

Article

From Skilled Workers to Smart Talent: AI-Driven Workforce Transformation in the Construction Industry

Xianhang Xu ^{1,2,*}, Mohd Anuar Arshad ^{2,*} , Yinglei He ³, Hong Liu ⁴, Qianqian Chen ^{1,*} and Jiejing Yang ²

¹ School of Management, Chongqing Institute of Engineering, Chongqing 400056, China

² School of Management, Universiti Sains Malaysia, Penang 11800, Malaysia; yangjiejing@student.usm.my

³ School of Foreign Languages and Literature, Heilongjiang University, Harbin 150080, China; heyinglei@hlju.edu.cn

⁴ School of Social Science, Universiti Sains Malaysia, Penang 11800, Malaysia; liuhong@student.usm.my

* Correspondence: xuxianhang@cqie.edu.cn (X.X.); anuar_arshad@usm.my (M.A.A.); 04390@cqie.edu.cn (Q.C.)

Abstract

Workforce transformation is one of the most pressing challenges in the AI-driven construction industry, as traditional skilled labour roles are rapidly evolving into more interdisciplinary, digitally enabled positions. This study aims to investigate how AI is fundamentally reshaping skill requirements within the construction sector, to analyse stakeholder perceptions and adaptive responses to workforce transformation, and to explore strategies for optimizing construction workforce development to facilitate the critical transition from traditional “skilled workers” to contemporary “smart talent.” It employs phenomenological qualitative research methodology to conduct in-depth interviews with 20 stakeholders in Chongqing, and uses NVivo 14 to conduct thematic analysis of the data. The findings indicate that AI has penetrated all areas of the construction process and is transforming jobs to more likely be digitalized, collaborative, and multi-faceted. However, significant cognitive disparities and varying adaptive capacities among different stakeholder groups have created structural imbalances within the workforce development ecosystem. Based on these key findings, a four-pillar talent development strategy is proposed, encompassing institutional support, educational reform, enterprise engagement, and group development, while stressing the necessity for systemic-orchestrated coordination to reimagine a smart talent ecosystem. This study advances theoretical understanding of digital transformation within construction labour markets, while offering real pathways and institutional contexts for developing regions that desire to pursue workforce transformation and sustainable industrial development in the AI era.

Keywords: construction industry; workforce transformation; talent development strategy; sustainable development; artificial intelligence



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1. Introduction

The construction industry is experiencing immense technological transformation driven by rapid progress in artificial intelligence (AI) [1]. AI technologies are increasingly embedded throughout project lifecycles, from intelligent construction and building information modelling (BIM) systems to automated construction equipment [2]. These technologies are redefining project management approaches and skills, making workforce transformation one of the most pressing challenges in the construction industry [3]. Among all occupational groups in construction, “skilled workers” appear to be the most directly affected by the rise of AI technologies. Their daily tasks—once grounded in manual effort and

experiential knowledge—are now being reshaped by machines, sensors, and digital platforms. As these changes take hold, many traditional positions are gradually disappearing or being redefined. In contrast, “smart talent”—those equipped with digital competencies, interdisciplinary insight, and the ability to work with intelligent systems—are in growing demand but remain scarce [4]. Facilitating the transition from skilled workers to smart talent is thus essential for the sustainable development of the construction workforce.

Automation technologies will soon displace up to 30% of workers by 2030 in a fundamental transformation across global labour markets [5]. Developed economies are addressing this transition through restructuring job roles and developing high-skill job growth in the labour force in construction [6]. In developing countries, workers face a contradiction within the structural workforce regarding generational divides and labour roles across manual skill transmission skills related to under-skilled workforce capacity [7]. Uniquely, the construction industry is likely to face more considerable transformation issues than the manufacturing or IT sectors considering the nature of labour intensity, project-based operability, and multi-trade collaborative work types [8]. Technological advancement continues to widen the skills gap and job loss challenges [9]. In addition, training systems and talent pathways for professional development do not sufficiently respond to the skills transition challenge; while those systems may be in place, there is not a needed scale or scope of practice in the systems [10]. This challenge is critical in western Chinese cities, such as Chongqing, where construction serves as a pillar industry and the transition from skilled workers to smart talent is essential for the high-quality development of the industry.

The sustainability of construction workforce transformation goes beyond simply adjusting skills. It involves the simultaneous transformation of education systems, decent jobs, and industrial systems—processes closely aligned to the United Nations Sustainable Development Goals (SDGs 4, 8, 9) [1]. To optimize construction workforce structures takes a move away from short-term job matching toward embedding environmental, social and governance (ESG)-oriented sustainable development logic. This discursive approach emphasizes institutional arrangements that facilitate skill transitions and social inclusion that ultimately establishes conditions to construct intelligent building ecosystems for future readiness [11].

Existing research has addressed talent shortages [2], skill mismatches [12], and training lags [13] within construction, but most is statistical analysis or macro policy studies. Although prior research has explored digital transitions and skill gaps, little is known about how AI technologies specifically influence workforce transformation processes, stakeholder coordination, and the development of effective workforce strategies—particularly in developing regions. This gap necessitates qualitative research approaches to systematically examine cognitive-behavioural mechanisms and institutional adaptation logic within construction workforce structural evolution.

This study employs the construction industry in Chongqing as a representative case and aims to analyse how AI technologies reshape skill structures and job requirements, examine how key stakeholders understand these changes, and develop workforce development strategies to support the transition from “skilled workers” to “smart talent.” It addresses two research questions (RQs):

RQ1: How AI technologies reshape job configurations and skill structures within the construction industry, and how do key stakeholders understand these changes?

RQ2: How should construction workforce development strategies be optimized to facilitate effective transition from “skilled workers” to “smart talent”?

Through in-depth interviews with key stakeholders and thematic analysis, this study integrates sustainable workforce development concepts to construct an analytical frame-

work spanning AI technology drivers—skill structure transformation, multi-stakeholder responses, and strategy system construction. The study proposes a construction workforce development pathway that progresses from skill restructuring toward ecosystem coordination, aiming to enhance long-term resilience and inclusiveness within construction talent systems. These findings contribute theoretical support and policy guidance for digital transformation and human capital upgrading in developing country construction industries, while expanding analytical perspectives for traditional industry workforce transformation research under AI contexts.

2. Literature Review

2.1. Construction Workforce Evolution Amid Digital Transformation

BIM systems, digital twin modelling, intelligent scheduling platforms, and construction robotics have made rapid inroads into the critical phases of design, construction, and operations [14], spurring widespread transformation from traditional ways of working to digitalized and more intelligent approaches across the construction sector [3]. A great deal of research explores to what extent digital construction [15], intelligent building processes [16], and information management systems reshape production efficiency and organizational structures [17]. Concurrently, this technological evolution reshapes the ecosystem of skill structures and the composition of job roles within the construction sector [18].

Research findings suggesting how automation will impact various occupations suggest that technology first eliminates low- to mid-skilled occupations characterized as repetitive [19,20]. In the construction sector, this process is evolving into a systemic restructuring, involving the redefinition of job functions from frontline workers to project managers [21]. AI in construction will experience three shifts in capability requirements: first, the phase out of low-skilled tasks, such as completing repetitive measurements as well as carrying basic materials; second, an evolution of skill set growth in complex skill positions, such as monitoring equipment, and data-driven scheduling; and third, elevated capacity for cross-domain knowledge integration [22,23]. As functionality demands, construction professionals will evolve beyond physical labour and experience to cross-technical understanding, data analysis, systems-based operations and problem solving capacities through becoming smart talent [24]. From a labour economics perspective, construction enters a skill transformation period characterized by coexisting “substitutive automation” and “augmentative collaboration” [25].

Indeed, AI-driven construction skill structure transformation has shifted workforce development from traditional single-supply models toward multi-centre collaborative governance systems [26], as individual entities cannot independently address systematic restructuring challenges. Governments function as institutional architects, advancing workforce development through policy guidance, occupational standard setting, and fiscal subsidies [27]. Enterprises serve as both technology demand drivers and job suppliers, playing crucial roles in position restructuring and employee training [28]. Educational institutions bear responsibility for talent pipeline development and knowledge system construction, increasingly expected to drive curriculum reform, build interdisciplinary competency models, and strengthen industry integration [29].

International organizations have developed multiple workforce development strategies centred on training and re-education to address skill transformation challenges. The OECD emphasizes constructing “lifelong learning mechanisms” and “skill update platforms [30],” while the European Union advances digital skill standardization and cross-national certification through its Blueprint for Sectoral Cooperation on Skills [31]. China has prioritized “industry–education integration” and “government–enterprise collaboration,”

gradually establishing diversified talent cultivation systems characterized by government leadership, enterprise participation, and university support [32].

However, practice reveals that government–industry–education tripartite coordination systems encounter persistent challenges including goal heterogeneity, resource asymmetry, and temporal imbalances [33]. These issues create disconnections between training, employment, and technology within workforce transformation pathways, generating institutional coordination barriers and strategic gaps [34]. Institutions of higher education have slow responses to technological change, failing to effectively align with professions requirements yet compounding goal dispersals and capability mismatches for workforce development [35].

Competency profiling and skill standard systems for smart construction, and approaches for talent development, have primarily examined conceptual approaches and expert analysis [7,36]. This work still does not adequately provide an empirical analysis of experienced work participants such as frontline workers, educational practitioners and project managers, and ignores their views on technological changes, the processes toward transformation, and influencing factors such as psychological barriers to organizational support and learning to adjust skills as they transfer. The literature consistently removes agency dimensions within these transformation processes, enhancing the area for inquiry and theory development in future initiatives.

2.2. Theoretical Foundations of Skill Reconstruction in the Construction Sector

Construction is fundamentally a labour-intensive industry, which has relied on systems of experience-based skilled labour [12]. Increased project complexity and heightened engineering standards have created structural issues with skill mismatches, talent shortages, and lagging training [17,23]. These issues are particularly pronounced in developing countries, where a lack of skills, low efficiency of skill transfer, and poorly developed on-the-job training systems are evident [37]. Population aging and out-migration of youth from the labour force have compounded these skill shortages. In fact, many countries have recognized these skill shortages as a significant bottleneck for sustainable construction development [38].

These intricate issues in the workforce necessitate expert theoretical frameworks to understand the mechanisms of transformation. Although human capital theory stresses the idea that human capital derives value from educational investment [39], it cannot fully explain transitions in dynamic capabilities or shifts within roles in the construction industry as impacted by technology. To close this theoretical gap, dynamic capabilities theory [40] and organizational learning theory [41] explain how organizations come to have exploratory learning and capability reconstruction of roles during transformations. The concept of skill polarization [42] also predicts that, in conjunction with technology advancement, middle-skill positions will progressively further diminish while high-cognitive and low-physical employment will increase. Collectively, these theories serve as macro-explanatory frameworks for understanding how construction organizations perceive and enact technological change, adjust job structures, and involve employees.

