

Article

Rethinking AI-Era Transformation of Architecture, Engineering and Construction Education: A Multi-Stakeholder Perspective

Panxiu Wang ^{1,2} , Zhiqiang Hua ¹, Dawei Wang ^{1,*}  and Zhifeng Liu ^{1,*}

¹ School of Architecture and Engineering, Jinling Institute of Technology, Nanjing 211169, China; wangpanxiu@jit.edu.cn (P.W.); 2506010004@stu.jit.edu.cn (Z.H.)

² College of Civil and Transportation Engineering, Hohai University, Nanjing 210098, China

* Correspondence: wangdawei@jit.edu.cn (D.W.); lzf@jit.edu.cn (Z.L.)

Abstract

Artificial intelligence (AI) is reshaping the architecture, engineering and construction (AEC) sector. However, AEC education remains rooted within traditional disciplinary boundaries and a technology-centric training model, creating a widening mismatch between graduates' capabilities and the cognitive, collaborative, and interdisciplinary demands of AI-enabled practice. Situated within the Chinese higher education context, this study bridges this gap through a multi-stakeholder survey ($n = 352$) noting perspectives from academia, industry and research. One-way ANOVA and Tukey's HSD test were used to examine differences across stakeholder groups and disciplines, while a Bayesian Network was developed to model competency pathways, simulate intervention scenarios and identify key leverage points for curriculum reform. The analysis reveals that meaningful AI integration requires a reconstruction of competency, rather than the mere addition of standalone technical or software courses; it calls for fundamental changes in professional formation, curricula and pedagogy. Four core competencies emerged from the data: professional expertise, systems thinking, interdisciplinary collaboration and AI-enabled problem-solving. Bayesian Network simulations further indicated that curriculum expansion alone improved AI knowledge acquisition by 39.6%, but yielded only modest gains in practical skills (13.9%) and application competencies (4.5%). By contrast, integrated interventions that combined teacher development, university–industry collaboration and project-based practice produced substantial improvements in AI application competencies (37.9%), employment adaptability (29.3%) and industry satisfaction (14.1%). These divergent findings highlight the necessity of coordinated educational interventions to reconcile stakeholder expectations and foster AI-oriented competency development. Based on this evidence, the study proposes a competency-oriented framework and a phased curriculum transformation pathway, providing an empirical foundation for AI-driven curriculum reform and competency reconstruction in AEC education.



Academic Editor: Nikos A. Salingaros

Received: 18 June 2026

Revised: 29 July 2026

Accepted: 1 August 2026

Published: 4 August 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

Keywords: artificial intelligence; architecture; engineering and construction education; curriculum transformation; stakeholder perspectives; professional competencies; educational reform; China

1. Introduction

The architecture, engineering and construction (AEC) sector is undergoing a profound epistemic shift. Artificial intelligence (AI) is now embedded across the industry through generative design, computer vision, digital twins, predictive analytics and intelligent construction systems [1,2]. These developments do not merely automate routine tasks; they

are restructuring the cognitive and collaborative framework within which built environment professionals operate [3–5]. Where expertise was once defined by disciplinary depth and representational craft, contemporary practice increasingly demands an integration of domain knowledge with computational reasoning, data-driven decision-making, and human–AI interaction [6,7]. As AI becomes embedded into professional workflows, long-standing assumptions about the competencies required for architectural and construction practice are being reconsidered [8,9]. Yet despite the urgency of this shift, the response from universities have consistently lagged behind the pace of industrial change. Existing research on digital transformation in architectural education has concentrated, for the most part, on discrete technological interventions—building information modeling, parametric design, virtual reality and computational design studios [10–12]. More recently, attention has shifted to the pedagogical integration of generative AI tools within architectural curricula [13,14]. These studies have explored instructional strategies for incorporating such tools, offering practical exemplars for advancing teaching methods, fostering students’ interdisciplinary thinking and mapping actionable pathways for the reconstruction of design pedagogy [15,16]. While a growing body of literature documents the incorporation of AI technologies into individual courses and instructional settings; broader questions concerning the educational implications of AI, however, remain insufficiently addressed [17].

The current discourse on AI integration AEC education reveals three limitations that this study confronts. First, most of the existing scholarship has adopted an instrumental lens, focusing on isolated technological interventions, specific software applications, or the grafting of technical modules onto existing curricula [18,19]. This preoccupation with technological supplementation obscures a more fundamental question: how does the introduction of computational intelligence alter the formation of a competent professional? By failing to interrogate how AI restructures learning pathways and the wider ecology of the curriculum, the literature reinforces a narrow, skills-based view of education, leaving the core epistemological traditions of the design studio unexamined [20,21]. This results in a deepening misalignment: graduates are technically introduced to new tools but left without the integrative judgment to deploy them critically [22]. Consequently, the relationship between emerging industry expectations and existing educational structures remains underexamined.

Second, the process of educational transformation is frequently discussed as a monolithic project, ignoring the contested terrain of pedagogical values. Stakeholder perceptions of AI-oriented talent development is likely to differ substantially across students, faculty members, industry practitioners and researchers. A student seeking professional relevance, a faculty member safeguarding disciplinary artistry and an industry practitioner demanding immediate productivity will naturally prioritize different competencies [23]. However, rigorous empirical work that systematically maps these perceptual cleavages among multi-stakeholder within AEC education remain limited [24,25]. The absence of such analysis narrows the scope of curriculum reform and risks overlooking competing educational priorities. This silence in the research allows a harmonious narrative, one that masks conflicts which, if left unaddressed, can derail reform efforts by producing curricula that satisfy no constituency and fail to cohere into a meaningful pedagogical vision. This result is a one-sided understanding of talent development objectives and curricular arrangements [26,27].

Third, the framing of AI integration as a technological problem to be solved precludes a more profound reckoning with institutional and pedagogical transformation. The dominant logic suggests that adding AI-related courses or mandating software literacy will equip students for the future. This is a category error. The challenge is not merely technological but pedagogical and structural; it demands a re-examination of how knowledge

is scaffolded across a degree program, how interdisciplinary collaboration is incentivized and how the design studio can evolve into a site for critical inquiry rather than stylistic production [28,29]. Without addressing these deeper institutional logics, AI in education risks becoming a simulacrum of innovation—a veneer of modernity applied to a fundamentally unchanged pedagogical core [30].

Moreover, existing studies overwhelmingly evaluate current educational practices but rarely examine how different educational reform strategies might influence future competency development under conditions of rapid AI technologies [31]. Given the uncertainty and accelerating pace of AI innovation, educational planning requires not only explanatory evidence but also predictive insights that can anticipate the potential consequences of alternative reform pathways [32]. However, conventional educational research methods are designed primarily to identify relationships or group differences; they offer limited support for forecasting the long-term effects of curriculum interventions within complex educational systems.

