei et al., 2026). Table 1 illustrates these pathways across diverse roles. For example, customer service agents may face more cognitively complex escalations, and physicians may carry greater diagnostic accountability, while administrative and warehouse workers may experience reduced workload through automation. At the same time, engineers and marketers can use AI to expand skill utilization and improve decision quality, whereas retail and gig workers may encounter diminished autonomy and social support under algorithmic management.

3.1.1. Increasing job demands

AI adoption can introduce new cognitive, emotional, and accountability pressures that make work more demanding. Interactions with AI agents may increase experiences of technostress, defined as the efforts

Table 1
AI impact on job design.

AI Impact	Job Role	Example
Increasing Job Demands	Customer Service	Employees handle only escalated issues unresolved by AI chatbots, increasing cognitive and emotional complexity.
	Healthcare	Doctors face pressure to interpret AI diagnostics and remain accountable for clinical decisions.
Decreasing Job Demands	Administrative Support	AI automates scheduling and data entry, reducing workload and freeing up cognitive capacity.
	Warehouse Operations	Robotic automation reduces physical strain by taking over heavy lifting and repetitive tasks.
Increasing Job Resources	Software Engineering	Engineers use tools like GitHub Copilot for real-time coding support, enhancing autonomy and skill development.
	Marketing	Marketers leverage AI analytics for data-driven decisions, improving strategic focus and effectiveness.
Decreasing Job Resources	Retail	Social interaction diminishes as AI self-checkouts replace cashier roles, reducing peer support and collaboration.
	Gig Work	Algorithmic control in ride-share platforms limits flexibility and worker autonomy, diminishing perceived control.

and energy devoted to coping with new (digital) technologies (Ayyagari

et al., 2011). Technostress¹ has multiple dimensions, including overload, invasion, complexity, uncertainty, and insecurity (Tarafdar et al., 2007). In a three-wave study among Taiwanese workers from diverse sectors, AI technostress related positively to exhaustion – indirectly resulting in higher work-family conflict (Chuang et al., 2025). Zooming in on the privacy invasion aspect, Verma and Singh (2024) found in a cross-sectional study of teleworkers that concerns about privacy invasion correlated positively with AI-induced overload, as well as reduced teleworking productivity. The invading nature of AI technology has also been documented in research on algorithmic management, demonstrating that algorithmic monitoring can make work more demanding for platform workers such as food delivery riders (e.g., Lippert et al., 2023; Scharp, Ter Hoeven et al., 2022).

Another mechanism through which AI adoption can make work more effortful is what we refer to as *job demand substitution*. We define job demand substitution as situations where AI or other intelligent systems take over certain work tasks (e.g., routinized activities), while the freed-up work time is filled with other, potentially more demanding work. This has been observed, for instance, in warehouse settings where workers had to pick up “left-over tasks” that could not be handled by an intelligent robot (Berkers et al., 2023). Job demand substitution effects can also be expected based on recent patterns in job vacancy data. Analyzing 12 million job vacancy postings, Mäkelä et al. (2024) noted that as AI adoption grows, job vacancies increasingly mention complementary human skills such as agility, teamwork, or resilience. However, whether requirements for higher-level skills translate into improved job quality often depends on other organizational characteristics. For example, Bienefeld et al. (2025) observed that AI may allow nurses to engage in more complex problem-solving skills to diagnose patient needs. Yet this potential shift toward more advanced skill use was constrained by the hierarchical structure of healthcare teams, which limited nurses’ opportunity to work on more intellectually stimulating tasks.

The growing adoption of AI threatens many professions and can heighten employees’ perceptions of job insecurity. Within the JD-R framework, AI-related job insecurity functions as a job demand that undermines well-being and performance. In a three-wave study of Chinese employees, Wu et al. (2024) showed that AI-induced job insecurity at Time 1 predicted lower informal learning, creativity, and psychological well-being at Time 3, with tech-learning anxiety at Time 2 mediating these effects. Perceptions of AI-related job insecurity are also socially determined. For example, Y. Zhou and Lyu (2025) found that employees reported greater insecurity when they believed their leaders feared job loss due to AI. Taken together, these findings suggest that AI adoption not only introduces new demands, such as technostress and learning anxiety, but can also intensify existing demands by amplifying uncertainty about roles, careers, and labor market prospects.

3.1.2. Decreasing job demands

AI adoption can potentially also reduce job demands and, thereby, lower work-related exhaustion (Demerouti et al., 2001). Employees can partially offload cognitively demanding activities (e.g., drafting, summarizing, and idea generation) to conversational AI agents such as ChatGPT. This has the potential to make work less demanding in various occupations. Teachers have reported workload reductions from AI-assistance in activities such as lesson planning or the development of

course materials (Ghamrawi et al., 2024). In healthcare, AI systems can help with reducing administrative burdens and mentally demanding diagnostic work (Bienefeld et al., 2025). In software development, the adoption of GitHub Copilot has been found to accelerate coding performance, with stronger benefits observed among less experienced developers (F. Xu et al., 2026).

The reduction in job demands, however, is neither uniform nor unequivocally beneficial. Rather than eliminating demands, AI often redistributes them. Xu et al. (2026) showed that although junior developers coded faster with GitHub Copilot, senior developers experienced higher workloads. After adoption, senior developers spent 6.5% more time reviewing code and became less productive in their own programming. Efficiency gains at one level thus translated into intensified evaluative demands at another, illustrating a shift of demands *between* roles. A similar substitution dynamic can occur *within* individuals. Jia et al. (2024) found that sales agents who delegated repetitive tasks to AI reallocated their effort to creative persuasion. Routine demands declined, but cognitive and emotional demands increased (i.e., *job demand substitution*). Consequently, AI-driven reductions in job demands should be understood not as simple relief, but as a reconfiguration of the demand structure.

When AI is integrated with physical technology, such as intelligent robots, its adoption can also lead to a reconfiguration of cognitive and physical demands. Intelligent robots have long been associated with industrial production and factory settings, where they primarily replaced physically strenuous, repetitive, and hazardous tasks (Ulfert et al., 2024). More recently, such robots can also be found in service settings. The effects on job demands not only depend on the technical functionalities of robots, but also on employees’ psychological reactions to them (J. Y. Bai et al., 2025). Counterintuitively, technical malfunctions can elicit positive psychological responses. In interviews reported by Goštautaitė et al. (2024), manufacturing workers described playfully “outsmarting” malfunctioning robots, which enhanced their sense of work meaningfulness. Rather than experiencing breakdowns solely as hindrances, they reframed them as challenges. This suggests that employee well-being depends less on whether intelligent systems increase or reduce job demands, and more on how workers interpret and optimize these changing demands (cf. Scharp et al., 2021).

3.1.3. Increasing job resources

We now turn to the question of how AI adoption may impact job resources. By mimicking human reasoning and decision-making processes, AI-based systems have the potential to augment employees’ cognitive job resources. Cognitive job resources refer to the information and knowledge needed to complete job tasks, as well as opportunities for switching between complex and simple tasks (de Jonge et al., 2012). The benefits of AI use for augmenting cognitive resources have been demonstrated by Sun et al. (2025) in a quasi-experimental field study among technology consultants in China. They found that the introduction of AI-assistance (access to LLMs such as ChatGPT) translated into higher levels of cognitive resources, which indirectly predicted higher supervisor ratings of employee creativity. These benefits were stronger among employees who possessed higher levels of meta-cognitive skills. Meta-cognitive skills refer to the ability to reassess and monitor one’s approach to work tasks (P. Chen et al., 2020). By simplifying work procedures, AI-based systems may have similar effects among operational employees in manufacturing (Goštautaitė et al., 2024) or warehouse settings (Berkers et al., 2023).

Beyond extending human workers’ cognitive resources, AI-based systems can function as a source of feedback. Through an experiment among call center agents of a financial service company, Tong et al. (2021) demonstrated that AI-based performance feedback led to higher employee performance because it increased the breadth of feedback-relevant information and stimulated a higher number of error-corrections among employees. Crucially, however, the positive effects of AI-based feedback diminished once employees were informed

¹ Technostress is treated here as a job demand because its commonly used facets (e.g., techno-overload, techno-complexity, techno-invasion, techno-uncertainty) describe taxing conditions that add to employees’ load and effort requirements. At the same time, consistent with the construct’s original definition as a stress response to technology-related stressors, technostress can also be conceptualized as a strain reaction that mediates the effects of such demands (i.e., technology stressors → technostress → well-being/performance outcomes).

that the feedback was generated by an AI system rather than a human manager. Research from educational psychology also supports the idea that AI-enabled feedback can stimulate learning (e.g., [Bauer et al., 2025](#)). It is possible that the benefits of AI-enabled feedback may not only be due to higher feedback breadth or feedback depth, but also higher feedback immediacy. For example, AI-enabled feedback can facilitate more rapid behavioral adjustment compared to (delayed) human feedback.

While considerable evidence demonstrates the benefits of AI adoption for cognitive job resources and task feedback, its effects on job autonomy are more complex. In a sample of employees from multiple manufacturing companies in China, self-reported AI usage was positively associated with perceived job autonomy and self-reported innovative work behavior ([Zheng et al., 2025](#)). Benefits of bottom-up AI adoption on perceived autonomy were stronger among employees with a promotion-oriented regulatory focus (i.e., individuals who focus on gains rather than losses). In contrast, [Giering and Kirchner \(2025\)](#) concluded that the “association between AI and autonomy is merely superficial and cannot be properly evaluated without considering workplace preconditions” (p. 1). Using a sample of more than 11,000 German workers, they observed that the association between AI use and job autonomy disappeared after controlling for other digital workplace characteristics (e.g., access to computers and digital software). Likewise, top-down implemented algorithmic management is associated with reduced autonomy ([Parent-Rocheleau et al., 2024](#)). This illustrates the importance of considering the level of AI adoption (top-down vs. bottom-up) in research on the impact of AI on job resources (see [Fig. 1](#)).

3.1.4. Decreasing job resources

The aforementioned studies on AI use and autonomy already suggest that AI adoption may not only increase but also decrease key job resources. Drawing from action regulation theory, [Röttgen and colleagues \(2024\)](#) developed a theoretical model of how algorithmic management reduces job resources by undermining task completeness. In action regulation theory ([Hacker, 2003](#)), task completeness refers to the extent to which a job comprises all phases of goal-directed action, including goal setting, planning, and execution. When task completeness is high, workers are more likely to experience their job as coherent and meaningful ([Frese & Zapf, 1994](#); [Mustapha & Rau, 2024](#)). It is possible that top-down implemented AI systems can undermine the completeness of action-regulation sequences, thereby reducing job resources such as autonomy and opportunities for development ([Ohly et al., 2025](#)). For example, in a sample of gig economy workers, [Parent-Rocheleau et al. \(2024\)](#) found that exposure to algorithmic management was negatively associated with work engagement due to reduced job autonomy and lower job complexity. Erosion of task completeness may also occur in the context of bottom-up AI adoption, due to increasing interruptions and the loss of meaningful task sequences ([Simkute et al., 2024](#)).

