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AI Adoption and Engineering Project Designers' Green Creativity in Construction Industry: A Dual-Path Moderated Mediation Model

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Abstract

Green creativity is critical for achieving green outcomes in engineering project design, where designers must address environmental goals under constraints of cost, functionality, and technical feasibility. Consistent with the increasing application of artificial intelligence (AI) in design practices, the psychological impact of AI adoption on designers' green creativity has been a central issue in green engineering designs. Drawing on conservation of resources (COR) theory, this study theorizes and tests a dual-path moderated mediation model, with job engagement and psychological detachment as two parallel mediating pathways of resource enhancement and maintenance, respectively, through which AI adoption influences designers' green creativity under the "immersion–recovery" resource mechanism. Furthermore, inclusive leadership is set as a key boundary condition to moderate the mediating pathways above. A multi-wave online survey of 312 engineering project designers from the Chinese construction industry is employed to examine the hypotheses. These findings not only extend theoretical understanding of the mechanisms underlying AI's impact in the green engineering domain but also provide new insights for leadership practices in complex engineering design contexts.

Keywords: AI adoption; green creativity; job engagement; psychological detachment; engineering design

1. Introduction

The construction industry faces increasing pressure to undergo a green transformation as resource scarcity and sustainability imperatives continue to reshape project development [1,2]. In the built environment, architectural and engineering design decisions made during the early project stages significantly influence a project's lifecycle environmental performance, including energy efficiency, carbon emissions, material consumption, and operational sustainability. Importantly, green engineering design is not merely concerned with material selection or energy conservation [3]. Instead, it requires engineering project designers to develop innovative solutions that balance environmental goals with economic feasibility, technical performance, and project-specific constraints [4]. These competing project demands make green creativity a critical capability for designers. Green creativity refers to individuals' abilities to develop novel and practical concepts in green products, services, processes, or practices [5]. While green creativity is of great significance in management practices, translating green values into reality is even more critical from an engineering design perspective. This is because engineering designers need creativity to achieve both financial and environmental success.



Academic Editor: Ahmed Senouci

Received: 8 May 2026

Revised: 13 July 2026

Accepted: 15 July 2026

Published: 17 July 2026

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The increasing adoption of Artificial Intelligence plays a strategic role in modifying designers' conduct and promoting innovation engineering design practices. AI technologies, such as Building Information Modeling (BIM), generative design, environmental simulation, algorithm optimization, and lifecycle performance analysis, provide designers with powerful analytical tools and data-driven insights. This enables engineering designers to develop better, environmentally sustainable, innovative solutions. For example, by automating repetitive analytical tasks, visualizing design alternatives, and supporting data-driven decision-making, AI enables designers to identify environmentally sustainable design opportunities more efficiently [6]. These technological capabilities create favorable conditions for fostering green creativity among engineering project designers.

Despite the growing recognition that AI adoption may benefit green design, existing knowledge suffers from a critical gap. Most prior research has treated AI as a technical tool for optimizing building-level environmental outcomes (e.g., energy consumption [7], emissions reduction [8], material selection [9]), focusing on objective performance metrics rather than on designers' individual cognitive processes. In fact, green creativity (the generation of new ideas) is fundamentally different from green performance (the implementation of ideas), and green creativity is a necessary but not sufficient prerequisite for achieving green performance. Consequently, it remains unclear how and under what conditions AI adoption influences the green creativity of engineering designers. This is mainly because green creativity is a complex phenomenon arising from multiple cognitive and psychological operations [10]. While some studies have explored AI adoption in the design field and the factors influencing green creativity [11,12], the psychological mechanisms through which AI adoption affects green creativity have not yet been explored in depth. Recent research has preliminarily found that human–AI co-creation may affect designers' creative self-efficacy [13], and factors such as creative control [14] and basic psychological needs [15] play a mediating role in the process of AI use. However, empirical research remains scarce in examining the psychological mechanisms through which AI adoption influences designers' green creativity [16]. Therefore, AI should not be viewed merely as an optimization tool [17]; instead, further exploration is needed to understand how AI stimulates designers' green creativity through psychological pathways.

To address the gap, this study draws on the Conservation of Resources (COR) theory [18]. COR theory posits that individuals strive to acquire, protect, and retain valued resources (e.g., cognitive capacity, time) [19]. According to COR theory, resource depletion impairs individual functioning and performance, whereas resource gain promotes adaptive outcomes. The theory further suggests that resource dynamics operate through two distinct mechanisms: resource investment (using existing resources to gain additional resources) and resource threat (anticipated or actual resource loss, which triggers defensive responses that may undermine performance). This theoretical framework is particularly suited to green engineering design, which is inherently resource-consuming [20]. Designers must simultaneously navigate multidisciplinary requirements from architects, structural engineers, and mechanical engineers while balancing environmental, economic, technical, and project-specific constraints [21]. The struggle accelerates resource depletion among the designers who may not break away from conventional approaches and produce creative green solutions.

Consistent with the COR theory, we propose a dual model in which AI adoption can foster designers' green creativity through two complementary resource pathways, subject to a boundary condition. Instead of exploring the relationship quality between AI and designers (e.g., AI trust), our study treats AI as a collaborative tool that can help designers psychologically strengthen resource allocation through two pathways, job engagement and psychological detachment, rather than AI trust. First, job engagement represents a resource

enhancement pathway. By providing intelligent design recommendations and visualizing sustainable design alternatives, AI can stimulate engineering project designers' involvement in complex project tasks and encourage greater investment of personal resources into green creative outputs [22]. Second, psychological detachment represents a resource maintenance pathway. By automating repetitive design analysis and facilitating strategic cognitive "micro-breaks" during project work, AI may reduce cognitive rigidity and promote resource recovery, thereby supporting green creativity [23]. These two pathways constitute an iteratively complementary mechanism of resource management. Furthermore, the inherent tensions among sustainability goals, project costs, client requirements, and technical constraints in construction projects require leaders to create a supportive environment for innovation [24].

To this end, this study introduces inclusive leadership, defined as the practice of motivating employees to actively participate in the organization's green initiatives and innovations through openness, support, and empowerment [25], as an important social context that influences the two-pathway mechanisms. Specifically, inclusive leaders can alleviate designers' concerns about green solutions and enhance their psychological safety [26]. Under such leadership, designers are more likely to view AI as a facilitator, either to enhance resource efficiency through job engagement or to reduce resource consumption through psychological detachment.

Based on a multi-wave online survey of 312 engineering project designers in the construction industry, this study makes some contributions to the current engineering project literature in the following ways. First, by identifying job engagement and psychological detachment as parallel resource pathways, we extend research on AI adoption and engineering designers' green creativity within the COR theory framework. Specifically, we demonstrate that AI adoption exerts a dual effect by simultaneously facilitating resource investment (via enhanced job engagement) and resource conservation (via increased psychological detachment). Second, by examining the moderating role of inclusive leadership, we examine the contextual conditions under which AI serves as a source of resource gains rather than losses. Finally, by treating job engagement and psychological detachment as dynamically complementary resource pathways, our study enriches the understanding of COR theory in the context of human-machine collaboration.

2. Theory and Hypothesis

As a critical organizational context, AI shapes designers' perceptions of resource availability through the synergistic interaction among "resources, motivation, and design," thereby influencing green creativity [27]. In construction projects, designers are often required to coordinate multidisciplinary design requirements, such as architecture, structural engineering, and electrical engineering, while balancing environmental sustainability, project cost, technical feasibility, and client expectations. Under such complex project conditions, AI has become an increasingly important technological resource for supporting green designs. Based on the COR theory [18], AI adoption can enhance designers' green creativity through dual cognitive pathways, enabling them to acquire, retain, and protect their valuable resources, including time, cognitive energy, design autonomy, and professional competence. In the context of green building projects, these resources are continuously consumed by iterative design revisions, interdisciplinary coordination, and sustainability evaluations. A central tenet of COR theory is that resource gains are crucial [28]. That is, either promoting resource acquisition or preventing resource loss initiates positive "gain spirals," ultimately enhancing their ability to generate innovative green design solutions.

2.1. The Dual-Pathway Effect of AI Adoption on Engineering Project Designers' Green Creativity

2.1.1. The Pathway of Job Engagement as Resource Investment and Gain

AI adoption creates critical project conditions for stimulating green creativity among engineering project designers in construction projects. By leveraging applications, including but not limited to Autodesk Revit-based BIM modeling, generative design, building energy simulation, carbon emission assessment, and sustainable material recommendation systems, AI provides designers with task-specific resources across the entire building lifecycle. These resources not only reduce repetitive drafting and data-processing tasks but also enhance designers' capabilities in green building optimization, lifecycle carbon analysis, and low-carbon material selection [29].

According to the COR theory, AI adoption in engineering design practices can be viewed as a critical pathway for designers to access green resources. First, AI tools can automate building performance simulations, optimize alternative design schemes, and provide access to large databases of precedent green building cases, thereby significantly reducing designers' cognitive workload and time pressure during project development [30]. This reduction in cognitive load enables the designers to reallocate their limited resources. Second, AI adoption enhances designers' professional resources by supporting multidisciplinary design integration. For example, AI can assist in identifying conflicts among architectural, structural, and MEP systems; evaluating constructability constraints; and screening sustainable materials based on project-specific environmental goals. These functions strengthen engineering designers' systems thinking and multidimensional green decision-making capabilities [31]. Finally, successfully leveraging AI to achieve design objectives can generate new psychological resources, such as a sense of accomplishment, mastery, and learning, further fueling a virtuous cycle of resource acquisition.

These resource gains, catalyzed by AI adoption, can directly promote job engagement—defined as a positive, fulfilling state of work characterized by vigor (high energy), dedication (strong involvement), and absorption (full concentration) [32]. According to the COR theory, when designers have access to more resources, they are more likely to channel them into green design work. The conservation of energy and time results in continuously increasing vigor. Enhanced feelings of competence and control foster greater dedication. Reduced focus on designing tasks with economic goals as the sole criterion, coupled with a shift toward meaningful green challenges [20], promotes deeper absorption. Overall, AI adoption initiates a positive iterative process for designers, moving them from resource acquisition to resource investment, thereby enhancing their job engagement. Therefore, we propose:

Hypothesis 1a. *AI adoption is positively related to job engagement among engineering project designers.*

When designers are engaged in their work, they draw upon a rich reservoir of psychological and cognitive resources. According to the COR theory, actively engaged designers are more likely to invest their extra resources in exploratory and role-exceeding activities, such as designing entirely new structures that integrate green functions [33]. Specifically, the vigor derived from job engagement provides designers with sustained energy, helping them navigate setbacks during the green design process. The sense of dedication inherent in job engagement sparks a desire to tackle challenges and an interest in exploring pathways for green innovation, thereby enhancing the quality of designers' green creative output. The absorptive aspect of job engagement enables designers to become deeply immersed in the task, which is crucial for generating implicit connections and insights into green creative ideas [34].

The positive correlation between job engagement and designers' green creativity may stem from cognitive and behavioral shifts triggered by a state of engagement: when designers are highly engaged, they typically demonstrate a more proactive incorporation of natural symbiotic thinking, a more systematic approach to green lifecycle considerations [35], and a more persistent attitude in the face of challenges. These psychological states are fundamental prerequisites for green creative output.