Unlike previous studies that emphasize AI tool adoption, curriculum enhancement, or isolated competency identification, this study conceptualizes AI-enabled educational transformation as a process of competency reconstruction driven by the co-evolution of technology, industry and education. We argue that AI fundamentally reshapes professional tasks, competency structures and educational ecosystems. To address the limitations identified above, this study adopts a multi-stakeholder perspective to investigate the systemic transformation of AI-integrated talent cultivation in undergraduate architectural education. We introduce a research framework adopting a mixed empirical research approach (Figure 1). This research is guided by four objectives: (1) to identify the core competency requirements for AI-oriented AEC professionals; (2) to examine differences among multiple stakeholders regarding curriculum design, teaching approaches and competency priorities; (3) to develop a systematic AI-integrated competency reconstruction framework and a phased curriculum transformation pathway based on multi-stakeholder perspectives; and (4) to construct a Bayesian Network model to simulate alternative educational reform pathways and identify effective intervention strategies for enhancing AI-oriented competency development. To achieve these objectives, the study first conducts a comprehensive literature review to identify major challenges associated with AI talent cultivation in the AEC industry. These challenges are further translated into educational terms, providing the theoretical basis for constructing the survey framework and competency assessment dimensions. Second, a questionnaire survey involving 352 participants drawn from multiple stakeholder groups, including students, faculty members, researchers and industry professionals, is conducted to capture diverse perspectives on AI-oriented AEC education. The resulting data are analyzed using descriptive statistics, one-way analysis of variance (ANOVA), Tukey's honestly significant difference (HSD) test, and Bayesian Network analysis to identify overall trends, stakeholder differences and potential causal relationships among educational factors.

This study contributes to the literature in three respects. First, it reconceptualizes AI-enabled educational transformation as a process of competency reconstruction rather than technology adoption, providing a new theoretical perspective for AI-oriented engineering education. Second, it proposes a dynamic, feedback-driven competency reconstruction framework that links technological evolution, professional task transformation, educational reform and talent cultivation into a continuous process of co-evolution. Third, recognizing that existing studies primarily explain current educational phenomena but rarely anticipate the future impacts of educational reform, this study integrates data-driven algorithms as a decision-support approach to simulate alternative competency development pathways and enable predictive, evidence-based curriculum planning under rapidly evolving AI-driven contexts.

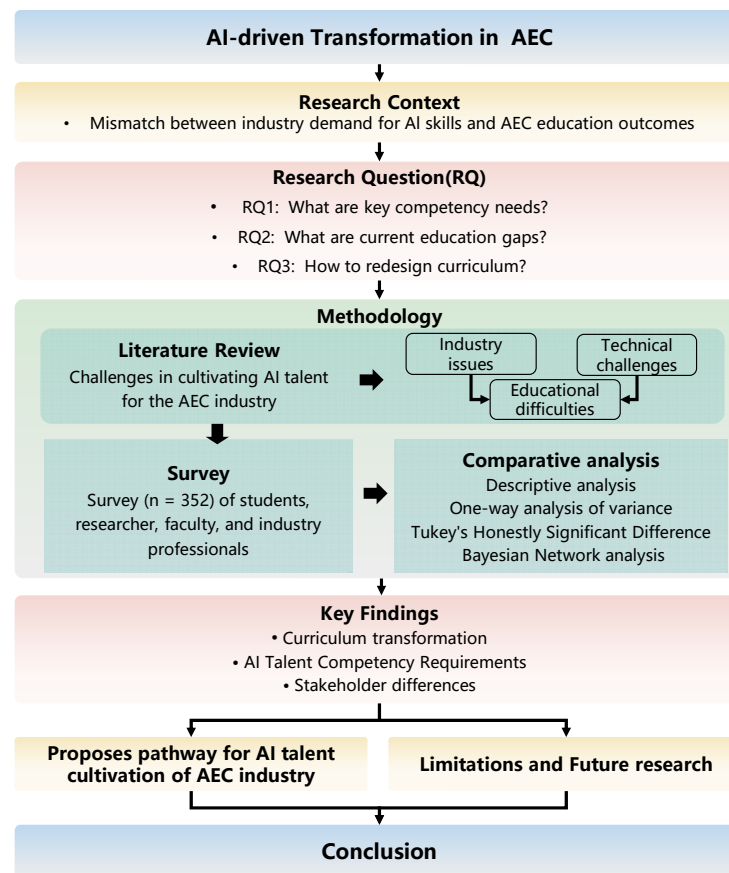


Figure 1. Research Framework.

The study is situated within China's higher education system, a compelling site for such an inquiry. As one of the world's largest construction markets and a state-prioritized arena for smart city development, digital infrastructure and sustainable urbanization, China offers a significant setting in which to examine how higher education institutions respond to AI-driven industrial transformation [33,34]. Each year, the country produces a vast cohort of graduates in architecture, urban planning, civil engineering and construction management. The capacity of its institutions to adapt will directly shape not only individual employability but also the productive and innovative potential of a global industry. The confluence of scale, state-driven technological ambition and deep-seated pedagogical tradition presents a sharpened set of both opportunities and systemic obstacles [35]. Thus, the pressures and negotiations observed within this context offer critical, transferable insights for educational systems worldwide grappling with the same paradigmatic transition.

2. Literature Review and Problem Analysis

2.1. Literature Retrieval and Identification

This study employed a scoping review methodology to systematically map and synthesize the existing literature on AI in the AEC domain. The review process was conducted in accordance with the PRISMA Extension for Scoping Reviews guidelines, encompassing all key stages, including research question formulation, search strategy development, eligibility criteria definition, independent study screening, data extraction, and evidence synthesis [36]. Its purpose was to ground the survey instrument in a systematic analysis of the existing literature. To ensure both the academic rigor and contemporary relevance, the Web of Science Core Collection was selected as the primary database because of its comprehensive coverage of high-quality international research. The search focused on

peer-reviewed journal articles and review papers addressing the intersection of AI and the AEC industry. Search terms were organized into three thematic groups—core keywords, technology-oriented keywords and education-oriented keywords—to capture the intersecting dimensions of AI, AEC, digital transformation, and talent cultivation (Table 1). The search covered publications from 2018 to 2025, a period corresponding to the acceleration of digital and intelligent transformation across the sector, chosen to ensure the relevance and currency of the reviewed material.

Table 1. List of search keywords.

Category	Search Terms	Search Period
Core Keywords	AI, Architecture, Engineering, Construction, Digitalization, Intelligent	2018–2025
Technology-oriented keywords	Building engineering, Intelligent construction, Generative AI, Innovation	
Education-oriented keywords	AI talent development, Talent cultivation systems, AEC education, Curriculum development	

The initial database search identified 906 records. After removing duplicates, 847 unique publications remained. Two independent reviewers then screened titles and abstracts, excluding 628 records that did not meet the inclusion criteria. The remaining 219 articles underwent full-text assessment, during which conference abstracts, non-empirical studies, and publications with insufficient relevance to the research objectives were excluded. Ultimately, 131 studies were included in the final review. To ensure the reliability of the screening process, two reviewers independently completed each stage of study selection. Inter-rater agreement was high, with a Cohen’s kappa coefficient of 0.87. Disagreements were resolved through discussion and consensus or, when necessary, by consultation with a third reviewer. The complete literature selection process is illustrated in Figure 2.