Similar concerns about the negative effects of AI adoption on job resources have been raised by research conducted in the healthcare sector. For instance, AI technology has been observed to pose a threat to the expertise of professionals such as radiologists ([Perez et al., 2024](#)). In radiology, AI systems are increasingly being used to analyze medical images and provide preliminary diagnoses, which can reduce workers’ involvement in the diagnostic process ([Budzyń et al., 2025](#)). Concerns about reduced skill development due to AI technologies have also been raised in other medical professions, such as pharmacy ([Zawiah et al., 2023](#)) and nursing ([Ramadan et al., 2024](#)). Negative effects on task variety have also been found in warehouse settings, where meaningful tasks have been taken over by robots ([Berkers et al., 2023](#)). Research from educational psychology echoes concerns about the negative impact of interactions with AI chatbots on (student) learning and development ([Bauer et al., 2025](#)). Together, this suggests that AI adoption can diminish learning resources that are inherent to complex work activities in various sectors.

Related to the potential loss of meaningful learning opportunities,

interactions with AI agents can also lead to a loss of interpersonal connections. In a series of four studies among workers from different regions (USA, Malaysia, Taiwan, and Indonesia), [Tang et al. \(2023\)](#) found that more frequent interactions with AI agents were associated with increased loneliness and a heightened need for affiliation. This suggests that AI use can reduce individuals’ social resources. Using a daily diary design, [Hai et al. \(2025\)](#) found that on days when employees interacted more extensively with AI agents, they reported higher levels of work alienation. This effect was more pronounced among employees who experienced high levels of digital job demands. Hence, excessive reliance on AI and other digital tools can dismantle the social fabric of work that makes jobs motivating. Taken together, these studies suggest that AI adoption can also lead to an erosion of job resources such as autonomy, opportunities for skill development, or social resources (e.g., support, feedback).

3.1.5. The automation-augmentation framework

These mixed findings suggest that AI effects depend on both who initiates adoption and how the technology is used. We therefore distinguish the level of adoption (i.e., top-down versus bottom-up) from the type of use (i.e., automation versus augmentation). Whereas top-down systems such as algorithmic management may reduce autonomy and job quality, bottom-up use may give employees more discretion over how AI enters their work. Similarly, automation shifts tasks from humans to technology, whereas augmentation involves closer human–AI collaboration. Drawing from [Raisch and Krakowski \(2021\)](#), automation-oriented forms of adopting AI would imply that technology largely takes on tasks with limited involvement by humans. Augmentation-oriented forms, in contrast, imply close interactions between humans and technology. We expect that these two prototypical forms of adopting AI may have vastly different psychological effects (see [Table 2](#)). Our recommendation for future research on AI adoption and job design is to clearly distinguish between the level and type of AI adoption. Doing so will enable a more nuanced understanding regarding the heterogeneous effects of AI adoption on job demands and job resources.

Guiding Principle 1: In studying the impact of AI adoption on job demands and job resources, researchers should distinguish between the level of adoption (top-down vs. bottom-up) and the type of adoption (automation vs. augmentation).

3.2. AI readiness resources

AI adoption does not affect all employees in the same way: some thrive, whereas others experience stress, resistance, or disengagement ([Bankins et al., 2024](#)). We use the term AI-readiness resources (AI-R resources) to explain this variability (see [Fig. 1](#)). AI-R resources are job and personal characteristics that help employees work effectively with AI, manage AI-related demands, and adapt to AI-driven changes in tasks, roles, and workflows. Building on JD–R theory, we differentiate between AI-R job resources and AI-R personal resources. While the former refers

Table 2
A typology for research on AI adoption and JD-R theory.

	Automation-oriented	Augmentation-oriented
Top-down adoption	Organizationally mandated use of AI or intelligent machines to take over routine or repetitive tasks with minimal human involvement.	Organizationally mandated use of AI or intelligent machines to support human decision-making or assist in complex tasks through close human-AI collaboration.
Bottom-up adoption	Self-initiated use of AI tools or intelligent machines to offload repetitive or burdensome tasks, streamline workflows, and reduce personal workload.	Self-initiated use of AI tools or intelligent machines to co-create outputs, augment human skills, and collaboratively perform knowledge-intensive or otherwise complex tasks.

to aspects of the job that enable employees to effectively work with AI (e.g., autonomy), the latter refers to personal characteristics that aid with the use and learning regarding AI tools (e.g., openness to experience).

3.2.1. AI-readiness job resources

According to JD-R theory (Bakker, Demerouti, & Sanz-Vergel, 2023), job resources help employees manage job demands. In the context of AI adoption, such resources enable employees to use AI effectively, cope with AI-related demands, and recognize opportunities created by AI-enabled changes in work. We refer to these as AI-readiness job resources. They include supportive leaders, colleagues, and organizations (Radic et al., 2025; Suseno et al., 2022). They also include learning and development infrastructures, such as AI-specific training (Rožman et al., 2023). Shown in Fig. 1, we position AI-R job resources as moderators that influence the extent to which AI adoption translates into motivational rather than health-impairment processes (Liang et al., 2022; Mo et al., 2024; Xie & Ma, 2026).

While AI adoption may increase uncertainty, complexity, or workload, AI-readiness job resources can protect employees from these health-impairing effects by helping them understand, manage, and integrate AI into their work. At the task level, relevant resources include human decision control over AI outputs, transparent and understandable AI recommendations, task-AI fit, and the preservation of core task characteristics such as autonomy, task identity, skill use, and meaningful human judgment. These resources allow employees to experience AI as a support for task accomplishment rather than as a replacement of their expertise. For example, research on human-AI collaboration suggests that decision control strengthens trust, understanding, and compliance with AI recommendations (Westphal et al., 2023), whereas high substitution of core task characteristics can weaken the motivational benefits of AI use and increase work alienation (Hai et al., 2025).

At the team level, AI-R job resources include shared norms for responsible AI use, psychological safety, clear allocation of responsibility between human and AI agents, and communication routines that enable teams to scrutinize AI outputs (Arslan et al., 2022). At the leadership level, constructive leadership is especially important (cf. Pletzer et al., 2024). Coaching leadership (J. Jeong et al., 2024), empowering leadership (S. Zhou et al., 2024), and servant leadership (Mo et al., 2025) have been found to attenuate health impairment processes instigated by AI adoption (Kim et al., 2025; Moin & Zhang, 2025). Additionally, organizational AI support has been shown to attenuate the relationship between AI-induced job insecurity and turnover intentions (J. Li et al., 2019). Similarly, Yin et al. (2024) demonstrated that in the absence of AI-R job resources, the perceived intelligence of AI assistants elicited fear of replacement. However, the availability of AI-R job resources buffered this effect (Kim & Lee, 2025).

Beyond attenuating health-impairment processes, AI-R job resources may also strengthen motivational processes (i.e., a *boosting* effect). Quan et al. (2025) showed that when organizational AI support was higher, AI adoption was indirectly associated with higher performance ratings through increased vigor. This suggests that AI-R job resources determine whether AI functions as a motivational asset or a motivational liability. Likewise, among nurses, Li et al. (2024) found that the indirect, positive association between AI implementation and innovation behaviors via AI self-efficacy was boosted in the presence of an ethical organizational climate. Similarly, Xiao et al. (2025) found that AI-enabled HR analytics only instigated the motivational process, promoting resilience through job crafting, when the HRM system strength was higher. This means that AI adoption benefits primarily arise when there is a shared perception of effective practices (Bowen & Ostroff, 2004). Digital resources embedded in digitally supportive organizational cultures have likewise been shown to buffer against burnout and enhance mental well-being (Y. Li et al., 2025). Further emphasizing the role of shared perceptions, Qi et al. (2025) found that the positive indirect associations between the use of generative AI with performance and innovation were amplified among

employees working in a more innovative culture. Taken together, this suggests that AI-R job resources can both boost motivational processes and buffer health-impairment processes elicited by AI adoption.

3.2.2. AI-readiness personal resources

In line with JD-R theory's conceptualization of personal resources as positive self-evaluations that help individuals to exert control over their work environment (Hobfoll et al., 2003; Xanthopoulou et al., 2009), AI-R personal resources refer to individual characteristics that enable employees to adapt to, engage with, and derive value from AI in the workplace. Key examples include AI self-efficacy – the belief in one's capability to effectively use AI tools (Chuang et al., 2025) – along with digital literacy, which encompasses the knowledge and skills required to navigate, interpret, and integrate AI technologies into daily tasks (Ding et al., 2025). From an information systems and user acceptance perspective, personal innovativeness with IT can also be considered an AI-R personal resource, capturing individual differences in willingness to experiment with and adopt new technologies, and thereby helping to connect JD-R research on AI to adjacent IS traditions (Jackson et al., 2013). Moreover, task expertise, domain experience, and a learning goal orientation can facilitate the accurate interpretation of complex AI-generated outputs (Allen & Choudhury, 2022; Küper & Krämer, 2025). In addition, personality traits such as openness to experience (McCrae & Costa, 1997) promote curiosity, cognitive flexibility, experimentation with AI, and more positive attitudes toward its use (Grassini et al., 2025). Together, these AI-R personal resources equip individuals to better deal with or benefit more from AI adoption (see Fig. 1; Wu et al., 2025; S. Zheng et al., 2025).

Several studies illustrate how AI-R personal resources attenuate the negative consequences of AI adoption (*buffering effect*). For instance, in a daily study among call center representatives, when employees used augmentation-based AI, they had difficulty detaching from work in the evening because they experienced more information overload (Shao et al., 2025). Yet, this process was weaker for individuals who were more open to experience (see also Xu et al., 2025). Likewise, in a time-separated study, Kim and Lee (2024) demonstrated that AI adoption only promoted burnout by increasing job stress for individuals who lacked self-efficacy (see also, X. Kong et al., 2026; Zhao, 2025). Similar buffering effects have been observed for workplace mindfulness (X. Zheng et al., 2023), defined as the ability to maintain nonjudgemental awareness of one's internal experiences and the work environment. In a three-wave lagged survey study, Wu et al. (2024) found that for mindful individuals, the association of job insecurity (resulting from AI adoption) with AI learning anxiety was weaker. One explanation is that the integration of AI into work elicits less hindrance appraisals among more mindful individuals (Huang & Gursoy, 2024).

AI-R personal resources do more than buffering the health-impairment process. They can also amplify the benefits of AI adoption. When individuals are equipped to engage constructively with AI, they are more likely to experience growth, learning, and motivation (H. Kong et al., 2024). For instance, Sha and Chai (2025) studied employees in organizations undergoing digital AI transformation – the process of adopting AI. They found that while AI adoption increased job crafting, this effect was stronger among individuals with more extensive AI knowledge. Similarly, the use of AI has been found to increase self-efficacy more for learning goal-oriented individuals (Han et al., 2025). An experiment and field study also revealed that using generative AI boosted creativity by increasing cognitive job resources, but only for individuals with high metacognitive skills (Sun et al., 2025). Bai and Wang (2025) found a comparable effect among university students. The learning and motivational benefits of using generative AI were greater among those with greater creative thinking ability. Thus, individuals who possess a variety of AI-R personal resources are expected to benefit more from AI adoption.

