Article:
Badi, S., Suliman, A., Torku, A. et al. (2026) How does AI adoption in construction organisations influence employee well-being? The mediating role of job crafting. Construction Management and Economics. ISSN: 0144-6193

https://doi.org/10.1080/01446193.2026.2669769

How does AI adoption in construction organisations influence employee well-being? The mediating role of job crafting

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This paper has been accepted to be published in *Construction Management and Economics*. Please cite as follows:
Badi, S.; Suliman, A, Torku, A & Yasin, K. (2026), How does AI adoption in construction organisations influence employee well-being? The mediating role of job crafting, Construction Management and Economics, https://doi.org/10.1080/01446193.2026.2669769

How does AI adoption in construction organisations influence employee well-being? The mediating role of job crafting

Abstract

This study examines the impact of organisational AI adoption on project managers' job crafting behaviours and subsequent effects on work engagement and emotional exhaustion in construction organisations. Drawing on the Job Crafting framework and the Job Demands–Resources (JD-R) model, we operationalised AI-related structural and social job resources, challenging job demands, and reduction of hindering demands. Data were collected from 393 project managers and analysed using structural equation modelling. Results indicate that AI adoption significantly enhances all dimensions of job crafting, with the strongest effects on structural and challenging job resources. Social job resources and challenging demands positively influenced work engagement, whereas structural resources did not, and reductions in hindering demands unexpectedly decreased engagement while increasing exhaustion. These findings reveal the dual-edged nature of AI in construction project management, highlighting the importance of combining technological adoption with social support and skill development. The study contributes to theory by integrating AI into job crafting and JD-R frameworks and offers practical guidance for enhancing employee well-being in AI-enabled construction projects.

Keywords: Artificial Intelligence Adoption; Job Crafting; Job Demands–Resources (JD-R) Model; Work Engagement; Emotional Exhaustion.

1. Introduction

By 2030, automation, including AI, could impact up to 40% of roles in the construction sector (PwC, 2018), with many tasks increasingly shared between humans and machines (World Economic Forum, 2025). This transition may reshape the work of hundreds of millions of construction project-management and on-site roles worldwide (Abioye et al., 2021). Organisations across industries are increasingly adopting AI technologies to enhance productivity, optimise decision-making, and gain a competitive advantage (Wamba, 2022). In the construction sector, AI applications, including predictive analytics for risk and schedule forecasting, autonomous earth-moving and inspection equipment, robotic process automation for back-office workflows, and computer-vision activity monitoring on sites, are already transforming traditional project delivery and risk-management practices (Abioye et al., 2021). This digital transformation is significant given long-standing productivity shortfalls in construction, together with persistent safety risks and low labour productivity growth, as identified in systematic reviews of the sector (Lee et al., 2023; Sarvari et al., 2024).

As the construction industry undergoes rapid digital transformation, there are growing calls to examine construction as a socio-technical system where human and technological factors interact to shape work processes and outcomes (Whyte, 2019). Within this context, AI is increasingly viewed as a transformative force, not only automating routine tasks but also reshaping managerial decision-making, communication, and planning processes (Engström et al., 2024; Pan & Zhang, 2021b). Recent industry surveys indicate that approximately 48% of construction firms now use AI-powered safety monitoring systems, 43% employ AI for predictive maintenance, and 40% have adopted AI-based project scheduling tools (WiFi Talents, 2025; Zipdo, 2025). However, despite this growing emphasis on AI-driven innovation, limited research has examined how such organisational changes affect employees' psychological experiences and well-being in construction settings. For instance, studies of AI-enabled collaborative robots in the Architecture, Engineering, and Construction (AEC) sector show that fear of job displacement is a significant psychological concern among workers, influencing trust in AI systems and perceptions of role security (Emaminejad et al., 2023). As organisations deploy AI at scale, employees may face increased job demands, role ambiguity, or fear of displacement (Kim & Kim, 2024; Nasaj et al., 2025). Such conditions can undermine mental health and engagement if not managed appropriately (Konuk et al., 2023). Thus, understanding the human dimension of AI adoption is critical to sustain construction workforce resilience and project success.

Emerging studies have begun to explore employee responses to AI adoption, often through lenses such as acceptance models (e.g. Ma et al., 2025; Na et al., 2023; Wang et al., 2023) or stress appraisals (e.g. Cheng et al., 2023; Dong et al., 2025; Huang & Gursoy, 2024). From a theoretical standpoint, recent applications of the Job Demands–Resources (JD-R) model (Bakker & Demerouti, 2007; Demerouti et al., 2001) suggest that digital technologies may serve as a job resource, acting as a tool that enhances employees' capacity to manage their workload, improve task efficiency, and increase autonomy (Scholze & Hecker, 2023). They may also act as a job demand, imposing hyperconnectivity, information overload, and digital interruptions that heighten strain and impair well-being (Scholze & Hecker, 2024). Emerging conceptual models in organisational psychology also suggest indirect pathways between technology use and well-being outcomes, mediated by mechanisms such as autonomy (Wan et al., 2024), self-efficacy (Dong, 2025), and work exhaustion (Wang et al., 2023).

In the context of AI, job crafting has been identified as one such mechanism which refers to employees' proactive behaviours to modify and optimise their work in response to the introduction of AI tools and technologies (He et al., 2023; Li et al., 2024; Li & Li, 2025; Xiao et al., 2023). Emerging research, mostly in the service industry, has begun to illuminate the relationship between AI adoption and job crafting, showing that leadership communication (He et al., 2023), organizational support (Li et al., 2024), employee perceptions of AI (Li & Li, 2025), and HR systems (Xiao et al., 2023) shape how employees redesign their roles and build resilience in the face of technological change. While these studies provide valuable knowledge, they remain focused on general management contexts and overlook industry-specific conditions. In construction project management, where uncertainty, complexity, and high work demands are pervasive, the implications of AI adoption for job crafting and project managers' well-being remain empirically unexamined (Adebayo et al., 2025). Specifically, three interrelated gaps exist in the current literature. First, existing studies of AI and job crafting (He et al., 2023; Li et al., 2024; Li & Li, 2025; Xiao et al., 2023) have been conducted exclusively in service and general management contexts; few studies have examined this relationship in the construction sector (e.g. AlMemari et al., 2025; Yang et al., 2025), where the nature of work, project complexity, and sociotechnical conditions differ substantially. Second, no validated measures of AI-related job crafting grounded in the JD-R framework exist for construction project management, leaving researchers without domain-appropriate instruments. Third, the downstream consequences of AI-related job crafting for construction workers' work engagement and emotional exhaustion remain entirely untested. Addressing this gap is therefore critical not only for advancing job crafting and JD-R theory in technology-intensive contexts, but also for understanding how AI can be harnessed in construction organisations to support workforce sustainability and well-being. The aim of this study is therefore to examine how organisational AI adoption influences construction employees' job crafting behaviours and, in turn, how these crafting behaviours affect work engagement and emotional exhaustion. This aim is pursued through the following two research questions:

RQ1: How does AI adoption in construction organisations influence construction employees' job crafting behaviours?

RQ2: How do different job crafting strategies impact employee outcomes, specifically work engagement and emotional exhaustion?

To answer the above two questions, we develop a model grounded in the Job Crafting theory and the Job Demands–Resources (JD-R) model (see Figure 1). The study is set within the context of the European construction industry, where digitalisation is accelerating in response to market pressures, policy directives, and workforce challenges (e.g. Chen et al., 2022; Zulu et al., 2024). The unit of analysis is the individual construction project manager, a role central to project delivery and increasingly impacted by technological transformation.

The research findings offer several key contributions. First, the study is the first to develop and operationalise measures of AI-related job crafting using the Job Demands–Resources (JD-R) conceptualisation in the domain-specific context of construction project management. Second, it challenges the conventional JD-R view that reducing hindering job demands necessarily improves well-being, showing instead that AI-enabled reductions can lower engagement and heighten exhaustion. Third, it introduces AI adoption as a novel antecedent of job crafting behaviours, highlighting technology as a structural enabler of proactive work design. Fourth, it refines the JD-R model by demonstrating that, in project-based environments, resources may drive engagement without necessarily buffering exhaustion. Managerially, it provides actionable recommendations for construction organisations on how to use AI not only to improve performance but also to design healthier and more fulfilling work roles. By positioning AI adoption as an enabler of job crafting and employee well-being, this study contributes to an emerging discourse on how organisations can balance technological advancement with employee well-being in high-demand environments (e.g. Rahmi et al., 2025; Zhang et al., 2025). From a policy perspective, the findings inform broader discussions on responsible AI adoption and digital well-being in the construction sector.

The remainder of this article is structured as follows. Section 2 reviews the relevant literature on AI in construction, job crafting, and employee well-being, while Section 3 develops the research hypotheses. Section 4 outlines the methodology, including the research design, data collection and analysis procedures. Section 5 discusses the findings in light of the literature and theory. Section 6 concludes with implications for theory, practice, and future research directions.

2. Frame of Reference

2.1 AI in Construction Project Management

The construction industry has witnessed a significant digital transformation in recent years, driven by the adoption of advanced technologies such as Artificial Intelligence (AI) (e.g. Abioye et al., 2021), Building Information Modelling (BIM) (e.g. Pan & Zhang, 2021a), and the Internet of Things (IoT) (Zhou et al., 2021). AI, in particular, has the potential to revolutionise the way construction projects are managed, executed, and optimised (Mohammadpour et al., 2019). AI brings increased automation, enhanced data analytics, and improved decision-making capabilities, which are crucial for overcoming the industry's traditional challenges, such as time delays, cost overruns, and inefficiencies (Egwim et al., 2021). In their studies, Pan and Zhang (2021b), Egwim et al. (2024), and Fridgeirsson et al. (2023) discussed automated project scheduling as one of the most prominent applications of AI, where AI algorithms predict the optimal sequence of tasks by considering variables such as material availability, workforce allocation, and weather conditions. AI can dynamically adjust project schedules through data-driven recommendations, contributing to cost savings and operational efficiency, thereby reducing delays and enhancing productivity (Amoah, 2025). AI has been shown to significantly enhance resource efficiency and minimise waste in construction projects by enabling predictive waste management, automated sorting, and optimised equipment utilisation, while also improving cost control through advanced machine learning–based forecasting models (e.g. Sun et al., 2024; Gao et al., 2024; Ottaviani et al., 2025; Harichandran et al., 2023). Moreover, predictive analytics enabled by AI helps identify potential risks before they escalate. For instance, AI can predict cost overruns, safety hazards, or delays by analysing historical patterns and real-time data from ongoing projects (Fridgeirsson et al., 2023; Pan & Zhang, 2021b). These predictive capabilities allow project managers to implement proactive measures, mitigating risks and improving decision-making processes. These developments matter for the present study because they indicate that AI adoption can alter project managers' task structure, decision routines, and coordination practices, which provides a basis for theorising proactive work redesign responses, captured here as AI-related job crafting.

From the above, it could be observed that AI's impact on project management roles and workflows in construction is profound. It offers the potential to shift the project manager's focus from manual, routine tasks to higher-level decision-making and strategic planning. With AI automating time-intensive tasks such as project scheduling (Yao et al., 2024; ElMenshawy et al., 2025) and resource allocation (Jiang et al., 2023), project managers are increasingly able to dedicate more time to managing stakeholder relationships, supporting collaboration, and addressing complex project challenges (Holzmann et al., 2022). Thus, AI has significant implications for how project managers perform their tasks. However, the behavioural and psychological implications of AI adoption for project managers have received limited attention. While AI is viewed as a tool for enhancing productivity and performance, its impact on wellbeing and performance remains under-explored, and the extent to which AI may influence job crafting behaviours, i.e the proactive modifications employees make to their work roles, remains an important, but scarce area for construction project management research. Accordingly, the next sections focus on the theoretical discussion on the specific links tested in the hypotheses, namely how organisational AI adoption relates to AI-related job crafting behaviours, and how those behaviours relate to work engagement and emotional exhaustion.

2.2 Employee Well-being in the Age of AI

Employee well-being is a multidimensional construct encompassing the physical, psychological, and emotional states that enable individuals to thrive at work (Danna & Griffin, 1999). Within organisational contexts, two key dimensions often used to evaluate well-being are *employee engagement* and *emotional exhaustion*. Employee engagement reflects a positive, fulfilling state of mind characterised by high levels of energy, dedication, and absorption in one's work (Schaufeli et al., 2006). In contrast, emotional exhaustion represents a core component of burnout and refers to feelings of being emotionally overextended and depleted of one's emotional resources (Maslach et al., 1996). High engagement is associated with enhanced motivation, performance, and satisfaction (e.g. Demerouti et al., 2010), whereas elevated emotional exhaustion is linked to stress, disengagement, and impaired health outcomes (e.g. Aronsson et al., 2017). Understanding how emerging technologies such as AI shape these critical facets of well-being is essential, as digital technologies can act both as a resource that supports engagement and as a demand that contributes to emotional strain (Scholze & Hecker, 2023; 2024). These dimensions also connect to the broader concept of happiness management; refering to organisational strategies aimed at sustaining employees' positive emotional states and fulfilment at work (Pryce-Jones, 2011), which underscores the importance of understanding how AI adoption shapes employee well-being in construction.

Indeed, recent research has begun to elucidate how AI adoption influences employee well-being within organisations. Trust in AI and effective employee-AI collaboration have been shown to enhance career sustainability and promote positive well-being outcomes (Kong et al., 2023). Conversely, exposure to AI-driven work environments can increase stress and reduce affective well-being if implementation is poorly managed or perceived as threatening (Jin et al., 2024). Strategic human resource management (HRM) frameworks integrating AI highlight both opportunities and risks, emphasising the importance of transparent governance and employee involvement to safeguard well-being (Malik et al., 2023). Similarly, broader reviews of AI in international HRM call for proactive practices to mitigate technostress and job insecurity while leveraging AI to support employee development and satisfaction (Budhwar et al., 2022). Together, these studies suggest that the impact of AI on employee well-being is not inherently positive or negative but is contingent upon organisational trust, implementation strategies, and the socio-technical context in which AI is deployed.