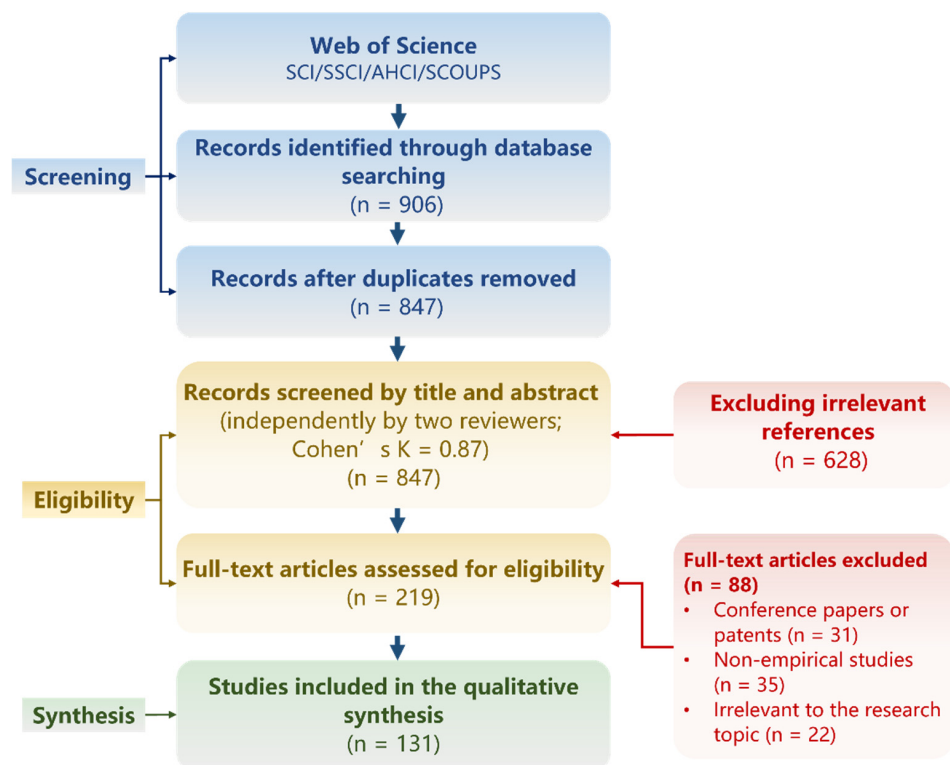


Figure 2. PRISMA Flowchart for Literature Selection.

2.2. Literature Analysis

The integration of AI into the AEC sector is not solely a technological undertaking; it is a challenge that implicates professional formation at every level. Industry transformation generates new competency demands, technical barriers define the knowledge and skills required in practice and educational systems determine whether such competencies can be developed at scale. These three dimensions—industry, technology and education—are not parallel concerns but tightly coupled: shortcomings in one cascade into the others. The literature review is therefore organized around these interconnected domains, examining in turn the challenges of AI integration, the competencies they necessitate, and the educational inadequacies they expose.

2.2.1. Challenges in Integrating AI with the AEC Industry

The literature reveals persistent obstacles across all three domains. At the industry level, data management in the AEC sector remains insufficiently standardized, limiting the capacity of AI technologies to adapt effectively to diverse project contexts and to integrate seamlessly into real-world workflows [37]. Moreover, the level of digital integration across disciplines remains low, and cross-disciplinary technological collaboration is still limited, hindering the emergence of an integrated operational framework [38–40]. Heterogeneous data formats, fragmented stakeholder collaboration and decentralized collection practices across project phases produce information environments in which data are isolated within organizational and temporal boundaries. This fragmentation impedes interoperability and limits the capacity of AI models to support the advanced analytics that large-scale construction projects demand [41,42].

These industry-level constraints are mirrored at the technology application level. Integration between AI technologies and mainstream AEC software ecosystems remains limited [43,44] and poor interoperability among heterogeneous platforms creates significant barriers to seamless data exchange [45,46]. Design and construction processes routinely involve multiple, competing objectives under conditions that require high computational efficiency—conditions that stretch the capabilities of current AI systems [47,48]. Furthermore, the performance of AI models depends heavily on the scale and diversity of training data. Where datasets are small or homogenous, model adaptability and generalizability degrade, limiting the reliable deployment of AI in complex real-world project settings [49,50].

At the educational level, these industry and technical challenges converge into a persistent talent deficit. The shortage of AI-capable professionals is widely acknowledged across the sector; however, understanding of AI among stakeholders remains limited, impeding the development of a systematic framework for integrating AI into AEC practice [51,52]. At the same time, educational institutions have struggled to keep pace with the rapid evolution of AI technologies, resulting in a growing mismatch between curricular content and professional requirements [53]. A substantial gap separates the routine use of general-purpose AI tools from the capacity to adapt, customise, or develop AI solutions for AEC-specific contexts [54]. Most students demonstrate basic competence in operating such tools but lack this deeper adaptive capacity and are able to perform basic operations, yet lack the capacity to adapt, customize, or develop AI solutions for AEC specific contexts [55]. Collaborative mechanisms linking universities, industry and individual learners remain underdeveloped and genuinely cross-disciplinary approaches to talent development are still exploratory [56,57]. The limited availability of educational resources that integrate knowledge across architecture, AI and data science further constrains the development of interdisciplinary professionals [58]. Collectively, these challenges contribute to a persistent gap between the competencies acquired by graduates and the skills required in industry, limiting their ability to meet the evolving demands of the AEC sector [59,60].

2.2.2. Competency Frameworks for AI-Oriented AEC Professionals

If the challenges documented above define the problem space, the competencies required to navigate it are beginning to crystallize in the literature—again clustering around the industry, technology and education dimensions. At the industry level, the literature points towards professionals who can develop AI solutions tailored to the specific demands of design, construction and operation scenarios, rather than merely applying generic tools [61,62]. Such professionals must be capable of integrating heterogeneous data from multiple sources, overcoming the system fragmentation described earlier and enabling data interoperability across the project lifecycle [63,64]. These integrative capabilities are regarded as prerequisite for any large-scale deployment of AI in the AEC sector [65].

At the technological level, the required competencies extend well beyond software proficiency. Professionals need the capacity to bridge AI technologies with industry-standard platforms [66,67] and to draw on both computational methods and domain expertise when addressing complex design and construction challenges [68,69]. They must also be able to manage the limitations associated with data availability, scale and diversity, thereby enhancing the applicability and robustness of AI models in real-world AEC contexts [70,71]. At the educational level, the competency framework shifts toward curricular and pedagogical leadership. AI-oriented AEC professionals should possess a systematic knowledge base spanning architecture, AI, and data science—not as separate domains but as an integrated foundation [72]. They are expected to drive curriculum innovation by integrating AI into interdisciplinary teaching and by strengthening students' capacity to apply computational approaches within professional practice [73,74]. The literature further suggests that such professionals should be able to design personalized learning pathways that improve curricular coherence and align graduate outcomes more closely with industry needs, thereby supporting the systematic cultivation of interdisciplinary talent for the AEC sector [75,76].

Existing studies have primarily focused on identifying AI-related competencies, evaluating curriculum implementation, or comparing stakeholder perceptions. However, limited attention has been paid to how alternative educational interventions influence competency development or how curriculum reform strategies can be evaluated before implementation. Consequently, educational reform remains largely experience-driven rather than evidence-driven (Table 2).

Table 2. AI-Related Challenges and Competency Requirements for Future AEC Professionals.