We recommend future research to investigate the role of AI-R resources, and to distinguish job from personal AI-R resources. This

distinction matters theoretically because job and personal resources may operate in different ways. Job-related AI-readiness resources may reduce uncertainty and prevent AI from becoming an additional demand. For example, when employees receive clear guidance, training, and managerial support, AI is less likely to be experienced as threatening or uncontrollable. Personal AI-readiness resources, by contrast, may determine whether employees feel capable of exploring AI, learning from mistakes, and integrating this new technology into their daily work. Employees with high AI self-efficacy and digital literacy may be more likely to see AI as a tool for learning and performance improvement rather than as a source of strain.

This distinction can also guide intervention design. When low readiness stems from the work environment, organizations should improve training, communication, participation, technical support, and opportunities for experimenting with AI. When it stems from personal resources, interventions should build skills, confidence, and learning orientation. In practice, both levels are likely needed: AI training has limited value without time, autonomy, and support to apply it, while a supportive implementation climate may not be enough when employees lack basic digital skills or confidence. Based on these considerations, we propose:

Guiding Principle 2: In studying the impact of AI adoption on employee well-being and performance, researchers should explicitly account for AI-R resources and distinguish between AI-R job resources and AI-R personal resources, as both determine whether AI adoption triggers health-impairment or motivational processes.

3.3. A dynamic model of AI readiness

As shown in Fig. 1, AI adoption changes job design by altering both job demands and job resources. AI may reduce some demands by, for instance, automating repetitive or cognitive effortful tasks while increasing resources such as access to information. Yet, the same technology may also introduce new job demands, including an accelerated work pace and uncertainty about changing role expectations (Tarafdar et al., 2007; Wu et al., 2024) while deteriorating job resources such as reduces autonomy, task completeness, meaningful human contact, or opportunities for skill use (Parent-Rochelleau et al., 2024; Tang et al., 2023). We therefore argue that AI adoption does not produce one uniform JD–R process. Its consequences depend on AI-readiness resources. When these resources are present, AI is more likely to activate the motivational pathway of the JD–R model. When employees feel competent, they learn faster, remain engaged, and perform better. Conversely, in the absence of these resources, AI is more likely to activate the health-impairment pathway.

Importantly, AI-readiness resources do not only facilitate successful AI adoption. We propose that they are also *outcomes* of JD–R gain and loss spirals. Consider a scientist with an enriched job who enjoys autonomy, access to training, and time to experiment. Because she is engaged, she starts using a large language model to search literature, generate alternative explanations, and improve code. These early successes increase her AI self-efficacy. She then asks colleagues for better prompts and develops new routines for integrating AI into her work. Her engagement therefore helps her mobilize new AI-readiness resources, which in turn make AI more useful and motivating. This exemplifies a positive gain spiral. Her resources foster engagement and the engagement stimulates proactive resource generation, and newly acquired resources further improve learning and performance (Bakker, Demerouti, & Sanz-Vergel, 2023; Demerouti & Bakker, 2026).

Now consider an employee in a constrained job, where work is tightly monitored, targets are rigid, and AI is introduced mainly to track output or standardize decisions. This employee is likely to experience AI as an additional demand. Exhaustion leaves little energy to explore the system, seek feedback, attend training, or experiment with alternative ways of working. Early mistakes may confirm the belief that “AI is not for me,” lowering AI self-efficacy and increasing resistance. From a JD–R

perspective, employees exposed to resource loss become more defensive and less able to invest in new resources (Bakker, Demerouti, & Sanz-Vergel, 2023; Hobfoll et al., 2003). Thus, a lack of readiness resources may produce health-impairment when AI adoption rises, while the resulting strain further undermines later AI readiness.

In short, in the proposed model, we also integrate reversed causal effects. AI-readiness resources determine how employees respond to AI, but employees’ responses also determine whether they accumulate or lose AI-readiness resources over time. AI adoption may therefore intensify inequality in job design. Employees in resource-rich jobs are better positioned to convert AI into learning, autonomy, and performance. Employees in resource-poor jobs may experience AI mainly as surveillance, pressure, and fragmentation. In this way, AI can create a “rich-get-richer, poor-get-poorer” dynamic where enriched jobs become more stimulating and future-oriented, whereas constrained jobs become more controlled, demanding, and developmentally impoverished (e.g., Hakanen et al., 2011). Prior JD–R research provides evidence for reciprocal gain and loss spirals between work characteristics, employee well-being, and employee behavior (Bakker et al., 2023a). Engaged employees who enjoy a resourceful environment tend to proactively ensure they stay engaged and benefit more from initiatives (Demerouti, 2026; Hakanen et al., 2018; Harju et al., 2016; Lu et al., 2014), whereas strained individuals with an impoverished job tend to showcase behaviors that inadvertently worsen outcomes and sensitivity to demands (Bakker et al., 2023b; Bakker & Wang, 2020; McLinton et al., 2023).

Thus, there is evidence that *well-being* is not merely an outcome of job design. It also influences proactive and dysfunctional work behaviors, which may create either more resources or more demands over time. However, there is only scant research on the extent to which gain and loss spirals over time influence AI adoption and AI-R resources. Preliminary evidence comes from a cross-national study conducted by Henseke (2026). Individuals who already had more human capital, cognitively rich jobs, and influence were more likely to adopt AI after exposure. Conversely, when these conditions were not present, they were less likely to start using AI after exposure. While this research was cross-sectional, it suggests that gain spirals may set the stage for individuals to develop AI-R resources, whereas loss spirals inhibit this process. Findings from longitudinal research on technology adoption resonate with this proposition. In a cross-lagged longitudinal study, Olivo et al. (2025) found that job autonomy positively predicted work engagement, which predicted more positive perceptions of technology as a work resource. These appraisals also predicted subsequent work engagement, suggesting a reciprocal process between gain spirals and the development of AI-R resources.

Guiding Principle 3: In studying the impact of AI adoption on employee well-being and performance, researchers should consider the possibility that health-impairment and motivational processes also influence AI readiness resources over time (i.e., recursive feedback loops).

4. Discussion

4.1. Theoretical implications

Integrating AI research with JD–R theory (Bakker, Demerouti, & Sanz-Vergel, 2023; Demerouti & Bakker, 2023) helps move the field beyond broad claims about “AI effects” toward more precise questions: which forms of AI adoption matter, for whom, through which mechanisms, and over what time frame? Table 3 translates our three guiding principles into an agenda for future research focused on adoption configuration, AI-readiness resources, and dynamic feedback loops.

First, the effects of AI adoption on job demands and job resources should not be treated as uniform. Research must distinguish both the origin of adoption (top-down vs. bottom-up) and the mode of use (automation vs. augmentation). This 2 × 2 framework (Table 2) differentiates organization-led – often embedded in performance monitoring and task allocation systems that may intensify job demands – from

Table 3
Future research outlooks.

Focus research area	Potential research questions (examples)
<i>Guiding Principle 1: Distinguish level × type</i>	
Top-down × automation (e.g., workflow redesign; monitoring/accountability; exception handling; pacing/targets; recovery/boundaries)	When does AI-driven automation <i>remove</i> demands versus <i>shift</i> them (e.g., to monitoring, exception handling, rework, accountability)? When does AI-enabled performance infrastructure intensify pace or time pressure and reduce recovery opportunities? Which governance designs prevent demand substitution and protect autonomy/meaningfulness?
Top-down × augmentation (e.g., copilots/scaffolds; decision support; AI-enabled feedback; well-being-oriented augmentation)	Under what conditions do AI scaffolds <i>build resources</i> (e.g., feedback, cognitive support) without adding cognitive load or technostress? Which augmentation features (e.g., suggestions vs. coaching vs. reframing) generate sustained improvements versus short-lived boosts? How does directionality (bilateral collaboration vs. unilateral control) influence resource gains and strain?
Bottom-up × automation (e.g., self-initiated workflow automation; “shadow AI”; diffusion and inequality; compliance/ethics)	Why do employees engage in self-initiated automation (overload relief, performance pressure, curiosity)? When does bottom-up automation reduce demands versus increase verification/worry/dependence? Does bottom-up diffusion create “power-user” inequality in resources, performance, or visibility?
Bottom-up × augmentation (e.g., job crafting; prompt-coaching; inclusive support under constrained autonomy)	Do AI prompts shift same-day crafting and next-day strain/engagement? When do employees benefit most from AI-supported augmentation (e.g., under high workload or constrained autonomy)? What personalization is needed so that augmentation supports thriving rather than becoming another demand?
<i>Guiding Principle 2: Model AI-readiness resources; distinguish AI-R job vs. AI-R personal resources shaping impairment vs. motivation</i>	
AI-R job resources (e.g., training; supportive leadership; governance; ethical climate; autonomy-preserving redesign; clarity of accountability)	Which job-level AI-R resources most effectively buffer AI-related demands (e.g., technostress, insecurity) and amplify resource gains (e.g., learning, feedback, autonomy)? What is the minimal “readiness bundle” required for safe scaling of mandated AI? How do autonomy-preserving designs shape whether AI triggers motivational vs. impairment processes?
AI-R personal resources (e.g., AI self-efficacy/literacy; metacognitive monitoring; openness/learning orientation; mindfulness; domain expertise)	Who thrives vs. strains under similar AI exposure, and why? Do metacognitive skills prevent overreliance and support critical evaluation of AI outputs? Which personal resources strengthen gain spirals (AI use → resources → engagement/thriving) and weaken loss spirals (AI demands → strain → maladaptive coping/self-undermining)?
Readiness fit/misfit (i.e., high adoption pressure with low readiness)	When AI is mandated but readiness is low, do we see disengagement, turnover intentions, unsafe workarounds, or skill erosion? Which organizational responses prevent “readiness gaps” from turning into chronic strain?
<i>Guiding Principle 3: Health-impairment and motivational processes may influence AI readiness resources (i.e., recursive feedback loops)</i>	
Motivational gain spirals AI adoption may strengthen job resources, engagement, learning, and AI-R personal resources over time.	Do employees who experience AI as useful, supportive, and autonomy-enhancing become more AI-ready over time? Does work engagement foster greater AI self-efficacy, AI literacy, and willingness to experiment with AI? When do AI-R job resources, such as

Table 3 (continued)

Focus research area	Potential research questions (examples)
Health-impairment/loss spirals AI adoption may increase demands, strain, exhaustion, and reduced capacity to develop AI-R resources.	training, leadership support, and transparent implementation, initiate gain spirals in which employees become increasingly capable of using AI to improve job design, well-being, and performance? Do AI-related demands, such as technostress, surveillance, accountability pressure, or task complexity, reduce AI readiness over time? Does exhaustion reduce employees' motivation or capacity to learn how to use AI effectively? Under what conditions do low AI-R resources and high AI-related demands reinforce one another, creating loss spirals in which employees fall further behind in AI-enabled work?
Diverging trajectories in AI-enabled job design Feedback loops may explain why the “rich get richer” and the “poor get poorer.”	Do employees in resource-rich jobs accumulate more AI-R resources over time, while employees in demanding or resource-poor jobs become less able to benefit from AI adoption? Which interventions can interrupt negative feedback loops and help employees in more vulnerable positions build AI readiness? How can longitudinal, diary, or intervention studies capture reciprocal effects between AI adoption, JD–R processes, and AI-R resources?

employee-initiated AI adoption that may operate as a job resource by representing a source of feedback or support. It also clarifies that top-down adoption varies in directionality: some systems enable bilateral human–AI collaboration that may build resources, whereas others impose unilateral control through algorithmic management, potentially amplifying demands and eroding resources. Consequently, AI’s impact on strain and engagement is conditional on adoption configuration rather than inherent technological features. Importantly, the adoption of AI by employees may itself be influenced by demands and resources. This may particularly be the case for bottom-up AI adoption, where employees need to make strategic choices regarding how to deploy AI to rebalance demands and strengthen resources. Hence, there likely exists a bi-directional relationship between AI adoption and JD–R configurations, especially in bottom-up AI adoption contexts (see lower part of Table 2).