In addition, and specifically to the context of this study, employee well-being has emerged as a critical concern in project-based work environments, particularly in high-pressure industries such as construction, where tight deadlines, high stakes, and dynamic coordination across multiple stakeholders create significant stressors for project teams (Pirzadeh & Lingard, 2021; Lingard & Turner, 2023; Mubarak, Khan, & Khan, 2022). For construction project managers, whose roles often involve intense emotional labour and high workloads, maintaining optimal levels of well-being is particularly challenging, with risks of burnout and job-related psychological distress affecting both individuals and project outcomes (Pinto, Dawood, & Pinto, 2014; Zhang, Yao, & Yiu, 2020). However, despite this growing interest in employee well-being in construction management, a significant research gap remains in understanding how technological advances, particularly the introduction of AI, may reshape the landscape of well-being in project-based environments (Holzmann et al., 2022). Current literature lacks a deeper understanding of how AI may act as an enabler of job control, autonomy, or task redefinition; factors known to be conducive to well-being (Deci & Ryan, 2000). Thus, there is a pressing need to explore the indirect pathways through which AI adoption might influence employee well-being, particularly through its potential to facilitate proactive work design such as job crafting, as will be elaborated upon in the following section. This framing motivates the model tested in this study, where AI-related job crafting behaviours serve as the behavioural mechanisms connecting AI adoption to engagement and emotional exhaustion.

3. Conceptual Framework & Hypotheses Development

3.1 Job Crafting & AI

Job crafting, as initially defined by Wrzesniewski and Dutton (2001), refers to the physical and cognitive changes employees make to reshape their work in terms of task, relational, and cognitive boundaries. Task crafting involves altering job tasks to better suit individual skills, relational crafting focuses on modifying work relationships, and cognitive crafting concerns reinterpreting one's role within the organisation. This conceptualisation, known as role-based job crafting, emphasises employees' proactive strategies for enhancing work meaning and identity (Wrzesniewski & Dutton, 2001; Bruning & Campion, 2018).

A parallel approach emerged through Tims and Bakker's (2010) work, rooted in the Job Demands-Resources (JD-R) model (Demerouti et al., 2001). They described job crafting as changes employees make to balance job demands and resources with personal abilities and needs. This resource-oriented perspective focuses on three strategies: increasing job resources (e.g., seeking feedback), increasing challenging demands (e.g., taking on new tasks), and reducing hindering demands (e.g., delegating complex decisions) (Tims et al., 2012). While role- and resource-based job crafting overlap conceptually (Hu et al., 2020), they have historically been assessed separately despite efforts to integrate them (Bruning & Campion, 2018; Zhang & Parker, 2019).

In the context of AI, job crafting refers to employees' proactive efforts to reshape their roles, responsibilities, and work environments to align with personal goals and the demands of emerging technologies (He et al., 2023). Several recent studies collectively highlight that AI integration fundamentally reshapes job crafting, though in nuanced and sometimes contradictory ways. He et al. (2023) emphasise the symbolic role of leaders in shaping employee attitudes, showing that leader-driven AI symbolisation supports proactive job crafting by instilling confidence and autonomy. Li et al. (2024) extend this to the organisational level, illustrating a trickle-down effect where AI adoption enhances motivation, resilience, and satisfaction through culturally embedded job crafting practices. However, Li & Li (2025) caution against an overly optimistic view, revealing that while AI collaboration can enable innovation and proactive role redesign, it also risks identity confusion and a reduced willingness to craft jobs when AI is perceived as a threat. Complementing these views, Xiao et al. (2023) demonstrate that AI-enabled HR analytics can bolster employee resilience, with strong HR systems amplifying the positive mediating role of job crafting. Collectively, these studies underscore the significance of AI in shaping job crafting, but they are largely situated in general management contexts and have not examined construction industry-specific conditions.

Addressing this gap, our study is the first to develop and operationalise measures of AI-related job crafting using the Job Demands–Resources (JD-R) conceptualisation in the domain-specific context of construction project management. We define AI-related job crafting in construction project management as employees' proactive behaviours to modify and optimise their work in response to the introduction of AI tools and technologies. Consistent with the Job Crafting framework (Tims et al., 2012), four distinct dimensions were defined as follows:

- *Increasing AI-related structural job resources* (JC_SJR) capture behaviours aimed at expanding one's knowledge, skills, and autonomy in using AI, such as developing AI capabilities, learning new AI-based methods, and making autonomous decisions in AI-supported tasks.
- *Increasing AI-related social job resources* (JC_SJR) reflect efforts to enhance support, feedback, and collaboration through AI, including seeking guidance from supervisors and colleagues, obtaining feedback on AI use, and using social interactions to improve AI integration.
- *Increasing AI-related challenging job demands* (JC_CJD) encompass behaviours in which employees voluntarily take on complex AI-driven tasks, experiment with innovative AI applications, and address strategic problems using AI, thereby stimulating growth and engagement.
- *Decreasing AI-related hindering job demands (JC_HJD)* captures behaviours aimed at using AI tools to reduce mentally, emotionally, or cognitively draining aspects of work, such as automating repetitive tasks, managing stressful interactions, or structuring workflows to reduce prolonged concentration demands.

These definitions are used directly in the hypotheses below, so that each hypothesised link is grounded in a specific job crafting dimension rather than a broad discussion of AI and work redesign. Together, these four dimensions provide a comprehensive operationalisation of AI-related job crafting, highlighting both resource-enhancing and demand-modifying strategies that employees can employ to adapt to AI-enabled work environments.

3.2 AI adoption and Job Crafting Behaviours among construction employees

Organisational AI adoption (ADO), as defined in this study, reflects the extent to which an organisation strategically implements and integrates AI tools to support decision-making and operational efficiency. Empirical evidence suggests that when AI technologies are embedded into core processes, employees are more likely to engage in job crafting behaviours, such as developing new skills, seeking feedback, taking on challenging tasks, and using AI to reduce hindering demands (Li et al., 2024; Xiao et al., 2023; He et al., 2023). These behaviours, captured across the four operationalised dimensions of AI-related job crafting (i.e. structural resources, social resources, challenging demands, and reduction of hindering demands), enable employees to leverage AI effectively, which was found to enhance performance and increase job satisfaction (Li et al., 2024; Xiao et al., 2023; He et al., 2023). Consequently, a higher level of organisational AI adoption is expected to provide the resources, opportunities, and support necessary for employees to actively reshape and enrich their roles.

Firstly, AI adoption provides employees with opportunities to increase *AI-related structural job resources (JC_SJR)* by enhancing their capabilities, knowledge, and autonomy in using AI tools for project tasks. Structural job resources, as defined in this study in consistency with the Job Crafting framework (Tims et al., 2012), refer to the aspects of work that enable employees to develop skills, make autonomous decisions, and use AI technologies to their fullest potential. In construction settings, AI technologies, such as machine learning-driven project analytics, predictive scheduling, and automated risk assessment, are increasingly embedded into workflows to support complex decision-making. These tools provide construction managers with real-time information into project progress, cost forecasts, and resource allocation, which improves task clarity, enhances feedback, and reduces uncertainty (Abioye et al., 2021; Mohammadpour et al., 2019; Egwim et al., 2024; Fridgeirsson et al., 2023; Amoah, 2025). For example, AI-powered Building Information Modelling (BIM) systems can dynamically update designs and detect clashes early in planning, allowing managers greater control and decision-making latitude (Pan & Zhang, 2021a, 2021b). As organisations invest in AI capabilities, employees are empowered to develop expertise in AI tools, apply AI methods independently, and innovate within their roles (He et al., 2023; Xiao et al., 2023). These enhancements to task-related resources may provide the foundation for employees to proactively craft their jobs by expanding their knowledge and autonomy in AI-enabled responsibilities (Tims et al., 2012). Thus, we forward our first hypothesis:

> ***H1:*** *Organisational AI adoption is positively associated with an increase in AI-related structural job resources among construction employees.*

In addition, the adoption of AI may also enhance AI-related social job resources (JC_SOJR) by encouraging communication, collaboration, and support among employees in using AI tools. Social job resources, as defined in this study, in line with the Job Crafting framework (Tims et al., 2012), refer to behaviours in which employees actively seek guidance, feedback, and advice from supervisors and colleagues regarding the effective use of AI in their work. AI technologies, such as machine learning-driven project analytics, predictive scheduling, and automated risk assessment, are increasingly integrated into construction workflows, providing construction managers with real-time information of project progress, cost forecasts, and resource allocation (Wijayasekera et al., 2022). These tools facilitate information sharing and collaborative problem-solving, making it easier for employees to ask for feedback, consult peers, and learn from supervisors experienced in AI integration (He et al., 2023). By creating a supportive environment for knowledge exchange and guidance, AI adoption may strengthen social connections and encourage employees to craft their jobs by leveraging these social resources. Therefore, we propose our second hypothesis:

> ***H2:*** *Organisational AI adoption is positively associated with an increase in AI-related social job resources among construction employees.*

Furthermore, AI implementation introduces new challenges and growth opportunities, motivating employees to engage in AI-related challenging job demands (JC_CJD). As defined in this study, and aligned with the Job Crafting framework (Tims et al., 2012), these refer to the frequency with which employees voluntarily take on AI-driven tasks, experiment with innovative AI applications, and use AI to address complex or strategic aspects of their work. Organisations adopting AI encourage employees to participate in AI-driven projects, stay updated on new AI developments, and explore innovative solutions, which stimulates proactive job crafting by encouraging skill development and promoting active engagement with AI's transformative potential (Xanthopoulou et al., 2009; Li et al., 2024; He et al., 2023). Accordingly, our hypothesis is as follows:

> ***H3:*** *Organisational AI adoption is positively associated with an increase in AI-related challenging job demands among construction employees.*

Finally, organisational AI adoption may enable employees to decrease hindering job demands (JC_HJD) by using AI tools to reduce mentally and emotionally draining tasks, structure workflows, and provide decision support. In this study, this construct was defined following the Job Crafting framework (Tims et al., 2012), as employees' frequent engagement in behaviours such as adjusting AI use to reduce mental intensity, using AI to lower emotional strain in tasks, filtering emotionally draining interactions through AI systems, managing unrealistic stakeholder expectations with AI, relying on AI decision-support to ease decision-making pressure, and structuring AI-based workflows to reduce prolonged concentration demands. By alleviating cognitive and emotional burdens, AI allows employees to focus on strategic and meaningful aspects of their work, thereby supporting job crafting behaviours that optimise work conditions and enhance well-being (Bakker & Demerouti, 2007). On this basis, we formulate the following hypothesis:

> ***H4:*** *Organisational AI adoption is positively associated with a greater decrease in AI-related hindering job demands among construction employees.*

3.3 Increases in AI-related structural and social Job Resources Predict Increases in Well-Being

The Job Demands–Resources (JD-R) model posits that job resources are inherently motivational and instrumental in promoting employee well-being (Bakker & Demerouti, 2007). Job resources are defined as the physical, psychological, social, or organisational aspects of a job that help achieve work goals, reduce job demands, or stimulate personal growth and development (Bakker & Demerouti, 2007). Empirical evidence by Schaufeli & Bakker (2004) and Schaufeli et al. (2009) demonstrates that increases in job resources lead to higher work engagement and reduce emotional exhaustion; two widely recognised indicators of positive work-related well-being. Recent evidence shows that organisational AI adoption enhances employees' ability to craft their jobs by developing AI-related skills, making autonomous decisions, and seeking feedback from supervisors and colleague, which in turn promotes proactive job crafting and higher engagement (Cheng et al., 2023). Similarly, a study by Li et al. (2024) in the service industry found that employees who actively integrate AI into their roles experience greater autonomy, task clarity, and social support, which are strongly linked to reduced emotional exhaustion and enhanced well-being.

By increasing decision-making autonomy, clarity, and social support, AI tools may therefore provide the conditions posited by the JD-R model for sustaining motivation and well-being. Employees who leverage these resources are likely to experience higher levels of engagement behaviours, such as feeling energetic, enthusiastic, absorbed, and proud of their work. At the same time, the presence of these resources can reduce frequent experiences of emotional exhaustion, helping employees manage the cognitive and emotional demands of their roles. In AI-enabled construction environments, construction managers who craft their roles by developing AI skills and seeking social support are likely to experience more frequent engagement behaviours and less frequent emotional exhaustion, consistent with evidence that proactive job crafting, facilitated by increases in job resources, supports sustained well-being and motivation (Tims, Bakker, & Derks, 2013). Consequently, we advance the following hypotheses:

H5: *Increases in AI-related structural job resources are positively associated with the frequency of work engagement behaviours among construction employees.*

H6: *Increases in AI-related social job resources are positively associated with the frequency of work engagement behaviours among construction employees.*

H7: *Increases in AI-related structural job resources are negatively associated with the frequency of emotional exhaustion among construction employees.*

H8: *Increases in AI-related social job resources are negatively associated with the frequency of emotional exhaustion among construction employees.*

3.4 Changes in AI-related Job Demands Predict Changes in Well-Being

While the integration of AI into construction project management provides valuable structural and social job resources, it also introduces new job demands. Drawing on the Job Demands–Resources (JD-R) model (Demerouti et al., 2001) and the challenge–hindrance stressor framework (LePine et al., 2005), job demands can be conceptualised as either challenging or hindering, each having distinct implications for employee well-being.

Challenging job demands are those that require sustained effort but are perceived as opportunities for learning, achievement, or growth (Crawford et al., 2010). In this study, AI-related challenging job demands (JC_CJD) were defined as the frequency with which employees voluntarily take on AI-driven tasks, experiment with innovative AI applications, and use AI to address complex or strategic aspects of their work. Examples include learning to operate advanced AI tools, interpreting predictive analytics, and adapting to data-driven decision-making processes.