Issue	Barrier Description	Talent Competency (Student and Teacher)	Corresponding Questionnaire Items
Industry-Related Challenges	Lack of standardized data management and limited technological adaptability across application scenarios	Ability to collaborate across disciplines and develop context-specific AI applications	II. Perceptions of AI Adoption in the AEC Industry IV. Required Competencies for Future AEC Professionals
	Limited integration of digital technologies across AEC disciplines	Ability to integrate AI technologies with domain-specific AEC knowledge	
	Limited inter-organizational collaboration and slow adoption of AI technologies	Ability to coordinate and utilize multi-source data for collaborative decision-making	

Table 2. *Cont.*

Issue	Barrier Description	Talent Competency (Student and Teacher)	Corresponding Questionnaire Items
Technical Challenges	Difficulty in integrating AI technologies with traditional architectural workflows	Ability to integrate AI tools into existing AEC workflows and professional software environments	III. Key Issues in AI-Enabled AEC Education IV. Required Competencies for Future AEC Professionals
	Trade-off between complex design objectives and computational speed constraints	Ability to understand and apply AI-assisted optimization methods for design and engineering problems	
	Software incompatibilities and the absence of unified industry standards	Ability to manage cross-platform data integration and adapt to emerging digital standards	
	Limited AI model adaptability due to insufficient data volume and diversity	Ability to understand data requirements and evaluate AI model applicability in professional contexts	
Educational Challenges	Fragmented and superficial student understanding of AI	Ability to develop structured understanding of AI concepts and their professional applications	IV. Required Competencies for Future AEC Professionals V. Reform in Curriculum Design and Teaching Practice VI. Assessment, Evaluation, and University–Industry Collaboration
	Lagging curriculum development behind rapid AI advancement	Ability to design and execute technology-integrated instructional schemes	
	Disconnect between traditional AEC education and AI tool application	Ability to align AI capabilities with professional domain requirements	
	Limited collaboration among universities, industry partners, and other stakeholders	Designing interdisciplinary curricula across multiple domains; Ability to collaborate in interdisciplinary teams across AEC and AI-related fields	
	Shortage of interdisciplinary AI course materials	Utilizing AI to design personalized learning pathways for students; Ability to identify and apply interdisciplinary AI learning resources	
	Misalignment between graduate competencies and industry requirements	Ability to continuously update professional competencies according to evolving industry requirements	

3. Methods

3.1. Questionnaire Design

3.1.1. Questionnaire Development and Sampling Strategy

The questionnaire items were developed based on previous studies on AI literacy, professional competency frameworks, digital transformation in AEC practice and built environment pedagogy. The questionnaire consisted of six measurement dimensions: (1) AI competency requirements, (2) interdisciplinary collaboration, (3) curriculum adaptability, (4) teaching challenges, (5) practical training demands, and (6) industry–education alignment. These variables were adapted from the existing literature on AI literacy, professional competency frameworks, and built environment pedagogy (Section 2). To ensure content validity and contextual relevance, the preliminary questionnaire was reviewed by experts from both academia and industry. Their feedback informed revisions to the wording,

improved the clarity of survey items, and ensured that the instrument accurately reflected the educational and professional realities of AI integration in the AEC field.

Given that AI-oriented educational transformation involves divergent expectations and systemic tensions among key actors, this study employed a purposive, multi-stakeholder sampling strategy. To move beyond a single-perspective bias, the survey targeted four distinct groups: undergraduate students, university faculty, academic researchers and industry professionals. This sampling design stems from the rationale that AI transformation in AEC education simultaneously intersects with institutional curriculum reform, evolving industry competency expectations, pedagogical challenges faced by educators, and students' authentic learning experiences. Consequently, elucidating these perceptual divergences is critical for identifying competency gaps and formulating actionable educational reform strategies. A total of 360 questionnaires were administered across these target cohorts. Following the exclusion of incomplete or inconsistent submissions, 352 valid responses were retained, yielding an effective response rate of 97.7%.

Although the multi-stakeholder sample provides diverse perspectives from major participants involved in AEC education and practice, potential selection bias should be acknowledged. Individuals with greater awareness of or interest in AI technologies may have been more willing to participate. To mitigate this potential bias, respondents were recruited from multiple AEC-related disciplines, including architecture, urban planning, civil engineering, intelligent construction and engineering software, ensuring broader representation of AI-related educational needs across different professional contexts.

3.1.2. Questionnaire Design and Content Validation

Given that this study employed a non-scale questionnaire consisting primarily of categorical, multiple-choice and scenario-based items, the instrument was designed to identify stakeholders' perceptions, expectations and preferences rather than to measure latent constructs through multiple reflective indicators. Therefore, conventional psychometric approaches, such as internal consistency reliability testing (e.g., Cronbach's α) and construct validity assessment (e.g., exploratory factor analysis), were not applicable. Instead, questionnaire quality was evaluated through expert-based content validation [77]. Prior to the formal survey, an expert panel of four specialists was invited to review the questionnaire. The panel comprised two academic experts and two industry professionals, together covering interdisciplinary expertise in AEC education, AI, the built environment, construction practice and architectural design. This composition was intentionally chosen to incorporate both educational perspectives and requirements of professional practice. The experts evaluated the clarity, relevance, accuracy and comprehensiveness of each item, while also identifying potential redundancy, ambiguity or logical inconsistencies. Based on their feedback, the questionnaire was revised and refined to improve content validity and to ensure its suitability for investigating stakeholders' perceptions and expectations regarding AI-oriented AEC education transformation (Table 3).

Table 3. Profiles of experts involved in questionnaire validation.

Expert	Professional Role	Position	Degree	Research/Professional Expertise	Relevant Experience
Expert 1	Faculty member	Professor	Ph.D.	Interdisciplinary research involving the built environment and energy technologies, artificial intelligence, and control engineering	International academic and professional experience, providing a global perspective

Table 3. *Cont.*

Expert	Professional Role	Position	Degree	Research/Professional Expertise	Relevant Experience
Expert 2	Researcher	Professor	Ph.D.	Indoor and outdoor air quality mechanisms and control, human–environment interaction	International academic and professional experience, providing a global perspective 10 years of construction engineering practice experience in China, with extensive practical expertise
Expert 3	Industry professional	Engineer	Master’s degree	Construction engineering, building construction, and operation management	20 years of experience in architectural design and construction practice in China, with expertise in building design
Expert 4	Industry professional	Engineer	Master’s degree	Architectural design and urban design practice	

3.2. Sampling Strategy and Data Collection

The survey employed an anonymous sampling approach targeting AEC professionals with some degree of exposure to or knowledge of AI. The instrument focused on respondents’ perceptions of AI-oriented competency requirements, curriculum reform priorities, interdisciplinary collaboration and barriers to AI-integrated talent cultivation at the undergraduate level. A total of 352 valid responses were collected. The sample was balanced by gender (male: 50.3%, $n = 177$; female: 49.7%, $n = 175$). The predominant age cohort was 22–30 years (40.6%, $n = 143$), followed by 18–22 years (31.2%, $n = 110$); the inclusion of participants over 30 years provided sufficient sample heterogeneity to capture career-stage-specific variations in perceptions of AI-integrated education. Students constituted the largest occupational cohort (64.2%, $n = 226$), followed by faculty (18.2%, $n = 64$), industry practitioners (9.4%, $n = 33$) and researchers (8.2%, $n = 29$). While student representation was substantial—appropriately so, given the study’s focus on undergraduate education—the inclusion of faculty, practitioners and researchers enabled the comparative, multi-stakeholder analysis that the research questions demand. Disciplinary composition reflected the multidisciplinary character of AI–AEC integration. Urban and rural planning represented the largest cohort (42.0%, $n = 148$), followed by architecture (28.1%, $n = 99$), civil engineering (13.1%, $n = 46$), intelligent construction (5.7%, $n = 20$), computer science (3.4%, $n = 12$) and other related fields (7.7%, $n = 27$). The sample thus encompassed both traditional built-environment disciplines and emerging technology-oriented fields, a spread that is necessary for examining how disciplinary socialization shapes perceptions of AI competency (Figure 3).

3.3. Statistical Analysis

The analysis proceeded in two stages. Descriptive statistics were first employed to map respondents’ overall perceptions of AI-integrated talent cultivation. One-way analysis of variance (ANOVA) and Tukey’s Honestly Significant Difference (Tukey HSD) post hoc tests were then applied to identify significant differences across stakeholder groups and disciplinary backgrounds. The choice of these methods was guided by the study’s central concern with perceptual divergence: ANOVA enables testing for structural differences among three or more groups, while Tukey’s HSD provides a conservative pairwise comparison procedure that controls the family-wise error rate when multiple group means are tested simultaneously.