Overall, job engagement provides the optimal state for designers' green creativity. Therefore, we propose:

Hypothesis 1b. *Job engagement is positively related to engineering project designers' green creativity.*

Job engagement is not only an indicator of the resource-enhancing conditions brought about by AI adoption but also an active, agentic state that channels these conditions into green creativity. The resource conditions provided by AI technology are first transformed into high levels of designers' job engagement; this positive, focused, and energetic psychological state, in turn, drives designers' green creativity. Therefore, job engagement, as a key psychological mechanism, enables AI adoption to serve as a starting point for green design, ultimately fostering green creative output. Job engagement implies that designers internalize the external resources provided by AI tools through a mediating process and actively reinvest them to promote their green creativity. Therefore, we propose:

Hypothesis 1c. *Job engagement mediates the positive effect of AI adoption on engineering project designers' green creativity.*

2.1.2. The Pathway of Psychological Detachment as Resource Protection and Recovery

While job engagement represents a state of active resource investment, psychological detachment, defined as a designer's ability to mentally distance themselves from their work assignments during brief breaks or intervals throughout the workday [36], serves as a complementary process for conserving and recovering resources. It is worth noting that, unlike the classic literature which emphasizes psychological detachment during non-work hours, this study focuses on designers' cognitive experiences of briefly and intentionally interrupting work-related thinking during work breaks. While this represents an extension of the classic construct within the emerging work environment of AI adoption, both reasonably share the same core psychological mechanism of temporarily disengaging from work-related cognition to restore psychological resources [37]. This process is essential for maintaining the resources AI acquires and preventing resource depletion.

Drawing upon the COR theory, psychologically detached designers are motivated to preserve and protect their valuable resources. The adoption of AI in design work can be viewed as a key strategy for resource conservation. Specifically, by automating routine design tasks, such as calculating green parameters throughout the entire lifecycle and conducting biodiversity assessments [38], or by releasing designers from attention-intensive green design tasks [39], AI tools can reduce the continuous depletion of designers' cognitive resources during their work. This reduction in resource expenditure is crucial because it alleviates the "burnout" pressure caused by prolonged concentration on design tasks.

The resource conservation effects facilitated by AI adoption require a cognitive prerequisite of psychological detachment during working hours. When designers' cognitive resources are not depleted by immediate tasks, they possess the "cognitive slack" for brief mental regulation during task intervals [40]. Conversely, if attention-intensive design tasks continuously consume cognitive resources, achieving psychological detachment becomes difficult [41]. Therefore, by reducing cognitive load and minimizing ruminative think-

ing about unfinished green design proposals, AI adoption not only conserves designers' personal resources but also fosters conditions for psychological detachment, enabling designers to experience "micro-recovery" from their work during the day.

Furthermore, according to the spiral of gain model in COR theory, psychological detachment during workdays is characteristic of resource acquisition [42]. Successful detachment experiences can promptly replenish depleted resources, interrupt the accumulation of resource exhaustion, and potentially enhance designers' sense of control over their work and cognitive states, which constitutes a gain in personal resources. Overall, we propose that:

Hypothesis 2a. *AI adoption is positively related to psychological detachment among engineering project designers.*

In addition, psychological detachment provides a complementary latent pathway linking AI adoption to designers' green creativity. This pathway significantly enhances designers' cognitive flexibility and fosters their green creativity.

By providing respite from the constant pressure of green design tasks, psychological detachment serves a dual resource function. Primarily, it reduces the consumption of cognitive resources, preventing resource depletion [43]. More importantly, this conservation of cognitive resources actively "unbinds" cognitive thinking. When designers temporarily detach from green fixation, the cognitive constraints imposed by the previous problem are weakened. This detached state allows designers to engage freely in spontaneous associations and conceptual restructuring, thereby fostering their green creativity [44]. In this state, previously acquired and seemingly unrelated green design elements can freely interact through nonlinear associative processes, giving rise to new green ideas. Based on the COR theory, the resources conserved during psychological detachment are automatically and efficiently reinvested into the generative cognitive process, serving as the "raw material" for creative insights.

Consequently, psychological detachment functions as a crucial cognitive reset in addition to resource recovery. It provides psychological distance to overcome functional fixedness—the cognitive bias that limits designers from continuing to rely on past examples of green design [45]. By temporarily distancing themselves from the cognitive rigidity induced by intense focus, designers reconstruct their mental schema. This detachment serves as the foundation for divergent thinking and problem-solving from new perspectives, thereby catalyzing flexible pathways for designers' green creativity [46]. Instead of interrupting productive work, psychological detachment within the workday, therefore, promotes integral phases of the green creative problem-solving cycle, facilitating incubation before insights.

Psychological detachment fosters green creativity not merely by replenishing resources but also by cultivating a cognitive environment conducive to the incubation of inspiration. It facilitates the deconstruction of existing thought patterns and the unconscious reorganization of fragments of green design knowledge, ultimately enhancing cognitive flexibility and helping designers generate novel green ideas. Thus, we propose that:

Hypothesis 2b. *Psychological detachment is positively related to engineering project designers' green creativity.*

Furthermore, we posit that psychological detachment is a critical mediating mechanism linking AI adoption to designers' green creativity. AI adoption is a resource-conserving process. By reducing the workload of routine tasks, such as calculating green parameters, AI preserves designers' finite cognitive resources, which might otherwise be depleted by

sustained attention. This conservative “cognitive slack” is a prerequisite for activating a state of psychological detachment to facilitate resource recovery and acquisition. Psychological detachment can prevent ongoing resource depletion and replenish cognitive capacity. Crucially, it provides the psychological distance required for cognitive unbinding, thereby enabling a significant departure from rigid green schemes and breaking fixation. Finally, the recovered and reconfigured resources are reinvested in the incubation of green creativity. The state of cognitive unbinding and spontaneous thought, under conditions of psychological detachment, facilitates the unconscious recombination of green knowledge fragments, yielding new associations and insights crucial to designers’ green creativity. Overall, we propose that:

Hypothesis 2c. *Psychological detachment mediates the positive effect of AI adoption on engineering project designers’ green creativity.*

2.2. The Moderating Role of Inclusive Leadership

Inclusive leadership reflects behaviors in which leaders prioritize openness, accessibility, availability, and fairness, emphasizing the integration of diverse employee contributions [47]. Such a leadership style is particularly prominent in the context of AI adoption in green engineering, where it may amplify the dynamic cycle of resource access.

According to the COR theory, the availability of green resources in the environment determines designers’ ability to acquire, retain, and invest in those resources [19]. Inclusive leadership constitutes a supportive organizational environment that influences how designers experience and respond to AI in green design. Inclusive leaders encourage designer participation, respect diverse green perspectives, and ensure equitable treatment [48]. These inclusive practices create a safe organizational atmosphere that empowers designers to experiment with unconventional green solutions. Specifically, these designers would like to propose novel green ideas and review new proposals without fear of embarrassment or punishment [25]. Given that AI adoption introduces some uncertainty or threats to the work environment, inclusive leadership serves as a supportive environment in organizations that integrate AI tools into designers’ daily work. Therefore, inclusive leadership can strengthen the positive relationship between AI adoption and job engagement by enhancing the returns on resources and safeguarding resource investments.

While AI adoption may allow designers to conserve their cognitive resources (e.g., reducing routine green parameter calculations and the burden of confirming green boundaries) [49], converting these additional resources into job engagement is not automatic. This process can be either facilitated or hindered by the current organizational environment. By encouraging designers to participate in the green change process and valuing their contributions, inclusive leaders provide crucial relational and emotional resources. These resources, such as a sense of organizational trust, support, and belonging, complement the cognitive resources saved through AI adoption. The resources inspired by inclusive leaders reduce designers’ anxiety during the AI adoption process, enabling them to more confidently reinvest their saved resources into green design work. Therefore, we propose:

Hypothesis 3. *Inclusive leadership will strengthen the positive relationship between AI adoption and job engagement such that the relationship is more pronounced under higher levels of inclusive leadership.*

Although job engagement provides designers with a source of vigor, dedication, and absorption required for green creativity, they need a safe and supportive environment to translate their efforts into creative outcomes effectively. Inclusive leadership fosters

such an environment by appreciating diverse green inspirations, encouraging the sharing of unconventional green solutions, and embracing the courage to confront the potential unreasonableness of green proposals [50]. In this environment, highly engaged designers are more likely to invest cognitive resources in exploratory and creative green design, knowing that their green ideas will be welcomed. This suggests that the indirect effect of AI adoption on designers' green creativity via job engagement depends on the level of inclusive leadership. Thus, we propose that:

Hypothesis 4. *Inclusive leadership will strengthen the mediating effect of job engagement on the relationship between AI adoption and engineering project designers' green creativity such that the effect is more pronounced under higher levels of inclusive leadership.*

Meanwhile, inclusive leadership alleviates the perceived threat to resources in AI adoption. When detached designers perceive inclusive leaders, their anxiety and insecurity about AI diminish [51]. Designers are more likely to view AI as a tool to assist with repetitive tasks in green creation rather than as a threat. This interpretation helps designers become less defensive about protecting resources. Consequently, designers feel psychologically safer and more empowered. They are more inclined to leverage the cognitive gaps created by AI and maintain psychological distance during design breaks, without feeling guilt or distress about their solutions. Thus, the social resources provided by inclusive leaders can amplify the resource-preserving effects of AI adoption, leading to stronger psychological detachment. Overall, we propose that:

Hypothesis 5. *Inclusive leadership will strengthen the positive relationship between AI adoption and psychological detachment such that the relationship is more pronounced under higher levels of inclusive leadership.*

Similarly, while psychological detachment can replenish cognitive resources, transforming these resources into green creativity requires a safe environment for experimentation [52]. Inclusive leadership ensures that detached designers who have recovered from design work are not only restored but also emboldened to invest their renewed cognitive flexibility and energy into green creative design [53]. These designers are more likely to explore unconventional green solutions, share emerging design concepts, and apply insights gained during the incubation period. Therefore, the indirect effect of AI adoption on designers' green creativity via psychological detachment depends on the level of inclusive leadership. When detached designers operate in a resource-rich, safe environment within an inclusive leadership framework, the mediating mechanism is strengthened. In sum, we propose that:

Hypothesis 6. *Inclusive leadership will strengthen the mediating effect of psychological detachment on the relationship between AI adoption and engineering project designers' green creativity such that the effect is more pronounced under higher levels of inclusive leadership.*

It is worth mentioning that inclusive leadership simultaneously strengthens both job engagement and psychological detachment, without requiring designers to be both highly engaged and frequently detached at the same time. The core lies in the tolerant nature of inclusive leadership, which accepts designers' diverse work styles when adopting AI. For designers who prefer engagement, leaders provide resources and encouragement; for those who need brief detachment to recover, leaders offer tolerance without interference.

Figure 1 presents the theoretical model, and Table 1 summarizes all hypotheses, including the proposed paths and expected directions.

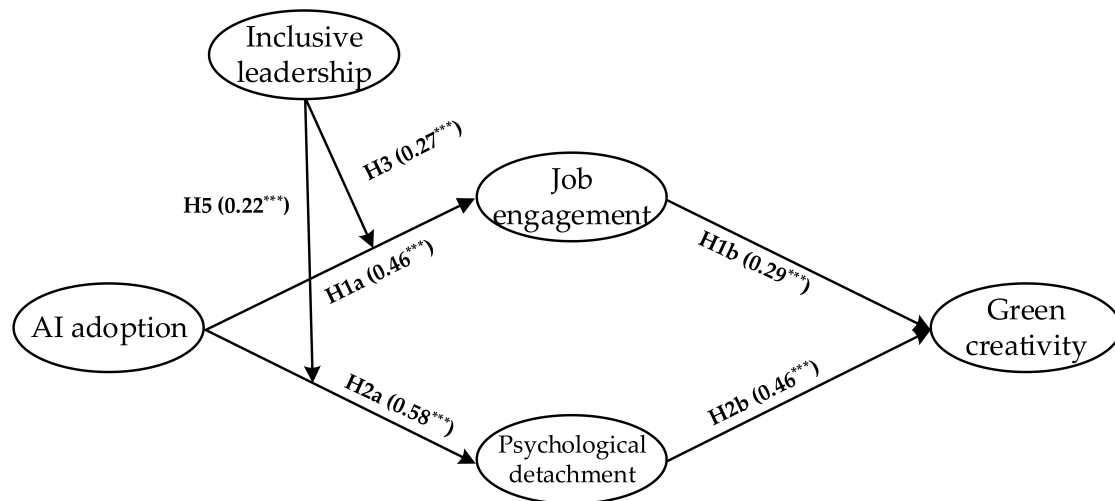


Figure 1. Theoretical model. Note: Arrows represent hypothesized relationships. *** $p < 0.001$, two-tailed.