According to LePine et al. (2005), challenging demands are often appraised positively, resulting in proactive coping and increased engagement. When employees actively engage with these demands, they are likely to experience more frequent work engagement behaviours, defined as feeling energetic, enthusiastic, absorbed, and purposeful in their work (Schaufeli et al., 2006). However, these demands can also contribute to emotional exhaustion, defined as the frequency of feeling emotionally drained, fatigued, or overextended, if not adequately supported (Maslach et al., 1996). Empirical evidence indicates that while challenging demands generally promote engagement and skill development, they may also have a modest association with emotional strain (Crawford et al., 2010). In AI-enabled construction environments, construction managers who engage with challenging AI-driven tasks are likely to experience increased engagement, but the cognitive and emotional effort required may elevate exhaustion if structural and social resources are insufficient. As a result, we suggest the following hypotheses:

H9: *Increases in AI-related challenging job demands are positively associated with the frequency of work engagement behaviours.*

H10: *Increases in AI-related challenging job demands are positively associated with the frequency of emotional exhaustion.*

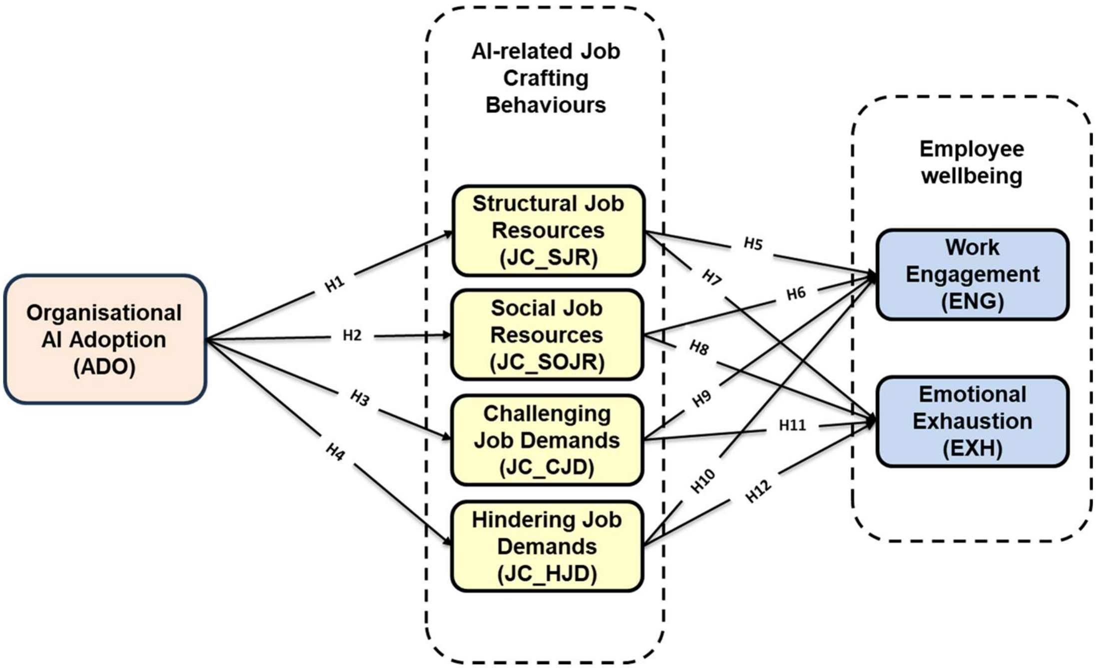
In addition, decreasing AI-related hindering job demands (JC_HJD) refers to the use of AI tools and systems to minimise or avoid mentally, emotionally, or cognitively draining aspects of work that hinder productivity and well-being. Proactively engaging in these behaviours allows employees to alleviate cognitive and emotional burdens, focus on meaningful work, and maintain motivation. In a study of Belgian home health care nurses, higher emotional demands and workload (job demands) were significantly positively associated with burnout, whereas greater job resources (e.g., social support) correlated with lower burnout and higher work engagement (Vander Elst et al., 2016). Empirical evidence suggests that reducing hindering job demands can decrease emotional exhaustion, defined as the frequency of feeling emotionally drained or fatigued, and increase work engagement, defined as the frequency of experiencing energy, enthusiasm, absorption, pride, and a sense of purpose in work (Van den Broeck et al., 2017). In AI-integrated construction projects, where coordination and complex decision-making are critical, managing hindering demands via AI enables employees to sustain engagement while mitigating the risk of burnout. Guided by this reasoning, we introduce these hypotheses:

H11: *Greater decreases in AI-related hindering job demands are negatively associated with the frequency of emotional exhaustion.*

H12: *Greater decreases in AI-related hindering job demands are positively associated with the frequency of work engagement behaviours.*

To summarise, Figure 1 presents the conceptual framework, highlighting the hypothesised relationships to be tested. The following section describes the methods we used to empirically examine these relationships.

Figure 1: Conceptual framework



Source: Authors' creation

4. Methods

4.1 Sampling and data collection

This study focuses on employees of construction firms in several highly digitised European countries, including the United Kingdom, Germany, Sweden, and the Netherlands. These countries were selected due to their digital maturity, making them suitable contexts for investigating AI adoption. Despite significant progress in digital transformation initiatives, such as the UK's BIM Level 2 mandate (Cabinet Office, 2011) and Germany's Industry 4.0 framework (Plattform Industrie 4.0; n.d.), the actual rate of AI adoption in the European construction sector remains relatively low, with an average of 6.09% across the EU in 2024 (Eurostat, 2024). According to Eurostat (2024), only around 12% of construction companies in the UK and 11.6% in Germany report using AI technologies, while in Denmark, 27.58% of all companies adopted AI in 2024, followed by Sweden (25.09%) and Belgium (24.71%), though construction-specific figures for these countries are unavailable. Large European enterprises (250+ employees) display a higher rate of adoption, at approximately 41.17%, whereas small firms lag significantly behind, with around 11.21% using AI. By focusing on these digitally advanced yet variably adopting countries, this study examines construction environments where AI integration is both feasible and its impacts most observable, offering a deeper understanding of the consequences of adoption.

Data for the research were collected through an online survey administered through a digital questionnaire platform. Participants were self-selected in response to an invitation to take part, resulting in a quasi-random sample. As explained above, the survey was distributed to employees from construction firms across several European nations, including the United Kingdom, Germany, Finland, Sweden, the Netherlands, France, Estonia, Denmark, Austria, and Norway. Specific selection criteria were established to ensure that the sample accurately represented the target population. To ensure the relevance and quality of responses, we used a set of targeted screeners to recruit suitable participants for this study. Specifically, we filtered for individuals who were currently residing in the countries mentioned above, employed either full-time or part-time in the construction industry and holding managerial roles such as project manager or construction manager (or Engineers, HR and finance managers and site supervisors). Additional filters ensured that participants had at least a moderate level of familiarity with AI-enabled or digital tools in the workplace. Two qualifying questions at the beginning of the survey confirmed this criterion as respondents were asked the following two questions: "*Are you currently working in a managerial position in a construction-related role?*" and "*Do you use any AI-enabled or digital tools to support project decision-making, planning, or communication in your work*?". Respondents who answered "Yes" to both questions proceeded to the main questionnaire, while those who answered "No" were redirected, and the survey was terminated.

To further minimise self-selection and social desirability bias, the study ensured anonymity and clarified that there were no right or wrong answers, encouraging honest and reflective responses. These measures collectively aimed to increase the reliability, validity, and generalisability of the findings. The questionnaire was distributed between 1st July and 16th September 2025, and 791 surveys were sent to the prescreened participants who met the criteria above. Of these, 418 responses were received, representing a response rate of 52.9%. A total of 25 participants were excluded due to incomplete or invalid responses, yielding a final sample of 393 with no missing values observed.

As Table 1 shows, the survey respondents represented a diverse range of organisations, roles, and experience levels within the construction industry. Most participants worked for main contractors (34.9%), subcontractors (17.8%), or consultants (12.5%), with the majority based in the United Kingdom (86.0%). Organisational sizes varied, with 34.6% of respondents from organisations with fewer than 50 employees and 27.5% from organisations with more than 1,000 employees. Respondents' tenure in their current organisation ranged from less than one year (12.5%) to over 15 years (12.2%). Regarding roles, project managers (17.6%), design/planning engineers (11.7%), and construction workers/tradespersons (10.2%) were the most common. Respondents' industry experience spanned from less than one year (3.3%) to more than 15 years (27.7%), and involvement with AI systems ranged from not at all (9.2%) to daily use (4.1%). The majority held a bachelor's (36.6%) or master's degree (22.1%), were aged 25–34 years (41.2%), and were male (66.4%).

Table 1. Frequency Distribution of Survey Respondents (N = 393)

Variable	Category	Count	% of Total	Cumulative %
Type of Organisation	Main Contractor	137	34.9%	34.9%
	Subcontractor	70	17.8%	52.7%
	Client / Developer	21	5.3%	58.0%
	Consultant (Architectural / Civil / Structural)	49	12.5%	70.5%
	MEP Consultant	16	4.1%	74.6%
	MEP Contractor	4	1.0%	75.6%
	Supplier / Manufacturer	32	8.1%	83.7%
	Project Management Consultancy (PMC)	12	3.1%	86.8%
	Quantity Surveying / Cost Consultancy	7	1.8%	88.5%
	Facilities Management / Operations Contractor	8	2.0%	90.6%
	BIM / Digital Solutions Provider	5	1.3%	91.9%
	Government / Regulatory Body	21	5.3%	97.2%
	Other	11	2.8%	100.0%
Organisation Location	Austria	1	0.3%	0.3%
	Denmark	1	0.3%	0.5%
	Estonia	3	0.8%	1.3%
	Finland	4	1.0%	2.3%
	France	5	1.3%	3.6%
	Germany	23	5.9%	9.4%
	Netherlands	9	2.3%	11.7%
	Norway	4	1.0%	12.7%
	Sweden	3	0.8%	13.5%
	United Kingdom	338	86.0%	99.5%
	Other	2	0.5%	100.0%
Organisation Size	Fewer than 50	136	34.6%	34.6%
Tenure in Current Organisation	51–200	81	20.6%	55.2%
	201–500	43	10.9%	66.2%
	501–1000	25	6.4%	72.5%
	More than 1000	108	27.5%	100.0%
	Less than 1 year	49	12.5%	12.5%
	1–3 years	118	30.0%	42.5%
	4–6 years	79	20.1%	62.6%
	7–10 years	58	14.8%	77.4%
	11–15 years	41	10.4%	87.8%
	More than 15 years	48	12.2%	100.0%
Job Role	Director / Executive / CEO	18	4.6%	4.6%
	Project Manager	69	17.6%	22.1%
	Site Engineer	16	4.1%	26.2%
	Construction Manager	35	8.9%	35.1%
	Construction Worker / Tradesperson	40	10.2%	45.3%
	Design/Planning Engineer	46	11.7%	57.0%
	Quantity Surveyor	21	5.3%	62.3%
	BIM / AI Specialist	3	0.8%	63.1%
	IT / Digital Transformation Specialist	19	4.8%	67.9%
	Health & Safety Officer	6	1.5%	69.5%
	Mechanical/Electrical Engineer	12	3.1%	72.5%
	Procurement Specialist	6	1.5%	74.0%
	Construction HR Manager	10	2.5%	76.6%
	Construction Finance Manager	24	6.1%	82.7%
	Other	68	17.3%	100.0%

Industry Experience	Less than 1 year	13	3.3%	3.3%
	1–3 years	66	16.8%	20.1%
	4–6 years	74	18.8%	38.9%
	7–10 years	81	20.6%	59.5%
	11–15 years	50	12.7%	72.3%
	More than 15 years	109	27.7%	100.0%
Highest Level of Education	High School Diploma or equivalent	62	15.8%	15.8%
	Vocational/Technical Certification	96	24.4%	40.2%
	Bachelor's Degree	144	36.6%	76.8%
	Master's Degree	87	22.1%	99.0%
	Doctorate (PhD)	2	0.5%	99.5%
	Other	2	0.5%	100.0%
Age Group	18–24	26	6.6%	6.6%
	25–34	162	41.2%	47.8%
	35–44	113	28.8%	76.6%
	45–54	62	15.8%	92.4%
	55–64	21	5.3%	97.7%
	Above 64	9	2.3%	100.0%
Gender	Male	261	66.4%	66.4%
	Female	132	33.6%	100.0%

Source: Authors' creation

4.2 Questionnaire design and measurement items

This study employed established measurement scales adapted to the context of AI use in construction project management. Where applicable, items were drawn from validated instruments in the literature and contextualised to reflect AI-related work environments. A complete list of items for each construct is provided in Table 2.

Organisational AI Adoption (ADO)(6 items) is a newly developed scale, based on common construction AI applications. It measures the extent to which an organisation strategically implements, integrates, and utilises artificial intelligence (AI) technologies across its construction operations to enhance decision-making, efficiency, safety, and project outcomes. An example item is *My organisation has integrated AI technologies into its core construction operations (e.g., scheduling, cost estimation, risk analysis)."* Items were scored using a 5-point agreement scale (1 = Strongly disagree, 5 = Strongly agree).

Job crafting behaviours were measured using the 21-item scale developed by Tims et al. (2012), with items adapted to reflect AI-specific behaviours in the workplace. Responses were recorded on a 5-point frequency scale (1 = Never, 5 = Always). The four dimensions of job crafting include:

- *Increasing AI-Related Structural Job Resources (JC_SJR)(5 items):* captures the proactive efforts employees make to enhance their personal and professional resources for using AI in their work, including developing skills, expanding knowledge, and increasing autonomy in AI use.. Example item*: "I try to develop my capabilities in using AI tools for project management."*
- *Increasing AI-Related Social Job Resources (JC_SOJR)(*5 items): measures the extent to which employees actively seek social support, guidance, and feedback from supervisors and colleagues to effectively integrate AI into their work. Example item*: "I ask my supervisor for support in understanding and applying AI technologies."*
- *Increasing AI-Related Challenging Job Demands (JC_CJD)(*5 items): assesses the intentional pursuit of AI-related tasks and responsibilities that go beyond routine work, aimed at stimulating professional growth, innovation, and engagement.. Example item*: "When an AI-driven project or pilot comes up, I volunteer to be involved."*
- *Decreasing Hindering Job Demands via AI (JC_HJD)* (6 items): reflect the use of AI tools and systems to minimise or avoid mentally, emotionally, or cognitively draining aspects of work that hinder productivity and well-being.. *Example item: "I try to use AI to reduce the emotional intensity of certain project tasks."*

Work Engagement (ENG) was measured using nine items from the Utrecht Work Engagement Scale (UWES-9) (Schaufeli et al., 2006) to assess the frequency with which employees experience energy, enthusiasm, inspiration, pride, absorption, and a sense of meaning and purpose in their work, as reflected in their day-to-day job activities. Example item: "*At my work, I feel bursting with energy*". Responses were provided on a 5-point frequency scale (1 = Never, 5 = Always).

Emotional Exhaustion (EXH) was measured using four items from the Maslach Burnout Inventory (Maslach et al., 1996) to measure the extent to which employees frequently experience emotional depletion and fatigue in relation to their job, particularly at the start or end of the workday, indicating a strain on their emotional resources. Example item: "*I feel emotionally drained from my work.*". Participants rated each item using a 5-point frequency scale (1 = Never, 5 = Always).