Based on these frameworks, perspectives in organizational learning illuminate adaptation processes toward transformation. Organizational learning theory emphasizes renewing knowledge through reflection during change [43] while ambidextrous learning frames propose a need for organizations to distinguish the functionality between dynamically balancing “exploiting previous experience” and “exploring to learn new capabilities” [44]. For construction contexts, these frameworks offer specificity for understanding how construction organizations respond to external technological disruption, as potentially experienced with AI, while continuing to maintain efficiency in construction and

further advance the transfer of talent systems within construction. Moreover, these provide foundational theories to understand the perceptions and stakeholder responses in the context of representatives from government, enterprise, higher educational institution, and worker constituencies.

The conceptual development herein demonstrates broad changes in the priorities of construction workforce research. Pressures of rapidly iterating technology have redirected research agendas away from sourcing labour to workforce agency and skill transition capabilities [4]; this indicates a strategic shift from responding to skilled workers towards smart talent [24]. However, taken in its totality, the evidenced thinking reveals significant barriers. Construction workforce development research predominately studies one dimension in isolation—such as educational supply, skill gaps, enterprise technology transformation, or policy inclination [22,45,46]—failing to consider the dynamic interplay and variations in cognition across multiple stakeholders all responding to AI transformation. Most of the literature focuses on phenomenon description versus enacting a systematic merger of perspectives that support the logical chain from AI technology drivers—skill structure transformation, multi-stakeholder responses, and strategy system construction. To respond to these limitations, institutional coordination and multi-governance theories provide systematic pathways to develop AI-oriented construction workforce strategies [47]. During systemic change, the process of workforce transformation requires the engagement of multiple actors. It is meaningful to develop an analytical framework that comprises varied theoretical perspectives to account for the transformation path of labour in the construction sector.

These theoretical foundations provide the basis for the study's analytical lens. Dynamic capabilities theory, organizational learning theory, and institutional coordination and multi-governance theories offer insights into how different stakeholder groups adjust to technological disruption by redefining roles, updating knowledge, and realigning strategies. Together, these perspectives inform the analysis of how key institutions in the construction sector interpret and respond to workforce transformation in an AI-driven context.

3. Methodology

3.1. Research Method

Existing research has primarily adopted quantitative approaches—such as surveys or secondary data analysis—which offer limited insight into lived experiences or cognitive variations during workforce transitions. To address this gap, this study investigates how the construction industry achieves workforce transformation from skilled workers to smart talent under AI technological contexts, encompassing complex processes of technological change, organizational adaptation, and institutional coordination.

Given the need to explore lived stakeholder experiences and perceptions, a phenomenological qualitative method was adopted [48]. This approach is particularly appropriate for examining how participants interpret organisational change and skill transformation within their social and institutional environments [49]. It enables in-depth understanding of how participants “experience” and “construct meaning” around skill reconstruction processes, revealing how organizations and individuals identify, integrate, and reconstruct capability resources to respond to technological change.

3.2. Research Sampling

This study selects Chongqing, a major western Chinese city, as the research area for several compelling reasons: construction serves as a pillar industry, the population structure demonstrates regional representativeness, and recent years have witnessed active promotion of intelligent construction transformation, providing valuable case study charac-

teristics. Sample selection employs purposive sampling techniques, utilising maximum variation sampling strategy to ensure comprehensive perspectives and data saturation [50].

Galvin [51] argued that a sample size of 15 participants is sufficient to obtain meaningful qualitative data, while Hennink et al. [52] suggested that data saturation typically occurs between 16 and 24 interviews. In line with these guidelines, this study includes 20 interview participants across four stakeholder categories. Government officials represent three departments: the Housing and Urban-Rural Development Commission, the Human Resources and Social Security Bureau, and the Education Commission. Higher educational institution representatives include professors from the construction major in applied undergraduate universities and vocational colleges. Enterprise managers encompass human resource managers, technical managers, and project managers from large construction companies, private building firms, and intelligent construction enterprises. Frontline workers include skilled technicians, young apprentices, team leaders, and female workers. This sample design ensures coverage across policy formulation, educational supply, organizational response, and operational perception dimensions, facilitating multi-dimensional theoretical understanding (see Table 1).

Table 1. Demographic characteristics of respondents.

S. No.	ID	Category	Gender	Age	Education	Working Experience
01	G1	Government Officer	Male	45	Master	20
02	G2		Male	42	Master	17
03	G3		Male	44	Master	20
04	E1	Higher Educational Institution Professor	Male	45	PhD	15
05	E2		Male	49	PhD	18
06	E3		Male	40	Master	14
07	E4		Male	43	Master	18
08	M1	Enterprise Manager	Male	45	Master	20
09	M2		Female	40	Master	14
10	M3		Female	38	Bachelor	16
11	M4		Male	36	Bachelor	14
12	M5		Male	35	Bachelor	12
13	W1	Frontline Worker	Male	32	Bachelor	10
14	W2		Male	33	Diploma	12
15	W3		Male	22	Diploma	1
16	W4		Male	22	Diploma	1
17	W5		Male	26	Diploma	5
18	W6		Male	26	Bachelor	4
19	W7		Female	25	Diploma	3
20	W8		Female	22	Diploma	1

Table 1 presents comprehensive demographic profiles of the 20 respondents, representing government officials, higher educational institution professors, enterprise managers, and frontline workers. The sample demonstrates male predominance at 75%. Educational backgrounds reveal distinct hierarchical patterns: government officials and higher educational institutions professors predominantly hold master's degrees or higher, while

frontline workers primarily possess associate degrees or below. Age and professional experience distributions show clear stratification, with government officials and higher educational institution professors averaging over 40 years of age and exceeding 15 years of professional experience. Enterprise managers average nearly 40 years of age with 12–16 years of experience, while frontline workers concentrate between 22–33 years of age with approximately 4 years of average tenure.

Among the 20 participants, 14 had direct experience with construction projects involving AI or digital technologies. Enterprise managers (M3–M5) and frontline workers (W1–W6, W8) participated in smart building developments, urban rail infrastructure, and intelligent supervision pilots, often using technologies such as BIM systems, AI-assisted scheduling, intelligent safety monitoring, and digital coordination platforms. Additionally, higher education participants (E1–E4) were exposed to AI applications through teaching and industry engagement, including BIM integration, construction robotics, and smart monitoring systems. Some also contributed to the development of standards and provided technical consulting in intelligent construction. This ensured that the sample reflected informed, experience-based perspectives across all stakeholder groups.

3.3. Data Collection

Data collection employed semi-structured in-depth interviews as the primary method. Prior to interviews, researchers contacted potential participants via telephone and email to confirm participation willingness and schedule interview appointments. The interview period extended from January to April 2025, with individual sessions lasting 30–60 min. Audio recordings were conducted with participant consent and subsequently transcribed for analysis.

The interview guide was structured around three core research dimensions. Impact assessment examined AI influences on skill structures and job requirements within the construction industry. Perception and response analysis explored multi-stakeholder cognitions and reactions to workforce transformation. Strategic development investigated individual and organizational approaches to facilitating construction workforce capability transitions and continuous adaptation within AI environments.

Representative interview questions included: “In which specific construction industry segments or workflow processes do you observe primary AI applications currently?” “What measures has your organization or those familiar to you implemented to address changing skill requirements, and how effective have these initiatives proven?” “To better respond to AI-driven skill transformation, which aspects should government, enterprises, and higher educational institutions respectively prioritize when optimizing construction workforce development strategies?”

3.4. Data Analysis

Thematic analysis served as the primary analytical approach for accomplishing data analysis objectives and exploring research goals. Following interpretive phenomenological principles, this study implemented a six-stage thematic analysis methodology designed to extract common structural elements while respecting participants’ experiential worlds [53].

The analytical process proceeded through multiple interconnected stages. Familiarization involved repeated reading of transcribed texts to develop comprehensive material understanding and record preliminary impressions. Initial coding employed gerund-based open coding units to capture individual behavioural tendencies and cognitive expressions when responding to AI disruption, generating open nodes. Theme identification aggregated similar codes to produce initial themes and establish potential categories. Theme review conducted case comparisons and negative case analysis to examine theme consistency

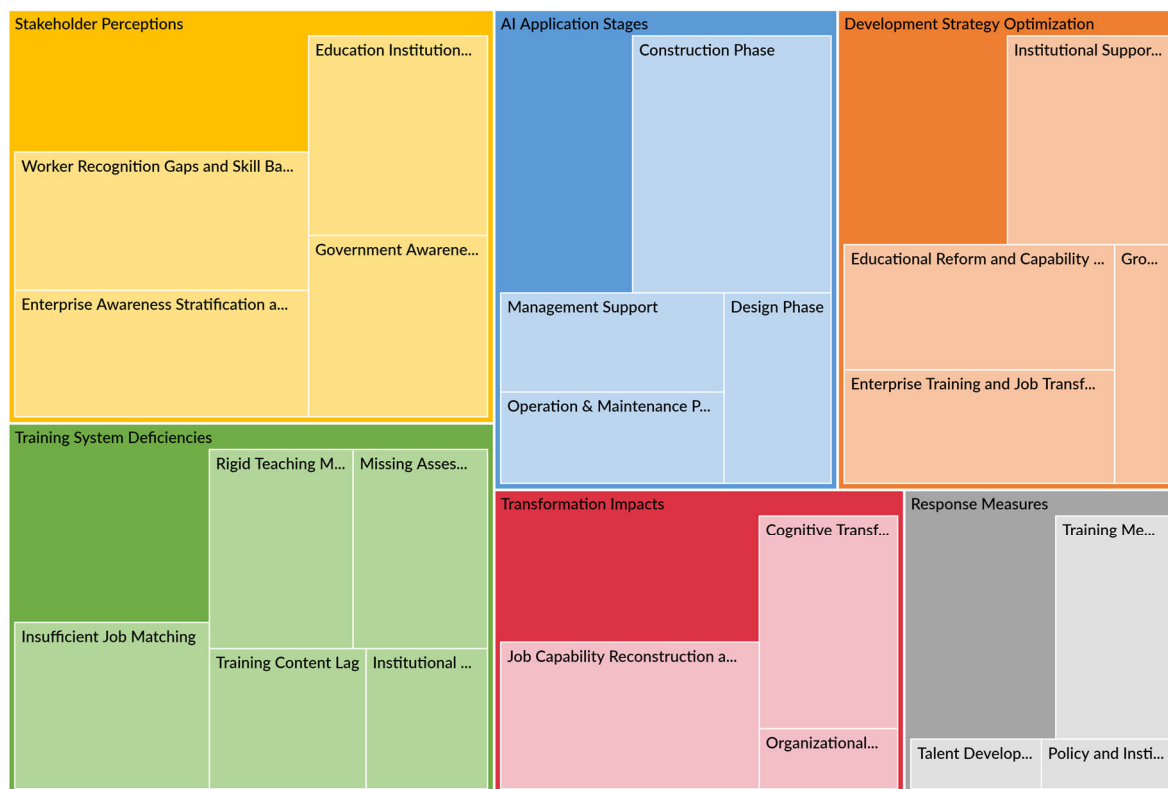


Figure 2. Extracted themes of the study in treemap chart.