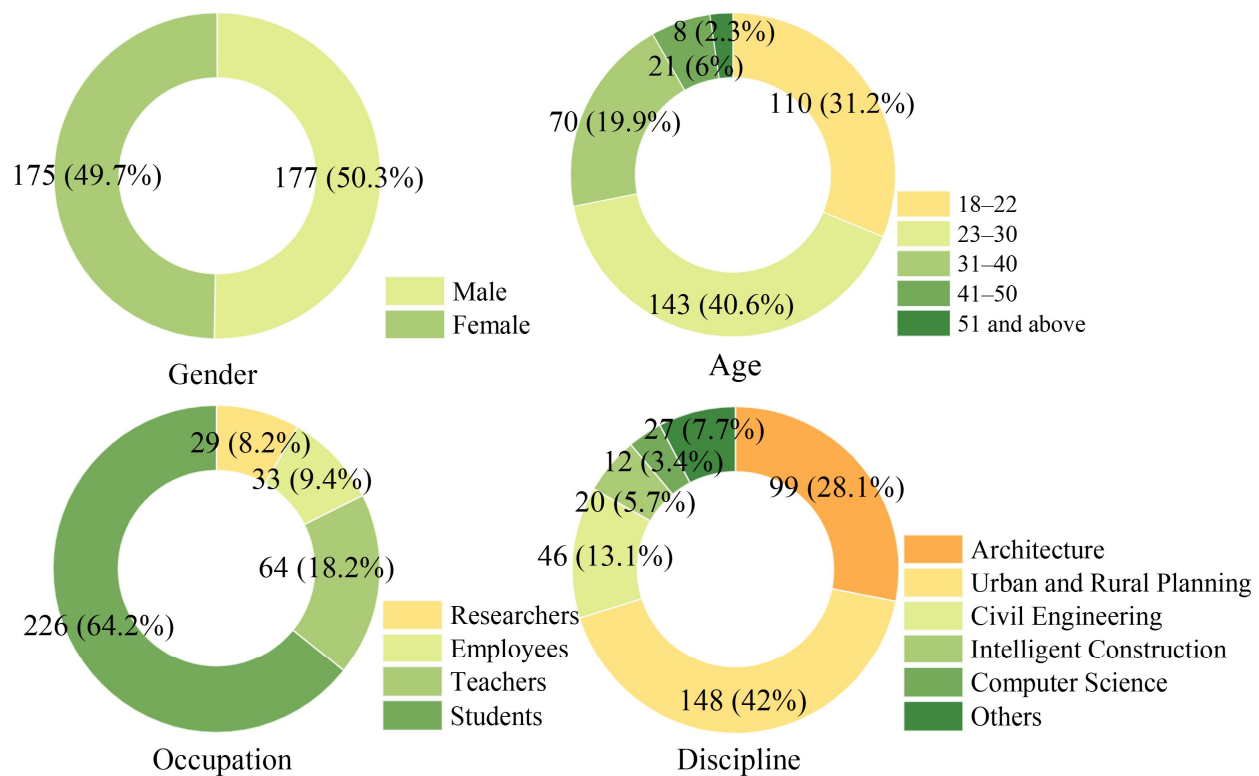


Figure 3. Descriptive statistics of the sample.

3.3.1. One-Way Analysis of Variance (ANOVA)

When the number of levels in a grouping variable (e.g., occupation, discipline, or age group) is three or more ($k \geq 3$), ANOVA is employed to examine differences in the mean values of a continuous variable across multiple groups. The fundamental principle of ANOVA is to partition the total variation into between-group variation and within-group variation, and to construct the F-statistic based on the ratio of their mean squares, as shown in Equations (1)–(3).

$$F = \frac{MS_B}{MS_W} = \frac{\frac{SS_B}{(k-1)}}{\frac{SS_W}{(N-k)}} \quad (1)$$

$$SS_B = \sum_{j=1}^k n_j (\bar{X}_j - \bar{X})^2 \quad (2)$$

$$SS_W = \sum_{j=1}^k \sum_{i=1}^{n_j} (x_{ij} - \bar{X}_j)^2 \quad (3)$$

In which, F denotes the ANOVA test statistic, which follows an F distribution with $k - 1$ degrees of freedom in the numerator and $N - k$ degrees of freedom in the denominator. MS_B denotes the mean square between, reflecting the dispersion of group means around the overall mean; MS_W denotes the mean square within, reflecting the dispersion of individual observations around their respective group means. SS_B denotes the sum of squares between groups, while SS_W denotes the sum of squares within groups. K is the number of groups, n is the total sample size, and n_j is the sample size of group j . $\bar{X}_j$ represents the mean of group j , and $\bar{X}$ represents the grand mean of all observations. x_{ij} denotes the i -th observation in group j . The subscript $j = 1, 2, \dots, k$ identifies different groups, whereas $i = 1, 2, \dots, n_j$ identifies individual observations within each group. If $p < 0.05$, the null hypothesis that all group means are equal is rejected, indicating statistically significant differences

among groups. In general, larger F values and smaller p values provide stronger evidence of significant between-group differences.

3.3.2. Tukey's Honestly Significant Difference (Tukey HSD)

When the overall ANOVA result is statistically significant ($p < 0.05$), Tukey's Honestly Significant Difference (HSD) test is subsequently performed to conduct pairwise comparisons among the k groups. The purpose of this post hoc analysis is to identify which specific pairs of groups differ significantly from one another while controlling the family-wise Type I error rate that may arise from multiple comparisons. The critical value of the HSD test is calculated according to Equation (4).

$$HSD = q_{\alpha,k,N-k} \cdot \sqrt{\frac{MS_W}{n}} \quad (4)$$

In Equation (4), HSD denotes the critical value of the honestly significant difference, which serves as the threshold for determining whether the difference between two group means is statistically significant. $q_{\alpha,k,N-k}$ represents the critical value of the studentized range distribution at the significance level α , with k groups and $N - k$ error degrees of freedom. This value can be obtained from statistical tables or generated directly by statistical software. The significance level α is typically set at 0.05. MS_W denotes the within-group mean square obtained from the preceding ANOVA, and n represents the sample size of each group. When group sizes are unequal, n is replaced by the harmonic mean of the group sample sizes.

3.3.3. Bayesian Network Analysis for AI-Driven AEC Education Reform Data

While ANOVA effectively identifies static group differences, it cannot model the causal chains underlying talent cultivation or simulate the downstream effects of alternative educational interventions. To move beyond confirmatory hypothesis testing and enable policy-oriented “what-if” scenario analysis, we adopt a Bayesian Network approach. This framework permits systematic sensitivity analysis by perturbing key input nodes and observing posterior fluctuations in outcome variables, thereby identifying the most influential leverage points for reform. In sum, the Bayesian Network analysis complements and extends the preceding frequentist comparisons by transforming static differences into actionable, causal insights that directly inform curriculum redesign and stakeholder governance.