Table 1. Summary of hypotheses.

Hypotheses	Proposed Relationship	Expected Direction
H1a	AI → JE	Positive
H1b	JE → GC	Positive
H1c	AI → JE → GC	Positive indirect
H2a	AI → PD	Positive
H2b	PD → GC	Positive
H2c	AI → PD → GC	Positive indirect
H3	AI × IL → JE	Positive (stronger at high IL)
H4	(AI → JE → GC) IL	Positive indirect (stronger at high IL)
H5	AI × IL → PD	Positive (stronger at high IL)
H6	(AI → PD → GC) IL	Positive indirect (stronger at high IL)

Note: AI = AI adoption, IL = inclusive leadership, JE = job engagement, PD = psychological detachment, GC = green creativity, AI × IL = Interaction term between AI and IL, (...) | IL means the indirect effect is moderated by IL.

3. Methods

3.1. Participants and Procedures

This study followed the positivist paradigm of Grix (2010) [54] and adopted a quantitative design to verify the hypothetical-deductive generalizations. The items of the questionnaire were derived from existing scales in previous research (Dong et al., 2025 [55]; Schaufeli et al., 2006 [56]; Sonnentag and Fritz, 2007 [57]; Carmeli et al., 2010 [51]; Farmer et al., 2003 [58]). These items were incorporated into the engineering design context. To enhance contextual relevance while preserving the original conceptual meaning of the items, only minor adjustments were made to the wording. Specifically, general workplace expressions were replaced with engineering design scenarios, psychological detachment items were explicitly restricted to experiences during working hours, and green creativity items were clearly set within the context of environmentally sustainable engineering projects.

The original items were developed in English, and we followed a rigorous translation and back-translation procedure to translate them into Chinese for the target samples. Subsequently, we invited two professors with abundant theoretical knowledge in engineering design to evaluate the content validity, clarity, and contextual appropriateness of the questionnaire. Following this, we conducted a pilot study with a small sample of targeted respondents to check the clarity and readability of the questionnaire items, and made minor

revisions to the wording before the formal survey. Meanwhile, we referred to Hair et al. [59] and used G*Power 3.1.9.7 software to determine a minimum sample size of 138 (medium effect size $f^2 = 0.15$, α error probability = 0.05, power ($1 - \beta$ error probability) = 0.95, number of predictors = 5) [60].

We collected data via the online platform Questionnaire Star (www.sojump.com) to obtain high-quality data comparable to that of international platforms [61]. The respondents are designers working in the engineering design field, such as architects, structural engineers, mechanical engineers, and electrical engineers. These designers are all experienced professionals, most of whom have over ten years of work experience and frequently collaborate with AI. To ensure this study focuses on the impact of AI adoption on engineering project design personnel, we conducted an online questionnaire survey with participants from various design institutions across different regions of China to enhance the representativeness of the research findings. Prior to participating in the survey, potential respondents were provided with detailed explanations regarding the research objectives, the three-round survey process (with two-week intervals between rounds), and a privacy protection statement. At the beginning of the questionnaire, we included a screening question to verify their experience using AI tools in practical work, requiring them to select the types of AI tools used (including but not limited to BIM, generative AI, etc.) and briefly describe a specific usage experience; this helped us identify and exclude random responses or unqualified replies. Our data collection included three phases since a multi-wave research design can mitigate the potential influence of common method bias [62]. In all rounds of surveys, we included a cover letter indicating that our study would be used solely for research on how AI adoption affects designers' green creativity and that participant privacy would be strictly protected.

The formal longitudinal data collection was carried out as shown in Figure 2. In late March 2026 (Time 1), we sent out our first-round survey and asked respondents to fill in information about their demographic characteristics, AI adoption, and inclusive leadership. Overall, we distributed a total of 397 questionnaires and received 377 valid responses, with a valid response rate of 95.0%. After two weeks (Time 2), we distributed our second-round survey to the respondents who provided valid responses in the first wave and requested them to answer questions relating to measures of job engagement and psychological detachment. Of the 377 questionnaires distributed, 339 valid responses were received, with a valid response rate of 89.9%. After another two-week interval (Time 3), we invited the above 339 valid respondents to participate, assessing their intrinsic work motivation and green creativity. We received 312 valid responses, with a valid response rate of 92.0%. During this process, we applied strict exclusion criteria: questionnaires from participants who failed to complete any round of the survey, took less than 2 min to complete any single questionnaire, or exhibited a straight-line response pattern (where over 80% of answers within the same scale were identical) were excluded and thus not included in the subsequent data analysis. Overall, we retained 312 valid questionnaires from 397 respondents (response rate: 78.6%). Among the respondents, 51.6% are male and 48.4% are female. Their average age is 36.76 years ($SD = 9.85$). Among them, the proportion of respondents aged 22–30 is 32.7%, aged 31–40 is 32.1%, aged 40–50 is 22.4%, and aged above 50 is 12.8%. Regarding education level, 35.6% held a junior college diploma or below, 39.7% held a bachelor's degree, 17.0% held a master's degree, and 7.7% held a doctoral degree. And their average number of years of work experience is 13.27 years ($SD = 11.18$).

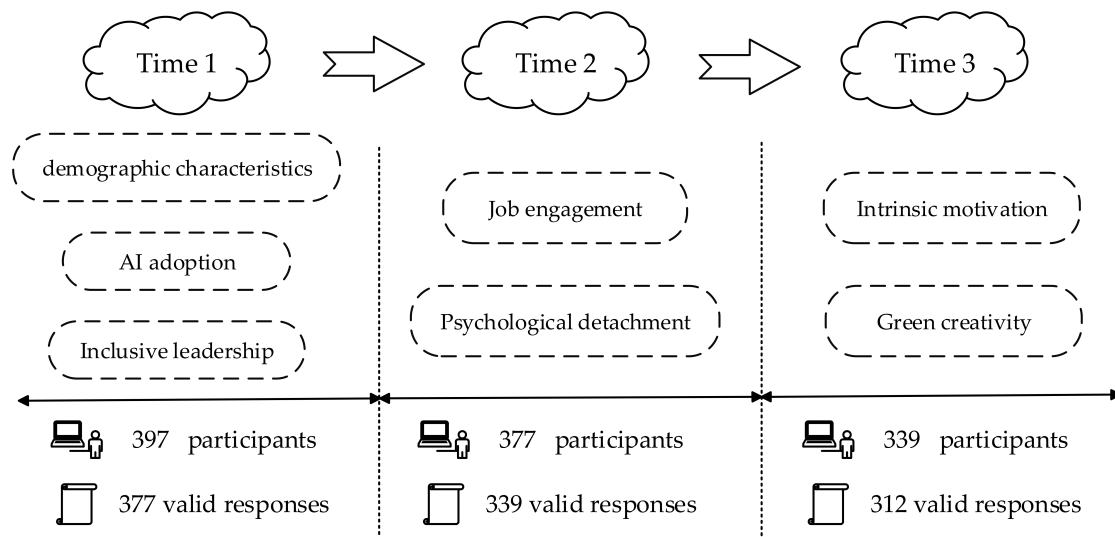


Figure 2. Multi-wave data collection.

3.2. Measures

Each item in our study was drawn from existing scales published in top-tier journals. All items were rated on a five-point Likert-type scale ranging from 1 (strongly disagree) to 5 (strongly agree).

AI Adoption. AI adoption was measured by the eight-item scale of Dong et al. [55]. A sample item is: “I need to interact with AI frequently during engineering design.” The observed Cronbach’s alpha coefficient for this scale was 0.89.

Job Engagement. Job engagement was measured by using the nine-item scale of Schaufeli et al. [56]. A sample item is: “At my work, I feel that I am bursting with energy.” The observed Cronbach’s alpha coefficient for this scale was 0.91.

Psychological Detachment. Psychological detachment was measured by using the four-item scale of Sonnentag and Fritz [57]. This study made reasonable adaptations to its context, clearly specifying that the measure refers to experiences during working hours. A sample item is: “I get a break from the demands of engineering design work.” According to methodological research, simply adjusting the context of a scale without altering the core content of its items can preserve the psychometric properties of the original scale, and the adapted scale demonstrates discriminant validity in the new context [63]. The observed Cronbach’s alpha coefficient for the scale was 0.86.

Inclusive Leadership. Inclusive leadership was measured by the nine-item scale of Carmeli et al. [51]. A sample item is: “The manager is open to hearing new ideas.” The observed Cronbach’s alpha coefficient for the scale was 0.92.

Green Creativity. Green creativity was measured by employing the four-item scale of Farmer [58]. This study specified the implementation background of this measure as “in the context of green engineering.” A sample item is: “Tries new ideas or methods first in green engineering design.” The observed Cronbach’s alpha coefficient for this scale was 0.88.

Control Variables. This study controlled for some variables that may influence the effects on green creativity. First, demographic characteristics, including gender, age, education level, industry, and years of work experience [64], were controlled to mitigate their potential confounding effects. Second, we controlled for intrinsic motivation, as it was found to be an important mechanism influencing green creativity [65]. Intrinsic motivation was measured by Gagné et al. [66]’s three-item scale. A sample item is: “For the moments of pleasure that this job brings me.” The observed Cronbach’s alpha coefficient for intrinsic motivation was 0.80. We conducted the same analyses with and without

the control variables suggested by Bernerth and Aguinis [67], and reached consistently significant results (see Tables A1–A3 in Appendix A for results without control variables).

3.3. Analytic Strategy

This study conducted data analyses through a series of statistical tools. First, we undertook a descriptive analysis and evaluated reliability and validity via SPSS 27 and AMOS 24. We assessed the internal consistency and reliability of the constructs by using the criteria of standardized factor loadings, Cronbach's alpha coefficient, composite reliability (CR), and average variance extracted (AVE). Then, confirmatory factor analysis (CFA) was conducted by using Mplus 8.3 and AMOS 24 to examine the consistency between multiple latent factor structures and observed data. We assessed the optimality and adequacy of the model fit by comparing model fit indices. Finally, the hypotheses were examined based on structural equation modeling (SEM) through Mplus 8.3. The moderated mediation effects were specified by taking Bauer et al. (2006)'s formula [68].

4. Results

Table 2 shows the values of CR and Cronbach's alpha coefficients for all variables, which exceeded the recommended threshold of 0.8 [69], thereby indicating good internal consistency of the scales. Furthermore, the values of standardized factor loadings and AVE were greater than the recommended standards of 0.6 and 0.5, respectively [69], thus demonstrating adequate convergent validity among the variables. Although this study employed multi-wave data collection (T1, T2, T3) to procedurally control for common method bias, we still conducted Harman's single-factor test to assess its severity. The results showed that the total variance explained by the initial unrotated factor was 30.24%, which is below 40% [62]. Therefore, this study was not significantly affected by common method bias.

Table 2. Validity and reliability of items.

Constructs and Items	Standardized Factor Loadings	AVE	CR	Cronbach's α
AI adoption		0.51	0.89	0.89
1. I need AI to provide information resources to get engineering design work done.	0.67			
2. I need AI to help me conduct engineering design.	0.72			
3. I need to interact with AI frequently during engineering design.	0.73			
4. I can use AI to complete design tasks independently.	0.79			
5. I see AI as my partner in engineering design.	0.67			
6. My collaboration with AI in engineering design is smooth and effective.	0.68			
7. AI supports my design work.	0.77			
8. I was able to have human-like communication with AI during design tasks.	0.68			
Job engagement		0.54	0.91	0.91
1. At my work, I feel that I am bursting with energy.	0.78			
2. At my job, I feel strong and vigorous.	0.74			
3. I am enthusiastic about my job.	0.68			
4. My job inspires me.	0.76			
5. When I get up in the morning, I feel like going to work.	0.73			
6. I feel happy when I am working intensely.	0.72			
7. I am proud of the work that I do.	0.78			
8. I am immersed in my work.	0.74			
9. I get carried away when I'm working.	0.71			

Table 2. Cont.