Table 2: Measurement items and confirmatory factor analysis (CFA) factor loadings

Construct	Item Code	Item Statement	Mean	Median	SD	Skewness	Kurtosis	Factor laoading (β)	p-value
AI Adoption (ADO)	ADO1	My organization has integrated AI technologies into its core construction operations (e.g., scheduling, cost estimation, risk analysis).	2.85	3	1.18	-0.098	-1.260	0.851	<.001
	ADO2	AI tools (e.g., predictive analytics, machine learning) are regularly used to support project decision-making in my organization.	2.85	3	1.15	-0.169	-1.100	0.874	<.001
	ADO3	There is a clear strategy for adopting AI technologies in our construction processes.	2.87	3	1.16	-0.036	-0.979	0.812	<.001
	ADO4	Employees in my organization are encouraged to work with or learn about AI systems and tools.	3.21	3	1.15	-0.329	-0.789	0.762	<.001
	ADO5	AI-based systems (e.g., computer vision, robotics, digital twins) are actively used in our ongoing construction projects.	2.82	3	1.21	-0.038	-1.140	0.856	<.001
	ADO6	My organization invests in AI to improve safety, productivity, and efficiency in construction work.	2.93	3	1.20	-0.220	-1.100	0.902	<.001
Job Crafting – Structural Job Resources (JC_SJR)	JC_SJR1	I try to develop my capabilities in using AI tools for project management. 'removed'	3.01	3	1.02	-0.298	-0.341	0.863	<.001
	JC_SJR2	I seek opportunities to expand my professional knowledge about AI applications in construction.	3.15	3	1.05	-0.219	-0.374	0.874	<.001
	JC_SJR3	I try to learn new AI-based methods and tools relevant to my work.	3.25	3	1.03	-0.407	-0.188	0.854	<.001
	JC_SJR4	I ensure that I use AI technologies to their fullest potential in my tasks. 'removed'	3.00	3	1.08	-0.128	-0.624	0.864	<.001
	JC_SJR5	I make autonomous decisions on how to use AI tools in my daily projects.	2.93	3	1.02	-0.117	-0.600	0.762	<.001
Job Crafting – Social Job Resources (JC_SOJR)	JC_SOJR1	I ask my supervisor for support in understanding and applying AI technologies.	2.20	2	1.11	0.652	-0.430	0.875	<.001
	JC_SOJR2	I ask whether my supervisor is satisfied with how I'm using AI in my work.	2.15	2	1.18	0.706	-0.580	0.909	<.001
	JC_SOJR3	I look to my supervisor as a role model in integrating AI into project management.	2.18	2	1.18	0.660	-0.652	0.850	<.001
	JC_SOJR4	I ask others for feedback on how effectively I'm using AI in my job.	2.31	2	1.18	0.537	-0.668	0.897	<.001

	JC_SOJR5	I ask colleagues for advice on using AI tools for specific project.	2.58	3	1.18	0.137	-0.927	0.865	<.001
Job Crafting – Challenging Job Demands (JC_CJD)	JC_CJD1	When an AI-driven project or pilot comes up, I volunteer to be involved. ‘removed’	2.73	3	1.18	0.071	-0.932	0.779	<.001
	JC_CJD2	I stay updated on new AI developments in construction and experiment with them when possible.‘removed’	2.93	3	1.10	-0.094	-0.746	0.827	<.001
	JC_CJD3	When routine work slows down, I use the time to explore innovative AI solutions for our processes.	2.78	3	1.10	-0.056	-0.774	0.837	<.001
	JC_CJD4	I regularly take on AI-related tasks or initiatives, even without extra compensation.	2.48	2	1.16	0.314	-0.864	0.805	<.001
	JC_CJD5	I use AI tools to analyse complex patterns and improve the strategic aspects of my job.	2.72	3	1.11	0.046	-0.808	0.895	<.001
Job Crafting – Hindering Job Demands (JC_HJD)	JC_HJD1	I adjust my use of AI systems to reduce mentally intense tasks.	3.08	3	1.09	-0.273	-0.541	0.789	<.001
	JC_HJD2	I try to use AI to reduce the emotional intensity of certain project tasks.	2.64	3	1.14	0.075	-0.886	0.863	<.001
	JC_HJD3	I use AI-based systems to filter or minimize emotionally draining interactions in project communications.	2.75	3	1.17	-0.067	-1.040	0.860	<.001
	JC_HJD4	I use AI to help manage unrealistic expectations from stakehlders.	2.36	2	1.13	0.398	-0.789	0.837	<.001
	JC_HJD5	I rely on AI decision-support tools to avoid making too many difficult decisions on my own.	2.40	2	1.08	0.217	-0.871	0.788	<.001
	JC_HJD6	I structure my AI-based workflows so I don’t need to concentrate for extended periods without a break.	2.41	2	1.14	0.344	-0.875	0.864	<.001
Work Engagement (ENG)	ENG1	At my work, I feel bursting with energy.	3.10	3	0.84	-0.210	-0.076	0.805	<.001
	ENG2	I am enthusiastic about my job.	3.48	4	0.88	-0.276	-0.125	0.862	<.001
	ENG3	I feel strong and vigorous.	3.36	3	0.90	-0.234	-0.004	0.748	<.001
	ENG4	My job inspires me.	3.20	3	1.00	-0.099	-0.347	0.873	<.001
	ENG5	I am proud of the work that I do.	3.78	4	0.95	-0.568	0.049	0.849	<.001
	ENG6	I find my work full of meaning and purpose.	3.39	3	1.05	-0.314	-0.507	0.917	<.001
	ENG7	I get carried away when I’m working.	3.11	3	0.98	-0.038	-0.371	0.679	<.001
	ENG8	I am immersed in my work.	3.41	3	0.94	-0.206	-0.249	0.823	<.001
	ENG9	I feel happy when I am working intensely.	3.44	3	0.95	-0.394	0.023	0.803	<.001
Emotional Exhaustion (EXH)	EXH1	I feel emotionally drained from my work.	2.48	2	0.94	0.831	0.239	0.884	<.001
	EXH2	I feel used up at the end of the workday.	2.69	2	1.02	0.441	-0.528	0.864	<.001
	EXH3	I feel fatigued when I get up in the morning and have to face another day on the job.	2.58	2	1.03	0.585	-0.228	0.912	<.001
	EXH4	I feel like I'm at the end of my rope.	1.90	2	1.00	1.220	1.080	0.870	<.001

4.3. Data Analysis

4.3.1 Data Screening and Assumptions

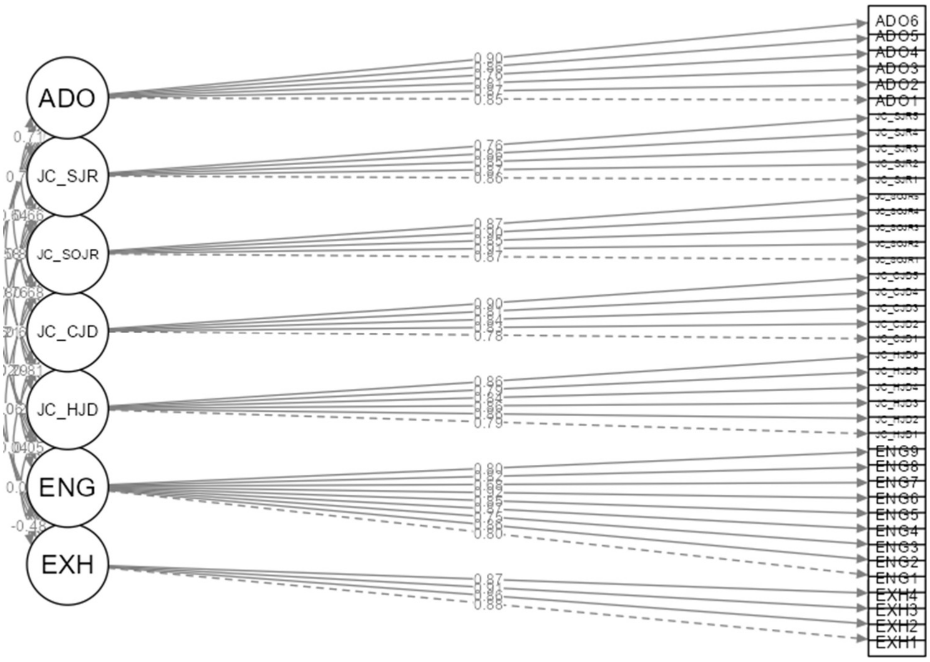
All statistical analyses were performed using Jamovi (version 2.6.26), an open-source statistical platform. Sample size adequacy was considered for CFA/SEM, as it impacts statistical power and model accuracy (Brown, 2015). While recommended sample sizes vary depending on model complexity, a minimum of 100 observations or 5–10 participants per indicator is often suggested (Schreiber et al., 2006). In the current study, 213 free parameters were estimated based on 40 observed indicators, using a sample of 393 participants, yielding a ratio of 9.8 participants per indicator. This exceeded the commonly cited minimum thresholds and was deemed acceptable for the analysis.

Data were screened to assess assumptions, including normality, outliers, multicollinearity, and factorability. Descriptive statistics are presented in Table 2. The descriptive statistics for all survey items (Table 2) indicate that the data approximated a normal distribution. Mean scores were generally close to the midpoint of the five-point Likert scale, suggesting no evidence of extreme response tendencies. Standard deviations ranged from 0.77 to 1.21, reflecting adequate variability without excessive dispersion. Skewness values fell between –1.09 and +1.22, and kurtosis ranged from –1.26 to +1.72. Both ranges fall within the commonly accepted thresholds of ±2 for social science research (George & Mallery, 2010), supporting the assumption of univariate normality. The Kaiser-Meyer-Olkin measure (KMO) was 0.935, indicating sampling adequacy, and Bartlett's Test of Sphericity was significant (χ^2 = 15,394, df = 1,431, $p < 0.001$), supporting factorability. These results suggest that the dataset is suitable for subsequent multivariate analyses such as factor analysis and structural equation modelling. Additionally, common method bias was assessed using Harman's single-factor test, in which all items were loaded onto a single factor in an exploratory factor analysis. The first factor explained 29.4% of the total variance, which is well below the 50% threshold commonly used to flag common method bias (Podsakoff et al., 2003).

4.3.2 Measurement Model and Model Fit

The measurement model demonstrated strong psychometric properties as shown in Table 2 and Figure 2. All indicators loaded significantly on their respective latent constructs, with standardised factor loadings ranging from 0.762 to 0.902 for ADO, 0.762 to 0.874 for JC_SJR, 0.850 to 0.909 for JC_SOJR, 0.805 to 0.895 for JC_CJD, 0.788 to 0.864 for JC_HJD, 0.679 to 0.917 for ENG, and 0.864 to 0.912 for EXH ($p < 0.001$ for all).

Figure 2: CFA Measurement Model with standardised path coefficients (β)



Source: Authors' creation

In addition, as shown in Table 3, the measurement model demonstrated good reliability and construct validity. All constructs exhibited strong internal consistency, with Cronbach's alpha (α) ranging from 0.894 to 0.928 and ordinal α from 0.916 to 0.944. Composite reliability indices (ω_1) ranged from 0.896 to 0.933, and Average Variance Extracted (AVE) values exceeded 0.688 for all constructs, indicating adequate convergent validity.

Table 3: Reliability indices

Variable	α	Ordinal α	ω_1	ω_2	ω_3	AVE
ADO	0.917	0.934	0.918	0.918	0.926	0.712
JC_SJR	0.903	0.921	0.904	0.904	0.915	0.713
JC_SOJR	0.915	0.938	0.925	0.925	0.943	0.773
JC_CJD	0.894	0.916	0.895	0.895	0.896	0.688
JC_HJD	0.907	0.926	0.914	0.914	0.932	0.696
ENG	0.928	0.944	0.933	0.933	0.950	0.673
EXH	0.896	0.928	0.902	0.902	0.916	0.779

*Note: α = Cronbach's alpha; Ordinal α = alpha for ordinal data; ω_1 = McDonald's omega total; ω_2 = omega hierarchical; ω_3 = omega subscale; AVE = Average Variance Extracted. ADO = AI Adoption; JC_SJR = Job Crafting – Structural Job Resources; JC_SOJR = Job Crafting – Social Job Resources; JC_CJD = Job Crafting – Challenging Job Demands; JC_HJD = Job Crafting – Hindering Job Demands; ENG = Work Engagement; EXH = Emotional Exhaustion.

Source: Authors' creation

In addition, discriminant validity, assessed using the Heterotrait-Monotrait (HTMT) ratio of correlations as shown in Table 4, showed that all construct correlations were below the recommended threshold of 0.85–0.90, supporting the distinctiveness of the constructs (Table 4).

Table 4: Heterotrait-monotrait (HTMT) ratio of correlations

	ADO	**JC_SJR**	**JC_SOJR**	**JC_CJD**	**JC_HJD**	**ENG**	**EXH**
ADO	1.0000	0.7225	0.7032	0.6351	0.5889	0.1479	0.0502
JC_SJR	0.7225	1.0000	0.6631	0.8834	0.7693	0.1908	0.0502
JC_SOJR	0.7032	0.6631	1.0000	0.6813	0.6461	0.2782	0.0672
JC_CJD	0.6351	0.8834	0.6813	1.0000	0.8167	0.2397	0.0463
JC_HJD	0.5889	0.7693	0.6461	0.8167	1.0000	0.0638	0.0665
ENG	0.1479	0.1908	0.2782	0.2397	0.0638	1.0000	0.4524
EXH	0.0502	0.0502	0.0672	0.0463	0.0665	0.4524	1.0000

*Note: ADO = AI Adoption; JC_SJR = Job Crafting – Structural Job Resources; JC_SOJR = Job Crafting – Social Job Resources; JC_CJD = Job Crafting – Challenging Job Demands; JC_HJD = Job Crafting – Hindering Job Demands; ENG = Work Engagement; EXH = Emotional Exhaustion.

Source: Authors' creation

The structural equation model demonstrated an acceptable fit to the data. The chi-square test was significant (χ^2 = 1,227, df = 719, p < .001), as expected given the sample size, and the scaled chi-square remained significant (χ^2_scaled = 1,481, df = 719, p < .001). Fit indices indicated good model fit: the Standardised Root Mean Square Residual (SRMR) was 0.045, and the Root Mean Square Error of Approximation (RMSEA) was 0.052 (95% CI: 0.048–0.056). Comparative fit indices were also high, including the Comparative Fit Index (CFI = 0.996), Tucker-Lewis Index (TLI = 0.996), Bentler-Bonett Non-normed Fit Index (NNFI = 0.996), Relative Noncentrality Index (RNI = 0.996), and Bentler-Bonett Normed Fit Index (NFI = 0.991), with the Parsimony Normed Fit Index (PNFI) at 0.913. Additional indices supported model adequacy, including the Goodness of Fit Index (GFI = 0.992), Adjusted GFI (AGFI = 0.990), and Hoelter's Critical N (α = 0.05 = 251). Overall, these results suggest that the proposed model provides a satisfactory representation of the observed data.