A Bayesian Network is a directed acyclic graph in which nodes represent random variables and directed edges denote conditional dependency relationships among these variables. A Bayesian Network with N nodes can be represented as $N = \langle V, E \rangle$, which consists of two components:

① $\langle V, E \rangle$ defines the directed acyclic graph structure of the Bayesian network, where $V = \{V_1, \dots, V_n\}$ is the set of nodes representing random variables, and E is the set of directed edges encoding conditional dependency relationships among these variables. Each node represents an abstract random variable in the problem domain. The directed edges generally imply causal dependencies, and thus Bayesian networks are often referred to as causal networks. For any directed edge (V_i, V_j) , V_i is the parent of V_j , and V_j is the child of V_i . Nodes without parents are called root nodes, whereas nodes without children are called leaf nodes. The parent set and the non-descendant set of nodes V_i are denoted by $Pa(V_i)$ and $A(V_i)$, respectively. The directed graph encodes the conditional independence assumptions of the Bayesian network. Specifically, given its parent set $Pa(V_i)$, node V_i is conditionally independent of its non-descendants $A(V_i)$.

$$P(V_i \mid Pa(V_i), A(V_i)) = P(V_i \mid Pa(V_i)) \quad (5)$$

② P denotes the set of conditional probability distributions associated with the nodes in the network. Owing to the conditional independence assumptions encoded by the Bayesian network, each node is characterized by a local conditional probability distribution, $P(V_i | Pa(V_i))$, which quantifies the probabilistic dependence between the node and its parent set. Consequently, given the prior probability distributions of the root nodes and the conditional probability distributions of all non-root nodes, the joint probability distribution over the entire network can be factorized as:

$$P(V) = P\{V_1, \dots, V_n\} = \prod_{i=1}^n P(V_i | V_1, \dots, V_{i-1}) \quad (6)$$

Following the standard Bayesian Network modelling framework, which consists of nodes, directed edges and conditional probability tables, the network was implemented in Python 3.14 by integrating theory-driven and data-driven approaches. Moving beyond descriptive analysis toward predictive decision support, this study constructs a Bayesian Network to simulate the probabilistic propagation effects of different educational intervention strategies. The network structure was developed using a custom theory-constrained association-screening procedure. Candidate edges were selected according to association strength within the predefined theoretical layer ordering, after which theoretically required pathway edges were added. This procedure was used to construct a transparent scenario-analysis structure rather than to identify a statistically optimal or causal DAG. Using the constructed network, conditional probabilistic inference was performed to estimate the posterior distributions of downstream outcome variables under different intervention scenarios, with key input variables assigned to different levels (high, medium, and low). This study conceptualizes the Bayesian Network as a probabilistic scenario analysis framework guided by theoretically informed relationships and empirical evidence. Table 4 summarizes its applications in network structure construction, conditional inference, and comparative scenario analysis.

Table 4. Bayesian Network scenario-analysis specification, inference settings, and analytical scope.

Component	Implemented Specification
Analytical purpose	Theory-weighted probabilistic scenario analysis of conditional changes under alternative educational-input configurations
Model interpretation	Conditional propagation through theory-informed weighted nodes; not causal identification or out-of-sample individual prediction
Structure ordering	Six theoretically ordered layers from background/input nodes to industry satisfaction
Association-screening score	$0.65 \times \text{mutual information} + 0.35 \times \text{Cramér's } V$
Edge inclusion threshold	Composite score ≥ 0.10
Maximum parents	No more than three data-selected parents per child node
Direction and DAG control	Direction fixed by layer ordering; acyclicity checked after each edge addition
Theory-informed completion	Thirteen theoretically required pathway edges added
Node states	Low, medium, and high
Missing composite values	Median imputation before discretisation
CPT estimation	Observed state frequencies with Laplace smoothing, $\alpha = 1$
Posterior inference	Likelihood-weighted sampling; 6000 samples per query and evidence configuration
Scenario-summary index	Low = 0, medium = 0.5, and high = 1, used only to summarise posterior state distributions
Input-state sensitivity analysis	One-at-a-time variation of three selected S4 input nodes; outcome = expected industry satisfaction
Analytical and validation scope	No cross-validation, hold-out prediction, or external predictive validation. The framework is used for internal conditional scenario analysis and is not interpreted as a causal or individual-level predictive model.

4. Results

4.1. Challenges, Capability Demands and Pathway Preferences

4.1.1. The Gap Between Educational Provision and Industry Transformation

The challenge facing AI-integrated AEC education is not whether AI should be introduced into the curriculum, but whether existing educational structures can adapt at the pace that industry transformation demands. A striking 86.6% of respondents perceived substantial gaps in current AI-related course offerings, and nearly half reported that their universities had yet to incorporate mandatory AI courses into AEC programs. Respondents identified three interconnected barriers: a shortage of up-to-date textbooks and case materials (70.7%); a misalignment between course content and industry innovation needs (67.3%), compounded by limited practical learning opportunities (56.0%); and institutional constraints, including outdated talent development structures (63.9%) and insufficient interdisciplinary integration (63.4%). Taken together, these patterns indicate that the current challenge extends beyond isolated curriculum deficiencies. Instead, they point to a structural misalignment between inherited educational systems and the evolving competency demands of AI-enabled professional practice. Addressing this gap will require systemic reform of curriculum structures, learning resources and talent development strategies.

4.1.2. Competency Requirements: Beyond Technical Skills

Respondents envisioned the future AEC professional as an applied interdisciplinary practitioner rather than algorithm developer, emphasizing the integration of AI capabilities with domain expertise. Cross-domain collaboration and disciplinary expertise emerged as the two most valued competencies, each selected by 77% of respondents ($n = 271$). Systems thinking and logical reasoning were also highly valued, receiving support from 63.1% of respondents. In addition, 42.3% emphasized the ability to apply AI to solve practical engineering and design problems. The most urgent skill demands included multimodal data processing (79%), training and deploying custom AI models (73.6%) and integrating AI tools with professional software platforms (62.5%). Despite this strong interest, respondents identified several barriers to competency development: weak mathematical and programming foundations (68.8%), limited understanding of how AI integrates with AEC domains (67.3%), and insufficient opportunities for authentic project-based practice (64.5%). These findings underscore that AI-oriented AEC education extends well beyond software proficiency or tool training. It requires the coordinated development of disciplinary expertise, computational capabilities and context-based problem-solving skills. Accordingly, curriculum redesign should follow a progressive pathway moving from disciplinary foundations through technical tools and systems integration to collaborative application.

4.1.3. Preferred Educational Pathways: Embedded AI Within Disciplinary Contexts

Respondents expressed a clear preference for integrating AI into existing disciplinary courses rather than delivering it through stand-alone modules. Incorporating AI applications and practical cases within professional courses received the strongest endorsement (75.9%), substantially exceeding support for dedicated AI–AEC innovation courses (63.4%), AI-based MOOCs (62.8%) and competition-driven learning models (55.1%). This pattern suggests that respondents believe AI is learned most effectively when situated within authentic disciplinary contexts. Embedded learning enables students to understand when, why and how AI tools should be deployed in professional practice, thereby reducing the gap between technical knowledge and domain-specific application. Curriculum design should therefore prioritize project-based and case-based learning, with an emphasis on the concurrent development of data-processing skills, AI-enabled problem-solving and professional decision-making capabilities.

The preferred entry point for AI introduction was the second year of undergraduate study (45.7%). This preference reflects an implicit pedagogical logic: the first year should concentrate on establishing a solid disciplinary foundation, while the second year provides an appropriate moment for introducing computational thinking and AI-related competencies. Such sequencing mitigates the risk of disconnecting technical learning from disciplinary knowledge when AI is introduced prematurely, while also reducing resistance to new technologies that can arise when professional thinking patterns become firmly established before computational perspectives are introduced. In this way, AI integration can be aligned with students' cognitive development and the progression of disciplinary learning.