Multiple validation strategies ensured research reliability and authenticity. Member checking invited participants to verify research perspectives against their experiences [58]. Investigator triangulation involved two researchers conducting independent coding and negotiating discrepancies before applying refined coding frameworks to remaining transcripts. Reflexivity documentation maintained continuous researcher reflection records throughout the process, monitoring potential bias and subjective positioning influences to ensure analytical transparency and credibility.

3.5. Ethical Considerations and Research Scope

This study adheres to rigorous academic ethical standards throughout all phases of investigation. All participants were informed of the purpose of this research and voluntarily agreed to take part in the interviews. Written informed consent was obtained from all participants prior to the interviews. All interview content underwent anonymization procedures, with collected materials exclusively utilized for academic research purposes without commercial or non-research applications. The study received ethical approval from the Ethics Committee of the School of Management Chongqing Institute of Engineering, with exemption status (Approval Number: 202505, dated 5 January 2025).

Case selection and limitations present important boundary considerations for interpretation. Chongqing's construction industry serves as the case study region based on its regional economic representativeness and data accessibility feasibility, making it suitable for preliminary theoretical mechanism exploration. Regional sample constraints, however, limit the findings' broader national representativeness. Methodological scope employs qualitative interviews and thematic analysis to elucidate mechanisms and construct strategies, while attribution analysis, trend prediction, and quantitative validation of construction workforce transformation require future research expansion and verification.

4. Findings

4.1. AI-Driven Changes in Skill Structures and Stakeholders' Perceptions (RQ1)

This section presents findings addressing the first research objective: analysing how AI technologies reshape skill structures and job requirements within the construction industry. NVivo 14 thematic analysis identified key themes related to AI-driven job position and skill reconstruction, as presented in Table 2.

Table 2. Job position and skill reconstruction themes.

Theme	Sub-Theme	Frequency (N)
AI Application Stages	Design Phase	11
	Construction Phase	19
	Operation & Maintenance Phase	12
	Management Support	12
Transformation Impacts	Job Capability Reconstruction and Skill Upgrading	18
	Cognitive Transformation and Learning Adaptation	13
	Organizational Response and Institutional Change	5
Stakeholder Perceptions	Government Awareness and Policy Guidance	19
	Educational Institution Recognition Lag	20
	Enterprise Awareness Stratification and Response Capacity	20
	Worker Recognition Gaps and Skill Barriers	20

4.1.1. AI Applications Across Construction Stages

Respondent accounts of AI applications in construction industry stages and workflows reveal multi-stage technological penetration patterns across design, construction, operations, and management functions. Government officials, university faculty, enterprise managers, and frontline workers collectively describe how AI technologies systematically embed within traditional construction processes.

Design Phase Applications centre on BIM modelling optimization, AI-assisted design enhancement, and intelligent collision detection. AI integration fundamentally transforms preliminary modelling and analytical capabilities within design workflows.

“The design phase includes BIM system integration and AI-driven parameter optimization.” (E1)

“AI-assisted modelling and intelligent collision detection in the design stage.” (M4)

Construction Phase Applications encompass progress monitoring and predictive analytics, image recognition for quality control, intelligent safety management with risk alerts, and construction robotics deployment. This stage demonstrates AI's transformation of traditional construction approaches from experience-based operations toward data-driven automated collaboration.

“Safety monitoring and scheduling management during construction... automated component installation and image recognition for quality control are gradually being promoted.” (E2)

“Video recognition systems can automatically identify whether personnel are wearing proper safety equipment... crane monitoring assists in determining whether operations meet standards.” (W5)

“Our project has smart crane systems that can automatically detect if people are approaching the lifting area, and some systems can even automatically warn about overload risks.” (W7)

Operation and Maintenance Applications involve structural health monitoring with predictive analytics, equipment condition monitoring and fault identification, intelligent inspection systems with image recognition, and building data analysis for smart facility management. These applications enhance scientific management and response efficiency during post-construction phases.

“Intelligent monitoring in operation and maintenance stages, like smart building systems, structural health monitoring, real-time early warning analysis of foundation settlement data.” (E1)

“Like equipment condition monitoring, measurement precision control, operational data analysis. During large equipment debugging, some systems can automatically identify abnormal parameters and provide timely warnings.” (W2)

“Dam deformation, seepage pressure, displacement data collected by sensors are automatically uploaded to the system, AI algorithms analyse whether risks exist... can also automatically identify abnormal images, reducing manual inspection burden.” (W8)

Management Support Applications span comprehensive project lifecycle management with cost control, intelligent logistics and material scheduling systems, and personnel behaviour management with real-time site monitoring. These applications significantly enhance project management capabilities regarding real-time responsiveness, visualization, and intelligent decision-making.

“Data analysis and management optimization throughout the entire project process.” (M2)

“Smart logistics, achieving optimization in material scheduling and transportation.” (W6)

“There are also intelligent access control and attendance systems that let project departments track worker dynamics in real time.” (W7)

Emerging themes concerning transformation patterns and changes to workforce development identified from respondent descriptions suggest that AI applications are being developed from relatively isolated technological interventions toward systematic integration, while moving from supporting function-based tasks and responsibilities to overall reconstruction of task and job processes. Technology embedding occurs in both specific stage-based tasks, as well as through sequencing and new logic of managerial and organizational constructs and abilities. Respondents affirmatively agree about AI contributing positively to efficiency, safety, and enhanced managerial effectiveness and job architecture; these contributions all provide moving pieces for workforce redevelopment and skill system action.

4.1.2. Observed Transformations

The description from respondents to “changes AI development brings to construction job responsibilities and skill requirements” reveals transformation impact associated with

three interrelated dimensions: reconstruction of job capabilities and responsibility skill development; cognitive transformation and corresponding mechanisms of adaptation and learning; and organizational response as institutional change. In particular, these dimensions reveal profound structural changes with the construction workforce system under the influence of AI technologies, or mindsets, thinking and capability of workforce systems.

Job Capability Reconstruction and Skill Upgrading represents what respondents referred to as the most frequent impact of transformation. The accountability of traditional construction employment associated with physical labour and experiential judgment is changing toward a composite framework of capabilities with skill systems that prioritize digital tools, data understanding and analysis, machine and human interaction, and advanced collaborative capacities. This transformation demonstrates how informatization penetrates and challenges grassroots positions while creating new capability requirements.

Government officials and experts in higher educational institutions emphasize systematic skill structure updates, while enterprise managers focus on evolving skill requirements across various construction site positions.

“Positions that were previously oriented toward physical labour and experience now increasingly require mastering software operation skills, data analysis abilities, even basic programming.” (E1)

“Job skill structures are transforming from single experience-based types toward composite, digital types.” (G1)

“Project managers need to understand how to analyse AI-provided data results and optimize resource allocation accordingly, technical personnel need to master coordinated use with intelligent tools, and frontline workers also need to learn to cooperate with digital platforms for construction data entry or site status feedback.” (M3)

Frontline worker groups directly experience rising skill thresholds and job structure reshaping through their daily work experiences.

“These changes have altered requirements for team leaders, they need to learn how to read platform data, understand system logic, and also know how to use electronic devices for daily reporting and problem feedback.” (W6)

“Job boundaries have become blurred... now I also need to learn to operate some systems, even understand basic data analysis.” (W8)

Cognitive Transformation and Learning Adaptation emerges as workers navigate shifting skill requirements. Transformation encompasses decision-making shifts from experience-oriented to data-driven approaches, enhanced lifelong learning consciousness with cross-disciplinary capability requirements, and digital skill generational gaps creating adaptation challenges.

Government officials, experts in higher educational institutions, and enterprise managers recognize AI development driving practitioners from experience-dependent judgment toward data comprehension and system coordination, while demanding enhanced lifelong learning capabilities and cross-disciplinary competencies.

“Traditional empiricism is being replaced by digitization and systematization.” (M1)

“This poses higher requirements for practitioners’ learning abilities and lifelong growth.” (G1)

“This compels construction practitioners to possess cross-disciplinary integration capabilities and continuous learning consciousness.” (E3)

Frontline worker feedback reveals generational gaps and adaptation difficulties during digital transformation, highlighting recognition differences between experienced and newer workers.

“We older workers, although we have experience, definitely adapt slowly to system software, we must keep learning continuously to keep up.” (W2)

“Like me, a young worker... I’m also learning some basic software operations myself, but I really feel my knowledge base is too narrow.” (W3)

“For young people it’s a challenge, for older workers the pressure is greater, some people who can’t keep up will be marginalized.” (W6)

Organizational Response and Institutional Change addresses how AI-induced job responsibility changes and skill structure reconstruction compel deep adjustments within construction industry vocational education systems, skill certification mechanisms, and human resource management institutions.

“This means vocational education must undergo deep transformation.” (E1)

“This transformation poses urgent requirements for systematic updates to professional skill level standards and skill certification systems.” (G2)

“These changes compel us to strengthen examination of ‘technological comprehension’ and ‘data literacy’ in recruitment and training processes.” (M2)

The description from respondents reveals AI technology profoundly reshaping construction industry job responsibilities and skill structures, transitioning from physical labour and experience-oriented approaches toward capability systems centred on data-driven operations, technological composites, and systematic collaboration. This transformation generates not only job capability upgrades and role integration but also compels practitioners to achieve deep adaptation in cognitive patterns and learning mechanisms, particularly highlighting significant skill gaps and adaptation pressures across generational lines. Simultaneously, AI development presents systematic challenges to vocational education, skill certification, and talent selection institutions, compelling organizational transformation in educational training, standard development, and recruitment mechanisms to support construction workforce transition from skilled workers to smart talent.