Constructs and Items	Standardized Factor Loadings	AVE	CR	Cronbach's α
Psychological detachment		0.61	0.86	0.86
1. During brief breaks in design tasks, I forget about work.	0.78			
2. I don't think about design tasks during short breaks.	0.80			
3. I can distance myself from engineering design tasks during work breaks.	0.78			
4. I get a break from the demands of engineering design work.	0.77			
Inclusive leadership		0.57	0.92	0.92
1. The manager is open to hearing new ideas.	0.75			
2. The manager is attentive to new opportunities to improve work processes.	0.75			
3. The manager is open to discuss the desired goals and new ways to achieve them.	0.77			
4. The manager is available for consultation on problems.	0.70			
5. The manager is an ongoing 'presence' in this team—someone who is readily available.	0.72			
6. The manager is available for professional questions I would like to consult with him/her.	0.79			
7. The manager is ready to listen to my requests.	0.77			
8. The manager encourages me to access him/her on emerging issues.	0.78			
9. The manager is accessible for discussing emerging problems.	0.77			
Green creativity		0.65	0.88	0.88
1. Tries new ideas or methods first in green engineering design.	0.82			
2. Seeks new ideas and ways to solve green engineering problems.	0.84			
3. Generates ground-breaking ideas related to sustainable engineering design.	0.75			
4. Is a good role model for creativity in green engineering design.	0.82			
Intrinsic motivation		0.57	0.80	0.80
1. Because I enjoy this work very much.	0.84			
2. Because I have fun doing my job.	0.73			
3. For the moments of pleasure that this job brings me.	0.70			

Table 3 presents the means, standard deviations, Cronbach's alpha, and correlation coefficients among the focal variables. Before examining the hypotheses, we conducted CFA analyses to evaluate whether the proposed structural model could be empirically distinguished. The model fit indices indicated that the hypothesized five-factor model that includes AI adoption, inclusive leadership, job engagement, psychological detachment, and green creativity ($\chi^2/\text{df} = 1.13$, RMSEA = 0.02, RMR = 0.05, CFI = 0.99, IFI = 0.99, TLI = 0.99) demonstrated excellent fit to the data. Our analysis also showed that our hypothesized model overperforms several alternative models: a four-factor model combining AI adoption and inclusive leadership ($\chi^2/\text{df} = 3.14$, RMSEA = 0.08, RMR = 0.13, CFI = 0.80, IFI = 0.80, TLI = 0.79); a three-factor model combining AI adoption, inclusive leadership, and job engagement ($\chi^2/\text{df} = 4.84$, RMSEA = 0.11, RMR = 0.14, CFI = 0.65, IFI = 0.65, TLI = 0.62); a two-factor model combining AI adoption, inclusive leadership, job engagement, and psychological detachment ($\chi^2/\text{df} = 5.47$, RMSEA = 0.12, RMR = 0.14, CFI = 0.59, IFI = 0.59, TLI = 0.56); and a single-factor model ($\chi^2/\text{df} = 6.18$, RMSEA = 0.13, RMR = 0.15, CFI = 0.52, IFI = 0.52, TLI = 0.49). These results provide strong evidence for the discriminant validity of the constructs.

Table 3. Means, standard deviations, reliability coefficient, and correlations.

Variables	M	SD	1	2	3	4	5	6	7	8	9	10
1. Gender	1.48	0.50										
2. Age	36.76	9.85	0.03									
3. Education	2.84	1.10	−0.01	−0.36 **								
4. Tenure	13.27	11.18	0.02	0.95 **	−0.59 **							
5. AI	3.55	0.75	−0.03	0.09	−0.06	0.09	(0.89)					
6. JE	3.26	0.87	0.14 *	0.13 *	−0.06	0.12 *	0.36 **	(0.91)				
7. PD	3.52	0.82	0.08	0.05	0.01	0.04	0.47 **	0.41 **	(0.86)			
8. GC	3.23	0.99	0.02	0.12 *	−0.09	0.13 *	0.51 **	0.44 **	0.46 **	(0.88)		
9. IL	3.35	0.83	−0.00	0.13 *	−0.02	0.11	0.27 **	0.40 **	0.35 **	0.31 **	(0.92)	
10. IM	3.65	0.90	0.03	0.17 **	−0.00	0.14 *	0.22 **	0.21 **	0.24 **	0.27 **	0.11 *	(0.80)

Note: $n = 312$, Cronbach's α coefficients are displayed on the diagonal, AI = AI adoption, JE = job engagement, PD = psychological detachment, GC = green creativity. IL = inclusive leadership, IM = intrinsic motivation. * $p < 0.05$, two-tailed. ** $p < 0.01$, two-tailed.

Hypothesis Testing

Before conducting the structural equation modeling analysis, we performed univariate normality tests on all continuous observed variables. The results showed that the absolute values of skewness for all variables ranged from 0.013 to 0.686, and the absolute values of kurtosis ranged from 0.072 to 1.164, both well below the critical thresholds (skewness < 3 , kurtosis < 10) [70], indicating that the data generally met the assumption of univariate normality.

Therefore, this study employs standard Maximum Likelihood (ML) estimation for model parameter estimation. According to the univariate normality tests mentioned above, the data all satisfy the normality assumption; additionally, the sample size is sufficient ($n = 312$). Under normality conditions, ML estimation is consistent and asymptotically efficient, making it suitable for the data analysis in this study.

The path analysis results are presented in Table 4. Our findings support Hypothesis 1a, showing a significantly positive effect of AI adoption on job engagement ($\gamma = 0.46$, $SE = 0.10$, $p < 0.001$). Similarly, we found a positive relationship between job engagement and green creativity ($\gamma = 0.29$, $SE = 0.06$, $p < 0.001$). Thus, Hypothesis 1b was supported.

Table 4. Path analysis results.

Variables	Job Engagement			Psychological Detachment			Green Creativity		
	Est	SE	p Value	Est	SE	p Value	Est	SE	p Value
Gender	0.24 *	0.09	0.010	0.12	0.08	0.123	−0.11	0.09	0.239
Age	0.01	0.03	0.844	−0.03	0.02	0.267	0.01	0.03	0.796
Education	−0.06	0.10	0.564	0.07	0.08	0.362	−0.08	0.10	0.437
Tenure	−0.01	0.03	0.869	0.02	0.02	0.346	−0.01	0.03	0.847
Intrinsic motivation	0.14 *	0.06	0.014	0.17 *	0.05	0.015	0.15 *	0.06	0.012
AI adoption	0.46 ***	0.10	0.000	0.58 ***	0.09	0.000			
Inclusive leadership	0.30 ***	0.06	0.000	0.18 ***	0.04	0.000			
Job engagement							0.29 ***	0.06	0.000
Psychological detachment							0.46 ***	0.08	0.000
AI adoption $\times$ Inclusive leadership	0.27 ***	0.08	0.000	0.22 ***	0.06	0.000			
R^2		0.36 ***			0.46 ***			0.41 ***	

Note: $n = 312$, Est = estimate, SE = standard error. * $p < 0.05$, two-tailed. *** $p < 0.001$, two-tailed.

Our results also supported Hypothesis 2a, which proposed a positive relationship between AI adoption and psychological detachment ($\gamma = 0.58$, $SE = 0.09$, $p < 0.001$). Further-

more, the results supported Hypothesis 2b, which posited a positive relationship between psychological detachment and green creativity ($\gamma = 0.46$, $SE = 0.08$, $p < 0.001$).

Hypothesis 1c proposed that AI adoption has a positive and significant indirect effect on green creativity through job engagement. The bootstrap indirect effect test confirmed this hypothesis (indirect effect = 0.14, 95% CI [0.04, 0.23], excluding zero). Simultaneously, Hypothesis 2c posited that AI adoption positively influences green creativity through psychological detachment. The results provided strong support for Hypothesis 2c (indirect effect = 0.27, 95% CI [0.11, 0.42], excluding zero).

Hypothesis 3 proposed that inclusive leadership moderates the relationship between AI adoption and job engagement. We found a significant positive interaction between AI adoption and inclusive leadership on job engagement ($\gamma = 0.27$, $SE = 0.08$, $p < 0.001$). A simple slope analysis was undertaken to illustrate this interaction [71]. As shown in Figure 3, under conditions of high inclusive leadership, the simple slope between AI adoption and job engagement was positive and significant ($\gamma = 0.73$, $SE = 0.17$, $p < 0.001$). In contrast, under conditions of low inclusive leadership, the simple slope was not significant ($\gamma = 0.20$, $SE = 0.14$, ns). The difference between the simple slopes for high and low levels of inclusive leadership was significant (difference = 0.53, $SE = 0.22$, $p < 0.05$; see Table 5). Therefore, Hypothesis 3 was partially supported.

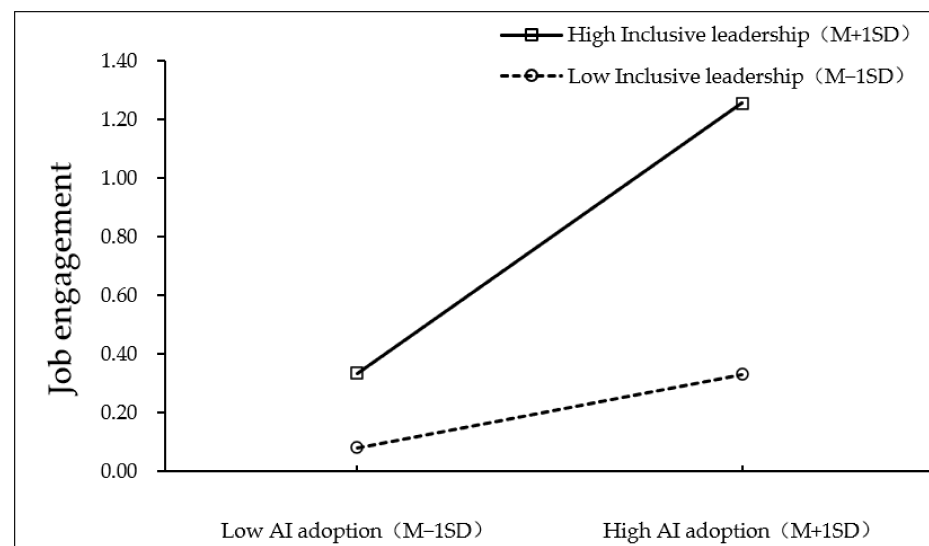


Figure 3. The moderating effect of inclusive leadership in the relationship between AI adoption and job engagement.

Table 5. Moderated path analysis results (mediation: job engagement).

Moderator: IL	AI Adoption (X) → Job Engagement (M1) → Green Creativity (Y)			
	Stage		Effect	
	First (P _{M1X})	Second (P _{YM1})	Indirect ^a (P _{M1X} P _{YM1})	95% CI Indirect Effect
High (+1 SD)	0.73 *** (0.17)	0.29 *** (0.06)	0.21 ** (0.08)	[0.07, 0.36]
Low (−1 SD)	0.20 (0.14)	0.29 *** (0.06)	0.06 (0.05)	[−0.03, 0.15]
Difference	0.53 * (0.22)		0.16 * (0.08)	[0.01, 0.30]

Note: $n = 312$, P_{M1X} = path from AI adoption to job engagement; P_{YM1} = path from job engagement to green creativity; IL = inclusive leadership, Arrows denote hypothesized paths. Superscript “a” indicates conditional indirect effects at moderator levels (± 1 SD), * $p < 0.05$, two-tailed. ** $p < 0.01$, two-tailed. *** $p < 0.001$, two-tailed.