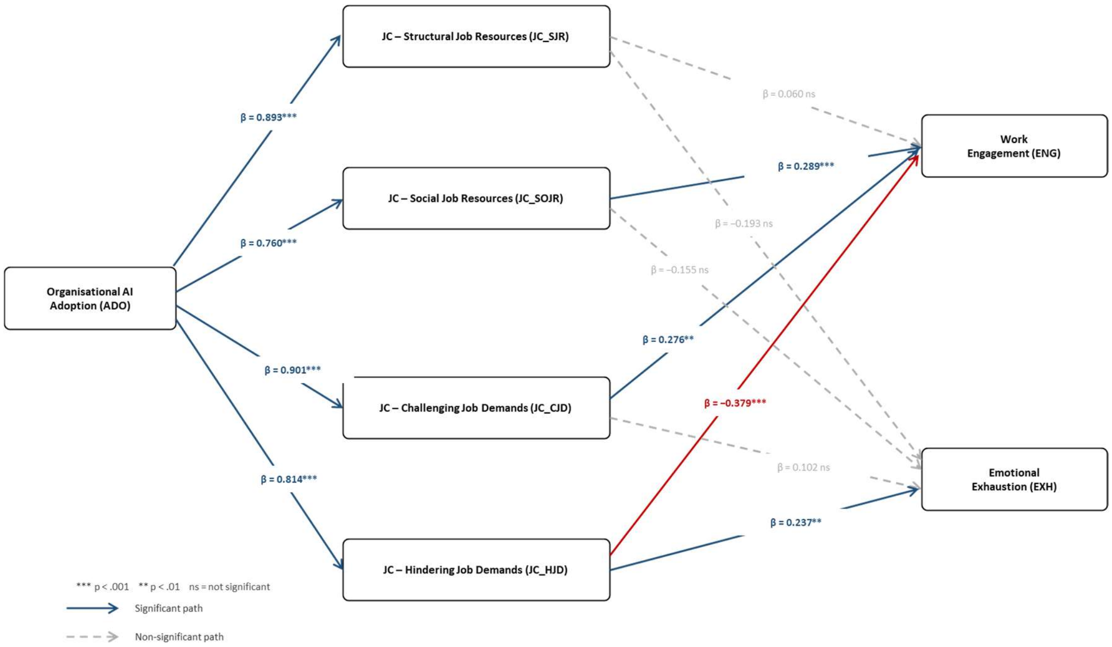
These results indicate that the measurement model is both reliable and valid, and that the SEM is appropriate for testing the hypothesised structural relationships among AI Adoption (ADO), the job crafting dimensions (Structural Job Resources (JC_SJR), Social Job Resources (JC_SJR), Challenging Job Demands (JC_CJD), and Hindering Job Demands (JC_HJD), and the outcome variables of work engagement (ENG) and emotional exhaustion (EXH).

4.3.4 Structural Model and Hypothesis Testing

SEM was conducted to test hypothesised relationships as shown in Figure 3. The structural equation model (SEM) demonstrated good fit to the data. The scaled fit indices indicated: chi-square (χ^2) = 2158 with 727 degrees of freedom, p < 0.001; Standardised Root Mean Square Residual (SRMR) = 0.061; and Root Mean Square Error of Approximation (RMSEA) = 0.071 (95% CI [0.067, 0.074]). Incremental fit indices were excellent, including Comparative Fit Index (CFI) = 0.988, Tucker-Lewis Index (TLI) = 0.987, Non-Normed Fit Index (NNFI) = 0.987, Incremental Fit Index (IFI) = 0.988, Normed Fit Index (NFI) = 0.982, Relative Fit Index (RFI) = 0.981, and Relative Noncentrality Index (RNI) = 0.988. Absolute and parsimony-adjusted indices also supported good fit: Goodness-of-Fit Index (GFI) = 0.985, Adjusted Goodness-of-Fit Index

(AGFI) = 0.980, Parsimony Normed Fit Index (PNFI) = 0.916, and Parsimony Goodness-of-Fit Index (PGFI) = 0.762.

Figure 3: Structural Equation Model Paths (standardised β)



Source: Authors' creation

Structural equation modeling results as show in Table 5, indicated that AI Adoption (ADO) significantly predicted all four job crafting dimensions: Job Crafting – Structural Job Resources (JC_SJR; β = 0.893, p < .001), Job Crafting – Social Job Resources (JC_SOJR; β = 0.760, p < .001), Job Crafting – Hindering Job Demands (JC_HJD; β = 0.814, p < .001), and Job Crafting – Challenging Job Demands (JC_CJD; β = 0.901, p < .001).

In turn, Work Engagement (ENG) was positively influenced by Job Crafting – Social Job Resources (β = 0.289, p < .001) and Job Crafting – Challenging Job Demands (β = 0.276, p = 0.003), but negatively associated with Job Crafting – Hindering Job Demands (β = −0.379, p < .001). Job Crafting – Structural Job Resources did not significantly impact engagement (β = 0.060, p = 0.552).

Regarding Emotional Exhaustion (EXH), only Job Crafting – Hindering Job Demands had a significant positive effect (β = 0.237, p = 0.006), whereas Structural, Social, and Challenging Job Demands crafting had non-significant effects (βs = −0.193, −0.155, 0.102; ps > 0.05).

Table 5: Structural Path Estimates and Hypothesis Testing Results

Hypothesis	Dependent Variable	Predictor	Estimate	SE	95% CI Lower	95% CI Upper	β	z	p	Result
H1	JC_SJR	ADO	0.9679	0.0338	0.9017	1.0341	0.8928	28.665	<.001	Supported
H2	JC_SOJR	ADO	0.8344	0.0366	0.7627	0.9061	0.7600	22.804	<.001	Supported
H3	JC_CJD	ADO	0.8783	0.0373	0.8052	0.9515	0.9012	23.528	<.001	Supported
H4	JC_HJD	ADO	0.8031	0.0398	0.7251	0.8810	0.8138	20.186	<.001	Supported
H5	ENG	JC_SJR	0.0555	0.0933	-0.1274	0.2384	0.0595	0.594	0.552	Not Supported
H6	ENG	JC_SOJR	0.2663	0.0688	0.1314	0.4012	0.2894	3.868	<.001	Supported
H7	EXH	JC_SJR	-0.1978	0.1096	-0.4127	0.0171	-0.1933	-1.804	0.071	Not Supported
H8	EXH	JC_SOJR	-0.1569	0.0935	-0.3401	0.0262	-0.1553	-1.679	0.093	Not Supported
H9	ENG	JC_CJD	0.2862	0.0967	0.0967	0.4756	0.2761	2.961	0.003	Supported
H10	EXH	JC_CJD	0.1166	0.1105	-0.1000	0.3331	0.1024	1.055	0.291	Not Supported
H11	ENG	JC_HJD	-0.3880	0.0818	-0.5483	-0.2277	-0.3790	-4.744	<.001	Supported
H12	EXH	JC_HJD	0.2666	0.0965	0.0775	0.4557	0.2371	2.763	0.006	Supported

To assess the robustness of the structural equation modelling results, we conducted bias-corrected bootstrapping with 5,000 resamples. The 95% bootstrapped confidence intervals (CIs) confirmed the structural relationships reported in Figure 3 and Table 5. AI adoption significantly predicted all four job-crafting dimensions: structural resources (b = 0.700, 95% CI [0.590, 0.818]), social resources (b = 0.724, 95% CI [0.618, 0.840]), challenging demands (b = 0.685, 95% CI [0.573, 0.815]) and reduced hindering demands (b = 0.558, 95% CI [0.444, 0.692]). For outcomes, social job resources (b = 0.181, 95% CI [0.088, 0.289]) and challenging demands (b = 0.241, 95% CI [0.076, 0.413]) increased engagement, whereas reducing hindering demands decreased engagement (b = –0.308, 95% CI [–0.469, –0.167]). For emotional exhaustion, only reduced hindering demands showed a significant positive effect (b = 0.206, 95% CI [0.006, 0.433]). All other bootstrapped CIs crossed zero. These results validate the robustness of the originally reported paths.

Finally, the sample characteristics revealed that 86.0% of respondents were based in the United Kingdom, which introduces a potential geographic concentration bias. To assess whether this imbalance may have affected the results, we compared United Kingdom and non-United Kingdom participants on all key study variables using independent samples t-tests. The results indicated no significant differences on the AI adoption items, job-crafting items, work engagement items, or emotional exhaustion items (ps > .05), with only a few isolated item-level differences observed (e.g., JC_SOJR1, EXH3). As the composite constructs used in the SEM were unaffected, these results suggest that the geographic concentration of United Kingdom respondents did not bias the study variables or the structural relationships.

These findings suggest that AI Adoption promotes proactive job crafting. Still, the effects of specific crafting strategies on employee outcomes differ: social and challenging crafting enhance engagement, whereas hindering crafting increases strain. These implications are further discussed in the following section.

5. Discussion

5.1 AI Adoption and Job Crafting Behaviours

Consistent with the Job Crafting framework (Tims et al., 2012) and recent empirical studies (Li et al., 2024; Xiao et al., 2023; He et al., 2023), our findings, shown in Figure 3 and Table 5, indicate that organisational AI adoption is positively associated with all four dimensions of job crafting. Given the cross-sectional and self-reported design, these coefficients are interpreted as evidence of association and pattern consistency rather than causal effects. Among these, the strongest effect was observed for structural job resources ($\beta = 0.893$, H1 supported), suggesting that AI tools enhance employees' skills, autonomy, and task-related expertise. This aligns with prior research indicating that AI-driven analytics, predictive scheduling, and automated decision-support systems allow employees to take proactive control of their work, thereby supporting role enrichment and innovation (Pan & Zhang, 2021a; Abioye et al., 2021). This interpretation is most applicable to construction project roles represented in the sample, and the strength of effects may vary with digital maturity, task standardisation, and project governance arrangements.

Our findings also resonate with studies that highlight the nuanced perceptions of AI adoption. Cheng et al. (2023) reported that employees appraise AI either as a challenge or a hindrance: challenge appraisals stimulate promotion-focused job crafting, whereas hindrance appraisals lead to avoidance or prevention-focused behaviours. Similarly, Tan (2024) found that while AI adoption can increase anxiety, it simultaneously encourages task and cognitive crafting. In line with these observations, our study indicates that employees actively leverage AI to enhance task structure and cognitive engagement, supporting the argument that AI can both challenge and empower employees in their work.

Moreover, the literature underscores the mediating role of job crafting in shaping work outcomes in AI-enabled contexts. Perez, Conway, and Roques (2022) highlighted that job crafting mediates the relationship between AI implementation and employee outcomes, while Law and Varanasi (2025) identified a novel form of job crafting in which employees delegate routine tasks to AI, focus on higher-value work, and engage in AI monitoring or curation. Our findings are consistent with these prior studies, suggesting that employees exploit AI capabilities to support efficiency and to shape new forms of work engagement and value.

Regarding social job resources, AI adoption significantly increased opportunities for collaboration, feedback, and knowledge exchange ($\beta = 0.760$, H2 supported). This confirms prior evidence that technological integration strengthens workplace social networks and peer learning (He et al., 2023), and it suggests that AI fosters a supportive environment conducive to social job crafting in construction contexts.

Challenging job demands were also positively influenced by AI adoption ($\beta = 0.901$, H3 supported), indicating that employees may perceive AI-enabled tasks as growth opportunities rather than stressors. This finding aligns with the challenge-hindrance stressor framework (LePine et al., 2005), showing that AI can stimulate proactive engagement with complex tasks.

Finally, AI adoption was positively associated with hindering job demands reduction ($\beta = 0.814$, H4 supported), which is interpreted as perceived reduction in hindering demands rather than objective workload change, reinforcing the JD-R model's claim that reducing hindering demands facilitates role optimisation (Bakker & Demerouti, 2007).

5.2. Job Resources and Employee Well-Being

The motivational potential of job resources, as proposed by the JD-R model (Bakker & Demerouti, 2007), was partially supported in this study. Social job resources positively influenced work engagement ($\beta = 0.289$, H6 supported), indicating that collaboration, feedback mechanisms, and knowledge-sharing opportunities enhance employees' energy, absorption, and enthusiasm. The interpretation of these effects is bounded by the measurement approach, because engagement and exhaustion were captured via self-reports, which may reflect perceptions shaped by current project pressures and organisational climate.

In contrast, structural job resources did not significantly impact engagement (H5 not supported), and neither structural nor social resources significantly affected emotional exhaustion (H7 to H8 not supported). This limits the strength of claims about resources acting as a universal buffer in AI-intensive construction work, and suggests that the motivational pathway may be more salient than the buffering pathway in this dataset. Because the design is cross-sectional, the possibility of reciprocal dynamics also remains, where engagement influences subsequent resource seeking, rather than resources solely driving engagement.

Several studies offer possible explanations for these discrepancies, specifically why structural resources were not significant for engagement and why neither resource type was significant for exhaustion in our sample. Uslukaya and Zincirli (2025) found that job resources and work engagement are reciprocally linked, with prior engagement predicting later resource acquisition. Bedendo et al. (2023) reported that job resources strongly predicted work engagement ($b = 3.09$, $p \leq .001$), while Bakker, Demerouti, and Xanthopoulou (2022), in a meta-analysis, confirmed strong positive associations between job resources and engagement ($r = 0.46$) and negative associations with burnout ($r = -0.38$).

Taken together, these findings suggest that the motivational effects of job resources are context-dependent. In AI-intensive construction environments, structural and social resources may enhance engagement but may not sufficiently counteract emotional strain, highlighting the need for complementary interventions, such as targeted training, workload management, or AI support systems, to sustain well-being.

5.3. Job Demands and Employee Well-Being

The results for job demands revealed important nuances in AI-enabled construction contexts. Engagement was positively associated with challenging job demands (H9 supported), consistent with the idea that employees perceive complex, stimulating tasks as opportunities for growth. However, contrary to expectations, reductions in hindering job demands negatively predicted engagement (H11 supported) and positively predicted emotional exhaustion (H12 supported). This pattern suggests that offloading routine tasks through AI, while intended to reduce strain, may inadvertently diminish meaningful engagement or increase perceived monitoring and performance pressure. However, because the study is cross-sectional, this interpretation is presented as a plausible explanation rather than a demonstrated mechanism, and reverse or reciprocal relationships cannot be ruled out.

Challenging job demands did not significantly affect emotional exhaustion (H10 not supported), indicating that when employees are equipped with AI skills and social support, cognitive and task-related challenges may be experienced as motivating rather than draining. These findings extend the challenge-hindrance literature by demonstrating that the effects of AI-enabled demands are highly context-dependent and shaped by the nature of work tasks and available resources.