4.2. Heterogeneity Across Stakeholder Groups

To examine whether perceptions of AI-enabled professional competencies and educational pathways differ across stakeholder groups, one-way ANOVA was performed using occupation (students, faculty, industry practitioners and researchers) and academic discipline (architecture, urban and rural planning, civil engineering, intelligent construction and engineering software) as grouping variables. Where significant overall effects were observed ($p < 0.05$), Tukey's HSD post hoc tests identified specific between-group differences.

4.2.1. Perceptions of AI-Enabled Talent Competencies

No significant occupational differences emerged for foundational competency requirements ($F = 1.337$, $p = 0.262$) or key skill requirements ($F = 0.698$, $p = 0.554$). This broad consensus across stakeholder groups is notable: respondents generally agreed that future AEC professionals should possess not only strong disciplinary foundations but also the capacity for interdisciplinary collaboration and the ability to apply AI technologies effectively. However, significant differences were identified across occupations in perceptions of individual learning capabilities ($F = 13.285$, $p < 0.001$) (Figure 4a).

Tukey's HSD post hoc comparisons localized these differences to the gap between students and the other three stakeholder groups (Table 5). Students reported significantly greater perceived challenges than faculty members, industry practitioners and researchers. Further analysis indicated that students' primary concerns were not merely related to the technical difficulty of learning AI. Rather, they centered on the challenge of integrating AI with discipline-specific problems, compounded by the absence of structured learning pathways and sustained instructional support (Figure 5a). Student, it appears, have registered the implication of AI for their future professional competencies, but existing curricula have yet to provide effective connections among disciplinary foundations, AI tools and authentic professional application.

Table 5. Tukey's HSD post hoc comparisons for individual learning capabilities by occupation (significant pairs only).

Group 1	Group 2	Mean Difference	p	Result
Student	Faculty	0.73	<0.001	Student > Faculty
Student	Industry practitioners	0.63	0.002	Student > Industry practitioners
Student	Researchers	0.52	0.028	Student > Researchers

Significant disciplinary differences emerged across all three competency dimensions: foundational requirements ($F = 4.524$, $p < 0.001$), key skill requirements ($F = 5.449$, $p < 0.001$), and individual learning capabilities ($F = 4.558$, $p < 0.001$) (Figure 4b). Tukey's HSD post hoc comparisons revealed that these differences were concentrated between architecture and urban–rural planning on one hand, and intelligent construction and engineering software on the other. Respondents from architecture and urban–rural planning placed

greater emphasis on interdisciplinary integration, multimodal data application and effective collaboration with AI tools. Those from intelligent construction and engineering software prioritized algorithm optimization and model development.

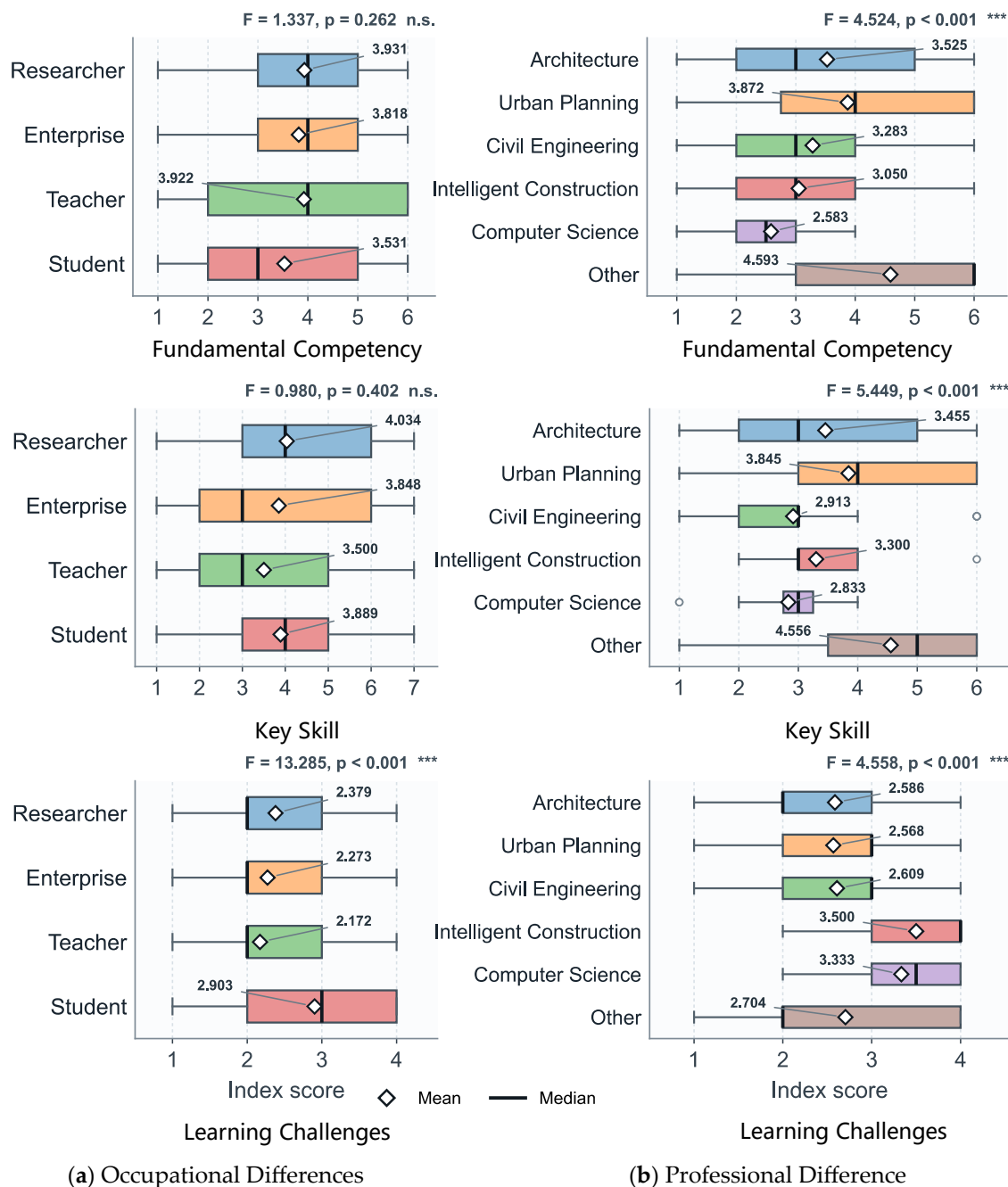


Figure 4. One-way ANOVA of perceptions of AI talent competencies across occupational and disciplines. *** indicates a highly significant difference at the $p < 0.001$ significance level, while “n.s.” indicates no statistically significant difference between groups ($p > 0.05$).

A clear stratification thus emerged in how disciplines understand AI-related competencies: design and planning fields emphasize the contextual application of AI, while technology-oriented fields foreground the technical development of AI systems themselves (Figure 5b–d). This divergence carries direct curricular implications. AI-oriented talent cultivation in AEC education cannot rely on a uniform curriculum structure. Architecture and urban–rural planning programs should prioritize integrating AI tools with disciplinary contexts, including areas such as generative design, digital twins and multimodal spatial

analysis. In contrast, programs such as intelligent construction may further strengthen competencies related to algorithmic foundations, model fine-tuning and technical customization. These findings provide an important empirical basis for the differentiated, progressive curriculum framework developed in the subsequent sections.