Hypothesis 4 proposed that inclusive leadership moderates the indirect effect of AI adoption on green creativity via job engagement. The results of the bootstrapping (see

Table 5) align with our expectations. Specifically, under high levels of inclusive leadership, the indirect relationship between AI adoption and green creativity was positive and significant (indirect effect = 0.21, SE = 0.08, 95% CI [0.07, 0.36], excluding zero). Conversely, under low levels of inclusive leadership, this indirect relationship was not significant (indirect effect = 0.06, SE = 0.05, 95% CI [−0.03, 0.15], including zero). The difference in the strength of the two indirect effects was significant (difference = 0.16, SE = 0.08, 95% CI [0.01, 0.30], excluding zero). Thus, Hypothesis 4 was partially supported.

Hypothesis 5 proposed that inclusive leadership moderates the relationship between AI adoption and psychological detachment. Our results showed a significant positive interaction effect between AI adoption and inclusive leadership on psychological detachment ($\gamma = 0.22$, SE = 0.06, $p < 0.001$). The simple slope plot is illustrated in Figure 4. Specifically, under high levels of inclusive leadership, the simple slope representing the relationship between AI adoption and psychological detachment was positive and significant ($\gamma = 0.80$, SE = 0.13, $p < 0.001$). Under low levels of inclusive leadership, the simple slope remained positive and significant ($\gamma = 0.36$, SE = 0.13, $p < 0.01$). The difference between the simple slopes for high and low levels of inclusive leadership was significant ($\gamma = 0.44$, SE = 0.17, $p < 0.01$; see Table 6). Therefore, Hypothesis 5 was supported.

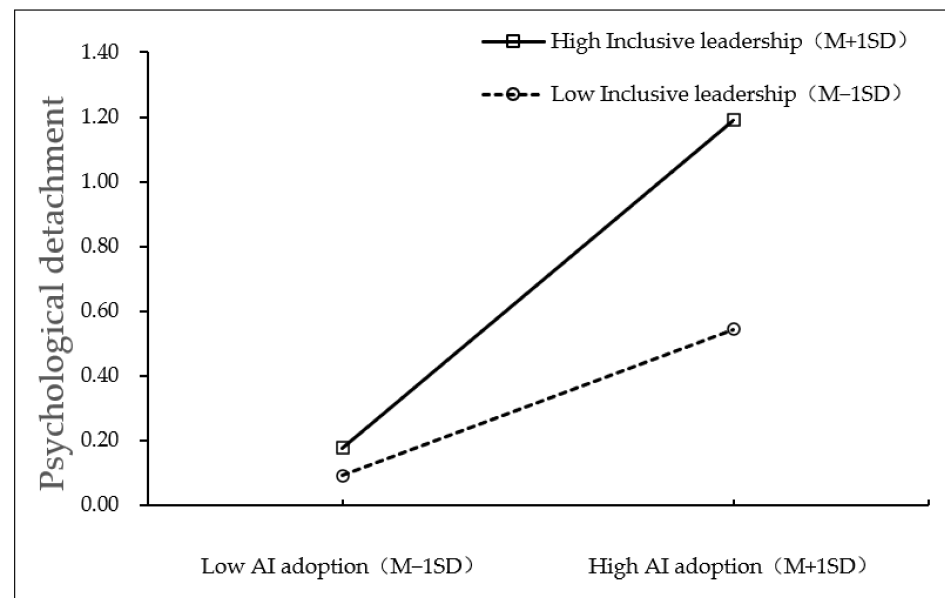


Figure 4. The moderating effect of inclusive leadership in the relationship between AI adoption and psychological detachment.

Table 6. Moderated path analysis results (mediation: psychological detachment).

Moderator: IL	AI adoption (X) → Psychological Detachment (M2) → Green Creativity (Y)			
	Stage		Effect	
	First (P_{M2X})	Second (P_{YM2})	Indirect ^a ($P_{M2X} P_{YM2}$)	95% CI Indirect Effect
High (+1 SD)	0.80 *** (0.13)	0.46 *** (0.08)	0.37 *** (0.10)	[0.17, 0.57]
Low (−1 SD)	0.36 ** (0.13)	0.46 *** (0.08)	0.16 * (0.08)	[0.02, 0.31]
Difference	0.44 ** (0.17)		0.20 * (0.09)	[0.04, 0.37]

Note: $n = 312$, P_{M2X} = path from AI adoption to psychological detachment; P_{YM2} = path from psychological detachment to green creativity; IL = inclusive leadership, Arrows denote hypothesized paths. Superscript “a” indicates conditional indirect effects at moderator levels (± 1 SD), * $p < 0.05$, two-tailed. ** $p < 0.01$, two-tailed. *** $p < 0.001$, two-tailed.

Hypothesis 6 proposed that inclusive leadership moderates the indirect effect of AI adoption on green creativity via psychological detachment. The results of the bootstrapping (see Table 6) are in line with our expectations. When inclusive leadership was high, the indirect relationship between AI adoption and green creativity was positive and significant (indirect effect = 0.37, SE = 0.10, 95% CI [0.17, 0.57], excluding zero). When inclusive leadership was low, this indirect relationship was also positive and significant (indirect effect = 0.16, SE = 0.08, 95% CI [0.02, 0.31], excluding zero). The difference in the strength of these two indirect effects was significant (difference = 0.20, SE = 0.09, 95% CI [0.04, 0.37], excluding zero). Therefore, Hypothesis 6 was supported.

We have summarized all the results of the hypothetical tests in Table 7 below to present the support for each hypothesis more clearly.

Table 7. Summary of Hypothesis Testing Results.

Hypothesis	Results
H1a	Supported
H1b	Supported
H1c	Supported
H2a	Supported
H2b	Supported
H2c	Supported
H3	Supported
H4	Partially Supported
H5	Supported
H6	Supported

5. Discussion

Understanding how AI adoption promotes green creativity in green engineering design has become an increasingly important topic. This study, grounded in the COR theory, finds that AI adoption positively influences the green creativity of project engineering team designers through two mediating pathways: enhancing job engagement and fostering psychological detachment. Furthermore, inclusive leadership not only strengthens the positive impact of AI adoption on these mediating variables but also indirectly enhances its effect on green creativity through both pathways. Specifically, the indirect effect of job engagement is significant only under high levels of inclusive leadership, whereas the indirect effect of psychological detachment is enhanced under both high and low levels of inclusive leadership.

5.1. Theoretical Implications

First, the supportive results of H1a–H1c indicate that the adoption of AI can promote designers' green creativity through the mediating path of job engagement. Building upon the research of Sun et al. [72] and Gurcham et al. [33], this study further bridges the theoretical gap between AI and green creativity. Meanwhile, the supportive results of H2a–H2c demonstrate that AI adoption can promote designers' green creativity through the mediating path of psychological detachment during working hours. This finding extends the research by Niks et al. [73] on the positive relationship between psychological detachment and creativity from non-working hours to working hours, and refines the scope from general creativity to green creativity within the field of engineering.

Overall, the findings of H1a–H2c positions AI as a complex cognitive regulator within the context of green engineering design, supplementing the binary framework of previous research, in which Li et al. [74] viewed AI as a promoter and Yao et al. [22] viewed it as an inhibitor of green creativity. By identifying two complementary mediating pathways, it

deepens the understanding of how human–AI collaboration fosters green creativity, directly filling the gap in comprehending the complementary dynamics between AI technology and green creativity. This study views AI as a collaborative partner whose adoption can simultaneously facilitate two complementary psychological mechanisms, helping designers achieve a nuanced balance across multiple goals, such as building energy consumption, material selection, environmental impact, and energy efficiency [75], thereby enhancing green creativity. Together, these two mechanisms constitute an “immersion–recovery” integration: high levels of job engagement increase the need for effective recovery, while high-quality psychological detachment replenishes resources to support deeper job engagement. Job engagement represents positive cognitive immersion. The mechanism of job engagement explains how AI enhances designers’ immersion by providing green performance predictions and a visual ecological model [76]. This is consistent with the findings of Cao and Zhou [77], suggesting that generative AI can significantly enhance design efficiency and scheme diversity while guiding the construction of sustainable dimensions. When designers’ cognitive resources are freed, and their sustainable connection with the environment is strengthened, they are more inclined to deepen green creative exploration. Meanwhile, psychological detachment represents a strategically work-related mental micro-break. The mechanism of psychological detachment reveals a resource restoration mechanism in which AI helps designers strategically achieve mental separation and recover cognitive resources when taking over repeated, high-cognitive-load iterative design tasks, such as optimizing green parameters and material screening, as discovered by Schwarzkopf et al. [78]. Designers can then redistribute their limited cognitive resources to high-value creative activities.

Second, the results regarding H3–H6 indicate that inclusive leadership is a critical boundary condition for the dual-path mechanisms through which AI enhances designers’ green creativity. This finding complements previous research by Cheung et al. [79], which focused on the functionality of AI, and by Murtagh et al. [80], which focused on designers’ personal traits, largely overlooking the key role of diverse leadership styles in fostering designers’ green output within the context of AI technology. Our findings then illustrate an integrated framework that considers the interactive role of technological, psychological, and organizational factors in green creativity. Our study reveals that the open, supportive, and affirming characteristics of inclusive leadership [51] create a safe psychological environment for designers, enhancing their perception of AI’s usefulness, encouraging them to think outside the box, and leveraging AI to explore diverse green pathways, thereby promoting its creative application and exploration in green design. This finding aligns with previous research by Ding et al. [81] on inclusive leadership in project-based organizations, indicating that leader openness can promote knowledge sharing and innovation within engineering teams. Conversely, our findings indicate that in contexts lacking inclusive leadership, AI tools may hinder designers’ green creative potential due to resistance or a perceived loss of autonomy. This echoes the concerns raised by Ma et al. [82] regarding the tension between human–computer interaction and professional identity; excessive AI intervention, if lacking sufficient human oversight, may undermine a designer’s sense of competence and intrinsic motivation. In the absence of organizational support, designers may perceive AI as a threat to their professional judgment rather than a collaborator, ultimately constraining rather than fostering green innovation.

Third, this study extends the application of COR theory to the domain of collaboration between AI and designers in green engineering. While the COR theory focuses on the acquisition and preservation of static resource reserves [18], our findings reveal that, as an active collaborator, AI’s core function lies in optimizing the allocation of global economic and green value. Through dynamic balancing, AI regulates the “depletion–regeneration” cycle of key resources (such as cognition and attention) in the

workflow, thereby proposing a theoretical shift from maintaining resource stockpiles to actively regulating resource enhancement.

This study deepens our understanding of psychological detachment. In the iterative process of green design, psychological detachment is no longer merely regarded as a passive and defensive recovery mechanism occurring outside the workflow [36]. Instead, it is viewed as an active and promotive mechanism within the design process. By taking over green optimization tasks such as environmental monitoring and energy conservation, AI frees up cognitive bandwidth for deep information integration, enabling engineering project designers to strategically and temporarily detach from cognitive fixation on green design proposals, thereby achieving an active state of “in-process detachment” [83]. This state of detachment transcends reactive recovery and can create the psychological conditions needed to reframe cognitive frameworks (e.g., through subconscious associations) [46]. Thus, psychological detachment plays a key role in supporting immediate creative efforts. Future research could focus on how engineering project teams design and embed “creative micro-pauses”, periods that support psychological detachment, into the workflow. Doing so would sustainably release the cognitive resources necessary for designers’ green creativity.

The results indicate that investigating the impact of AI on green engineering design requires an interactionist perspective to examine the green creativity of engineering project designers. The findings show that designers’ green creativity is the product of a synergy among technological empowerment, individual psychological processes, and enabling environments [84]. Our study complements earlier research on how broader organizational contextual factors, such as team climate or organizational culture, interact with human–AI systems to shape designers’ green creativity [85]. Inclusive leadership is a critical context that ensures AI is recognized as a green enabling resource, and designers feel both empowered and capable when practicing green creativity.