Existing management research provides both supporting and contrasting evidence. Dlouhy, Schmitt, and Kandel (2024) reported that job demands increase emotional exhaustion, while job resources enhance engagement and buffer some negative effects of demands. Similarly, Rahnfeld, Wendsche, and Wegge (2023) found that time pressure and social conflict predicted exhaustion and intention to leave, with job resources mitigating these relationships and certain effects moderated by health and age. Claes, Vandepitte, Clays, and Annemans (2023) reported that work demands negatively affect well-being, whereas job resources exert positive effects, with job satisfaction mediating these associations. Zhou et al. (2022) observed that healthcare workers' burnout and anxiety were positively linked to job demands, while social and organisational support promoted well-being. Thapa et al. (2022) similarly found that high demands such as emotional strain and workload predicted poorer health outcomes, but employees with greater resources coped more effectively.

Together, these studies suggest that while job resources generally promote engagement and buffer strain, the relationship between job demands and well-being is complex and highly context-dependent. In AI-intensive construction projects, reducing hindering demands may not always yield the expected benefits, as such reductions can unintentionally limit opportunities for meaningful work and professional growth. Accordingly, the practical implication is not that hindering demand reduction is harmful in general, but that in some AI-mediated arrangements, how tasks are offloaded and monitored may shape whether reductions in hindering demands translate into improved well-being

5.4. Synthesis of Findings

Taken together, the findings indicate that AI adoption strongly relates to proactive job crafting across multiple dimensions. Social resources and challenging demands reliably promote engagement, but structural resources and reduction of hindering demands produce mixed effects on well-being. These conclusions are intentionally framed as context-specific and association-based, reflecting the cross-sectional design, the construction-focused sample, and the self-reported measurement approach. The findings underscore the double-edged nature of AI in construction: while AI empowers employees with new capabilities and opportunities, it may simultaneously introduce subtle stressors or reduce engagement when it replaces meaningful task interactions.

The differential impact of these dimensions on work engagement and emotional exhaustion warrants further examination, particularly in light of the shifting age demographic within the construction industry. The construction workforce in most developed countries are ageing (Chartered Institute of Building, 2015). Older construction workers often face compounded challenges including physical strain, age-related health concerns, and evolving technological demands (World Health Organization, 2007). AI technologies (ranging from wearable assistive devices to intelligent scheduling systems) have the potential to support older workers by enabling proactive job crafting. The positive influence of social job resources and challenging job demands on engagement suggests that AI tools which foster collaboration, mentorship, and cognitively stimulating roles may be particularly beneficial for older workers.

Conversely, the finding that structural job resources did not significantly influence engagement implies that simply modifying task structures or increasing autonomy may not suffice for older workers unless these changes are accompanied by meaningful social or cognitive opportunities. This is especially relevant in construction settings where autonomy may be constrained by safety protocols and project timelines. While it is essential to mitigate physical and psychological stressors for older workers, over-reduction of demands may inadvertently diminish their perceived value and contribution. In this context, AI should be leveraged to support continued participation through supportive technologies (such as exoskeletons, and adaptive tools) that reduce strain without compromising engagement, while recognising that the effectiveness of such interventions should be tested using longitudinal or field evaluation designs.

6. Conclusion

6.1 Summary of findings

This study examined how organisational AI adoption influences construction employees' job crafting behaviours and how these crafting behaviours, in turn, affect work engagement and emotional exhaustion. Drawing on Job Crafting theory and the Job Demands–Resources (JD R) model, the study developed and empirically validated AI related job crafting measures tailored to construction project management contexts, and tested a 12 hypothesis structural model using SEM with data from 393 construction professionals across European countries.

In response to RQ1, the findings indicate that, within the studied context, organisational AI adoption was a significant and positive antecedent of all four job crafting dimensions: structural job resources (β = 0.893), challenging job demands (β = 0.901), social job resources (β = 0.760), and hindering job demand reduction (β = 0.814). These results suggest that when organisations strategically adopt AI, employees respond proactively by developing new capabilities, seeking collaboration, taking on complex AI driven tasks, and using AI to reduce strain inducing aspects of their work. The strongest effects were observed for structural resources and challenging demands, consistent with the interpretation that AI adoption can empower employees to grow their task expertise and engage with cognitively stimulating challenges.

In response to RQ2, the effects of job crafting dimensions on well being were more nuanced. Social job resources (β = 0.289) and challenging job demands (β = 0.276) positively predicted work engagement, consistent with the JD R model's motivational pathway. Structural job resources, however, did not significantly predict engagement (β = 0.060, p = .552), nor did they significantly reduce emotional exhaustion. Most strikingly, reductions in hindering job demands, contrary to theoretical expectations, negatively predicted engagement (β = −0.379) and positively predicted emotional exhaustion (β = 0.237). This counterintuitive pattern suggests that when AI assumes cognitively demanding or emotionally taxing tasks, employees may lose access to the stimulating aspects of their work that previously sustained meaning, purpose, and engagement. Taken together, these findings highlight the double-edged nature of AI in construction: it can empower employees with new capabilities and may risk eroding meaningful engagement when it over-automates the demanding tasks that give work its motivational character.

6.2 Theoretical Contributions

This study contributes to the growing body of research at the intersection of AI, job crafting, and employee well-being in project-based contexts. While existing literature has extensively examined the JD-R model and job crafting in traditional organisational settings, limited attention has been given to how emerging technologies such as AI reshape these dynamics in complex and high-pressure industries such as construction. By empirically testing the effects of AI adoption on multiple dimensions of job crafting and their consequences for work engagement and emotional exhaustion, this study advances theoretical understanding in several important ways.

First, based on Tims et al. (2012), our study developed and operationalised measures of AI-related job crafting within the JD-R framework, tailored to the domain-specific context of construction project management, and these measures provide an empirical basis for examining the proposed relationships within the studied context. This contribution enables future research to capture how construction employees reshape tasks and interactions in response to AI-enabled changes in work design. Second, the study introduces AI adoption as a novel antecedent of job crafting behaviours, extending the scope of the Job Crafting framework (Tims et al., 2012). By showing that AI adoption significantly predicts structural, social, challenging, and hindering job crafting dimensions, the research advances understanding of how technology itself can act as a resource that reshapes employee agency. Prior work largely conceptualised job crafting as an individual-level initiative shaped by personal or social factors; this study highlights the organisational adoption of AI as a structural enabler of proactive work design. This offers new theoretical directions into the role of digital transformation in shaping employee behaviours and provides a foundation for integrating technology-related constructs into job crafting theory.

Third, the study extends the JD-R model by empirically demonstrating that AI-enabled resources and demands have differential effects on work engagement and exhaustion in construction project management. Whereas earlier studies found consistent positive associations between job resources and both engagement and reduced exhaustion (Schaufeli & Bakker, 2004; Tims et al., 2013), this study reveals a more complex picture: social resources reliably enhance engagement, but structural resources do not, and neither type of resource significantly reduces exhaustion. These findings refine the JD-R model by suggesting that in high-demand, project-based environments, the motivational role of resources may outweigh their buffering role. This extension adds contextual specificity to JD-R theory, emphasising that resource effects may vary in technology-intensive, project-driven sectors.

A fourth contribution lies in challenging the conventional JD-R assumption that reducing hindering job demands invariably benefits well-being. Contrary to prior research (e.g., Van den Broeck et al., 2017; Vander Elst et al., 2016), this study demonstrates that decreases in hindering demands, when mediated through AI systems, can paradoxically lower engagement and heighten emotional exhaustion. This challenges the dominant narrative that technological tools only alleviate strain and suggests that, in AI-intensive work contexts, reducing routine or cognitively draining tasks may inadvertently diminish meaningful engagement opportunities or introduce new forms of pressure. This reconceptualisation calls for more fine-grained theorisation of hindering demands in technologically mediated environments.

Finally, this study fills a gap in the literature on AI and human resource practices in construction, an industry where digital transformation is rapidly advancing but empirical evidence remains scarce (Abioye et al., 2021; Amoah, 2025). By focusing on construction project professionals, the study responds to calls for research examining the implications of AI adoption for employee behaviour and well-being in dynamic, safety-critical, and innovation-driven settings. It also empirically validates the integration of AI adoption within job crafting and JD-R frameworks, thereby extending these theories into a novel domain and setting a foundation for future cross-sectoral investigations.

6.3 Managerial Contributions

The findings of this study offer several context-specific recommendations for managers, policymakers, and organisational leaders seeking to leverage AI in construction project management while safeguarding employee well-being. Given the cross-sectional, self-reported design, these recommendations are framed as practical considerations that are consistent with the observed associations, rather than as guaranteed effects.

First, organisations can view AI adoption not merely as a technological upgrade but as a catalyst for proactive job crafting. In line with the observed positive associations between AI adoption and job crafting dimensions in this sample, managers can support job crafting by integrating AI tools and work practices that strengthen structural and social resources, such as opportunities for skills development, decision support, and collaboration. This requires aligning AI deployment with employee capabilities and providing clear guidance on how technology can support meaningful work tasks, recognising that the most effective configurations may vary by role, project phase, and organisational AI maturity.

Second, the study highlights the double-edged nature of AI: while reducing hindering demands may appear beneficial, it can coincide with lower engagement and higher emotional strain in some AI-mediated arrangements. Managers should therefore monitor how AI redistributes workload and cognitive demands, ensuring that automation or task offloading does not unintentionally remove opportunities for skill use, problem-solving, and decision-making autonomy. Because the evidence is correlational, managers should treat this as a signal to review job design and AI use practices, rather than as evidence that hindering demand reduction is inherently harmful.

Third, organisational policies can prioritise ongoing AI literacy and skills development. Providing employees with training on AI tools, analytics, and decision support can help them engage with challenging tasks as opportunities for growth, and it may reduce uncertainty that contributes to strain. Given that training effects were not tested directly in this study, this implication is presented as a reasonable managerial lever that should be evaluated and refined through local implementation and feedback.

Fourth, managers can cultivate a culture of collaboration and feedback around AI use. Encouraging peer support, knowledge sharing, and mentorship can strengthen social resources, which in this study were positively associated with engagement in AI-enabled project contexts. To reduce reliance on perceptions alone, organisations may complement surveys with behavioural indicators such as participation in learning sessions, help-seeking patterns, or uptake of collaboration tools.

Finally, policymakers and industry regulators can encourage AI adoption frameworks that balance efficiency aims with employee well-being considerations. Standards for AI implementation can consider not only technical performance but also how technologies influence work design, engagement, and strain, supporting sustainable workforce practices in safety-critical project environments. Given the construction-focused sample, such frameworks should be developed with sector-specific consultation and then tested across settings before broad generalisation.

6.4 Limitations & Future Research Directions

This study has several limitations. First, it relied on cross-sectional survey data, which constrains the ability to draw causal inferences. Second, the focus on construction managers and professionals may limit the generalizability of findings to other industries or job types. Third, the use of self-reported measures may introduce common method bias, although steps were taken to ensure the reliability and validity of the scales. Future research could address these limitations in several ways. Longitudinal studies could examine the temporal effects of AI adoption on job crafting and well-being. The moderating role of AI competence and training also warrants investigation. Additionally, exploring sector-specific variations may clarify how AI adoption impacts employee outcomes across different organisational contexts.

Experimental or diary-based designs could provide deeper insights into causal mechanisms and the temporal dynamics of engagement and emotional exhaustion. Future studies might also leverage physiological, behavioural, and cognitive data captured through wearable sensors to better understand discrepancies between perceived and actual levels of engagement or exhaustion. Accounting for such individual variability could offer novel insights into how AI influences well-being in the workplace. Finally, given the increasingly intergenerational composition of the construction workforce, it would be valuable to examine how AI adoption differs across age groups and how these differences affect well-being both within and between age cohorts.

Data availability statement

Data will be available upon request.

Conflict of interest statement

The authors declare no conflict of interst.

References

Abioye, S. O., Oyedele, L. O., Akanbi, L., Ajayi, A., Delgado, J. M. D., Bilal, M., & Ahmed, A. (2021). Artificial intelligence in the construction industry: A review of present status, opportunities and future challenges. *Journal of Building Engineering, 44*, 103299.

Adebayo, Y., Udoh, P., Kamudyariwa, X. B., & Osobajo, O. A. (2025). Artificial intelligence in construction project management: A structured literature review of its evolution in application and future trends. Digital, 5(3), 26.

AlMemari, M., Khalid, K., & Osman, A. (2025). Job crafting-job embeddedness linkage of construction professionals: moderating effect of career stages. *Journal of Engineering, Design and Technology*, *23*(1), 108-125.

Amoah, K. B. (2025). The artificial intelligence (AI) impact on construction project management. In *ISARC. Proceedings of the International Symposium on Automation and Robotics in Construction* (Vol. 42, pp. 1284–1291). IAARC Publications.

Aronsson, G., Theorell, T., Grape, T., Hammarström, A., Hogstedt, C., Marteinsdottir, I., … Hall, C. (2017). A systematic review including meta-analysis of work environment and burnout symptoms. *BMC Public Health, 17*(1), 264.

Bakker, A. B., & Demerouti, E. (2007). The job demands–resources model: State of the art. *Journal of Managerial Psychology, 22*(3), 309–328.

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.

Bakker, A. B., Demerouti, E., Taris, T. W., Schaufeli, W. B., & Schreurs, P. (2003). A multi-group analysis of the job demands–resources model in four home care organizations. *International Journal of Stress Management, 10*(1), 16–38.

Bakker, A. B., Demerouti, E., & Xanthopoulou, D. (2022). Revisiting the job demands–resources model: A meta-analysis of job resources and employee well-being. *European Journal of Work and Organizational Psychology, 31*(4), 515–535. https://doi.org/10.1080/1359432X.2021.2004799

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Prentice-Hall.

Bedendo, A., Papworth, A., Taylor, J., et al. (2023). Work-related resources and demands predicting the psychological well-being of staff in children's hospices. *Palliative and Supportive Care, 21*(6), 1024–1033. https://doi.org/10.1017/S147895152300161X

Belousova, O., & Gailly, B. (2013). Firm intrapreneurship in a dispersed setting: Actors, behaviors, and processes. *The International Entrepreneurship and Management Journal, 9*, 361–377.

Berg, J. M., & Dutton, J. E. (2008). Crafting a fulfilling job: Bringing passion into work. Retrieved from Positive Organizational Scholarship website: https://positiveorgs.bus.umich.edu

Blanka, C. (2018). An individual-level perspective on intrapreneurship: A review and ways forward. *Review of Managerial Science, 12*(1), 1–43.

Brattberg, E., Rugova, V., & Csernatoni, R. (2020). *Europe and AI: Leading, lagging behind, or carving its own way?* Carnegie Endowment for International Peace.