4.1.3. Stakeholder Perceptions of AI-Driven Workforce Changes

Respondent accounts of how different groups—government, enterprises, vocational training institutions, and workers—perceive AI-driven workforce changes reveal distinct cognitive patterns and coordination gaps across four key stakeholder categories. These perspectives illuminate knowledge distribution patterns and coordination mechanism deficiencies within construction workforce systems under AI technological influence.

Government Awareness and Policy Guidance demonstrates relatively clear strategic recognition and top-level design, with multiple policies promoting intelligent construction and digital building development.

“We attach great importance to the intelligent development of the construction industry, and have issued the ‘Chongqing Smart Construction Pilot City Construction Implementation Plan’ as a special document.” (G1)

“The government already has clear recognition at the policy level, we are also promoting digital housing and construction, accelerating the intelligent transformation and upgrading of the construction industry.” (G2)

However, respondents identify policy implementation mechanism obstacles and insufficient grassroots policy awareness during policy transmission processes.

“The government has macro planning for developing intelligent construction direction, but policy transformation into frontline implementation mechanisms still needs strengthening.” (E4)

“The government has certain strategic deployment awareness, like promoting intelligent construction demonstration projects, but there are still gaps in grassroots implementation.” (M4)

Educational Institution Recognition Lag emerges as institutions demonstrate overall cognitive delays and sluggish responses, characterized by outdated curriculum content, slow training responses, and poor industry-education integration.

“Vocational colleges and training institutions’ curriculum updates can’t keep up with technological evolution, most still focus mainly on traditional crafts.” (M3)

“Training schools update curricula slowly, when I was in vocational school I hadn’t really been exposed to BIM, AI equipment and such content, only after entering construction sites did I discover they were already being used, showing education and industry are still disconnected.” (W4)

“Some courses still lean traditional, understanding of AI remains at the conceptual level, lacking scenario-based teaching.” (W6)

Enterprise Awareness Stratification and Response Capacity reveals distinct cognitive stratification and response capability differences. Large enterprises generally possess digital transformation awareness, while most small and medium enterprises remain in observational and passive response states.

“Large enterprises have already begun strategic deployment of intelligent construction, while most small and medium enterprises are still in exploration and observation stages.” (M3)

“Large enterprises have relatively clear recognition, especially state-owned enterprises like ours, basically all are promoting systematic ‘smart construction’ development.” (W6)

Worker Recognition Gaps and Skill Barriers represent widespread cognitive gaps and transformation obstacles among worker groups. Frontline workers demonstrate relatively vague AI understanding, generally existing in states of “confusion,” “observation,” and “anxiety.” Experienced workers exhibit resistance psychology toward technological change, while some younger workers show proactive learning willingness but lack clear pathway support.

“Some people hear about AI and think they’re going to be replaced, feeling very unsettled inside.” (W1)

“We workers are often used to the old ways, finding new things both complex and somewhat off-putting.” (W2)

“On one hand I find these technologies quite fresh, on the other hand I don’t know specifically how to learn or what to learn.” (W3)

Coordination challenges across stakeholder groups indicate that while AI’s impact on construction workforce structures manifests across multiple levels, significant information gaps and adaptation disparities persist from strategic recognition to practical response. The cognitive chain connecting government, enterprises, educational institutions, and workers has not yet been truly integrated, preventing policy implementation, skill transformation, and learning support mechanisms from forming effective closed loops. This necessitates promoting multi-stakeholder collaborative responses to AI-driven workforce reconstruction challenges.

4.2. Optimizing Construction Workforce Development Strategies (RQ2)

This section outlines findings addressing the third research objective: proposing talent development strategies to support the construction workforce’s adaptation to AI and to transition from skilled workers to smart talent. NVivo 14 thematic analysis identified strategic approaches and systematic deficiencies in current development practices, as detailed in Table 3.

Table 3. Workforce development strategy themes.

Theme	Sub-Theme	Frequency (N)
Response Measures	Policy and Institutional Level Changes	3
	Talent Development Content and Method Transformation	4
	Training Mechanisms and Organizational Approaches	15
Training System Deficiencies	Training Content Lag	12
	Institutional and Resource Imbalance	15
	Insufficient Job Matching	16
	Rigid Teaching Methods	15
	Missing Assessment Incentives	15
Development Strategy Optimization	Institutional Support and Resource Guarantee	18
	Educational Reform and Capability Building	20
	Enterprise Training and Job Transformation	20
	Group Support and Growth Pathways	8

4.2.1. Organizational Response Measures to Skill Changes

Respondent descriptions of “organizational measures in response to skill changes” reveal systematic approaches across three interconnected dimensions: policy and institutional level changes, talent development content and method transformation, and training mechanism and organizational approach reconstruction. These responses demonstrate how the construction industry organizes collective responses to AI-driven workforce skill structure transformation challenges.

Policy and Institutional Level Changes show government departments actively promoting skill system updates and occupational classification optimization, focusing on establishing new institutional foundations adapted to intelligent construction contexts.

“Working with relevant departments to formulate ‘intelligent construction technician’ position standards and talent evaluation indicator systems.” (G1)

“Including new occupations like ‘technical personnel for intelligent construction systems’ in updated catalogues.” (G2)

“Organizing professional skill level certification pilots, promoting integration of ‘academic certificates + skill level certificates’ dual certification.” (G3)

Talent Development Content and Method Transformation demonstrates training institutions implementing multi-dimensional initiatives through curriculum system reforms, practical base construction, and school–enterprise integration to enhance construction

talent adaptability to AI applications. These changes help optimize talent supply structures from the source, reducing gaps between education and job requirements.

“Our college has added intelligent construction, construction informatization and AI technology content to the curriculum system in recent years, while promoting the construction of school-enterprise joint training bases and introducing project case teaching.” (E2)

“My college has made positive attempts in curriculum system reform, integrating modules like intelligent construction, data-driven design, BIM applications, and promoting the integration of practical teaching with project-based teaching.” (E4)

Training Mechanisms and Organizational Approaches reveal strong practical orientation and job adaptability at the enterprise level. Organizations implement “project-driven learning,” “experienced worker mentoring,” and “learning while doing” approaches to achieve on-site skill transformation.

“Our company mainly promotes technology upgrades through project practice, for example introducing AI-assisted systems in some projects and arranging training, with project management personnel leading frontline workers in learning.” (M3)

“Sometimes the project department has us learn while working, like assigning a leader to learn system operations first then teach everyone hands-on.” (W2)

Online learning platforms and digital learning resources are gradually penetrating, achieving organic integration of temporal–spatial flexibility with content diversity.

“The company also has an internal online course platform, specifically with learning videos on BIM and smart construction sites.” (W4)

The description demonstrates that construction industry organizations are actively responding to AI-driven skill transformation pressures through the triple pathways of institutional driving, content reform, and mechanism innovation. However, interview evidence reveals varying implementation degrees across different organizations and groups, presenting patterns of “leading organization momentum, middle-tier response, grassroots differentiation.” Future development requires strengthening institutional–practical linkage mechanisms and promoting widespread penetration of standards, resources, and capabilities within organizations to achieve deep structural transition and comprehensive adaptation of construction workforce structures.

4.2.2. Current Training System Deficiencies

Respondent perspectives on “deficiencies in current construction training systems when addressing skill transformation brought by AI” reveal systematic gaps across five interconnected dimensions that constrain training system responsiveness and expose structural defects under AI-driven environments.

Training Content Lag emerges as widespread consensus among respondents. Current training curricula remain centred on traditional trade skills, lacking content aligned with emerging technologies and unable to provide support for smart talent development.

“Content disconnection, curriculum systems haven’t kept up with frontier technologies like intelligent construction, AI tools, data analysis.” (M3)

“Training systems still emphasize traditional crafts and static knowledge, lacking dynamic capability development for intelligent construction.” (M5)

Institutional and Resource Imbalance significantly constrains training quality. Respondents identify concentrated resource allocation, uneven geographical coverage, and weak school–enterprise collaboration mechanisms, resulting in insufficient training opportunities and support for remote construction sites and frontline workers.

“Existing resources are mostly concentrated on technical management personnel, while training coverage for grassroots construction workers is low.” (M3)

“Training opportunities aren’t many, especially on remote projects, there’s nowhere to go for further education even if you want to.” (W1)

“Most equipment is normally used by management, we workers can’t touch it, no chance to practice even if we want to.” (W3)

Training scheduling inadequacies compound implementation difficulties.

“Forms aren’t flexible enough, many training sessions are scheduled at fixed time periods that conflict with construction schedules.” (W7)

Gender and experience-based barriers further limit access to learning resources.

“Many technical contents weren’t taught in school, and at work you can only rely on self-study or asking seniors. Also, some male colleagues think women aren’t suitable for operating complex equipment or participating in AI-related technical positions. It’s not that we can’t learn, but there’s a lack of learning platforms suitable for newcomers and a gender-friendly atmosphere.” (W8)

Insufficient Job Matching represents a critical bottleneck constraining training effectiveness. Training content lacks targeting, failing to provide classification and stratification based on job levels, trade categories, and learning foundations, resulting in outcomes that are “unusable, unmemorable, and difficult to transfer.”

“The biggest problem is unclear level differentiation and lack of targeting. For example, young workers like us who are new to the industry need simple, practical introductory training, not advanced functions right from the start.” (W3)

“Many courses are one-size-fits-all, young and old, technicians and general workers mixed together learning, low efficiency, and can’t provide individualized instruction. What we need is hands-on training classified by trade.” (W4)

Rigid Teaching Methods directly impact training experiences. Current training predominantly employs PowerPoint presentations, lacking immersive, hands-on, and project-based teaching approaches. Workers struggle to understand skills through real scenarios, reducing learning engagement and effectiveness.

“Lacks integration with actual operation scenarios, training methods are too rigid, just PowerPoint presentations, no chance to actually touch equipment.” (W2)

“Some new technology training still stays at PowerPoint explanations, without on-site drills or virtual operation environments.” (W8)

Missing Assessment Incentives weaken intrinsic learning motivation. Training systems lack scientific effectiveness evaluation systems and promotion incentive mechanisms. Training outcomes fail to generate substantial returns, resulting in reduced learning willingness among frontline workers.