5.2. Practical Implications

Our study provides three important managerial implications for engineering project management practices in the construction industry. First, our findings indicate that AI adoption promotes engineering designers’ green creativity by enhancing job engagement. This finding is consistent with previous studies demonstrating that AI-supported work environments directly foster employee eco-initiative creative behavior [86]. Therefore, the engineering design organization should redefine the role of artificial intelligence in green design practices, transforming it from a technical auxiliary tool into an intelligent collaborative partner. In architectural and engineering design processes, project organizations can intentionally delegate repetitive yet cognitively demanding tasks, such as Autodesk Revit-based green information retrieval, preliminary low-carbon scheme generation, building energy simulation, and lifecycle environmental data analysis, to AI systems. This approach not only improves design efficiency under project constraints such as cost and schedule, but also liberates designers from low-value, high-consumption tasks, encouraging them to focus their cognitive resources on resolving complex sustainability trade-offs between architectural aesthetics, constructability, and environmental performance. Our research results further indicate that designers can benefit when they are able to dynamically control the pace of AI-assisted work; the engineering design organization should provide AI-oriented training programs to help designers quickly apply AI to interdisciplinary green design. This recommendation is also supported by Van Dongen et al. (2016), who stated that engineering design organizations ought to realize that training effects will not be immediate [87]; therefore, it is recommended that organizations set reasonable performance expectations during the initial stages of training and allow for a sufficient evaluation cycle for training effectiveness to balance initial investments against potential long-term benefits.

This can be achieved by holding weekly experience-sharing sessions, which can encourage designers to demonstrate new techniques for using AI to solve green design challenges while also allowing them to raise their own difficulties or answer others' questions.

Second, the implementation of AI in the engineering design industry should be advanced in parallel with leadership development. Managers should grant designers sufficient autonomy, encouraging and supporting them to explore and integrate AI-generated insights into the specific design requirements of a project. When faced with green solutions that may break away from traditional project practices, managers can maintain an open mind, for instance, by collaborating with designers to identify feasible elements or by establishing dedicated project funding to test high-potential but risky components of a proposal, thereby motivating designers to pursue continuous green innovation. Furthermore, our results further reveal that inclusive leadership amplifies the positive effects of AI adoption. This finding aligns with previous research showing that inclusive leadership positively predicts employees' innovation performance in the AI era [88] by clarifying goals and reducing uncertainty around technology use. Accordingly, in the process of advancing green objectives, managers can continuously communicate project sustainability goals, such as achieving LEED certification, reducing lifecycle carbon emissions, or improving building energy performance, so that designers perceive AI as a strategic partner in achieving green project objectives rather than a threat to their professional identity. These practices can reduce designers' anxiety and defensiveness toward AI while maximizing its empowering potential in green project innovation.

Third, although AI demonstrates substantial empowering potential in engineering design, construction organizations should remain cautious regarding the delegation of design decision-making authority to AI systems. Previous studies indicate that AI systems frequently fail to substitute for designers' holistic judgment when addressing design tasks that involve normative issues and conflicting values [89]. Specifically, in design tasks that involve significant engineering judgment, occupant well-being, project safety, regulatory compliance, or high professional accountability, the principle of "human-centered design decision-making" should be strictly adhered to. AI adoption should be strategically limited to areas such as conceptual green design generation, parametric optimization, building performance simulation, clash detection, and environmental scenario analysis, while engineering designers retain final authority over design approval, solution selection, and project-specific sustainability trade-offs. Such a governance approach allows construction organizations to leverage the computational efficiency of AI while preserving designers' professional autonomy, engineering responsibility, and exploratory space for green creativity. When designers feel trusted and empowered in terms of their professional value, their intrinsic sense of work meaning and belonging is significantly enhanced, thereby stimulating higher job engagement and ultimately translating into green creative output.

5.3. Limitations and Directions for Future Research

Our study also has certain limitations that can provide directions for future research. First, although we designed a multi-wave survey to reduce common method bias, our data are based on self-reports from an online survey platform. Future research could incorporate multi-source data (such as leadership evaluations and objective green creativity outputs) and consider conducting replication studies across different organizational and cultural contexts. Second, although the longitudinal design aids in inferring temporal relationships among variables, we cannot fully rule out the influence of reverse causality. Future research may employ match-pair surveys, experience sampling or daily diary methods to capture the short-term dynamic fluctuations of the resource spiral. It may also adopt field experiments or intervention studies, randomly assigning designers' AI

usage permissions to explore causal relationships among variables. Third, future research could further explore the moderating mechanisms of inclusive leadership on the effects of AI adoption on green creativity. In this study, when the level of inclusive leadership is low, its moderating effect on the mediating path of “AI adoption influences designers’ green creativity through job engagement” is not significant. This may be due to the lack of supportive resources and psychological safety in low-inclusive environments, which suppresses positive changes in designers’ job engagement and prevents the mediating mechanism from emerging. These results provide insights into how leadership influences the impact of AI technology on designers’ green creativity. Future research can explore whether individual traits (e.g., creative self-efficacy), emotional responses (e.g., technostress, AI anxiety), work characteristics (e.g., perceived autonomy), and relational quality (e.g., AI trust) can sustain the positive impact of technology adoption on designers’ green creativity in environments with insufficient leadership support. Furthermore, the negative impact of AI systems’ own resource consumption (such as energy and water) and carbon footprint on their sustainability also warrants further examination. Meanwhile, future research should focus on contextualization, expanding to more specific organizational settings such as construction sites, onsite design teams, and contractors while employing objective indicators (e.g., project sustainability ratings, supervisor evaluations) to supplement self-reported data, thereby narrowing the gap between perception and actual behavior. Last but not least, our study provides a comprehensive overview of the broad adoption of AI. Future research may distinguish among different types of AI (e.g., generative, analytical), application focus (e.g., low-carbon design, precise modeling), usage patterns (perceptive, exploratory), and how they facilitate this transformation process from green creativity to green performance, thereby offering more nuanced and context-specific theoretical explanations of its impact on designers’ green creativity.

6. Conclusions

This study developed and examined a moderated dual-mediation model, demonstrating that AI adoption enhances engineering project designers’ green creativity by increasing job engagement and promoting psychological detachment, with inclusive leadership further amplifying these effects. Theoretically, it regards AI as a cognitive rhythm regulator in green engineering design, viewing psychological detachment as an active incubator of green creativity, while integrating technological, psychological, and contextual perspectives, which provides a more holistic understanding of the mechanisms and boundary conditions underlying AI-driven green innovation. Practically, it suggests work redesign, inclusive leadership development, and improved AI governance to unlock the potential of green creativity through human–AI collaboration. In essence, we advocate for a shift from viewing AI as a mere tool to embracing it as a strategic partner in the pursuit of sustainable engineering design. Future research may further explore the effectiveness of AI adoption across different organizational and work environments.

Author Contributions: Conceptualization, Y.Q., S.X. and J.C.; data curation, Y.Q. and S.X.; methodology, Y.Q. and S.X.; investigation, S.X. and Y.Q.; funding acquisition, Y.Q. and S.X.; project administration, Y.Q., S.X. and J.C.; software, Y.Q., S.X. and J.C.; supervision, S.X. and Y.Q.; writing—original draft preparation, Y.Q. and S.X.; writing—review and editing, Y.Q., S.X. and J.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki, and approved by the Institutional Review Board of Nanjing Tech University (protocol code NTJTECH-1-45 and 24 March 2026).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Path analysis results (without control variables).

Variables	Job Engagement			Psychological Detachment			Green Creativity		
	Est	SE	p Value	Est	SE	p Value	Est	SE	p Value
AI adoption	0.52 ***	0.10	0.000	0.62 ***	0.09	0.000			
Inclusive leadership	0.31 ***	0.06	0.000	0.18 ***	0.04	0.000			
Job engagement							0.32 ***	0.06	0.000
Psychological detachment							0.50 ***	0.08	0.000
AI adoption × Inclusive leadership	0.28 ***	0.08	0.000	0.22 ***	0.06	0.000			
R ²		0.33 ***			0.42 ***			0.37 ***	

Note: $n = 312$, Est = estimate, SE = standard error. *** $p < 0.001$, two-tailed.

Table A2. Moderated path analysis results (mediation: job engagement; without control variables).

Moderator: IL	AI adoption (X) → Job Engagement (M1) → Green Creativity (Y)			
	Stage		Effect	
	First (P _{M1X})	Second (P _{YM1})	Indirect ^a (P _{M1X} P _{YM1})	95% CI Indirect Effect
High (+1 SD)	0.80 *** (0.16)	0.32 *** (0.06)	0.26 ** (0.08)	[0.10, 0.39]
Low (−1 SD)	0.25 (0.13)	0.32 *** (0.06)	0.08 (0.05)	[−0.02, 0.16]
Difference	0.55 * (0.22)		0.18 * (0.08)	[0.02, 0.31]

Note: $n = 312$, P_{M1X} = path from AI adoption to job engagement; P_{YM1} = path from job engagement to green creativity; IL = inclusive leadership, Arrows denote hypothesized paths. Superscript “a” indicates conditional indirect effects at moderator levels (± 1 SD), * $p < 0.05$, two-tailed. ** $p < 0.01$, two-tailed. *** $p < 0.001$, two-tailed.

Table A3. Moderated path analysis results (mediation: psychological detachment; without control variables).

Moderator: IL	AI adoption (X) → Psychological Detachment (M2) → Green Creativity (Y)			
	Stage		Effect	
	First (P _{M2X})	Second (P _{YM2})	Indirect ^a (P _{M2X} P _{YM2})	95% CI Indirect Effect
High (+1 SD)	0.84 *** (0.13)	0.50 *** (0.08)	0.42 *** (0.10)	[0.21, 0.59]
Low (−1 SD)	0.40 ** (0.12)	0.50 *** (0.08)	0.20 * (0.08)	[0.05, 0.32]
Difference	0.45 ** (0.17)		0.22 * (0.09)	[0.05, 0.37]

Note: $n = 312$, P_{M2X} = path from AI adoption to psychological detachment; P_{YM2} = path from psychological detachment to green creativity; IL = inclusive leadership, Arrows denote hypothesized paths. Superscript “a” indicates conditional indirect effects at moderator levels (± 1 SD), * $p < 0.05$, two-tailed. ** $p < 0.01$, two-tailed. *** $p < 0.001$, two-tailed.