Second, we foreground AI-readiness resources as central boundary conditions for whether AI adoption amplifies strain or supports work engagement. Distinguishing AI-R job resources (e.g., AI-training or supportive leadership) from AI-R personal resources (e.g., AI self-efficacy or meta-cognitive skills) refines JD–R theorizing by specifying when AI exposure is more likely to translate into exhaustion rather than engagement. This distinction also highlights the importance of readiness fit. That is, when AI is mandated, but readiness resources are insufficient, organizations may anticipate higher disengagement, resistance, and unsafe or noncompliant workarounds. The distinction between AI-R personal and AI-R job resources is also valuable from a practical perspective because it can inform AI readiness interventions. Subsequent intervention research could, then, investigate both single and combined effects of AI-R personal and AI-R job resource interventions (cf. Van Wingerden et al., 2017).

Third, we developed a dynamic JD–R perspective recognizing that health-impairment and motivational processes also have an influence on AI-R resources (see feedback loops in Fig. 1). In other words, AI-R resources are not only antecedents or moderators of AI adoption, but may themselves be influenced by ongoing JD–R processes. Employees embedded in resource-rich jobs may have more energy to further develop AI-related skills and access organizational support. By contrast,

employees facing high demands may have fewer opportunities to invest in AI learning or to benefit from available AI-R job resources. This recursive perspective helps explain why AI adoption may widen differences between employees over time (cf. Karunakaran et al., 2025). Those already positioned in resource-rich work environments may become increasingly ready and capable of using AI constructively, whereas those in more demanding or resource-poor contexts may fall further behind. Thus, the dynamic model highlights how AI adoption, JD-R processes, and AI-readiness resources may mutually reinforce one another over time.

4.2. Directions for future research

Our review suggests that AI adoption does not uniformly benefit or harm job design. Because the literature remains immature for definitive conclusions, several important avenues for future research emerge. First, future research should develop and validate measures that distinguish top-down from bottom-up AI adoption and capture whether AI is implemented primarily through an automation or augmentation logic (see Table 2). Although this distinction has been theorized in prior work (e.g., Parent-Rochelleau & Parker, 2022; Raisch & Krakowski, 2021), empirical research still often treats AI adoption as a broad and undifferentiated construct. This limits the ability to explain why similar AI technologies produce divergent outcomes across contexts. The 2×2 framework may inspire novel hypotheses. This could, for example, lead to investigations of whether automation-oriented AI adoption is more strongly associated with reduced hindrance job demands (e.g., fewer repetitive demands), whereas augmentation-oriented AI adoption is more strongly associated with increased job resources (e.g., feedback, opportunities for learning). The taxonomy provided in Table 2 could also help to review emerging evidence regarding the impact of AI adoption on job design in a more systematic way. This could pave the way for meta-analyses examining how relationships with JD-R outcomes differ.

Second, the presence and implications of AI may vary from one task to the next. Emerging applications of the Day Reconstruction Method (Bakker & Oerlemans, 2019; Kahneman et al., 2004) could offer an empirical approach to examine how AI reshapes job demands and job resources at the task level. Employees can reconstruct specific work episodes (e.g., completing a task with AI support) and report the demands they faced, available resources, and engagement or strain they experienced. These episode-level data can reveal when AI reduces hindering demands, builds resources, or instead intensifies workload and cognitive strain. Repeated assessments across days or weeks would allow researchers to test whether such micro-level shifts accumulate into gain spirals (increasing engagement and resource building) or loss spirals (exhaustion and rising demands). Moreover, by also including a general assessment of stable organizational conditions, this method enables examination of the extent to which enduring factors qualify the gain and loss spirals (i.e., person $\times$ situation approach: Bakker et al., 2023a). For instance, by assessing AI-supportive organizational climate in a general survey, future research may assess to what extent this readiness resource strengthens weekly gain spirals and weakens weekly loss spirals.

Third, JD-R theory suggests that job resources and personal resources may reinforce one another over time (Bakker et al., 2023a; Xanthopoulou et al., 2009). This reciprocal logic is particularly relevant for AI readiness. AI-readiness job resources, such as training, supervisory support, and opportunities to experiment with AI, may strengthen AI-readiness personal resources, including AI self-efficacy, AI literacy, and confidence in using AI at work (e.g., Bankins et al., 2024; D. Jeong et al., 2025). This is consistent with self-efficacy theory (Bandura, 2001), which identifies mastery experiences, modelling, and feedback as key sources of efficacy beliefs, as well as evidence showing that training can enhance self-efficacy (Demerouti, 2026; Täschner et al., 2025). Conversely, employees with stronger AI-readiness personal resources

may be better able to mobilize job resources, for instance by seeking advanced training, requesting feedback, joining AI pilot projects, or crafting their jobs toward AI-enabled learning. Future research should therefore examine reciprocal effects between AI-readiness job and personal resources, and test whether a high-readiness work environment can compensate for initially low personal AI readiness.

Fourth, this past decade, research has convincingly demonstrated that job crafting is a particularly relevant proactive behavior for facilitating change (Demerouti, 2026). Hence, another important research direction concerns how job crafting is linked with AI adoption. Future research should clarify when AI adoption stimulates job crafting and how individuals may craft their jobs using AI in automation or augmentation-oriented ways (i.e., bottom-up AI adoption). For instance, emerging evidence suggests that AI adoption may especially foster job crafting in the presence of AI-R resources (cf. Fig. 1; Bai et al., 2025). Popular generative AI tools such as ChatGPT can facilitate job crafting in various forms (Fong et al., 2025). Moreover, in an interview study among 27 junior consultants, Mayer et al. (2025) identified diverse ways through which entry-level professionals crafted their work with the help of generative AI. They used AI to automate repetitive tasks, develop and refine ideas, and obtain career decision-making and networking advice. These findings suggest AI adoption may directly stimulate and enable job crafting. Therefore, we call for research examining when AI adoption stimulates job crafting and how individuals adopt AI as a tool for job crafting.

Fifth, we call for research examining how AI adoption creates (or restricts) affordances for playful work design. Within JD-R theory, playful work design (PWD; Scharp et al., 2023) can be conceived of as an approach to performing a given set of work activities rather than a change in the activities themselves. For example, employees can use humor and imagination to have fun while performing a task, or strive for small wins and personal records during tasks. In this way, PWD has the potential to alter the experience of tasks (rather than changing the tasks or activities as is the case for job crafting; Bakker & Scharp, 2025). This potential becomes especially relevant when individuals have limited control over how AI is adopted. Initial evidence suggests that useful and easy-to-use Industry 4.0 technologies (including AI) stimulate PWD (I.-S. Chen & Choi, 2025). At the same time, future research may investigate when bottom-up AI adoption is done playfully. Playful engagement with technologies may itself enhance creativity and motivation (I.-S. Chen & Choi, 2026). Future research should, therefore, investigate when AI adoption inspires PWD and the implications of playfully interacting with AI.

4.3. Implications for practice

Organizations should treat AI implementation as a form of job redesign. Before, during, and after implementation, they should assess how AI changes job demands and resources. This could entail evaluations of how AI reduces hindering job demands such as administrative burden and whether it strengthens or erodes critical resources such as autonomy or social support (Demerouti, 2022). Importantly, reductions in routine workload may trigger demand substitution effects, whereby time saved is reinvested in more complex or intensified tasks. Without careful monitoring, such reconfigurations can activate health-impairment processes despite apparent productivity gains (Bakker, Demerouti, & Sanz-Vergel, 2023). AI integration should therefore be evaluated not only through performance and output metrics, but also through indicators of job design and employee well-being. This would allow organizations to determine whether AI adoption is promoting resource gain spirals or inadvertently initiating loss dynamics (Hobfoll et al., 2003; Xanthopoulou et al., 2009), while accounting for differences across job, team, and organizational levels (Hernaus et al., 2026).

Second, organizations must deliberately build AI-R resources at both the job and personal levels. From a JD-R perspective, the impact of AI

adoption depends less on the technology itself than on whether employees have the resources to regulate AI-related demands and effectively use AI-enabled opportunities. AI-readiness job resources such as training and support may buffer technostress and general exhaustion, while amplifying motivational processes (Demerouti & Bakker, 2023; Tarafdar et al., 2007). In parallel, AI-readiness personal resources such as meta-cognitive skills, enable employees to critically evaluate AI outputs and integrate them effectively into their work. Empirical evidence suggests that AI use enhances creativity primarily when such readiness resources are present (e.g., Sun et al., 2025). Consequently, organizations should prioritize readiness development before mandating widespread AI adoption.

Third, AI can be strategically deployed to institutionalize job crafting as an embedded, scalable organizational practice rather than a discretionary individual effort. JD–R theory assumes employee agency in optimizing demands and resources, yet crafting requires cognitive and motivational capacity that is often depleted under high workload (Bakker & Oerlemans, 2019). The paradox is that when redesign is most needed, employees have the least bandwidth to initiate it (Bakker & de Vries, 2021). AI can resolve this by functioning as a scaffolding mechanism. Workflow-integrated micro-prompts (e.g., “Which task could be simplified?”, “What feedback would help you progress?”, “What boundary protects recovery today?”) externalize executive control and lower the activation threshold for increasing resources or recalibrating demands (Bakker & Slemp, 2026). Critically, such systems must remain autonomy-supportive rather than surveillance-driven to ensure that AI augments, rather than intensifies, job demands.

Fourth, preserving autonomy and task completeness should be a central design principle in AI-mediated environments. As automation becomes more embedded in coordination, planning, and evaluation, organizations risk fragmenting work in ways that relocate discretion from employees to systems (Parker & Grote, 2022). This is especially salient in algorithmic management contexts, where control can become opaque and create perceptions of surveillance (Kellogg et al., 2020). Designing AI to augment rather than replace human discretion (e.g., by preserving human judgment) protects motivational resources and reduces the probability that control-centric implementations trigger health-impairment processes (Bakker, Demerouti, & Sanz-Vergel, 2023; Kellogg et al., 2020).