“Career development paths aren’t connected, causing workers who complete skills training to struggle with reflecting value in job promotion and salary treatment, thereby affecting training enthusiasm and sustainability.” (G2)

“Training lacks continuity and incentive mechanisms, whether learning is useful, whether doing well provides promotion opportunities, it’s all unclear.” (W3)

Respondent descriptions indicate that current construction industry training systems have not yet established supply logic and structural mechanisms deeply aligned with AI environments. From content to methods, from institutions to incentives, all demonstrate

disconnection from digital transformation requirements. To effectively support a structural transformation of the construction workforce, urgent systematic reconstruction and supply-side upgrading of training systems is needed, centred on task orientation, competency-based approaches, and job matching as core logic.

4.2.3. Optimizing Construction Workforce Development Strategies

Respondent perspectives on “how government, enterprises, and training institutions should respectively optimize construction workforce development strategies to address skill transformation brought by AI” reveal collaborative governance directions and critical mechanism gaps across four strategic dimensions that illuminate coordination requirements for construction workforce systems under AI technological influence.

Institutional Support and Resource Guarantee represents the foundational prerequisite for building intelligent construction talent ecosystems. Government leadership in top-level institutional design and dedicated funding support, including intelligent construction occupational skill standards, certification systems, and comprehensive education and training infrastructure, provides both strategic elevation for talent development and a policy basis for resource allocation.

“Government should formulate special plans for construction industry AI talent development, introduce ‘digital craftsman’ cultivation policies, establish dedicated funds to support secondary and higher vocational colleges in opening intelligent construction-related majors, and promote the establishment of intelligent construction vocational education standard systems.” (E1)

“Government should lead in constructing policy systems and standard frameworks for intelligent construction talent development, establish dedicated funds to support regional training bases and curriculum content research and development, and promote the establishment of certification systems covering the entire occupational chain.” (G1)

Educational Reform and Capability Building emerges as the core mission for achieving structural talent transformation. Higher educational institutions must closely follow AI and intelligent construction technology evolution, introducing real engineering cases to reconstruct curriculum systems and promoting shifts from theoretical instruction toward project-driven and scenario-based practical training. Teaching method innovation and industry–education integration enhance training effectiveness and experiential learning.

“Training institutions and universities should proactively reform curriculum systems, introduce actual AI cases in construction, supervision, and testing processes, promote synchronous updates of teaching content with technology, enhance training precision and effectiveness, and jointly advance construction workforce toward digital and intelligent level advancement.” (M3)

“Training institutions need to leave the classroom and come to project sites, designing targeted hands-on courses according to different trades, so we can truly ‘learn it and use it.’” (W2)

Enterprise Training and Job Transformation functions as the execution hub for driving workforce structural transition. Organizations should establish job-oriented training mechanisms, clarify internal job transfer channels and capability advancement pathways, and improve training incentives linked with performance mechanisms to stimulate employee technical growth willingness and career advancement motivation.

“Enterprises should make training routine and structured, from executives to frontline workers everyone should have clear skill transformation paths, and incorporate training results into assessment and promotion mechanisms.” (M4)

“Companies can implement refined management of training through hierarchical classification, like setting up ‘youth worker growth programs,’ allowing us apprentices to master skills in stages with advancement channels.” (W4)

“Enterprises should establish ‘position-skill-incentive’ linkage mechanisms, like workers who learn drones or scheduling systems can receive technical allowances or star rating promotions.” (W5)

Group Support and Growth Pathways reflects profound attention to workforce diversity and developmental stage differences. Respondents propose constructing refined training pathways based on job levels, trade characteristics, age structure, and gender differences, forming growth closed loops from entry to mastery, from training to promotion, achieving employee capability transition.

“We can’t continue using ‘old people adapting to new tools’ thinking for training, but need to reshape the growth pathways for the new generation of ‘intelligent construction talent.’” (E1)

“Overall, workforce development needs to upgrade from ‘supplementing skills’ to ‘building ecosystems,’ achieving comprehensive transformation from ‘skilled workers’ to ‘smart talent.’” (M1)

Special attention to youth workers, women, and career changers supports their transition toward “smart talent.”

“Enterprises should incorporate intelligent equipment training into new employee onboarding processes, specifically establishing ‘youth technical talent advancement channels.’” (W3)

“Establish specialized classes for female construction talent, encouraging more people to transform from ‘assistant workers’ to ‘smart workers.’” (W7)

Respondent insights reveal that addressing AI-driven construction workforce transformation challenges requires breaking through traditional training system fragmentation and lag, achieving efficient coordination among government, enterprises, and educational institutions.

Through the four-pillar framework of institutional guarantee, educational innovation, enterprise engagement, and group development, comprehensive and multi-layered workforce development systems can be developed that involve multiple actors, follow the development of new technologies, and promote the structural transition of the construction industry from skilled worker to smart talent.

5. Discussion

5.1. Skill Reconstruction and Stakeholders’ Perceptions Under AI

AI technologies are being deeply embedded through core construction activities—designing, making, operating, and managing—resulting in fundamental shifts in the industry skill structure, moving away from physical work and experiential judgment to composite capacity system approaches based on digital tools, system interoperability, and the integration of capabilities across professions. This aspect of change not only influences the composition of available capacities within job roles in construction, but also the nature of talent competency profiles that increasingly demonstrate tendencies toward job boundarylessness and shared expectations of performance capabilities [4]. Patterns and trends were suggested in the profiles that closely align with the notion of “skill polarization” as described in Autor [42] and govern the empirical evidence supporting “collaborative technology extension” arguments [59].

Transition pathways emerge through findings that suggest constructor capacity shifts in specificity from “cognitive transformation” to “tool adaptation”, and finally to “task integration”. While frontline workers (non-supervisory personnel) shift from “experience-based constructors” towards “platform collaborators”, project manager workers slowly change from “experience-based coordinators”, towards “data-driven decision makers”, as the skill boundaries between worker positional roles become less distinct. As these transition pathways suggest, the construction talent of the future will need not only skills in singular positional roles, but generalized adaptive competencies across roles and systems [23]. This view is further supported by empirical evidence suggesting that AI technologies increasingly blur the boundaries between traditional skill domains [56,57].

Additionally, the influence of AI extends beyond automating task performance in narrow technology positional roles and is now penetrating all levels of management support and frontline operational roles to restructure and reconstruct within occupational systems in construction. This extends beyond “marginal position replacement” [60] as a largely unthinkable change, but as an evolution towards the future organization of construction roles characterized as “tool substitution”, or via “system coordination” [20]. Consistent in the responses are indications that contemporary construction scheduling, risk alerting, and progress control require and will increasingly require collaborative human-algorithm decision making and execution. This suggests that the ability to coordinate human-machine collaboration in construction will become a standardized paradigm for role and function reorganization [61].

For this reason, the impact of AI on construction roles will extend beyond marginal occupational replacement for a subset of competencies in the workplace, but will involve reconstruction of comprehensive role and job capability structures [18]. Reconstruction should focus on the composite competencies of “collaboration capability, system comprehension, and judgment skills” [22], providing the construction industry of the future with a capacity distinct to systems thinking and adaptive competencies across positional roles and tasks requiring collective inputs, as opposed to providing technology based on mastery of tools generally. These perspectives on the future of construction occupations provide both theoretical frameworks and practical steps forward in supporting job redesign and vocational education systems reform initiatives.

The development of an AI-enabled construction workforce, characterized by multi-stakeholder cognitive stratification and inconsistent response capacities, results in structural disconnections between policy intentions, organizational practices, and individual behaviours. Even though a policy framework has established transformation layouts, there remain significant disconnects between institutional mobilization and on-the-ground implementation, an observation that confirms multi-stakeholder coordination challenges do exist, including varied stakeholder objectives, cognitive lag, and inconsistent response pathways, echoing previous research [47,62,63].

The limitations of government policy penetration expose strong material and strategic initiative at the macro level, mainly using policies that aim to drive industrial upgrading through institutional design, with a focus on intelligent construction and developing digital skills. However, the policy fructification process shows low levels of organizational penetration, often in highly vertical dissemination processes. Grassroots workers and small-to-medium enterprises tend to have little or no awareness of certain aspects of policy, public policy and other wise, or an understanding of the policy shifts, reflecting a “last mile” disconnect in the institutional dissemination chains. These findings contrast with established research indicating policy effectiveness often constrained by execution-level institutional transmission mechanisms [64].

Enterprise response stratification emerges through pronounced hierarchical trends. Large construction enterprises possess strong resource mobilization capabilities and technological pilot foundations, initiating strategic intelligent construction deployment and establishing preliminary “technology introduction–position transformation–training mechanism” closed-loop systems. Conversely, small-to-medium enterprises remain constrained by funding, cognitive, and organizational capacity limitations, predominantly maintaining observational and passive response stances. This inter-enterprise adaptive capability variation intensifies structural inequality in construction workforce transformation while echoing resource-based “resource–action–performance pathway” asymmetric relationships [65].

Educational institution response lag demonstrates curriculum content lagging behind position evolution, teaching methods lacking hands-on and scenario-based support, and faculty insufficient AI technology understanding and application capabilities, resulting in severe disconnection between skill supply and position demands. These findings further substantiate existing research criticisms regarding vocational education content update delays, inadequate faculty structures, and industry disconnection [66,67], highlighting construction vocational education system inadequacy in intelligent transformation responses.

Individual worker barriers reflect dual obstacles of “generational cognitive differences” and “emotional resistance intersection.” Traditional older employees simply do not understand AI systems, in addition to concerns such as “replacement related to machines” and “wasting time learning,” which is a clear rejection of the psychological harm. The willingness to accept of newer, younger employees is certainly there; however, organizational structures may not provide systematic training pathways, practical training hours, nor a structured incentive system for learning and transformation, which hinders genuine transition from “willingness to learn” to “capability to transform.” Differences in individual response revealed by the research contribute depth to the technology acceptance model in terms of pathways through individual beliefs, capability assessments, and transformation behaviours [68].

Collectively, these findings indicate coordination dilemmas in the construction industry under the pressures of AI impact, as the construction industry struggles to develop effective linkage channels from institutional design to capability transformation. Patterns of ruptures at multi-levels present primary barriers to the transformation of the construction workforce, and require more penetrative policy transmission mechanisms, more flexible educational supply systems, and more holistic organizational support structures to achieve the fundamental transformation from structural fragmentation toward systematic coordination.

5.2. Toward an Ecosystem Approach to Workforce Development

To adequately address the multi-level coordination challenges, a focus on amalgamated modes of learning and training towards comprehensive force ecosystem-wide development is required, rather than a focus on the various fragmented or levels involved in training. The identified skill mismatches, cognitive gaps, and response fragmentation necessitate a four-pillar framework integrating institutional support, educational reform, enterprise engagement, and group development pathways to facilitate transition from skilled workers to smart talent. This ecosystem approach aligns with OECD (2021) [69] “lifelong learning + multi-party participation” frameworks while demonstrating high compatibility with China’s industry–education integration, and government–enterprise collaboration policy systems [32].