Budhwar, P., Malik, A., De Silva, M. T. T., & Thevisuthan, P. (2022). Artificial intelligence – challenges and opportunities for international HRM: A review and research agenda. *International Journal of Human Resource Management, 33*(6), 1065–1097.

Cabinet Office. (2011). *Government construction strategy*. https://www.gov.uk/government/publications/government-construction-strategy

Chartered Institute of Building. (2015). *Exploring the impact of the ageing population on the workforce and built environment*. https://www.ciob.org/media/61/download

Chen, X., Chang-Richards, A. Y., Pelosi, A., Jia, Y., Shen, X., Siddiqui, M. K., & Yang, N. (2022). Implementation of technologies in the construction industry: A systematic review. *Engineering, Construction and Architectural Management, 29*(8), 3181–3209.

Cheng, B., Lin, H., & Kong, Y. (2023). Challenge or hindrance? How and when organizational artificial intelligence adoption influences employee job crafting. *Journal of Business Research, 164*, 113987.

Claes, S., Vandepitte, S., Clays, E., & Annemans, L. (2023). How job demands and job resources contribute to our overall subjective well-being. *Frontiers in Psychology, 14*, 1220263. https://doi.org/10.3389/fpsyg.2023.1220263

Crant, J. M. (1995). The proactive personality scale and objective job performance among real estate agents. *Journal of Applied Psychology, 80*(4), 532–537.

Crawford, E. R., LePine, J. A., & Rich, B. L. (2010). Linking job demands and resources to employee engagement and burnout: A theoretical extension and meta-analytic test. *Journal of Applied Psychology, 95*(5), 834–848.

Danna, K., & Griffin, R. W. (1999). Health and well-being in the workplace: A review and synthesis of the literature. *Journal of Management, 25*(3), 357–384. https://doi.org/10.1177/014920639902500305

Deci, E. L., & Ryan, R. M. (2000). The "what" and "why" of goal pursuits: Human needs and the self-determination of behaviour. *Psychological Inquiry, 11*(4), 227–268. https://doi.org/10.1207/S15327965PLI1104_01

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., Mostert, K., & Bakker, A. B. (2010). Burnout and work engagement: A thorough investigation of the independency of both constructs. *Journal of Occupational Health Psychology, 15*(3), 209–222.

Doden, W., Bindl, U. K., & Unger, D. (2022). Implications of daily relational job crafting in the context of task interdependence. In *Academy of Management Proceedings* (Vol. 2022, No. 1, p. 14034). Academy of Management.

Dong, D. (2025). Self-determination theory perspectives on the influence of digital learning engagement on motivation in extracurricular learning activities: Considering the mediating role of digital self-efficacy. *Learning and Motivation, 90*, 102135.

Dong, X., Tian, Y., He, M., & Wang, T. (2025). When knowledge workers meet AI? The double-edged sword effects of AI adoption on innovative work behavior. *Journal of Knowledge Management, 29*(1), 113–147.

Egwim, C. N., Alaka, H., Luqman Toriola-Coker, O., Balogun, H., & Sunmola, F. (2021). Applied artificial intelligence for predicting construction projects delay. *Machine Learning with Applications, 6*(1), 100166.

Egwim, C. N., Alaka, H., Demir, E., Balogun, H., Olu-Ajayi, R., Sulaimon, I., Wusu, G., Yusuf, W., & Muideen, A. A. (2024). Artificial intelligence in the construction industry: A systematic review of the entire construction value chain lifecycle. *Energies, 17*(1), 182.

ElMenshawy, M., Wu, L., Gue, B., & AbouRizk, S. (2025). Automating pipe spool fabrication shop scheduling for modularized industrial construction projects using reinforcement learning. *Journal of Computing in Civil Engineering, 39*(3), 04025013.

Emaminejad, N., Kath, L., & Akhavian, R. (2023, August 28). Assessing trust in construction AI-powered collaborative robots using structural equation modeling [Preprint]. *arXiv*. https://arxiv.org/abs/2308.14697

Engström, A., Pittino, D., Mohlin, A., Johansson, A., & Edh Mirzaei, N. (2024). Artificial intelligence and work transformations: Integrating sensemaking and workplace learning perspectives. *Information Technology & People, 37*(7), 2441–2461.

Eurostat. (2024). Use of artificial intelligence in enterprises. https://shorturl.at/6CXC5

Farrukh, M., & Ghazzawi, I. (2024). Intrapreneurship research: What have we learned and where can we go from here? *International Journal of Innovation Science*. Advance online publication. https://doi.org/10.1108/IJIS-11-2023-0237

Feldmann, A., & Teuteberg, F. (2020). Intrapreneurship: Outside the project box and into the unknown. *Journal of Business Strategy, 41*(3), 45–55.

Fridgeirsson, T. V., Ingason, H. T., Jonasson, H. I., & Gunnarsdottir, H. (2023). A qualitative study on artificial intelligence and its impact on the project schedule, cost and risk management knowledge areas as presented in PMBOK. *Applied Sciences, 13*(19), 11081.

Gao, Y., Wang, J., & Xu, X. (2024). Machine learning in construction and demolition waste management: Progress, challenges, and future directions. *Automation in Construction, 162*, 105380.

Gawke, J. C., Gorgievski, M. J., & Bakker, A. B. (2017). Employee intrapreneurship and work engagement: A latent change score approach. *Journal of Vocational Behavior, 100*, 88–100.

Gawke, J. C., Gorgievski, M. J., & Bakker, A. B. (2019). Measuring intrapreneurship at the individual level: Development and validation of the Employee Intrapreneurship Scale (EIS). *European Management Journal, 37*(6), 806–817.

George, D., & Mallery, P. (2010). *SPSS for Windows step by step: A simple guide and reference* (10th ed.). Pearson.

Ghimire, P., Kim, K., & Acharya, M. (2024). Opportunities and challenges of generative AI in construction industry: Focusing on adoption of text-based models. *Buildings, 14*(1), 220.

Globocnik, D., & Salomo, S. (2015). Do formal management practices impact the emergence of bootlegging behavior? *Journal of Product Innovation Management, 32*, 505–521.

Guerrero, M., & Peña-Legazkue, I. (2013). The effect of intrapreneurial experience on corporate venturing: Evidence from developed economies. *The International Entrepreneurship and Management Journal, 9*, 397–416.

Hackman, J. R., & Oldham, G. R. (1976). Motivation through the design of work: Test of a theory. *Organizational Behavior and Human Performance, 16*(2), 250–279.

Haffer, R., Haffer, J., & Morrow, D. L. (2021). Work outcomes of job crafting among the different ranks of project teams. *Project Management Journal, 52*(2), 146–160.

Han, X., Chen, F., Wang, H., & Xu, S. (2025). Unlocking innovation: Artificial intelligence usage and innovative behavior in the workplace. *Social Behavior and Personality: An International Journal, 53*(3), e13851.

Harichandran, A., Raphael, B., & Mukherjee, A. (2023). Equipment activity recognition and early fault detection in automated construction through a hybrid machine learning framework. *Computer-Aided Civil and Infrastructure Engineering, 38*(2), 253–268.

He, G., Liu, P., Zheng, X., Zheng, L., Hewlin, P. F., & Yuan, L. (2023). Being proactive in the age of AI: Exploring the effectiveness of leaders' AI symbolization in stimulating employee job crafting. *Management Decision, 61*(10), 2896–2919.

Heng, H. K. S., & Loosemore, M. (2013). Structural holes in hospital organisations: Facilities managers as intrapreneurial brokers in the tertiary health sector. *Engineering, Construction and Architectural Management, 20*(5), 474–487.

Holzmann, V., Zitter, D., & Peshkess, S. (2022). The expectations of project managers from artificial intelligence: A Delphi study. *Project Management Journal, 53*(5), 438–455.

Hornung, S., Rousseau, D. M., Glaser, J., Angerer, P., & Weigl, M. (2010). Beyond top–down and bottom–up work redesign: Customizing job content through idiosyncratic deals. *Journal of Organizational Behavior, 31*, 187–215.

Huang, Y., & Gursoy, 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*, 103700.

Jiang, C., Li, X., Lin, J. R., Liu, M., & Ma, Z. (2023). Adaptive control of resource flow to optimize construction work and cash flow via online deep reinforcement learning. *Automation in Construction, 150*, 104817.

Jin, G., Jiang, J., & Liao, H. (2024). The work affective well-being under the impact of AI. *Scientific Reports, 14*, 25483.

Kass, S. J., Vodanovich, S. J., & Callender, A. (2001). State-trait boredom: Relationship to absenteeism, tenure, and job satisfaction. *Journal of Business and Psychology, 16*(3), 317–327.

Kim, B. J., & Kim, M. J. (2024). How artificial intelligence-induced job insecurity shapes knowledge dynamics: The mitigating role of artificial intelligence self-efficacy. *Journal of Innovation & Knowledge, 9*(4), 100590.

Kong, H., Yin, Z., Baruch, Y., & Yuan, Y. (2023). The impact of trust in AI on career sustainability: The role of employee–AI collaboration and protean career orientation. *Journal of Vocational Behavior, 146*, 103928.

Konuk, H., Ataman, G., & Kambur, E. (2023). The effect of digitalized workplace on employees' psychological well-being: Digital Taylorism approach. *Technology in Society, 74*, 102302.

Kulik, C. T., Oldham, G. R., & Hackman, J. R. (1987). Work design as an approach to person–environment fit. *Journal of Vocational Behavior, 31*(3), 278–296.

Law, M., & Varanasi, R. A. (2025). Generative AI and changing work: Systematic review of practitioner-led work transformations through the lens of job crafting. In *International Conference on Human–Computer Interaction* (pp. 131–152). Cham: Springer Nature Switzerland.

Lee, T. Y., Ahmad, F., & Sarijari, M. A. (2023). Current status and future research trends of construction labor productivity monitoring: A bibliometric review. *Buildings, 13*(6), 1479.

LePine, J. A., Podsakoff, N. P., & LePine, M. A. (2005). A meta-analytic test of the challenge stressor–hindrance stressor framework: An explanation for inconsistent relationships among stressors and performance. *Academy of Management Journal, 48*(5), 764–775.

Li, H., & Li, H. (2025). The double-edged sword effect of employee-AI collaboration on job crafting: A cognitive experiential perspective on work identity. *Journal of Managerial Psychology*, 1–15.

Li, W., Qin, X., Yam, K. C., Deng, H., Chen, C., Dong, X., & Tang, W. (2024). Embracing artificial intelligence (AI) with job crafting: Exploring trickle-down effect and employees' outcomes. *Tourism Management, 104*, 104935.

Lingard, H., & Turner, M. (2023). Measuring sense of place in project environments to promote positive mental wellbeing. *International Journal of Project Management, 41*(6), 102503. https://doi.org/10.1016/j.ijproman.2023.102503

Ma, J., Wang, P., Li, B., Wang, T., Pang, X. S., & Wang, D. (2025). Exploring user adoption of ChatGPT: A technology acceptance model perspective. *International Journal of Human–Computer Interaction, 41*(2), 1431–1445.

Malik, A., Budhwar, P., & Kazmi, B. A. (2023). Artificial intelligence (AI)-assisted HRM: Towards an extended strategic framework. *Human Resource Management Review, 33*(1), 100940.

Maslach, C., Jackson, S. E., & Leiter, M. P. (1996). Maslach Burnout Inventory – General Survey. In C. Maslach, S. E. Jackson, & M. P. Leiter (Eds.), *Maslach Burnout Inventory Manual* (3rd ed., pp. 191–218). Mind Garden.

McKevitt, D., Carbery, R., & Collins, S. (2022). Job crafting in project management: Implications for project success and career satisfaction. *International Journal of Project Management, 40*(7), 741–749.

Mohammadpour, A., Karan, E., & Asadi, S. (2019). Artificial intelligence techniques to support design and construction. In *ISARC. Proceedings of the International Symposium on Automation and Robotics in Construction* (Vol. 36, pp. 1282–1289). IAARC Publications.

Mubarak, N., Khan, J., & Khan, A. K. (2022). Psychological distress and project success: The moderating role of employees' resilience and mindfulness. *International Journal of Project Management, 40*(5), 566–576. https://doi.org/10.1016/j.ijproman.2022.05.004

Na, S., Heo, S., Choi, W., Kim, C., & Whang, S. W. (2023). Artificial intelligence (AI)-based technology adoption in the construction industry: A cross-national perspective using the technology acceptance model. *Buildings, 13*(10), 2518.

Nasaj, M., Badi, S., Murtagh, N., & Ding, L. (2025). Collective AI anxiety and team innovative behaviour: The role of coping strategies. *Construction Innovation*. https://doi.org/10.1108/CI-08-2024-0222

Newman, C., Edwards, D., Martek, I., Lai, J., Thwala, W. D., & Rillie, I. (2021). Industry 4.0 deployment in the construction industry: A bibliometric literature review and UK-based case study. *Smart and Sustainable Built Environment, 10*(4), 557–580.

Ni, G., Zhang, Q., Fang, Y., Zhang, Z., Qiao, Y., Wang, W., & Deng, Y. (2023). How resilient safety culture corrects unsafe behavior of new generation of construction workers: The mediating effects of job crafting and perceived work meaningfulness. *Engineering, Construction and Architectural Management, 30*(10), 4821–4845. https://doi.org/10.1108/ECAM-04-2022-0325

Niessen, C., Weseler, D., & Kostova, P. (2016). When and why do individuals craft their jobs? The role of individual motivation and work characteristics for job crafting. *Human Relations, 69*(6), 1287–1313.

Ottaviani, F. M., Ballesteros-Pérez, P., & Narbaev, T. (2025). Automated machine learning pipeline for robust project cost and duration forecasting. *Automation in Construction, 178*, 106426.

Pan, Y., & Zhang, L. (2021a). Automated process discovery from event logs in BIM construction projects. *Automation in Construction, 127*, 103713.

Pan, Y., & Zhang, L. (2021b). Roles of artificial intelligence in construction engineering and management: A critical review and future trends. *Automation in Construction, 122*, 103517.

Park, S. H., Kim, J. N., & Krishna, A. (2014). Bottom-up building of an innovative organization: Motivating employee intrapreneurship and scouting and their strategic value. *Management Communication Quarterly, 28*, 531–560.

Parker, S. K., & Collins, C. G. (2010). Taking stock: Integrating and differentiating multiple proactive behaviors. *Journal of Management, 36*(3), 633–662.

Pearce, J. L., & Gregersen, H. B. (1991). Task interdependence and extra-role behavior: A test of the mediating effects of felt responsibility. *Journal of Applied Psychology, 76*(6), 838.