Finally, organizations must actively anticipate and prevent AI-induced self-undermining. When AI-related demands outstrip employees’ resources, they can experience difficulties in self-regulation. Employees may then cope in counterproductive ways: compulsive checking of outputs, blind overreliance on systems, or allowing work to spill into recovery time. From a JD–R perspective, such imbalances initiate loss spirals in which strain erodes performance, and declining performance further increases pressure (Bakker, Xanthopoulou, & Demerouti, 2023). Prevention requires structural and not individual solutions. Organizations can implement calibrated trust cues (clarifying when AI should and should not be relied upon), protect opportunities for human skill maintenance, and establish explicit norms around digital boundaries and response times. Continuous demand–resource monitoring is essential, so that early warning signals are addressed by appropriate job redesign. The default response should not be “more training,” but rather recalibrating job demands and resources (Demerouti & Bakker, 2023; Tarafdar et al., 2007).

5. Conclusion

Artificial intelligence is not a peripheral digital layer added to existing jobs. It is a socio-technical force that reconfigures the demand–resource architecture of jobs and organizations at large. Drawing on JD–R theory, this article outlined how AI adoption reshapes job demands and job resources, thereby activating either health-impairment processes or motivational processes. By distinguishing levels of adoption (top-down versus bottom-up), types of use

(automation versus augmentation), and the availability of AI-readiness resources at both job and personal levels, we provide a framework for understanding when AI integration generates work engagement and adaptive performance, and when it triggers strain and self-undermining dynamics. Importantly, the societal impact of AI-enabled work depends less on technological capability than on how organizations govern, embed, and regulate these systems. A JD–R perspective foregrounds job design choices as the key lever through which intelligent technologies translate into sustainable productivity, workforce well-being, and long-term organizational resilience.

CRedit authorship contribution statement

Arnold B. Bakker: Writing – original draft, Supervision, Investigation, Formal analysis, Conceptualization. **Tom L. Junker:** Writing – original draft, Investigation, Conceptualization, Formal analysis. **Yuri S. Scharp:** Writing – original draft, Investigation, Conceptualization, Formal analysis. **Matej Cerne:** Writing – original draft, Investigation, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT-5 to improve the readability and language of the manuscript, as none of the authors is a native English speaker. After using this tool, the authors carefully reviewed and edited the text as needed and take full responsibility for the content of the article.

Declaration of competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

References

- Arslan, A., Cooper, C., Khan, Z., Golgeci, I., & Ali, I. (2022). Artificial intelligence and human workers interaction at team level: A conceptual assessment of the challenges and potential HRM strategies. *International Journal of Manpower*, 43(1), 75–88. <https://doi.org/10.1108/IJM-01-2021-0052>
- Ayyagari, R., Grover, V., & Purvis, R. (2011). Technostress: Technological antecedents and implications. *MIS Quarterly*, 35(4). <https://doi.org/10.2307/41409963>, 831–A10.
- Bai, J. Y., Tc Huan, T. C., Leong, A. M. W., Luo, J. M., & Fan, D. X. F. (2025). Examining the influence of AI event strength on employee performance outcomes: Roles of AI rumination, AI-supported autonomy, and felt obligation for constructive change. *International Journal of Hospitality Management*, 126, Article 104111. <https://doi.org/10.1016/j.ijhm.2025.104111>
- Bai, Y., & Wang, S. (2025). Impact of generative AI interaction and output quality on university students' learning outcomes: A technology-mediated and motivation-driven approach. *Scientific Reports*, 15(1), Article 24054. <https://doi.org/10.1038/s41598-025-08697-6>
- Bajaba, S., Bajaba, A., & Fuller, B. (2022). Enduring exploitative leaders at work: The buffering role of proactive personality on employee job strain. *Organization Management Journal*, 19(2), 60–71. <https://doi.org/10.1108/OMJ-11-2020-1090>
- Bakker, A. B., & de Vries, J. D. (2021). Job demands–resources theory and self-regulation: New explanations and remedies for job burnout. *Anxiety, Stress & Coping*, 34(1), 1–21. <https://doi.org/10.1080/10615806.2020.1797695>
- Bakker, A. B., & Demerouti, E. (2024). Job demands–resources theory: Frequently asked questions. *Journal of Occupational Health Psychology*, 29(3), 188–200. <https://doi.org/10.1037/ocp0000376>
- Bakker, A. B., Demerouti, E., & Euwema, M. C. (2005). Job resources buffer the impact of job demands on burnout. *Journal of Occupational Health Psychology*, 10(2), 170–180. <https://doi.org/10.1037/1076-8998.10.2.170>
- Bakker, A. B., Demerouti, E., & Sanz-Vergel, A. (2023). Job demands–Resources theory: Ten years later. *Annual Review of Organizational Psychology and Organizational Behavior*, 10(1), 25–53. <https://doi.org/10.1146/annurev-orgpsych-120920-053933>