Institutional infrastructure development emerges as foundational to addressing current policy system deficiencies in cross-level coordination and job-matching orientation, which create audible but imperceptible policy transmission effects. Evidence points toward constructing institutional guaranteed closed-loops through skill standard systems, certifica-

tion mechanisms, and fiscal subsidies to enhance structural penetration of transformation strategies. This approach resonates with Cejudo and Michel's [70] "policy integration tools" logic, emphasizing requirements for both top-level design and deep execution capabilities with resource implementation mechanisms.

Educational system transformation addresses revealed inadequacies in curriculum content lag, singular teaching modalities, and regional resource imbalances that fail to support composite capability formation in AI environments. Educational innovation requires coordinated advancement of curriculum content, teaching methods, and practical training platforms, introducing BIM, AI platform operations, and data analysis modules while incorporating virtual simulation and project-based teaching approaches to enhance practicality and immersion. This transformation direction aligns closely with Tan et al. [71] and their "transition from knowledge supply to capability generation" objectives, matching digital era higher education transformation directions [72].

Enterprise capability building responds to identified deficiencies in systematic job training pathways and skill incentive mechanisms that result in worker "willingness to learn but difficulty transforming." Strategic development requires constructing job-chain-based skill advancement channels, including position transition re-education, grade certification, and performance linkage mechanisms to create synergistic effects between skill enhancement and career development. This strategy aligns itself with "dynamic capability reconfiguration" theory [40], which stresses that an enterprise creates organizational learning channels in uncertain environments [73].

Inclusive group support systems confront identified issues facing youth workers and women and career transition workers lacking institutional support for adaptation and differentially limits growth and momentum for developing diverse talent. Development requires building differentiated learning support systems and inclusive pathways for growth, such as "female construction talent specialized classes," "youth technical channels," and "career transition worker training camp" learning supports provide individual development of capabilities. This approach extends behavioural motivation elements using the technology acceptance model emphasizing the supporting role of contextual embedding and institutional support for development behind training behaviours [74].

Indeed, a critical insight emerges: training approaches must move beyond "adapting existing workers to new tools" toward "reshaping growth pathways for next-generation smart construction talent." This perspective embodies transformation from deficit-based training to ecosystem-based cultivation logic, representing core manifestations of exploratory organizational learning—organizations and individuals should collaboratively construct capability systems adapted to future environments rather than constraining themselves to linear upgrades of existing experience [41].

Considering the above findings and discussions, the construction sector is experiencing transformational challenges related to AI adoption. It is therefore essential to implement sustainable workforce development concepts, establish a multi-stakeholder collaborative system, and facilitate the workforce transition from skilled workers to smart talent. In summary, this study proposes a four-pillar workforce development framework, encompassing institutional support, educational reform, enterprise engagement, and group development (see Figure 3).

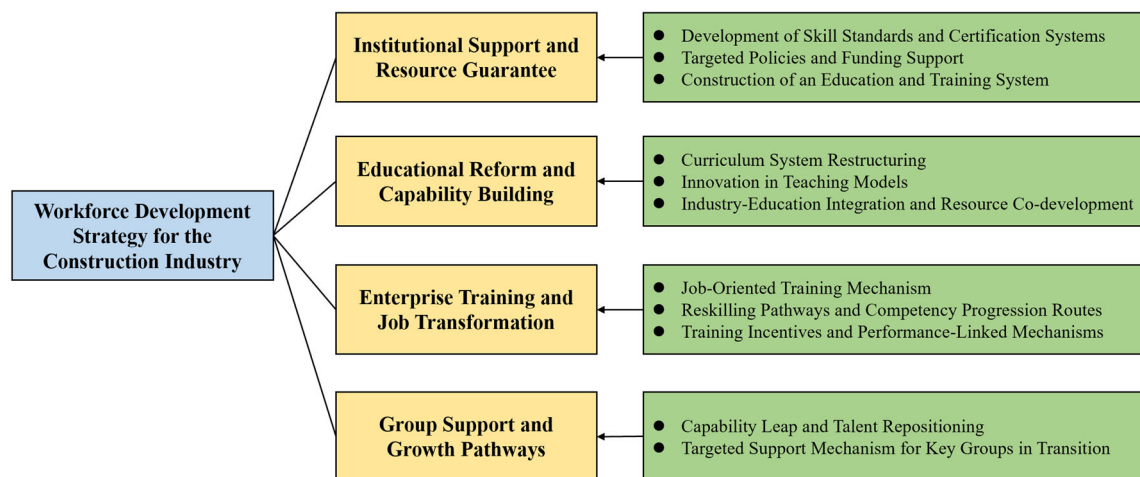


Figure 3. Workforce development strategy for the construction industry.

5.3. Research Implications

This investigation examines construction workforce transformation pathways and multi-stakeholder coordination mechanisms under AI influence, addressing the transition from skilled labour to smart talent through theoretical, practical, and methodological implications.

Theoretical contributions extend beyond linear AI technology drivers—skill structure transformation, multi-stakeholder responses, and strategy system construction analytical paradigms by integrating dynamic capability theory, organizational learning perspectives, and skill ecosystem frameworks. The resulting “job transformation—cognitive response—coordination strategy” multi-dimensional analytical framework systematically reveals structural mechanisms of AI-driven construction workforce transformation and adaptation relationships among multiple stakeholders. These insights advance understanding of skill reconstruction and institutional evolution in digital transformation contexts.

Practical implications emerge through in-depth interviews with respondents in Chongqing’s construction industry, identifying cognitive differentiation, response delays, and institutional fragmentation challenges in construction workforce development processes. Analysis generated an “institutional support—educational reform—enterprise engagement—group development” four-pillar coordination strategy, providing operational pathways and policy recommendations for developing region practitioners transitioning from passive adaptation toward proactive advancement. Unlike existing linear skill development models, this ecosystem-oriented strategy emphasizes simultaneous cognitive, institutional, and capability transformation.

Methodological implications combine phenomenological qualitative research approaches with six-stage thematic analysis procedures, ensuring systematic analytical processes and interpretive depth. Through open coding and thematic deduction, multi-level, cross-stakeholder thematic networks were constructed, enriching research paradigms for workforce transformation issues under complex technological change contexts while providing methodological guidance for subsequent qualitative research on similar topics.

5.4. Limitations and Future Research Directions

Although this study offers an initial exploration into the transformation pathways of the construction workforce and the mechanisms of multi-stakeholder collaboration, there are still several limitations that need further expansion and deepening in future research.

First, the sample is concentrated in the Chongqing, China. Although the respondents include diverse stakeholders such as government officials, enterprise managers, educa-

tional lecturers, and frontline workers, there are still limitations in terms of geographic distribution, enterprise types, and job levels. These constraints may affect the external generalizability of the findings. Future research could broaden the scope and structure of the sample, especially by incorporating small and medium-sized enterprises, urban–rural areas, and workers from various occupational categories, in order to construct a more representative map of construction workforce transformation [15].

Secondly, this study adopts qualitative interviews as the primary method, focusing on an in-depth analysis of the perceptions and practices of multiple stakeholders. While this approach is valuable for capturing the cognitive logic and interactive mechanisms in complex contexts, it lacks support from quantitative data. Future research could incorporate methods such as surveys, structural equation modelling, system dynamics, or multi-agent interaction models to examine the causal mechanisms and interaction pathways among training investment, cognitive differences, and job-role alignment, thereby enhancing the explanatory power of the theoretical framework [75].

Thirdly, this study primarily focuses on the static current state of construction workforce development, with limited attention to the dynamic adaptation mechanisms under the ongoing evolution of AI technologies. As a result, it does not fully reveal the temporal relationships among policy adjustments, job changes, and worker adaptation. Future studies could employ process tracing or longitudinal comparative approaches to explore learning feedback, path dependency, and capability upgrading mechanisms throughout the long-term technological evolution of the construction workforce [76].

Finally, although this study includes perspectives from various groups, it lacks sufficient depth in addressing the specific adaptation barriers and developmental trajectories of marginalized groups such as women, young workers, and job-transitioning individuals. Future research could focus on the reconstruction of occupational identity, the evolution of technological perceptions, and the development of motivational mechanisms among these groups [77], systematically examining the institutional support and empowerment strategies needed to facilitate their inclusion in the AI-driven transformation of the construction industry, thereby providing stronger support for inclusive workforce development policies.

6. Conclusions

This study centres on the core theme of “From Skilled Worker to Smart Talent,” focusing on the structural transformation of the construction workforce driven by AI technologies. It systematically addresses three key questions: how AI reshapes job roles and skill structures in the construction industry; how different stakeholders differ in their understanding and responses to workforce transformation; and how to develop workforce strategies that support continuous adaptation and capability upgrading in the AI era.

Based on in-depth interviews with 20 respondents in Chongqing, the study finds that AI technologies have been deeply embedded across the full process of design, construction, operation, and management, driving a shift in job roles toward data-driven and system-operation-oriented positions, and accelerating the transition of skill structures toward greater complexity and digitalization. At the same time, there is a systemic disconnect among stakeholders in terms of cognitive understanding and responsive actions, characterized by a fragmented pattern: government initiatives exist, enterprises respond at different levels, educational institutions react slowly, and workers tend to adopt a wait-and-see attitude. Frontline workers encounter multiple barriers including limited skill foundations, time conflicts, and psychological stress, while existing training programs commonly suffer from obsolete content, inflexible formats, and insufficient motivation. In response, this study proposes a collaborative workforce development strategy centred on institutional support, educational reform, enterprise engagement and group development to enhance

the resilience and inclusiveness of the labour system and promote sustainable development in the construction industry.

Theoretically, this study integrates the perspectives of dynamic capabilities, organizational learning, and skill ecosystems to construct an analytical framework of “Job Transformation—Cognitive Response—Collaborative Strategies,” thereby deepening the understanding of labour force transformation mechanisms driven by AI in the construction sector and addressing how workforce development can contribute to the United Nations Sustainable Development Goals. Practically, it identifies key challenges in workforce development within the construction industry through multi-stakeholder interviews and proposes a four-pillar collaborative strategy tailored to developing countries. Methodologically, by adopting a phenomenological orientation and thematic analysis process, it establishes a multi-level thematic model, enriching the application paradigm of qualitative research in the context of complex technological change.