References

1. Zhong, X.; Deetman, S.; Tukker, A.; Behrens, P. Increasing Material Efficiencies of Buildings to Address the Global Sand Crisis. *Nat. Sustain.* **2022**, *5*, 389–392. [\[CrossRef\]](#)
2. Umoh, A.A.; Adefemi, A.; Ibewe, K.I.; Etukudoh, E.A.; Ilojiana, V.I.; Nwokediegwu, Z.Q.S. Green architecture and energy efficiency: A review of innovative design and construction techniques. *Eng. Sci. Technol. J.* **2024**, *5*, 185–200. [\[CrossRef\]](#)
3. Delaney, E.; Liu, W. Insights into Environmental Sustainability Implementation during the Design Stage of New Product Development: An Industry Perspective. *J. Eng. Technol. Manag.* **2024**, *71*, 101803. [\[CrossRef\]](#)
4. Ballard, G.; Howell, G. Shielding Production: Essential Step in Production Control. *J. Constr. Eng. Manag.* **1998**, *124*, 11–17. [\[CrossRef\]](#)
5. Chen, Y.-S.; Chang, C.-H. The Determinants of Green Product Development Performance: Green Dynamic Capabilities, Green Transformational Leadership, and Green Creativity. *J. Bus. Ethics* **2013**, *116*, 107–119. [\[CrossRef\]](#)
6. Ashkbous, M.; Ghorbani, E.; Keivanpour, S. Artificial Intelligence for Eco-Design: A Systematic Review. *Adv. Eng. Inform.* **2026**, *69*, 103989. [\[CrossRef\]](#)
7. Woldegiyorgis, T.A.; Li, H.X.; Asmare, E.; Assamnew, A.D.; Admassu, F.C.; Desalegn, G.A.; Asefa, S.K.; Mossie, S.Y. Harnessing Artificial Intelligence to Improve Building Performance and Energy Use: Innovations, Challenges, and Future Perspectives. *Energy Inf.* **2025**, *8*, 138. [\[CrossRef\]](#)
8. Ain, O.; Khalil, H.B.; El-Maraghy, M.; Marzouk, M. Generative Design and Multi-Objective Optimization for Enhanced Building Thermal Performance. *Case Stud. Therm. Eng.* **2025**, *73*, 106621. [\[CrossRef\]](#)
9. Bibri, S.E.; Huang, J. AI and AI-Powered Digital Twins for Smart, Green, and Zero-Energy Buildings: A Systematic Review of Leading-Edge Solutions for Advancing Environmental Sustainability Goals. *Environ. Sci. Ecotechnol.* **2025**, *28*, 100628. [\[CrossRef\]](#) [\[PubMed\]](#)
10. Saleh, R.; Brem, A. Creativity for Sustainability: An Integrative Literature Review. *J. Clean. Prod.* **2023**, *388*, 135848. [\[CrossRef\]](#)
11. Choudhury, M.M.; Eisenbart, B.; Kuys, B. Artificial Intelligence (AI) in the Design Process—a Review and Analysis on Generative AI Perspectives. *Proc. Des. Soc.* **2025**, *5*, 631–640. [\[CrossRef\]](#)
12. Maitlo, Q.; Wang, X.; Yan, J.; Lashari, I.A.; Faraz, N.A.; Hajaro, N.H. Exploring Green Creativity: The Effects of Green Transformational Leadership, Green Innovation Climate, and Green Autonomy. *Front. Psychol.* **2022**, *13*, 686373. [\[CrossRef\]](#) [\[PubMed\]](#)
13. Habib, S.; Gardiner, Z. Generative AI and Creative Self-Efficacy: A Systematic Review. *Think. Ski. Creat.* **2026**, *62*, 102234. [\[CrossRef\]](#)
14. Gong, W.; Chen, X. The Double-Edged Sword of Creative Control in Designer-AI Co-Creation with Design Experience as a Boundary Condition. *Behav. Sci.* **2026**, *16*, 570. [\[CrossRef\]](#) [\[PubMed\]](#)
15. Fan, L.; Lai, S.; Zhang, S.; Cheng, C.; Wu, F.; Zeng, C.; Wang, X. A Study on User Innovative Behavior of AI Painting Tools Integrating SOR and Self-Determination Theory. *Sci. Rep.* **2026**, *16*, 8741. [\[CrossRef\]](#) [\[PubMed\]](#)
16. Tsao, J.; Liang, C.X.; Nogues, C.; Wong, A. Perceptions and Integration of Generative Artificial Intelligence in Creative Practices and Industries: A Scoping Review and Conceptual Model. *AI Soc.* **2026**, *41*, 2259–2278. [\[CrossRef\]](#)
17. El Moussaoui, M. Architectural Practice Process and Artificial Intelligence—an Evolving Practice. *Open Eng.* **2025**, *15*, 20240098. [\[CrossRef\]](#)
18. Hobfoll, S.E. Conservation of Resources: A New Attempt at Conceptualizing Stress. *Am. Psychol.* **1989**, *44*, 513. [\[CrossRef\]](#) [\[PubMed\]](#)
19. Halbesleben, J.R.B.; Neveu, J.-P.; Paustian-Underdahl, S.C.; Westman, M. Getting to the “COR”: Understanding the Role of Resources in Conservation of Resources Theory. *J. Manag.* **2014**, *40*, 1334–1364. [\[CrossRef\]](#)
20. Chen, Y.; Qin, Z.; Sun, L.; Wu, J.; Ai, W.; Chao, J.; Li, H.; Li, J. GDT Framework: Integrating Generative Design and Design Thinking for Sustainable Development in the AI Era. *Sustainability* **2025**, *17*, 372. [\[CrossRef\]](#)
21. Zozul'ak, J.; Zozul'aková, V. Ethical and Ecological Dilemmas of Environmental Protection. *Manag. Syst. Prod. Eng.* **2022**, *30*, 282–290. [\[CrossRef\]](#)
22. Yao, J.; Jian, Y.; Huang, C.; Yuan, L.; Ye, J.; Shi, Z.; Calautit, J.K.; Wei, S.; Deng, X.; Broyd, T.; et al. Artificial Intelligence for Sustainable Architectural Design. *Nexus* **2025**, *2*, 100100. [\[CrossRef\]](#)
23. Chen, I.-S.; Choi, J.N. Industry 4.0 Technologies and Green Creativity: Mediating Roles of Playful Work Design and Leisure Crafting. *J. Bus. Res.* **2025**, *188*, 115103. [\[CrossRef\]](#)
24. Wang, M.; Qi, Y.; Cheng, J. Motivating Green Knowledge Behavior by Mindfulness Leadership in Engineering Design: The Role of Moral Identity. *Buildings* **2025**, *15*, 1602. [\[CrossRef\]](#)
25. Zhang, S.; Li, Y.; Hong, A. The Impact of Green Inclusive Leadership on Green Innovation in Chinese SMEs: The Mediating Roles of Green Knowledge Sharing and Green Organizational Identity. *Sustainability* **2025**, *17*, 1180. [\[CrossRef\]](#)
26. Nouri, A.; Hu, M. Democratizing Environmental Impact Assessment: An AI-Augmented Framework for Sustainable Building Design. *iScience* **2026**, *29*, 114589. [\[CrossRef\]](#) [\[PubMed\]](#)

27. Yang, X.; Yan, L.; Arshad, D. From Green Orientation to Sustainable Outcomes: Exploring Employee Creativity and AI-Driven Psychological Mechanisms. *Acta Psychol.* **2025**, *259*, 105367. [[CrossRef](#)] [[PubMed](#)]
28. Hobfoll, S.E. Conservation of Resource Caravans and Engaged Settings. *J. Occup. Organ. Psychol.* **2011**, *84*, 116–122. [[CrossRef](#)]
29. Ukamaka, A.C.; Sanusi, A.N.; Asere, J.B.; Sanusi, H.K. Machine Learning for Predicting Environmental Impact in Green Buildings: A Systematic Review. *Asian J. Geo. Res.* **2025**, *8*, 187–197. [[CrossRef](#)]
30. Li, M.; Wang, Z.; Chang, H.; Wang, Z.; Guo, J. A Novel Multi-Objective Generative Design Approach for Sustainable Building Using Multi-Task Learning (ANN) Integration. *Appl. Energy* **2024**, *376*, 124220. [[CrossRef](#)]
31. Zeng, P.; Dai, Y.; Yin, J.; Zhong, J.; Han, Z.; Shi, C.; Jin, Z.; Jiang, M.; Han, Y.; Lu, S. GreenPlanner: Practical Floorplan Layout Generation via an Energy-Aware and Function-Feasible Generative Framework. *arXiv* **2025**, arXiv:2512.00406.
32. Schaufeli, W.B.; Salanova, M.; González-Romá, V.; Bakker, A.B. The Measurement of Engagement and Burnout: A Two Sample Confirmatory Factor Analytic Approach. *J. Happiness Stud.* **2002**, *3*, 71–92. [[CrossRef](#)]
33. Gurcham, K.; Karatepe, O.M.; Rescalvo-Martin, E.; Avci, T. Work Engagement, Job Crafting, and Their Effects on Green Work Outcomes. *Sustainability* **2025**, *17*, 10090. [[CrossRef](#)]
34. Nawaz, A.; Soomro, S.A.; Mansoor Kundi, Y. Linking engagement for innovation with innovative performance: The role of discretionary efforts and knowledge-sharing behaviour. *Int. J. Innov. Manag.* **2023**, *27*, 2350027. [[CrossRef](#)]
35. Ahmed, Z.; Khosa, M.; Nguyen, N.T.; Faqera, A.F.O.; Rehman, S.U. Green HRM Fostering Followers' Green Creativity: Unfolding the Role of Environmental Concern and Employee Engagement with Eco-initiatives as a Serial Mediation. *Creat. Innov. Manag.* **2024**, *33*, 742–765. [[CrossRef](#)]
36. Sonnentag, S. Psychological Detachment from Work During Leisure Time: The Benefits of Mentally Disengaging from Work. *Curr. Dir. Psychol. Sci.* **2012**, *21*, 114–118. [[CrossRef](#)]
37. Etzion, D.; Eden, D.; Lapidot, Y. Relief from Job Stressors and Burnout: Reserve Service as a Respite. *J. Appl. Psychol.* **1998**, *83*, 577–585. [[CrossRef](#)] [[PubMed](#)]
38. Miller, T.; Michoński, G.; Durlík, I.; Kozłowska, P.; Biczak, P. Artificial Intelligence in Aquatic Biodiversity Research: A PRISMA-Based Systematic Review. *Biology* **2025**, *14*, 520. [[CrossRef](#)] [[PubMed](#)]
39. Fu, J.; Zhong, W.; Shen, M.; Chen, D. Evaluating the Impact of AIGC-Supported Design Ideation on Designers' Cognitive Load and Creativity. *Displays* **2026**, *91*, 103275. [[CrossRef](#)]
40. Sonnentag, S.; Fritz, C. Recovery from Job Stress: The Stressor-Detachment Model as an Integrative Framework: The Stressor-Detachment Model. *J. Organ. Behav.* **2015**, *36*, S72–S103. [[CrossRef](#)]
41. Rosado-Solomon, E.H.; Thatcher, S.M.B.; Strizver, S.D. Navigating Mental Illness at Work Using Disengagement and Engagement Pathways. *Acad. Manag. J.* **2025**, *68*, 971–999. [[CrossRef](#)]
42. Hobfoll, S.E.; Halbesleben, J.; Neveu, J.-P.; Westman, M. Conservation of Resources in the Organizational Context: The Reality of Resources and Their Consequences. *Annu. Rev. Organ. Psychol. Organ. Behav.* **2017**, *5*, 103–128.
43. Lajom, J.A.L.; Teo, S.; De Carvalho Filho, M.K.; Stanway, A. Passionate and Psychologically-undetached: A Moderated-mediated Investigation of Psychological Distress among Engaged Employees. *Stress Health* **2023**, *39*, 1026–1036. [[CrossRef](#)] [[PubMed](#)]
44. Faber, M.; De Rooij, A. Is a Wandering Mind a Novelty-Seeking Mind? The Curious Case of Incubation. *Behav. Brain Sci.* **2024**, *47*, e97. [[CrossRef](#)] [[PubMed](#)]
45. Liberman, N.; Trope, Y. Traversing Psychological Distance. *Trends Cogn. Sci.* **2014**, *18*, 364–369. [[CrossRef](#)] [[PubMed](#)]
46. Benedek, M.; Jauk, E.; Fink, A.; Koschutnig, K.; Reishofer, G.; Ebner, F.; Neubauer, A.C. To Create or to Recall? Neural Mechanisms Underlying the Generation of Creative New Ideas. *NeuroImage* **2014**, *88*, 125–133. [[CrossRef](#)] [[PubMed](#)]
47. Bao, P.; Xiao, Z.; Bao, G.; Noorderhaven, N. Inclusive Leadership and Employee Work Engagement: A Moderated Mediation Model. *Balt. J. Manag.* **2022**, *17*, 124–139. [[CrossRef](#)]
48. Murad, M.; Li, C. Impact of Green Inclusive Leadership on Employee Green Creativity: Mediating Roles of Green Passion and Green Absorptive Capacity. *Leadersh. Organ. Dev. J.* **2025**, *46*, 118–138. [[CrossRef](#)]
49. Yang, L. AI-Enhanced BIM Systems for Real-Time Energy Performance Simulation. *Front. Sci. Eng.* **2025**, *5*, 29–43. [[CrossRef](#)]
50. Vijayalakshmi, M.; Subramani, A.K.; Dhinesh, M.; Prabu, A. Green Inclusive Leadership and Green Creativity: A Moderated Mediation Model Through Employee Voice Behaviour and Organisational Justice. In *The Impact of Innovation in Leadership*; Paradiso-Testa, M., Ed.; IGI Global Scientific Publishing: Hershey, PA, USA, 2025; pp. 185–218, ISBN 979-8-3373-2402-9.
51. Carmeli, A.; Reiter-Palmon, R.; Ziv, E. Inclusive Leadership and Employee Involvement in Creative Tasks in the Workplace: The Mediating Role of Psychological Safety. *Creat. Res. J.* **2010**, *22*, 250–260. [[CrossRef](#)]
52. Barik, B.; Gupta, R.; Kumari, M.; Kumar, V.V. Fostering Sustainability: The Role of Green Inclusive Leadership in Enhancing Green Organizational Citizenship Behaviour through Happiness at Work and Self-Efficacy. *J. Manag. Dev.* **2026**, *45*, 207–225. [[CrossRef](#)]
53. Edmondson, A.C.; Lei, Z. Psychological Safety: The History, Renaissance, and Future of an Interpersonal Construct. *Annu. Rev. Organ. Psychol. Organ. Behav.* **2014**, *1*, 23–43. [[CrossRef](#)]
54. Grix, J. *Foundations of Research*, 2nd ed.; Palgrave: London, UK, 2010.