- Bakker, A. B., & Oerlemans, W. G. M. (2019). Daily job crafting and momentary work engagement: A self-determination and self-regulation perspective. *Journal of Vocational Behavior*, 112, 417–430. <https://doi.org/10.1016/j.jvb.2018.12.005>
- Bakker, A. B., & Sanz-Vergel, A. I. (2013). Weekly work engagement and flourishing: The role of hindrance and challenge job demands. *Journal of Vocational Behavior*, 83(3), 397–409. <https://doi.org/10.1016/j.jvb.2013.06.008>
- Bakker, A. B., & Scharp, Y. S. (2025). It pays to play: Playful work design. In S. K. Parker, F. E. Klonek, C. Knight, & F. Zhang (Eds.), *Transformative work design* (1st ed., pp. 465–480). Oxford University Press <https://academic.oup.com/book/60029/chapter/513542637>
- Bakker, A. B., & Slemp, G. R. (2026). Advancing research on job crafting and playful work design. *Journal of Business and Psychology*, 41(3), 527–538. <https://doi.org/10.1007/s10869-025-10095-8>
- Bakker, A. B., & Wang, Y. (2020). Self-undermining behavior at work: Evidence of construct and predictive validity. *International Journal of Stress Management*, 27(3), 241–251. <https://doi.org/10.1037/str0000150>
- Bakker, A. B., Xanthopoulou, D., & Demerouti, E. (2023). How does chronic burnout affect dealing with weekly job demands? A test of central propositions in JD-R and COR-theories. *Applied Psychology*, 72(1), 389–410. <https://doi.org/10.1111/apps.12382>
- Bandura, A. (2001). Social cognitive theory: An agentic perspective. *Annual Review of Psychology*, 52(1), 1–26. <https://doi.org/10.1146/annurev.psych.52.1.1>
- Bankins, S., Ocampo, A. C., Marrone, M., Restubog, S. L. D., & Woo, S. E. (2024). A multilevel review of artificial intelligence in organizations: Implications for organizational behavior research and practice. *Journal of Organizational Behavior*, 45(2), 159–182. <https://doi.org/10.1002/job.2735>
- Bauer, E., Greiff, S., Graesser, A. C., Scheiter, K., & Sailer, M. (2025). Looking beyond the hype: Understanding the effects of AI on learning. *Educational Psychology Review*, 37(2), 45. <https://doi.org/10.1007/s10648-025-10020-8>
- Berkers, H. A., Rispens, S., & Le Blanc, P. M. (2023). The role of robotization in work design: A comparative case study among logistic warehouses. *International Journal of Human Resource Management*, 34(9), 1852–1875. <https://doi.org/10.1080/09585192.2022.2043925>
- Bienefeld, N., Keller, E., & Grote, G. (2025). AI interventions to alleviate healthcare shortages and enhance work conditions in critical care: Qualitative analysis. *Journal of Medical Internet Research*, 27, Article e50852. <https://doi.org/10.2196/50852>
- Bowen, D. E., & Ostroff, C. (2004). Understanding HRM–firm performance linkages: The role of the “strength” of the HRM system. *Academy of Management Review*, 29(2), 203–221. <https://doi.org/10.5465/amr.2004.12736076>
- Breevaart, K., & Bakker, A. B. (2018). Daily job demands and employee work engagement: The role of daily transformational leadership behavior. *Journal of Occupational Health Psychology*, 23(3), 338–349. <https://doi.org/10.1037/ocp0000082>
- Budzyń, K., Romańczyk, M., Kitala, D., Kołodziej, P., Bugajski, M., Adami, H. O., Blom, J., Buszkiewicz, M., Halvorsen, M., Hassan, C., Romańczyk, T., Holme, Ø., Jarius, K., Fielding, S., Kunar, M., Pellise, M., Pilonis, N., Kamiński, M. F., Kalager, M., ... Mori, Y. (2025). Endoscopist deskilling risk after exposure to artificial intelligence in colonoscopy: A multicentre, observational study. *The Lancet Gastroenterology & Hepatology*, 10(10), 896–903. [https://doi.org/10.1016/S2468-1253\(25\)00133-5](https://doi.org/10.1016/S2468-1253(25)00133-5)
- Chen, I.-S., & Choi, J. N. (2025). Industry 4.0 technologies and green creativity: Mediating roles of playful work design and leisure crafting. *Journal of Business Research*, 188, Article 115103. <https://doi.org/10.1016/j.jbusres.2024.115103>
- Chen, I.-S., & Choi, J. N. (2026). Who are the champions of workplace innovations? Playful use of technology and psychological ownership for championing Industry 4.0 technologies. *Industry & Innovation*, 1–22. <https://doi.org/10.1080/13662716.2026.2617173>
- Chen, P., Powers, J. T., Katragadda, K. R., Cohen, G. L., & Dweck, C. S. (2020). A strategic mindset: An orientation toward strategic behavior during goal pursuit. *Proceedings of the National Academy of Sciences*, 117(25), 14066–14072. <https://doi.org/10.1073/pnas.2002529117>
- Chuang, Y.-T., Chiang, H.-L., & Lin, A.-P. (2025). Insights from the Job Demands–Resources model: AI’s dual impact on employees’ work and life well-being. *International Journal of Information Management*, 83, Article 102887. <https://doi.org/10.1016/j.jinfomgt.2025.102887>
- De Jonge, J., Spoor, E., Sonnentag, S., Dormann, C., & van den Tooren, M. (2012). “Take a break?” Off-job recovery, job demands, and job resources as predictors of health, active learning, and creativity. *European Journal of Work & Organizational Psychology*, 21(3), 321–348. <https://doi.org/10.1080/1359432X.2011.576009>
- Demerouti, E. (2022). Turn digitalization and automation to a job resource. *Applied Psychology*, 71(4), 1205–1209. <https://doi.org/10.1111/apps.12270>
- Demerouti, E. (2026). Job crafting revisited: Current insights, emerging challenges, and future directions. *Annual Review of Organizational Psychology and Organizational Behavior*, 13(1), 195–220. <https://doi.org/10.1146/annurev-orgpsych-020924-064242>
- Demerouti, E., & Bakker, A. B. (2023). Job demands-resources theory in times of crises: New propositions. *Organizational Psychology Review*, 13(3), 209–236. <https://doi.org/10.1177/20413866221135022>
- Demerouti, E., & Bakker, A. B. (2024). Job crafting: A powerful job redesign approach. In M. C. W. Peeters, J. De Jonge, & T. Taris (Eds.), *An introduction to contemporary work psychology*. Wiley.
- Demerouti, E., & Bakker, A. B. (2026). Beyond burnout: Advancing work engagement through job Demands–Resources theory. In K. Teoh, D. Xanthopoulou, J. Hassard, D. Ripa, & S. Agostinho Silva (Eds.), *Occupational health psychology: An EAOHP textbook* (pp. 103–134). EAOHP.
- Demerouti, E., Bakker, A. B., Nachreiner, F., & Schaufeli, W. B. (2001). The job demands-resources model of burnout. *Journal of Applied Psychology*, 86(3), 499–512. <https://doi.org/10.1037/0021-9010.86.3.499>
- Demerouti, E., Peeters, M., & van den Heuvel, M. (2025). Job crafting interventions. In *Transformative work design* (pp. 439–464). Oxford University Press. <https://doi.org/10.1093/oso/9780197692554.003.0017>
- Ding, N., Chen, M., & Hu, L. (2025). The design industry in the AI era: How AI awareness and AI literacy influence the innovative work behavior of Chinese generation Y designers. *Acta Psychologica*, 260, Article 105650. <https://doi.org/10.1016/j.actpsy.2025.105650>
- Eloundou, T., Manning, S., Mishkin, P., & Rock, D. (2024). GPTs are GPTs: Labor market impact potential of LLMs. *Science*, 384(6702), 1306–1308. <https://doi.org/10.1126/science.adj0998>
- Felten, E., Raj, M., & Seamans, R. (2021). Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses. *Strategic Management Journal*, 42(12), 2195–2217. <https://doi.org/10.1002/smj.3286>
- Fong, C. Y. M., Leung, Y. K., Junker, T., & Kooij, D. (2025). Generative AI crafting: A job crafting perspective on employees’ proactive usage of generative ai. *Academy of Management Proceedings*, 2025(1). <https://doi.org/10.5465/AMPROC.2025.14447abstract>
- Frese, M., & Zapf, D. (1994). Action as the core of work psychology: A German approach. In H. C. Triandis, D. Dunnette, & L. M. Hough (Eds.), *Handbook of industrial and organizational psychology* (2nd ed., pp. 271–340). Consulting Psychologists Press.
- Ghamrawi, N., Shal, T., & Ghamrawi, N. A. R. (2024). Exploring the impact of AI on teacher leadership: Regressing or expanding? *Education and Information Technologies*, 29(7), 8415–8433. <https://doi.org/10.1007/s10639-023-12174-w>
- Giering, O., & Kirchner, S. (2025). Artificial intelligence and autonomy at work: Empirical insights from Germany. *Journal for Labour Market Research*, 59(1), 20. <https://doi.org/10.1186/s12651-025-00401-5>
- Goštautaitė, B., Liubertė, I., Parker, S. K., & Bučiūnienė, I. (2024). Can you outsmart the robot? An unexpected path to work meaningfulness. *Academy of Management Discoveries*, 10(3), 416–437. <https://doi.org/10.5465/amd.2022.0113>
- Grassini, S., Thorp, S. O., Ree, A. S., Sevic, A., & Cipriani, E. (2025). Distinct predictors of positive attitudes toward artificial intelligence and general technology: Big five traits, gender, and age. *Behaviour & Information Technology*, 1–14. <https://doi.org/10.1080/0144929X.2025.2598623>
- Hacker, W. (2003). Action regulation theory: A practical tool for the design of modern work processes? *European Journal of Work & Organizational Psychology*, 12(2), 105–130. <https://doi.org/10.1080/13594320344000075>
- Hackman, J. R., & Oldham, G. R. (1976). Motivation through the design of work: Test of a theory. *Organizational Behavior & Human Performance*, 16(2), 250–279. [https://doi.org/10.1016/0030-5073\(76\)90016-7](https://doi.org/10.1016/0030-5073(76)90016-7)
- Hai, S., Long, T., Honora, A., Japutra, A., & Guo, T. (2025). The dark side of employee-generative AI collaboration in the workplace: An investigation on work alienation and employee expediency. *International Journal of Information Management*, 83, Article 102905. <https://doi.org/10.1016/j.jinfomgt.2025.102905>
- Hakanen, J. J., Bakker, A. B., & Demerouti, E. (2005). How dentists cope with their job demands and stay engaged: The moderating role of job resources. *European Journal of Oral Sciences*, 113(6), 479–487. <https://doi.org/10.1111/j.1600-0722.2005.00250.x>
- Hakanen, J. J., Bakker, A. B., & Jokisaari, M. (2011). A 35-year follow-up study on burnout among Finnish employees. *Journal of Occupational Health Psychology*, 16(3), 345–360. <https://doi.org/10.1037/a0022903>
- Hakanen, J. J., Peeters, M. C. W., & Schaufeli, W. B. (2018). Different types of employee well-being across time and their relationships with job crafting. *Journal of Occupational Health Psychology*, 23(2), 289–301. <https://doi.org/10.1037/ocp0000081>
- Han, Z., Song, G., Zhang, Y., & Li, B. (2025). Trust the machine or trust yourself: How AI usage reshapes employee self-efficacy and willingness to take risks. *Behavioral Sciences*, 15(8), 1046. <https://doi.org/10.3390/bs15081046>
- Harju, L. K., Hakanen, J. J., & Schaufeli, W. B. (2016). Can job crafting reduce job boredom and increase work engagement? A three-year cross-lagged panel study. *Journal of Vocational Behavior*, 95–96, 11–20. <https://doi.org/10.1016/j.jvb.2016.07.001>
- Henseke, G. (2026). From exposure to adoption: Generative AI in European workplaces. *Preprint*. <https://doi.org/10.48550/arXiv.2604.18849>
- Hernaus, T., Černe, M., Sitar, A. S., Marić, M., & Melkić, S. (2026). Contextualizing job design for individual work performance: The role of organizational strategy and structure. *Technology in Society*, 85, Article 103147. <https://doi.org/10.1016/j.techsoc.2025.103147>
- Hobfoll, S. E., Johnson, R. J., Ennis, N., & Jackson, A. P. (2003). Resource loss, resource gain, and emotional outcomes among inner city women. *Journal of Personality and Social Psychology*, 84(3), 632–643. <https://doi.org/10.1037/0022-3514.84.3.632>
- Huang, Y., & Gurosoy, D. (2024). How does AI technology integration affect employees’ proactive service behaviors? A transactional theory of stress perspective. *Journal of Retailing and Consumer Services*, 77, Article 103700. <https://doi.org/10.1016/j.jretconser.2023.103700>
- Jackson, J. D., Yi, M. Y., & Park, J. S. (2013). An empirical test of three mediation models for the relationship between personal innovativeness and user acceptance of technology. *Information & Management*, 50(4), 154–161. <https://doi.org/10.1016/j.im.2013.02.006>
- Jeong, D., Lee, H., Yang, H., Park, J. C., & Lee, S. M. (2025). AI integration in counseling training: Aiding counselors-in-training in self-efficacy enhancement and anxiety reduction. *Journal of Counseling and Development*, 103(3), 346–360. <https://doi.org/10.1002/jcad.12560>