Although this study provides structural insights into the mechanism of labour force transformation in the context of AI from a multi-stakeholder collaboration perspective, it still has certain limitations, such as the concentration of sample regions, the singularity of methodological approaches, and insufficient analysis of dynamic processes. Future research could further expand by broadening the sample scope, introducing mixed methods, strengthening long-term process tracking, and focusing on the adaptation mechanisms of marginalized groups. These efforts may contribute to building a resilient, inclusive, and sustainable construction workforce development system, offering more universal and forward-looking theoretical support for developing countries facing the challenges of intelligent transformation.

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References

1. Regona, M.; Yigitcanlar, T.; Hon, C.; Teo, M. Artificial Intelligence and Sustainable Development Goals: Systematic Literature Review of the Construction Industry. *Sustain. Cities Soc.* **2024**, *108*, 105499. [\[CrossRef\]](#)
2. Juricic, B.B.; Galic, M.; Marenjak, S. Review of the Construction Labour Demand and Shortages in the EU. *Buildings* **2021**, *11*, 17. [\[CrossRef\]](#)
3. Pan, Y.; Zhang, L. Integrating BIM and AI for Smart Construction Management: Current Status and Future Directions. *Arch. Comput. Methods Eng.* **2023**, *30*, 1081–1110. [\[CrossRef\]](#)
4. Zhang, W.; Lai, K.H.; Gong, Q. The Future of the Labor Force: Higher Cognition and More Skills. *Humanit. Soc. Sci. Commun.* **2024**, *11*, 479. [\[CrossRef\]](#)
5. Jonathan, W.; Jeongmin, S.; Leung, N.; Ngai, J.; Chen, L.-K.; Tang, V.; Wang, B.; Agarwal, S. *Reskilling China: Transforming the World's Largest Workforce into Lifelong Learners*; McKinsey Global Institute: New York, NY, USA, 2021.
6. Liang, H.; Fan, J.; Wang, Y. Artificial Intelligence, Technological Innovation, and Employment Transformation for Sustainable Development: Evidence from China. *Sustainability* **2025**, *17*, 3842. [\[CrossRef\]](#)

7. Torrejón Pérez, S.; Fernández-Macías, E.; Hurley, J. *Global Trends in Job Polarisation and Upgrading: A Comparison of Developed and Developing Economies*; Palgrave Macmillan: London, UK, 2025; ISBN 9783031762284.
8. Hwang, B.G.; Ngo, J.; Teo, J.Z.K. Challenges and Strategies for the Adoption of Smart Technologies in the Construction Industry: The Case of Singapore. *J. Manag. Eng.* **2022**, *38*, 5021014. [[CrossRef](#)]
9. Morandini, S.; Fraboni, F.; De Angelis, M.; Puzzo, G.; Giusino, D.; Pietrantonio, L. The Impact of Artificial Intelligence on Workers' Skills: Upskilling and Reskilling in Organisations. *Informing Sci. Int. J. Emerg. Transdiscipl.* **2023**, *26*, 39–68. [[CrossRef](#)]
10. Opatha, H.H.D.N.P.; Olivia, K.A.D.; Perera, G.D.N. Construction Industry and Human Resource Management: A Conceptual Study. *Sri Lankan J. Hum. Resour. Manag.* **2024**, *14*, 64–89.
11. Ebolor, A.; Agarwal, N.; Brem, A. Sustainable Development in the Construction Industry: The Role of Frugal Innovation. *J. Clean. Prod.* **2022**, *380*, 134922. [[CrossRef](#)]
12. Elbashbishy, T.; El-adaway, I.H. Skilled Worker Shortage across Key Labor-Intensive Construction Trades in Union versus Nonunion Environments. *J. Manag. Eng.* **2024**, *40*, 04023063. [[CrossRef](#)]
13. Zulu, S.L.; Saad, A.M.; Ajayi, S.O.; Dulaimi, M.; Unuigbo, M. Digital Leadership Enactment in the Construction Industry: Barriers Undermining Effective Transformation. *Eng. Constr. Archit. Manag.* **2024**, *31*, 4062–4078. [[CrossRef](#)]
14. Sepasgozar, S.M.E.; Khan, A.A.; Smith, K.; Romero, J.G.; Shen, X.; Shirowzhan, S.; Li, H.; Tahmasebinia, F. BIM and Digital Twin for Developing Convergence Technologies as Future of Digital Construction. *Buildings* **2023**, *13*, 441. [[CrossRef](#)]
15. García de Soto, B.; Isolda, A.-J.; Samuel, J.; Hunhevicz, J. Implications of Construction 4.0 to the Workforce and Organizational Structures. *Int. J. Constr. Manag.* **2022**, *22*, 205–217. [[CrossRef](#)]
16. Bajpai, A.; Misra, S.C. Evaluation of Success Factors to Implement Digitalization in the Construction Industry. *Constr. Innov.* **2024**, *24*, 865–891. [[CrossRef](#)]
17. Osorio-Gómez, C.C.; Herrera, R.F.; Prieto-Osorio, J.M.; Pellicer, E. Conceptual Model for Implementation of Digital Transformation and Organizational Structure in the Construction Sector. *Ain Shams Eng. J.* **2024**, *15*, 102749. [[CrossRef](#)]
18. Adekunle, S.A.; Aigbavboa, C.O.; Ejorwomu, O.A. Understanding the BIM Actor Role: A Study of Employer and Employee Preference and Availability in the Construction Industry. *Eng. Constr. Archit. Manag.* **2022**, *31*, 160–180. [[CrossRef](#)]
19. Osborne, S.; Hammoud, M.S. Effective Employee Engagement in the Workplace. *Int. J. Appl. Manag. Technol.* **2017**, *16*, 50–67. [[CrossRef](#)]
20. Liu, L. Job Quality and Automation: Do More Automatable Occupations Have Less Job Satisfaction and Health? *J. Ind. Relat.* **2023**, *65*, 72–87. [[CrossRef](#)]
21. Stride, M.; Renukappa, S.; Suresh, S.; Egbu, C. The Effects of COVID-19 Pandemic on the UK Construction Industry and the Process of Future-Proofing Business. *Constr. Innov.* **2023**, *23*, 105–128. [[CrossRef](#)]
22. van der Heijden, J. Construction 4.0 in a Narrow and Broad Sense: A Systematic and Comprehensive Literature Review. *Build. Environ.* **2023**, *244*, 110788. [[CrossRef](#)]
23. Hajirasouli, A.; Assadimoghadam, A.; Bashir, M.A.; Banihashemi, S. Exploring the Impact of Construction 4.0 on Industrial Relations: A Comprehensive Thematic Synthesis of Workforce Transformation in the Digital Era of Construction. *Buildings* **2025**, *15*, 1428. [[CrossRef](#)]
24. Regona, M.; Yigitcanlar, T.; Xia, B.; Li, R.Y.M. Opportunities and Adoption Challenges of AI in the Construction Industry: A PRISMA Review. *J. Open Innov. Technol. Mark. Complex.* **2022**, *8*, 45. [[CrossRef](#)]
25. Raisch, S.; Krakowski, S. Artificial Intelligence and Management: The Automation–Augmentation Paradox. *Acad. Manag. Rev.* **2021**, *46*, 192–210. [[CrossRef](#)]
26. Bai, W.; Wang, J.; Yu, X. Spatiotemporal Characteristics and Obstacle Factors of Coupling Coordination Degree between the Digital Economy and the High-Quality Development of the Construction Industry: Evidence from China. *Eng. Constr. Archit. Manag.* **2025**, *4*, 1645. [[CrossRef](#)]
27. Ding, R.; Ren, C.; Hao, S.; Lan, Q.; Tan, M. Polycentric Collaborative Governance, Sustainable Development and the Ecological Resilience of Elevator Safety: Evidence from a Structural Equation Model. *Sustainability* **2022**, *14*, 7124. [[CrossRef](#)]
28. Huang, Y. Digital Transformation of Enterprises: Job Creation or Job Destruction? *Technol. Forecast. Soc. Change* **2024**, *208*, 123733. [[CrossRef](#)]
29. Hassan, M.U.; Murtaza, A.; Rashid, K. Redefining Higher Education Institutions (HEIs) in the Era of Globalisation and Global Crises: A Proposal for Future Sustainability. *Eur. J. Educ.* **2025**, *60*, e12822. [[CrossRef](#)]
30. Oliinyk, O.; Bilan, Y.; Mishchuk, H.; Akimov, O.; Vasa, L. The Impact of Migration of Highly Skilled Workers on the Country's Competitiveness and Economic Growth. *Montenegrin J. Econ.* **2021**, *17*, 7–19. [[CrossRef](#)]
31. Almevik, G.; Corr, S.; Hannes, A.; Lagerqvist, B.; Marçal, E.; Mignosa, A.; Roche, N. *Forecast to Fill Gaps Between Education and Training Supply and Labour Market Needs. A Preliminary Analysis*; CHARTER Consortium. 2023. Available online: <https://charter-alliance.eu/wp-content/uploads/2023/12/D4.2.-Forecast-to-fill-gaps-between-education-and-training-supply-and-labo.alysis.pdf> (accessed on 12 July 2025).