Perez, F., Conway, N., & Roques, O. (2022). The autonomy tussle: AI technology and employee job crafting responses. *Relations Industrielles / Industrial Relations, 77*(3), 1–19. https://www.jstor.org/stable/27221324

Pinchot, G. (1985). *Intrapreneurship*. Harper and Row.

Pinto, J. K., Dawood, S., & Pinto, M. B. (2014). Project management and burnout: Implications of the demand–control–support model on project-based work. *International Journal of Project Management, 32*(4), 578–587. https://doi.org/10.1016/j.ijproman.2013.09.003

Pirzadeh, P., & Lingard, H. (2021). Working from home during the COVID-19 pandemic: Health and well-being of project-based construction workers. *Journal of Construction Engineering and Management, 147*(2), 04021048. https://doi.org/10.1061/(ASCE)CO.1943-7862.0002102

Plattform Industrie 4.0. (n.d.). Home. German Federal Ministry for Economic Affairs and Climate Action. Retrieved September 8, 2025, from https://www.plattform-i40.de/IP/Navigation/EN/Home/home.ht

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of applied psychology*, *88*(5), 879.

Pryce-Jones, J. (2011). *Happiness at work: Maximizing your psychological capital for success*. John Wiley & Sons.

PWC (PricewaterhouseCoopers LLP). (2018). *Will robots really steal our jobs? An international analysis of the potential long term impact of automation.* https://www.pwc.co.uk/economic-services/assets/international-impact-of-automation-feb-2018.pdf

Rahmi, K. H., Fahrudin, A., Supriyadi, T., Herlina, E., Rosilawati, R., & Ningrum, S. R. (2025). Technostress and cognitive fatigue: Reducing digital strain for improved employee well-being: A literature review. *Multidisciplinary Reviews, 8*(12), 2025380.

Rahnfeld, M., Wendsche, J., & Wegge, J. (2023). Job demands and resources as drivers of exhaustion and leaving intentions: A prospective analysis with geriatric nurses. *BMC Geriatrics, 23*, 167. https://doi.org/10.1186/s12877-023-03829-x

Rigtering, J. P. C., & Weitzel, U. (2013). Work context and employee behaviour as antecedents for intrapreneurship. *The International Entrepreneurship and Management Journal, 9*, 337–360.

Sarvari, H., Edwards, D. J., Rillie, I., & Posillico, J. J. (2024). Building a safer future: Analysis of studies on safety I and safety II in the construction industry. *Safety Science, 178*, 106621.

Schaufeli, W. B., & Bakker, A. B. (2004). Job demands, job resources, and their relationship with burnout and engagement: A multi-sample study. *Journal of Organizational Behavior, 25*(3), 293–315. https://doi.org/10.1002/job.248

Schaufeli, W. B., Bakker, A. B., & Salanova, M. (2006). The measurement of work engagement with a short questionnaire: A cross-national study. *Educational and Psychological Measurement, 66*(4), 701–716.

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.

Scholze, A., & Hecker, A. (2023). Digital job demands and resources: Digitization in the context of the job demands-resources model. *International Journal of Environmental Research and Public Health, 20*(16), 6581.

Scholze, A., & Hecker, A. (2024). The job demands-resources model as a theoretical lens for the bright and dark side of digitization. *Computers in Human Behavior, 155*, 108177.

Sun, Y., Gu, Z., & Yang, S. B. (2024). Probing vision and language models for construction waste material recognition. *Automation in Construction, 166*, 105629.

Tan, K. L., Hofman, P. S., Noor, N., Tan, S. R., Hii, I. S. H., & Cham, T. H. (2024). Does artificial intelligence improve hospitality employees' individual competitive productivity? A time-lagged moderated-mediation model involving job crafting and meaningful work. *Current Issues in Tourism, 28*(20), 3284–3301. https://doi.org/10.1080/13683500.2024.2391114

Thapa, D. R., Stengård, J., Ekström-Bergström, A., et al. (2022). Job demands, job resources, and health outcomes among nursing professionals in private and public healthcare sectors in Sweden – a prospective study. *BMC Nursing, 21*, 140. https://doi.org/10.1186/s12912-022-00924-z

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. https://doi.org/10.4102/sajip.v36i2.841

Tims, M., Bakker, A. B., & Derks, D. (2012). Development and validation of the job crafting scale. *Journal of Vocational Behavior, 80*(1), 173–186.

Tims, M., Bakker, A. B., & Derks, D. (2013). The impact of job crafting on job demands, job resources, and well-being. *Journal of Occupational Health Psychology, 18*(2), 230–240. https://doi.org/10.1037/a0032141

Uslukaya, A., & Zincirli, M. (2025). Reciprocal relationships between job resources and work engagement in teachers: A longitudinal examination of cross-lagged and simultaneous effects. *Social Psychology of Education, 28*, 127. https://doi.org/10.1007/s11218-025-10085-x

Valsania, S. E., Moriano, J. A., & Molero, F. (2016). Authentic leadership and intrapreneurial behavior: Cross-level analysis of the mediator effect of organizational identification and empowerment. *The International Entrepreneurship and Management Journal, 12*, 131–152.

Van den Broeck, A., Vander Elst, T., Baillien, E., Sercu, M., Schouteden, M., De Witte, H., & Godderis, L. (2017). Job demands, job resources, burnout, work engagement, and their relationships: An analysis across sectors. *Journal of Occupational and Environmental Medicine, 59*(4), 369–376.

Vander Elst, T., Cavents, C., Daneels, K., Johannik, K., Baillien, E., Van den Broeck, A., & Godderis, L. (2016). Job demands–resources predicting burnout and work engagement among Belgian home health care nurses: A cross-sectional study. *Nursing Outlook, 64*(6), 542–556.

Wamba, S. F. (2022). Impact of artificial intelligence assimilation on firm performance: The mediating effects of organizational agility and customer agility. *International Journal of Information Management, 67*, 102544.

Wan, Z., Zhang, L., Wang, L., & Zhang, F. (2024). Navigating autonomy: Unraveling the dual influence of job autonomy on workplace well-being in the gig economy. *Frontiers in Psychology, 15*, 1369495.

Wang, C., Ahmad, S. F., Ayassrah, A. Y. B. A., Awwad, E. M., Irshad, M., Ali, Y. A., & Han, H. (2023). An empirical evaluation of technology acceptance model for artificial intelligence in E-commerce. *Heliyon, 9*(8).

Wang, H., Ding, H., & Kong, X. (2023). Understanding technostress and employee well-being in digital work: The roles of work exhaustion and workplace knowledge diversity. *International Journal of Manpower, 44*(2), 334–353.

Wang, Y. Y., & Chuang, Y. W. (2024). Artificial intelligence self-efficacy: Scale development and validation. *Education and Information Technologies, 29*(4), 4785–4808.

Whyte, J. (2019). How digital information transforms project delivery models. *Project Management Journal, 50*(2), 177–194.

WiFi Talents. (2025). Digital transformation in the AEC industry: Statistics & insights. Retrieved September 29, 2025, from https://wifitalents.com/digital-transformation-in-the-aec-industry-statistics/

Wijayasekera, S. C., Hussain, S. A., Paudel, A., Paudel, B., Steen, J., Sadiq, R., & Hewage, K. (2022). Data analytics and artificial intelligence in the complex environment of megaprojects: Implications for practitioners and project organizing theory. *Project Management Journal*, *53*(5), 485-500.

World Economic Forum. (2025). *The Future of Jobs Report 2025*. Retrieved from https://shorturl.at/AkH3S

World Health Organization. (2007). *Global age-friendly cities: A guide*. Retrieved from https://www.who.int/publications/i/item/9789241547307

Wrzesniewski, A., & Dutton, J. E. (2001). Crafting a job: Revisioning employees as active crafters of their work. *Academy of Management Review, 26*, 179–201.

Xanthopoulou, D., Bakker, A. B., Demerouti, E., & Schaufeli, W. B. (2009). Work engagement and financial returns: A diary study on the role of job and personal resources. *Journal of Occupational and Organizational Psychology, 82*, 183–200.

Xiao, Q., Yan, J., & Bamber, G. J. (2023). 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.*

Yang, F., Fei, Y., Guo, L., Bai, X., & Li, X. (2025). Job crafting intervention for job burnout and work engagement among young construction project management practitioners in China. *Engineering, Construction and Architectural Management*, *32*(1), 536-555.

Yao, Y., Tam, V. W. Y., Wang, J., Le, K. N., & others. (2024). Automated construction scheduling using deep reinforcement learning with valid action sampling. *Automation in Construction, 166*, 105622.

Young, L., Gauci, S., Scholey, A., White, D., & Pipingas, A. (2020). Self-selection bias: An essential design consideration for nutrition trials in healthy populations. *Frontiers in Nutrition, 7*. https://doi.org/10.3389/fnut.2020.587983

Zhang, L., Yao, Y., & Yiu, T. W. (2020). Job burnout of construction project managers: Exploring the consequences of regulating emotions in the workplace. *Journal of Construction Engineering and Management, 146*(10). https://doi.org/10.1061/(ASCE)CO.1943-7862.0001913

Zhang, P., Dillard, N., & Cavallo, T. (2025). Navigating the limitations of algorithmic management: An integrative framework of sociotechnical systems theory (STS) and strategic HRD. *Human Resource Development Review*. https://doi.org/10.1177/15344843251320252

Zipdo. (2025). Digital transformation in the building industry: Statistics & trends. Retrieved September 29, 2025, from https://zipdo.co/digital-transformation-in-the-building-industry-statistics/

Zhou, J. X., Shen, G. Q., Yoon, S. H., & Jin, X. (2021). Customization of on-site assembly services by integrating the internet of things and BIM technologies in modular integrated construction. *Automation in Construction, 126*, 103663.

Zhou, T., Xu, C., Wang, C., et al. (2022). Burnout and well-being of healthcare workers in the post-pandemic period of COVID-19: A perspective from the job demands-resources model. *BMC Health Services Research, 22*, 284. https://doi.org/10.1186/s12913-022-07608-z

Zulu, S. L., Saad, A., Ajayi, S., Unuigbe, M., & Dulaimi, M. (2024). A thematic analysis of the organisational influences on digitalisation in construction firms. *Journal of Engineering, Design and Technology, 22*(6), 1755–1772.

Appendix A: Measurement Scales

Table A1 presents the full measurement scales for all seven constructs included in the theoretical model, with item codes, item statements, response formats, and sources.

Table A1. Measurement Scales for Study Constructs

Construct	Code	Item Statement	Response Format	Source
AI Adoption (ADO)	ADO1	My organisation has integrated AI technologies into its core construction operations (e.g., scheduling, cost estimation, risk analysis).	5-point agreement (1=Strongly Disagree, 5=Strongly Agree)	Newly developed for this study
	ADO2	AI tools (e.g., predictive analytics, machine learning) are regularly used to support project decision-making in my organisation.		
	ADO3	There is a clear strategy for adopting AI technologies in our construction processes.		
	ADO4	Employees in my organisation are encouraged to work with or learn about AI systems and tools.		
	ADO5	AI-based systems (e.g., computer vision, robotics, digital twins) are actively used in our ongoing construction projects.		
	ADO6	My organisation invests in AI to improve safety, productivity, and efficiency in construction work.		
Structural Job Resources (JC_SJR)	JC_SJR1	I try to develop my capabilities in using AI tools for project management.	5-point frequency (1=Never, 5=Always)	Adapted from Tims et al. (2012)
	JC_SJR2	I seek opportunities to expand my professional knowledge about AI applications in construction.		
	JC_SJR3	I try to learn new AI-based methods and tools relevant to my work.		
	JC_SJR4	I ensure that I use AI technologies to their fullest potential in my tasks.		
	JC_SJR5	I make autonomous decisions on how to use AI tools in my daily projects.		
Social Job Resources (JC_SOJR)	JC_SOJR1	I ask my supervisor for support in understanding and applying AI technologies.	5-point frequency (1=Never, 5=Always)	Adapted from Tims et al. (2012)
	JC_SOJR2	I ask whether my supervisor is satisfied with how I'm using AI in my work.		
	JC_SOJR3	I look to my supervisor as a role model in integrating AI into project management.		
	JC_SOJR4	I ask others for feedback on how effectively I'm using AI in my job.		
	JC_SOJR5	I ask colleagues for advice on using AI tools for specific projects.		
Challenging Job Demands (JC_CJD)	JC_CJD1	When an AI-driven project or pilot comes up, I volunteer to be involved.	5-point frequency (1=Never, 5=Always)	Adapted from Tims et al. (2012)
	JC_CJD2	I stay updated on new AI developments in construction and experiment with them when possible.		

	JC_CJD3	When routine work slows down, I use the time to explore innovative AI solutions for our processes.		
	JC_CJD4	I regularly take on AI-related tasks or initiatives, even without extra compensation.		
	JC_CJD5	I use AI tools to analyse complex patterns and improve the strategic aspects of my job.		
Hindering Job Demands (JC_HJD)	JC_HJD1	I adjust my use of AI systems to reduce mentally intense tasks.	5-point frequency (1=Never, 5=Always)	Adapted from Tims et al. (2012)
	JC_HJD2	I try to use AI to reduce the emotional intensity of certain project tasks.		
	JC_HJD3	I use AI-based systems to filter or minimise emotionally draining interactions in project communications.		
	JC_HJD4	I use AI to help manage unrealistic expectations from stakeholders.		
	JC_HJD5	I rely on AI decision-support tools to avoid making too many difficult decisions on my own.		
	JC_HJD6	I structure my AI-based workflows so I don't need to concentrate for extended periods without a break.		
Work Engagement (ENG)	ENG1	At my work, I feel bursting with energy.	5-point frequency (1=Never, 5=Always)	UWES-9 (Schaufeli et al., 2006)
	ENG2	I am enthusiastic about my job.		
	ENG3	I feel strong and vigorous.		
	ENG4	My job inspires me.		
	ENG5	I am proud of the work that I do.		
	ENG6	I find my work full of meaning and purpose.		
	ENG7	I get carried away when I'm working.		
	ENG8	I am immersed in my work.		
	ENG9	I feel happy when I am working intensely.		
Emotional Exhaustion (EXH)	EXH1	I feel emotionally drained from my work.	5-point frequency (1=Never, 5=Always)	MBI (Maslach et al., 1996)
	EXH2	I feel used up at the end of the workday.		
	EXH3	I feel fatigued when I get up in the morning and have to face another day on the job.		
	EXH4	I feel like I'm at the end of my rope.		

Note: MBI = Maslach Burnout Inventory; UWES-9 = Utrecht Work Engagement Scale (9-item version).