- Jeong, J., Kim, B.-J., & Lee, J. (2024). Navigating AI transitions: How coaching leadership buffers against job stress and protects employee physical health. *Frontiers in Public Health*, 12. <https://doi.org/10.3389/fpubh.2024.1343932>
- Jia, J., Ning, X., & Liu, W. (2025). The consequences and theoretical explanation of workplace AI on employees: A systematic literature review. *Journal of Digital Management*, 1(1), 14. <https://doi.org/10.1007/s44362-025-00016-3>
- Jia, N., Luo, X., Fang, Z., & Liao, C. (2024). When and how artificial intelligence augments employee creativity. *Academy of Management Journal*, 67(1), 5–32. <https://doi.org/10.5465/amj.2022.0426>
- Jooss, S., Solnet, D., Knight, C., Worsteling, A., Rinta-Kahila, T., & Hansen, A. (2026). Artificial intelligence and work design: Implications for frontline service employees and future research. *Journal of Service Management*, 37(4), 622–643. <https://doi.org/10.1108/JOSM-12-2024-0535>
- Kahneman, D., Krueger, A. B., Schkade, D. A., Schwarz, N., & Stone, A. A. (2004). A survey method for characterizing daily life experience: The day reconstruction method. *Science*, 306(5702), 1776–1780. <https://doi.org/10.1126/science.1103572>
- Karunakaran, A., Lebovitz, S., Narayanan, D., & Rahman, H. A. (2025). Artificial intelligence at work: An integrative perspective on the impact of AI on workplace inequality. *The Academy of Management Annals*, 19(2), 693–735. <https://doi.org/10.5465/annals.2023.0230>
- Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *The Academy of Management Annals*, 14(1), 366–410. <https://doi.org/10.5465/annals.2018.0174>
- Kim, B.-J., Kim, M.-J., & Lee, J. (2025). The dark side of artificial intelligence adoption: Linking artificial intelligence adoption to employee depression via psychological safety and ethical leadership. *Humanities and Social Sciences Communications*, 12(1), 704. <https://doi.org/10.1057/s41599-025-05040-2>
- Kim, B.-J., & Lee, J. (2024). The mental health implications of artificial intelligence adoption: The crucial role of self-efficacy. *Humanities and Social Sciences Communications*, 11(1), 1561. <https://doi.org/10.1057/s41599-024-04018-w>
- Kim, B.-J., & Lee, J. (2025). AI adoption, employee depression and knowledge: How corporate social responsibility buffers psychological impact. *Journal of Innovation & Knowledge*, 10(6), Article 100815. <https://doi.org/10.1016/j.jik.2025.100815>
- Kong, H., Yin, Z., Chon, K., Yuan, Y., & Yu, J. (2024). How does artificial intelligence (AI) enhance hospitality employee innovation? The roles of exploration, AI trust, and proactive personality. *Journal of Hospitality Marketing & Management*, 33(3), 261–287. <https://doi.org/10.1080/19368623.2023.2258116>
- Kong, X., Yuan, W., & Ma, C. (2026). Service robots, artificial intelligence awareness, self-efficacy and work engagement. *Management Decision*, 64(5), 1960–1977. <https://doi.org/10.1108/MD-05-2024-1058>
- Kovjanic, S., Schuh, S. C., & Jonas, K. (2013). Transformational leadership and performance: An experimental investigation of the mediating effects of basic needs satisfaction and work engagement. *Journal of Occupational and Organizational Psychology*, 86(4), 543–555. <https://doi.org/10.1111/joop.12022>
- Kulikowski, K. (2026). Exploring the role of cognitive job demands in job demands-resources theory. *Journal of Occupational and Organizational Psychology*, 99(1). <https://doi.org/10.1111/joop.70095>
- Küper, A., & Krämer, N. (2025). Psychological traits and appropriate reliance: Factors shaping trust in AI. *International Journal of Human-Computer Interaction*, 41(7), 4115–4131. <https://doi.org/10.1080/10447318.2024.2348216>
- Lavoie-Tremblay, M., Trépanier, S., Fernet, C., & Bonneville-Roussy, A. (2014). Testing and extending the triple match principle in the nursing profession: A generational perspective on job demands, job resources and strain at work. *Journal of Advanced Nursing*, 70(2), 310–322. <https://doi.org/10.1111/jan.12188>
- Lesener, T., Gusy, B., & Wolter, C. (2019). The job demands-resources model: A meta-analytic review of longitudinal studies. *Work & Stress*, 33(1), 76–103. <https://doi.org/10.1080/02678373.2018.1529065>
- Li, J., Bonn, M. A., & Ye, B. H. (2019). Hotel employee's artificial intelligence and robotics awareness and its impact on turnover intention: The moderating roles of perceived organizational support and competitive psychological climate. *Tourism Management*, 73, 172–181. <https://doi.org/10.1016/j.tourman.2019.02.006>
- Li, X., Zong, Q., & Cheng, M. (2024). The impact of medical explainable artificial intelligence on nurses' innovation behaviour: A structural equation modelling approach. *Journal of Nursing Management*, Article 885760. <https://doi.org/10.1155/2024/8885760>, 2024.
- Li, Y., Zhao, L., Cao, C., & Yang, D. (2025). The double-edged sword effect of algorithmic transparency: An empirical study of gig workers' work disengagement under algorithmic management. *Information & Management*, 62(2), Article 104100. <https://doi.org/10.1016/j.im.2025.104100>
- Liang, X., Guo, G., Shu, L., Gong, Q., & Luo, P. (2022). Investigating the double-edged sword effect of AI awareness on employee's service innovative behavior. *Tourism Management*, 92, Article 104564. <https://doi.org/10.1016/j.tourman.2022.104564>
- Lippert, I., Kirchner, K., & Saunders, C. (2023). The dynamic relationships between algorithmic management and workers' occupational well-being: A job demands-resources perspective. In *Proceedings of the ECIS 2023 research papers*.
- Liu, Y., Fang, Q., Rofcanin, Y., Heras, M. L., & Xie, X. (2026). The meaning of work in the digital era: A systematic review and research agenda. *Human Resource Management Journal*. <https://doi.org/10.1111/1748-8583.70041>
- Lu, C., Wang, H., Lu, J., Du, D., & Bakker, A. B. (2014). Does work engagement increase person-job fit? The role of job crafting and job insecurity. *Journal of Vocational Behavior*, 84(2), 142–152. <https://doi.org/10.1016/j.jvb.2013.12.004>
- Mäkelä, E., Bone, M., Sehr, M., Nanji, F., & Stephany, F. (2024). Complement or substitute? How AI increases the demand for human skills. *Preprint*. <https://doi.org/10.48550/arXiv.2412.19754>
- Mayer, A.-S., Baygi, R. M., & Buwalda, R. (2025). Generation AI: Job crafting by entry-level professionals in the age of generative AI. *Business & Information Systems Engineering*, 67(5), 595–613. <https://doi.org/10.1007/s12599-025-00959-x>
- McCrae, R. R., & Costa, P. T. (1997). Conceptions and correlates of openness to experience. In R. Hogan, J. Johnson, & S. Briggs (Eds.), *Handbook of personality psychology* (pp. 825–847). Academic Press. <https://linkinghub.elsevier.com/retrieve/pii/B9780121346454500329>
- McElheran, K., Li, J. F., Brynjolfsson, E., Kroff, Z., Dinlersoz, E., Foster, L., & Zolas, N. (2024). AI adoption in America: Who, what, and where. *Journal of Economics and Management Strategy*, 33(2), 375–415. <https://doi.org/10.1111/jems.12576>
- McLinton, S. S., Jamieson, S. D., Tuckey, M. R., Dollard, M. F., & Owen, M. S. (2023). Evidence for a negative loss spiral between co-worker social support and burnout: Can psychosocial safety climate break the cycle? *Healthcare*, 11(24), 3168. <https://doi.org/10.3390/healthcare11243168>
- Mo, Z., Liu, M. T., Chark, R., Zeng, S., & Song, X. (2025). How AI adoption in human resource management practices can enhance tourism employees' organizational commitment. *Journal of Hospitality and Tourism Management*, 63, 54–67. <https://doi.org/10.1016/j.jhtm.2025.03.003>
- Mo, Z., Liu, M. T., & Ma, Y. (2024). How AI awareness can prompt service performance adaptivity and technologically-environmental mastery. *Tourism Management*, 105, Article 104971. <https://doi.org/10.1016/j.tourman.2024.104971>
- Moin, M. F., & Zhang, J. Z. (2025). Stemming the tide: Linking AI technology with workers retention. *International Journal of Managing Projects in Business*, 18(4–5), 721–732. <https://doi.org/10.1108/IJMPB-01-2024-0015>
- Mustapha, V., & Rau, R. (2024). Das konstrukt der „vollständigen tätigkeit“ als ziel guter arbeitsgestaltung. *Zeitschrift Für Arbeits- Und Organisationspsychologie A&O*, 68(2), 67–81. <https://doi.org/10.1026/0932-4089/a000420>
- Ohly, S., Granica, A., Herwig, H., Kühlewind, N., Paetzold, T., Vinhoven, L., Wiemers, L., & Zhang, X. (2025). Humane work design: How does the digitization of work change core work characteristics in different occupations? *Zeitschrift für Arbeitswissenschaft*, 79(4), 569–580. <https://doi.org/10.1007/s41449-025-00491-4>
- Olivo, I., Ghezzi, V., Marzocchi, I., Fusco, L., Spinella, F., Isolani, S., Ronchetti, M., Ghelli, M., Russo, S., Barbaranelli, C., Persechino, B., & Iavicoli, S. (2025). Beyond boundaries: How autonomy and technology promote work engagement and well-being in remote workers. *Frontiers in Public Health*, 13, Article 1659185. <https://doi.org/10.3389/fpubh.2025.1659185>
- Oprea, B. T., Barzin, L., Virgă, D., Iliescu, D., & Rusu, A. (2019). Effectiveness of job crafting interventions: A meta-analysis and utility analysis. *European Journal of Work & Organizational Psychology*, 28(6), 723–741. <https://doi.org/10.1080/1359432X.2019.1646728>
- Parasuraman, A. (2000). Technology readiness index (TRI): A multiple-item scale to measure readiness to embrace new technologies. *Journal of Service Research*, 2(4), 307–320. <https://doi.org/10.1177/109467050024001>
- Parent-Rochelleau, X., & Parker, S. K. (2022). Algorithms as work designers: How algorithmic management influences the design of jobs. *Human Resource Management Review*, 32(3), Article 100838. <https://doi.org/10.1016/j.hrmr.2021.100838>
- Parker, S. K. (2014). Beyond motivation: Job and work design for development, health, ambidexterity, and more. *Annual Review of Psychology*, 65(1), 661–691. <https://doi.org/10.1146/annurev-psych-010213-115208>
- Parker, S. K., & Grote, G. (2022). Automation, algorithms, and beyond: Why work design matters more than ever in a digital world. *Applied Psychology*, 71(4), 1171–1204. <https://doi.org/10.1111/apps.12241>
- Perez, F., Conway, N., Peterson, J., & Roques, O. (2024). Me, my work and AI: How radiologists craft their work and identity. *Journal of Vocational Behavior*, 155, Article 104042. <https://doi.org/10.1016/j.jvb.2024.104042>
- Petrou, P., Demerouti, E., Peeters, M. C. W., Schaufeli, W. B., & Hetland, J. (2012). Crafting a job on a daily basis: Contextual correlates and the link to work engagement. *Journal of Organizational Behavior*, 33(8), 1120–1141. <https://doi.org/10.1002/job.1783>
- Pletzer, J. L., Breevaart, K., & Bakker, A. B. (2024). Constructive and destructive leadership in job demands-resources theory: A meta-analytic test of the motivational and health-impairment pathways. *Organizational Psychology Review*, 14(1), 131–165. <https://doi.org/10.1177/20413866231197519>
- Qi, Z., Zhang, X., Ma, L., & Wang, G. (2025). Generative artificial intelligence use and employees' digital performance. *Management Decision*. <https://doi.org/10.1108/MD-09-2024-2060>
- Quan, J., Li, Y., Zhang, M., & Wu, Z. (2025). Gain or pain: The double-edged sword effect of artificial intelligence adoption on employee service performance. *Journal of Organizational Behavior*. <https://doi.org/10.1002/job.70023>
- Radic, A., Singh, S., Singh, N., Ariza-Montes, A., Calder, G., & Han, H. (2025). The good shepherd: Linking artificial intelligence (AI)-Driven servant leadership (SEL) and job demands-resources (JD-R) theory in tourism and hospitality. *Journal of Hospitality and Tourism Insights*, 8(4), 1494–1521. <https://doi.org/10.1108/JHTI-06-2024-0628>
- Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation-augmentation paradox. *Academy of Management Review*, 46(1), 192–210. <https://doi.org/10.5465/amr.2018.0072>
- Ramadan, O. M. E., Alruwaili, M. M., Alruwaili, A. N., Elsehrawy, M. G., & Alanazi, S. (2024). Facilitators and barriers to AI adoption in nursing practice: A qualitative study of registered nurses' perspectives. *BMC Nursing*, 23(1), 891. <https://doi.org/10.1186/s12912-024-02571-y>
- Rocznińska, M., & Bakker, A. B. (2021). Burnout and self-regulation failure: A diary study of self-undermining and job crafting among nurses. *Journal of Advanced Nursing*, 77(8), 3424–3435. <https://doi.org/10.1111/jan.14872>
- Röttgen, C., Herbig, B., Weinmann, T., & Müller, A. (2024). Algorithmic management and human-centered task design: A conceptual synthesis from the perspective of