55. Dong, X.; Tian, Y.; He, M.; Wang, T. When Knowledge Workers Meet AI? The Double-Edged Sword Effects of AI Adoption on Innovative Work Behavior. *J. Knowl. Manag.* **2025**, *29*, 113–147. [\[CrossRef\]](#)
56. Schaufeli, W.B.; Bakker, A.B.; Salanova, M. The Measurement of Work Engagement With a Short Questionnaire: A Cross-National Study. *Educ. Psychol. Meas.* **2006**, *66*, 701–716. [\[CrossRef\]](#)
57. Sonnentag, S.; Fritz, C. The Recovery Experience Questionnaire: Development and Validation of a Measure for Assessing Recuperation and Unwinding from Work. *J. Occup. Health Psychol.* **2007**, *12*, 204–221. [\[CrossRef\]](#) [\[PubMed\]](#)
58. Farmer, S.M.; Tierney, P.; Kung-McIntyre, K. Employee creativity in Taiwan: An application of role identity theory. *Acad. Manag. J.* **2003**, *46*, 618–630. [\[CrossRef\]](#)
59. Hair, J.F.; Risher, J.J.; Sarstedt, M.; Ringle, C.M. When to Use and How to Report the Results of PLS-SEM. *Eur. Bus. Rev.* **2019**, *31*, 2–24. [\[CrossRef\]](#)
60. Faul, F.; Erdfelder, E.; Buchner, A.; Lang, A.-G. Statistical Power Analyses Using G*Power 3.1: Tests for Correlation and Regression Analyses. *Behav. Res. Methods* **2009**, *41*, 1149–1160. [\[CrossRef\]](#) [\[PubMed\]](#)
61. Peer, E.; Brandimarte, L.; Samat, S.; Acquisti, A. Beyond the Turk: Alternative Platforms for Crowdsourcing Behavioral Research. *J. Exp. Soc. Psychol.* **2017**, *70*, 153–163. [\[CrossRef\]](#)
62. Podsakoff, P.M.; MacKenzie, S.B.; Lee, J.-Y.; Podsakoff, N.P. Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies. *J. Appl. Psychol.* **2003**, *88*, 879–903. [\[CrossRef\]](#) [\[PubMed\]](#)
63. Rice, S.P.M. Does Changing a Scale’s Context Impact Its Psychometric Properties? A Comparison Using the PERMA-Profiler and the Workplace PERMA-Profiler. *Merits* **2024**, *4*, 109–117. [\[CrossRef\]](#)
64. Spector, P.E.; Brannick, M.T. Methodological Urban Legends: The Misuse of Statistical Control Variables. *Organ. Res. Methods* **2011**, *14*, 287–305. [\[CrossRef\]](#)
65. Shalley, C.E.; Zhou, J.; Oldham, G.R. The Effects of Personal and Contextual Characteristics on Creativity: Where Should We Go from Here? *J. Manag.* **2004**, *30*, 933–958. [\[CrossRef\]](#)
66. Gagné, M.; Forest, J.; Gilbert, M.-H.; Aubé, C.; Morin, E.; Malorni, A. The Motivation at Work Scale: Validation Evidence in Two Languages. *Educ. Psychol. Meas.* **2010**, *70*, 628–646. [\[CrossRef\]](#)
67. Bernerth, J.B.; Aguinis, H. A Critical Review and Best-Practice Recommendations for Control Variable Usage. *Pers. Psychol.* **2016**, *69*, 229–283. [\[CrossRef\]](#)
68. Bauer, D.J.; Preacher, K.J.; Gil, K.M. Conceptualizing and Testing Random Indirect Effects and Moderated Mediation in Multilevel Models: New Procedures and Recommendations. *Psychol. Methods* **2006**, *11*, 142–163. [\[CrossRef\]](#) [\[PubMed\]](#)
69. Hair, J.F., Jr.; Black, W.C.; Babin, B.J.; Anderson, R.E. Multivariate Data Analysis. In *Multivariate Data Analysis*; Cengage: Andover, UK, 2010; p. 785.
70. Kline, R.B. *Principles and Practice of Structural Equation Modeling*; Guilford Press: New York City, NY, USA, 2016.
71. Aiken, L.S.; West, S.G.; Reno, R.R. *Multiple Regression: Testing and Interpreting Interactions*; Sage: Thousand Oaks, CA, USA, 1991.
72. Sun, L.; Hu, R.; Su, H. Unlocking Human Potential in the AI Age: How Employee-AI Collaboration Transforms Work Engagement through Dual Psychological Pathways. *Front. Psychol.* **2026**, *16*, 1705671. [\[CrossRef\]](#) [\[PubMed\]](#)
73. Niks, I.M.W.; De Jonge, J.; Gevers, J.M.P.; Houtman, I.L.D. Divergent Effects of Detachment from Work: A Day-Level Study on Employee Creativity. *Eur. J. Work Organ. Psychol.* **2017**, *26*, 183–194. [\[CrossRef\]](#)
74. Li, Y.; Antwi-Afari, M.F.; Anwer, S.; Mehmood, I.; Umer, W.; Mohandes, S.R.; Wuni, I.Y.; Abdul-Rahman, M.; Li, H. Artificial Intelligence in Net-Zero Carbon Emissions for Sustainable Building Projects: A Systematic Literature and Science Mapping Review. *Buildings* **2024**, *14*, 2752. [\[CrossRef\]](#)
75. Khan, A.M.; Tariq, M.A.; Rehman, S.K.U.; Saeed, T.; Alqahtani, F.K.; Sherif, M. BIM Integration with XAI Using LIME and MOO for Automated Green Building Energy Performance Analysis. *Energies* **2024**, *17*, 3295. [\[CrossRef\]](#)
76. Ehtsham, M.; Parisi, G.; Pedone, F.; Rossi, F.; Zinani, M.; Congiu, E.; Marchionni, C. AI-Powered Advanced Technologies for a Sustainable Built Environment: A Systematic Review on Emerging Challenges. *Sustainability* **2025**, *17*, 8005. [\[CrossRef\]](#)
77. Cao, Q.; Zhou, Y. Research on the Application Effectiveness of Generative AI in Design Projects from Data-Driven and Sustainable Perspectives. *Sustainability* **2025**, *17*, 10643. [\[CrossRef\]](#)
78. Schwarzkopf, V.; Wu, P.-Y.; Nolte, T.; De Wolf, C. Fostering Creativity Using AI towards a Circular Economy in Architectural Engineering Design. In *Structures and Architecture*; CRC Press: London, UK, 2025; pp. 3–10, ISBN 978-1-003-65864-1.
79. Cheung, L.H.; Agkathidis, A.; Dall’Asta, J.C.; Di Marco, G. AI-Enhanced Conversational Design Processes: A Systematic Review. *Int. J. Archit. Comput.* **2026**, 14780771261425268. [\[CrossRef\]](#)
80. Murtagh, N.; Roberts, A.; Hind, R. The Relationship between Motivations of Architectural Designers and Environmentally Sustainable Construction Design. *Constr. Manag. Econ.* **2016**, *34*, 61–75. [\[CrossRef\]](#)
81. Ding, G.; Ren, X.; Lin, F. Adopting Active or Passive Leadership in Project-Based Organizations? The Role of Inclusive Leadership in Remote Work Environment. *Int. J. Proj. Manag.* **2024**, *42*, 102623. [\[CrossRef\]](#)
82. Ma, L.; Chen, J.; Hou, X.; Qiao, Y.; Gao, X.; Feng, Y.; Chen, D. Rethinking Design Roles: A Study on Designer and User Perceptions during Human-AI Co-Creation. *Univers. Access Inf. Soc.* **2026**, *25*, 56. [\[CrossRef\]](#)

83. Grinschgl, S.; Neubauer, A.C. Supporting Cognition with Modern Technology: Distributed Cognition Today and in an AI-Enhanced Future. *Front. Artif. Intell.* **2022**, *5*, 908261. [[CrossRef](#)] [[PubMed](#)]
84. Yu, G.; Nie, Q.; Peng, J. The Predictors of Employee Green Creativity: Individual Factors, Contextual Factors and Their Interactions. *Adv. Psychol. Sci.* **2024**, *32*, 1709. [[CrossRef](#)]
85. Al Koliby, I.S.; Al-Swidi, A.K.; Al-Hakimi, M.A.; Farhan, S.A.G. How Green Knowledge-Oriented Leadership Drives Green Innovation in SMEs: The Mediating Role of Environmental Strategy and the Moderating Role of Green AI Capability. *Cogent Bus. Manag.* **2025**, *12*, 2520914. [[CrossRef](#)]
86. Yang, Y.; Yan, L.; Alshuaibi, M.S.I.; Chethiyar, S.D.M. Harnessing AI-Supported Work Environments: Unveiling Micro-Psychological Pathways to Employee Eco-Initiative Creative Behavior. *Acta Psychol.* **2025**, *261*, 105869. [[CrossRef](#)] [[PubMed](#)]
87. Van Dongen, J.M.; Van Berkel, J.; Boot, C.R.L.; Bosmans, J.E.; Proper, K.I.; Bongers, P.M.; Van Der Beek, A.J.; Van Tulder, M.W.; Van Wier, M.F. Long-Term Cost-Effectiveness and Return-on-Investment of a Mindfulness-Based Worksite Intervention: Results of a Randomized Controlled Trial. *J. Occup. Environ. Med.* **2016**, *58*, 550–560. [[CrossRef](#)] [[PubMed](#)]
88. Zhao, X.; Ma, Z.; Yang, M. The Impact of Inclusive Leadership on Employee Innovation Performance in the Era of Artificial Intelligence. In *Proceedings of the 2025 13th International Conference on Orange Technology (ICOT), Bandung, Indonesia, 1–3 December 2025*; IEEE: New York City, NY, USA, 2025; pp. 1–5.
89. Rahwan, I.; Cebrian, M.; Obradovich, N.; Bongard, J.; Bonnefon, J.-F.; Breazeal, C.; Crandall, J.W.; Christakis, N.A.; Couzin, I.D.; Jackson, M.O.; et al. Machine Behaviour. *Nature* **2019**, *568*, 477–486. [[CrossRef](#)] [[PubMed](#)]

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