32. Cao, L. Localizing Human Resource Development through Higher Education: Local Education Clusters Involving Universities and Regional Stakeholders in China. *Cogent Educ.* **2024**, *11*, 2402147. [\[CrossRef\]](#)
33. Shou, S.; Li, Y. Exploring the Collaborative Innovation Operational Model of Government-Industry-Education Synergy: A Case Study of BYD in China. *Asian J. Technol. Innov.* **2024**, 1–36. [\[CrossRef\]](#)
34. Goulart, V.G.; Liboni, L.B.; Cezarino, L.O. Balancing Skills in the Digital Transformation Era: The Future of Jobs and the Role of Higher Education. *Ind. High. Educ.* **2022**, *36*, 118–127. [\[CrossRef\]](#)
35. Gkrimpizi, T.; Peristeras, V.; Magnisalis, I. Classification of Barriers to Digital Transformation in Higher Education Institutions: Systematic Literature Review. *Educ. Sci.* **2023**, *13*, 746. [\[CrossRef\]](#)
36. Ying, D.; Li, N. Research on the Cultivation of Skilled Talent in Intelligent Construction to Facilitate a Model of Shared Prosperity. *Int. J. Front. Sociol.* **2023**, *5*, 120–124. [\[CrossRef\]](#)
37. Mer, A.; Virdi, A.S. Decoding the Challenges and Skill Gaps in Small- and Medium-Sized Enterprises in Emerging Economies: A Review and Research Agenda. In *Contemporary Challenges in Social Science Management: Skills Gaps and Shortages in the Labour Market*; Contemporary Studies in Economic and Financial Analysis; Thake, A.M., Sood, K., Özen, E., Grima, S., Eds.; Emerald Publishing Limited: Leeds, UK, 2024; Volume 112B, pp. 115–134, ISBN 978-1-83753-171-4..
38. CITB. *Construction Workforce Outlook Explained*; Construction Industry Training Board: Peterborough, UK, 2025.
39. Becker, G.S. *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education*; National Bureau of Economic Research: New York, NY, USA, 1964.
40. Teece, D.J. Explicating Dynamic Capabilities: The Nature and Microfoundations of (Sustainable) Enterprise Performance. *Strateg. Manag. J.* **2007**, *28*, 1319–1350. [\[CrossRef\]](#)
41. Basten, D.; Haamann, T. Approaches for Organizational Learning: A Literature Review. *SAGE Open* **2018**, *8*, 1–20. [\[CrossRef\]](#)
42. Autor, D.H. Why Are There Still So Many Jobs? The History and Future of Workplace Automation. *J. Econ. Perspect.* **2015**, *29*, 3–30. [\[CrossRef\]](#)
43. Evenseth, L.L.; Sydnes, M.; Gausdal, A.H. Building Organizational Resilience Through Organizational Learning: A Systematic Review. *Front. Commun.* **2022**, *7*, 837386. [\[CrossRef\]](#)
44. Li, P.P.; Liu, H.; Li, Y.; Wang, H. Exploration–Exploitation Duality with Both Tradeoff and Synergy: The Curvilinear Interaction Effects of Learning Modes on Innovation Types. *Manag. Organ. Rev.* **2023**, *19*, 498–532. [\[CrossRef\]](#)
45. Karakhan, A.A.; Nnaji, C.A.; Gambatese, J.A.; Simmons, D.R. Best Practice Strategies for Workforce Development and Sustainability in Construction. *Pract. Period. Struct. Des. Constr.* **2023**, *28*, 04022058. [\[CrossRef\]](#)
46. Xue, H.; Zhang, S.; Wu, Z.; Zhang, L. How to Improve the Smart Construction Technology Usage Behavior of Construction Enterprise Employees?—TOE Framework Based on Configuration Study. *Eng. Constr. Archit. Manag.* **2025**, *32*, 785–804. [\[CrossRef\]](#)
47. De Burca, G.; Keohane, R.O.; Sabel, C. New Modes of Pluralist Global Governance. *J. Int. Law Politics* **2013**, *45*, 723–786.
48. Friesen, L.; Gaine, G.; Klaver, E.; Burbach, L.; Agyapong, V.; Carrà, G. Key Stakeholders' Experiences and Expectations of the Care System for Individuals Affected by Borderline Personality Disorder: An Interpretative Phenomenological Analysis towards Co-Production of Care. *PLoS ONE* **2022**, *17*, e0274197. [\[CrossRef\]](#) [\[PubMed\]](#)
49. Giorgi, A.; Giorgi, B.; Morley, J.; Carrà, G. The Descriptive Phenomenological Psychological Method. In *The SAGE Handbook of Qualitative Research in Psychology*; Sage Publications: Thousand Oaks, CA, USA, 2017; pp. 176–192. [\[CrossRef\]](#)
50. Bekele, W.B.; Ago, F.Y. Sample Size for Interview in Qualitative Research in Social Sciences: A Guide to Novice Researchers. *Res. Educ. Policy Manag.* **2022**, *4*, 42–50. [\[CrossRef\]](#)
51. Galvin, R. How Many Interviews Are Enough? Do Qualitative Interviews in Building Energy Consumption Research Produce Reliable Knowledge? *J. Build. Eng.* **2015**, *1*, 2–12. [\[CrossRef\]](#)
52. Hennink, M.M.; Kaiser, B.N.; Marconi, V.C. Code Saturation Versus Meaning Saturation: How Many Interviews Are Enough? *Qual. Health Res.* **2017**, *27*, 591–608. [\[CrossRef\]](#)
53. Naeem, M.; Ozuem, W.; Howell, K.; Ranfagni, S. A Step-by-Step Process of Thematic Analysis to Develop a Conceptual Model in Qualitative Research. *Int. J. Qual. Methods* **2023**, *22*, 1–18. [\[CrossRef\]](#)
54. Albasyouni, W.; Kamara, J.; Heidrich, O. Key Challenges and Opportunities to Improve Risk Assessments in the Construction Industry. *Buildings* **2025**, *15*, 1832. [\[CrossRef\]](#)
55. Moncada, M. Should We Use NVivo or Excel for Qualitative Data Analysis? *Bull. Sociol. Methodol. Bull. De Méthodologie Sociol.* **2025**, *165*, 186–211. [\[CrossRef\]](#)
56. Bonello, M.; Meehan, B. Transparency and Coherence in a Doctoral Study Case Analysis: Reflecting on the Use of Nvivo within a 'Framework' Approach. *Qual. Rep.* **2019**, *24*, 483–498. [\[CrossRef\]](#)
57. Chawla, S.; Sareen, P.; Gupta, S.; Joshi, M.; Bajaj, R. Technology Enabled Communication during COVID 19: Analysis of Tweets from Top Ten Indian IT Companies Using NVIVO. *Int. J. Inf. Technol.* **2023**, *15*, 2063–2075. [\[CrossRef\]](#)
58. Ahmed, S.K. The Pillars of Trustworthiness in Qualitative Research. *J. Med. Surg. Public Health* **2024**, *2*, 100051. [\[CrossRef\]](#)
59. Parvez, M.O.; Arasli, H.; Ozturen, A.; Lodhi, R.N.; Ongsakul, V. Antecedents of Human-Robot Collaboration: Theoretical Extension of the Technology Acceptance Model. *J. Hosp. Tour. Technol.* **2022**, *13*, 240–263. [\[CrossRef\]](#)

60. Frey, C.B.; Osborne, M.A. The Future of Employment: How Susceptible Are Jobs to Computerisation? *Technol. Forecast. Soc. Change* **2017**, *114*, 254–280. [[CrossRef](#)]
61. Ordieres-Meré, J.; Gutierrez, M.; Villalba-Díez, J. Toward the Industry 5.0 Paradigm: Increasing Value Creation through the Robust Integration of Humans and Machines. *Comput. Ind.* **2023**, *150*, 103947. [[CrossRef](#)]
62. Martin, A.K.; Green, T.L.; McCarthy, A.T.; Sowa, P.M.; Laakso, E.-L. Allied Health Transdisciplinary Models of Care in Hospital Settings: A Scoping Review. *J. Interprof. Care* **2023**, *37*, 118–130. [[CrossRef](#)] [[PubMed](#)]
63. Faulconbridge, J.; Sarwar, A.; Spring, M. How Professionals Adapt to Artificial Intelligence: The Role of Intertwined Boundary Work. *J. Manag. Stud.* **2025**, *62*, 1991–2024. [[CrossRef](#)]
64. Wei, Y.M.; Chen, K.; Kang, J.N.; Chen, W.; Wang, X.Y.; Zhang, X. Policy and Management of Carbon Peaking and Carbon Neutrality: A Literature Review. *Engineering* **2022**, *14*, 52–63. [[CrossRef](#)]
65. D’Oria, L.; Crook, T.R.; Ketchen, D.J.; Sirmon, D.G.; Wright, M. The Evolution of Resource-Based Inquiry: A Review and Meta-Analytic Integration of the Strategic Resources–Actions–Performance Pathway. *J. Manag.* **2021**, *47*, 1383–1429. [[CrossRef](#)]
66. Yu, J.; Ma, X. Exploring the Management Policy of Marine Microplastic Litter in China: Overview, Challenges and Prospects. *Sustain. Prod. Consum.* **2022**, *32*, 607–618. [[CrossRef](#)]
67. He, Y.; Cheng, H.; Zou, P.; Zhou, Y.; Zhang, X.; Chen, J. Multi-Subject Collaboration in Agricultural Green Production: A Tripartite Evolutionary Game of Central Government, Local Governments, and Farmers. *Environ. Dev. Sustain.* **2025**. [[CrossRef](#)]
68. Mahmoodi, A.; Hashemi, L.; Tahan, M.M.; Jasemi, M.; Millar, R.C. Design a Technology Acceptance Model by Applying System Dynamics: An Analysis Based on Key Dimensions of Employee Behavior. *J. Model. Manag.* **2023**, *18*, 1454–1475. [[CrossRef](#)]
69. OECD. *OECD Skills Outlook 2021 Learning for Life*; OECD Publishing: Paris, France, 2021; ISBN 9789264203983.
70. Cejudo, G.M.; Michel, C.L. Instruments for Policy Integration: How Policy Mixes Work Together. *SAGE Open* **2021**, *11*, 1–10. [[CrossRef](#)]
71. Tan, S.C.; Chan, C.; Bielaczyc, K.; Ma, L.; Scardamalia, M.; Bereiter, C. Knowledge Building: Aligning Education with Needs for Knowledge Creation in the Digital Age. *Educ. Technol. Res. Dev.* **2021**, *69*, 2243–2266. [[CrossRef](#)]
72. Akour, M.; Alenezi, M. Higher Education Future in the Era of Digital Transformation. *Educ. Sci.* **2022**, *12*, 784. [[CrossRef](#)]
73. Gemici, E.; Zehir, C. High-Performance Work Systems, Learning Orientation and Innovativeness: The Antecedent Role of Environmental Turbulence. *Eur. J. Innov. Manag.* **2023**, *26*, 475–503. [[CrossRef](#)]
74. Al-Nuaimi, M.N.; Al-Emran, M. Learning Management Systems and Technology Acceptance Models: A Systematic Review. *Educ. Inf. Technol.* **2021**, *26*, 5499–5533. [[CrossRef](#)]
75. Abdalla, A.; Li, X.; Yang, F. Expatriate Construction Professionals’ Performance in International Construction Projects: The Role of Cross-Cultural Adjustment and Job Burnout. *J. Constr. Eng. Manag.* **2024**, *150*, 04024005. [[CrossRef](#)]
76. Geels, F.W. Causality and Explanation in Socio-Technical Transitions Research: Mobilising Epistemological Insights from the Wider Social Sciences. *Res. Policy* **2022**, *51*, 104537. [[CrossRef](#)]
77. Galego, D.; Moulaert, F.; Brans, M.; Santinha, G. Social Innovation & Governance: A Scoping Review. *Innov. Eur. J. Soc. Sci. Res.* **2022**, *35*, 265–290. [[CrossRef](#)]

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