- action regulation and sociomaterial systems theory. *Frontiers in Artificial Intelligence*, 7, Article 1441497. <https://doi.org/10.3389/frai.2024.1441497>
- Rožman, M., Tominc, P., & Milfelner, B. (2023). Maximizing employee engagement through artificial intelligent organizational culture in the context of leadership and training of employees: Testing linear and non-linear relationships. *Cogent Business & Management*, 10(2), Article 2248732. <https://doi.org/10.1080/23311975.2023.2248732>
- Scharp, Y. S., Bakker, A. B., Breevaart, K., Kruup, K., & Uusberg, A. (2023). Playful work design: Conceptualization, measurement, and validity. *Human Relations*, 76(4), 509–550. <https://doi.org/10.1177/00187267211070996>
- Scharp, Y. S., Breevaart, K., & Bakker, A. B. (2021). Using playful work design to deal with hindrance job demands: A quantitative diary study. *Journal of Occupational Health Psychology*, 26(3), 175–188. <https://doi.org/10.1037/ocp0000277>
- Scharp, Y. S., Ter Hoeven, C., Bakker, A. B., Gorgievski, M., Den Dulk, L., & Koster, F. (2022). Samenhang van platformwerk met werkomstandigheden en welzijn. *Tijdschrift Voor Arbeidsvraagstukken*, 38(4), 580–600. <https://doi.org/10.5117/TVA2022.4.008.SCHA>
- Schaufeli, W. B., Bakker, A. B., & Van Rhenen, W. (2009). How changes in job demands and resources predict burnout, work engagement, and sickness absenteeism. *Journal of Organizational Behavior*, 30(7), 893–917. <https://doi.org/10.1002/job.595>
- Sha, C., & Chai, T. (2025). When digital-AI transformation Sparks adaptation: Job crafting and AI knowledge in job insecurity contexts. *Frontiers in Psychology*, 16. <https://doi.org/10.3389/fpsyg.2025.1612245>
- Shao, Y., Huang, C., Song, Y., Wang, M., Song, Y. H., & Shao, R. (2025). Using augmentation-based AI tool at work: A daily investigation of learning-based benefit and challenge. *Journal of Management*, 51(8), 3352–3390. <https://doi.org/10.1177/01492063241266503>
- Simkute, A., Tankelevitch, L., Kewenig, V., Scott, A. E., Sellen, A., & Rintel, S. (2024). Ironies of generative AI: Understanding and mitigating productivity loss in human-AI interaction. *International Journal of Human-Computer Interaction*, 1–22. <https://doi.org/10.1080/10447318.2024.2405782>
- Stollberger, J., Anand, S., & Dick, P. (2025). Capturing a moving target: Developing research on and with AI for human relations. *Human Relations*, 78(5), 499–516. <https://doi.org/10.1177/00187267251332075>
- Sun, S., Li, Z. A., Foo, M.-D., Zhou, J., & Lu, J. G. (2025). How and for whom using generative AI affects creativity: A field experiment. *Journal of Applied Psychology*, 110(12), 1561–1573. <https://doi.org/10.1037/apl0001296>
- Suseno, Y., Chang, C., Hudik, M., & Fang, E. S. (2022). Beliefs, anxiety and change readiness for artificial intelligence adoption among human resource managers: The moderating role of high-performance work systems. *International Journal of Human Resource Management*, 33(6), 1209–1236. <https://doi.org/10.1080/09585192.2021.1931408>
- Tadić, M., Bakker, A. B., & Oerlemans, W. G. M. (2015). Challenge versus hindrance job demands and well-being: A diary study on the moderating role of job resources. *Journal of Occupational and Organizational Psychology*, 88(4), 702–725. <https://doi.org/10.1111/joop.12094>
- Tang, P. M., Koopman, J., Mai, K. M., De Cremer, D., Zhang, J. H., Reynders, P., Ng, C. T. S., & Chen, I.-H. (2023). No person is an island: Unpacking the work and after-work consequences of interacting with artificial intelligence. *Journal of Applied Psychology*, 108(11), 1766–1789. <https://doi.org/10.1037/apl0001103>
- Tarafdar, M., Tu, Q., Ragu-Nathan, B. S., & Ragu-Nathan, T. S. (2007). The impact of technostress on role stress and productivity. *Journal of Management Information Systems*, 24(1), 301–328. <https://doi.org/10.2753/MIS0742-1222240109>
- Täschner, J., Dicke, T., Reinhold, S., & Holzberger, D. (2025). “Yes, I can!” A systematic review and meta-analysis of intervention studies promoting teacher self-efficacy. *Review of Educational Research*, 95(1), 3–52. <https://doi.org/10.3102/00346543231221499>
- Tims, M., & Bakker, A. B. (2010). Job crafting: Towards a new model of individual job redesign. *South African Journal of Industrial Psychology*, 36(2), 1–9.
- Tims, M., Bakker, A. B., & Derks, D. (2012). Development and validation of the job crafting scale. *Journal of Vocational Behavior*, 80(1), 173–186. <https://doi.org/10.1016/j.jvb.2011.05.009>
- Tong, S., Jia, N., Luo, X., & Fang, Z. (2021). The Janus face of artificial intelligence feedback: Deployment versus disclosure effects on employee performance. *Strategic Management Journal*, 42(9), 1600–1631. <https://doi.org/10.1002/smj.3322>
- Ulfert, A.-S., Le Blanc, P., González-Romá, V., Grote, G., & Langer, M. (2024). Are we ahead of the trend or just following? The role of work and organizational psychology in shaping emerging technologies at work. *European Journal of Work & Organizational Psychology*, 33(2), 120–129. <https://doi.org/10.1080/1359432X.2024.2324934>
- Van den Broeck, A., Vansteenkiste, M., De Witte, H., & Lens, W. (2008). Explaining the relationships between job characteristics, burnout, and engagement: The role of basic psychological need satisfaction. *Work & Stress*, 22(3), 277–294. <https://doi.org/10.1080/02678370802393672>
- Van Wingerden, J., Derks, D., & Bakker, A. B. (2017). The impact of personal resources and job crafting interventions on work engagement and performance. *Human Resource Management*, 56(1), 51–67. <https://doi.org/10.1002/hrm.21758>
- Venkatesh, V., Thong, J. Y. L., & Xu, X. (2016). Unified theory of acceptance and use of technology: A synthesis and the road ahead. *Journal of the Association for Information Systems*, 17(5), 328–376.
- Verma, S., & Singh, V. (2024). Investigating the mediating role of willingness to use enterprise bots on white-collar teleworker productivity: An extended job demands-resources (JD-R) perspective. *Behaviour & Information Technology*, 43(15), 3616–3632. <https://doi.org/10.1080/0144929X.2023.2285945>
- Wei, X., Tan, W., & Tian, R. (2026). The double-edged sword effects of STARA use on employee performance and well-being: A meta-analysis based on job demands-resources (JD-R) model. *Information Technology & People*, 39(5), 2312–2340. <https://doi.org/10.1108/ITP-01-2025-0020>
- Westphal, M., Vössing, M., Satzger, G., Yom-Tov, G. B., & Rafaeli, A. (2023). Decision control and explanations in human-AI collaboration: Improving user perceptions and compliance. *Computers in Human Behavior*, 144, Article 107714. <https://doi.org/10.1016/j.chb.2023.107714>
- Wrzesniewski, A., & Dutton, J. E. (2001). Crafting a job: Revisioning employees as active crafters of their work. *Academy of Management Review*, 26(2), 179–201. <https://doi.org/10.2307/259118>
- Wu, T.-J., Liang, Y., & Wang, Y. (2024). The buffering role of workplace mindfulness: How job insecurity of human-artificial intelligence collaboration impacts employees' work-life-related outcomes. *Journal of Business and Psychology*, 39(6), 1395–1411. <https://doi.org/10.1007/s10869-024-09963-6>
- Wu, T.-J., Zhang, R.-X., & Zhang, Z. (2025). Navigating the human-artificial intelligence collaboration landscape: Impact on quality of work life and work engagement. *Journal of Hospitality and Tourism Management*, 62, 276–283. <https://doi.org/10.1016/j.jhtm.2025.02.005>
- Xanthopoulou, D., Bakker, A. B., Demerouti, E., & Schaufeli, W. B. (2009). Reciprocal relationships between job resources, personal resources, and work engagement. *Journal of Vocational Behavior*, 74(3), 235–244. <https://doi.org/10.1016/j.jvb.2008.11.003>
- Xiao, Q., Yan, J., & Bamber, G. J. (2025). How does AI-enabled HR analytics influence employee resilience: Job crafting as a mediator and HRM system strength as a moderator. *Personnel Review*, 54(3), 824–843. <https://doi.org/10.1108/PR-03-2023-0198>
- Xie, P., & Ma, L. (2026). How hotel AI adoption shapes employee performance? A study based on the transactional theory of stress and coping. *Journal of Hospitality and Tourism Technology*, 17(1), 176–191. <https://doi.org/10.1108/JHTT-09-2024-0606>
- Xu, F., Medappa, P. K., Tunc, M. M., Vroegindewij, M., & Fransoo, J. C. (2026). AI-assisted programming decreases the productivity of experienced developers by increasing the technical debt and maintenance burden. *Preprint*. <https://doi.org/10.48550/arXiv.2510.10165>
- Xu, J.-Q., Wu, T.-J., Duan, W.-Y., & Cui, X.-X. (2025). How the human-artificial intelligence (ai) collaboration affects cyberloafing: An AI identity perspective. *Behavioral Sciences*, 15(7), 859. <https://doi.org/10.3390/bs15070859>
- Yin, M., Jiang, S., & Niu, X. (2024). Can AI really help? The double-edged sword effect of AI assistant on employees' innovation behavior. *Computers in Human Behavior*, 150, Article 107987. <https://doi.org/10.1016/j.chb.2023.107987>
- Zawiah, M., Al-Ashwal, F., Gharaibeh, L., Abu Farha, R., Alzoubi, K., Abu Hammour, K., Qasim, Q. A., & Abrah, F. (2023). ChatGPT and clinical training: Perception, concerns, and practice of pharm-d students. *Journal of Multidisciplinary Healthcare*, 16, 4099–4110. <https://doi.org/10.2147/JMDH.S439223>
- Zhao, H. (2025). The effect of the risk of job substitution by AI, digital transformation stress and digital self-efficacy on employee deviant behavior. *Information Development*. <https://doi.org/10.1177/02666669251345458>
- Zheng, S., Guo, Z., Liao, C., Li, S., Zhan, X., & Peng, X. (2025). Booster or stumbling block? Unpacking the ‘double-edged’ influence of artificial intelligence usage on employee innovative performance. *Current Psychology*, 44(9), 7800–7817. <https://doi.org/10.1007/s12144-025-07358-1>
- Zheng, X., Ni, D., Liu, X., & Liang, L. H. (2023). Workplace mindfulness: Multidimensional model, scale development and validation. *Journal of Business and Psychology*, 38(4), 777–801. <https://doi.org/10.1007/s10869-022-09814-2>
- Zhou, S., Yi, N., Rasiyah, R., Zhao, H., & Mo, Z. (2024). An empirical study on the dark side of service employees' AI awareness: Behavioral responses, emotional mechanisms, and mitigating factors. *Journal of Retailing and Consumer Services*, 79, Article 103869. <https://doi.org/10.1016/j.jretconser.2024.103869>
- Zhou, Y., & Lyu, B. (2025). How does leadership AI awareness shape employee voice behavior? Based on the framework of hindrance and challenge stressors. *Work: A Journal of Prevention, Assessment & Rehabilitation*, 82(1), 289–305. <https://doi.org/10.1177/10519815251341816>

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