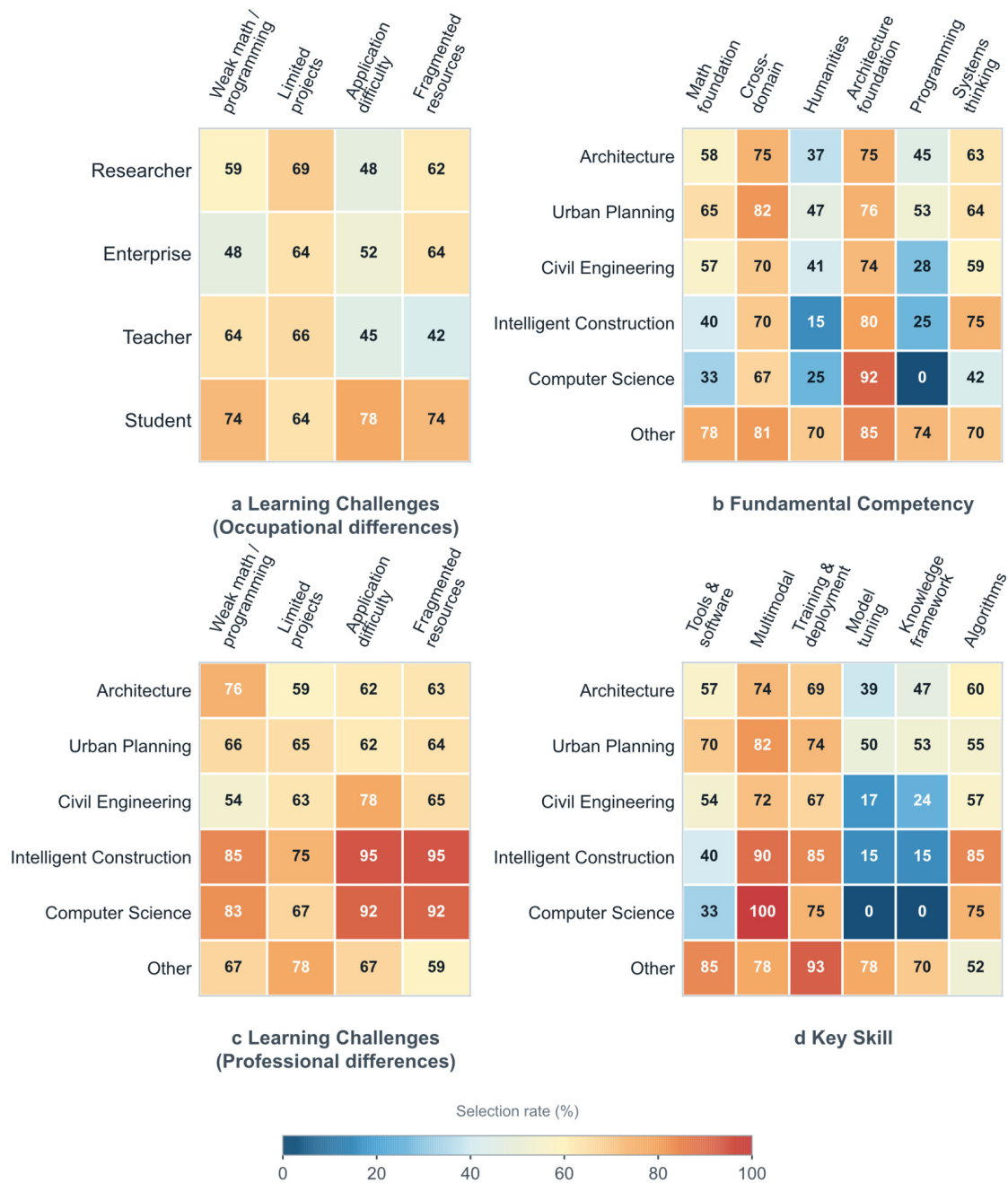


Figure 5. Perceptions of AI talent competencies across occupations and disciplines.

4.2.2. Perceptions of AI Curriculum Systems

No significant occupational differences were observed for interdisciplinary courses ($F = 2.017$, $p = 0.111$), assessment and evaluation approaches ($F = 0.252$, $p = 0.860$), or industry–university collaboration models ($F = 1.753$, $p = 0.156$) (Figure 6a). Curriculum design approached but did not reach significance ($F = 2.568$, $p = 0.054$). This general convergence suggests that stakeholders share a broad understanding of the direction for AI-oriented curriculum development: AI education should be embedded within existing

disciplinary training systems and delivered through a combination of core courses, electives and frontier-oriented seminars or lectures (Figure 7a).



Figure 6. One-way ANOVA of perceptions of curriculum development across occupations and disciplines. *** indicates a highly significant difference at the $p < 0.001$ significance level, while “n.s.” indicates no statistically significant difference between groups ($p > 0.05$). * $p < 0.05$; ** $p < 0.01$.

Tukey’s HSD post hoc comparisons revealed that the near-significant effect for curriculum design was driven by differences between faculty members and industry practitioners. This divergence centered on the timing of AI introduction. Researchers and faculty members favored introducing AI courses at earlier stages of undergraduate education in order to foster students’ computational thinking and interest in emerging technologies. By contrast, industry practitioners emphasized on a disciplinary-foundation-first approach, arguing that AI instruction should build upon students’ prior development of disciplinary knowledge and engineering understanding. These positions reflect distinct talent development logics:

academic stakeholders prioritize early cultivation of innovation-oriented capabilities, while industry stakeholders foreground alignment with authentic engineering contexts.



Figure 7. Perceptions of curriculum development across occupations and disciplines.

Significant disciplinary differences emerged for preferred course types ($F = 2.560$, $p = 0.027$), directions for interdisciplinary course development ($F = 7.897$, $p < 0.001$), and assessment and evaluation approaches ($F = 3.600$, $p = 0.004$) (Figure 6b). Tukey's HSD comparisons again located these differences between architecture and urban–rural planning on one side, and intelligent construction and engineering software on the other. Architecture and urban–rural planning programs emphasized practice-based courses, the application of AI across diverse professional contexts, and interdisciplinary expansion to broaden students' knowledge boundaries. Intelligent construction and engineering software programs focused on deepening technical competencies, expressing stronger demand for shared teaching resources, industry-based project practice and hands-on AI

training, while showing comparatively limited support for expanding interdisciplinary content (Figure 7b–d).

These disciplinary differences in perceptions of AI education fundamentally reflect two distinct competency development pathways. First, a broad-based interdisciplinary integration pathway, represented by architecture and urban–rural planning, which prioritizes knowledge integration and contextual application. Second, a specialized deep-development pathway, represented by intelligent construction and engineering software, which emphasizes modular, progressive cultivation of advanced AI competencies.

4.3. Predictive Analysis of Talent Cultivation Paths Based on a Bayesian Network Model

The network structure and edge directions were constrained according to the proposed competency development pathway: background characteristics and industry awareness→curriculum reform, teacher training, university–industry collaboration and project-based practice→knowledge and skills→application competencies→employment adaptability→industry satisfaction. Mutual information and Cramér’s V were subsequently used to identify the primary dependency relationships among the discretised nodes. The network structure was then refined by incorporating theoretically motivated dependency edges, resulting in a directed acyclic graph (Figure 8). All nodes were discretised into three states (low, medium and high). The prior probabilities of the root nodes were estimated from the marginal frequencies of the observed data, while the conditional probability tables of non-root nodes were estimated from the parent–state configurations. To avoid zero-probability estimates caused by sparse parent–state combinations, Laplace smoothing was applied during parameter estimation.

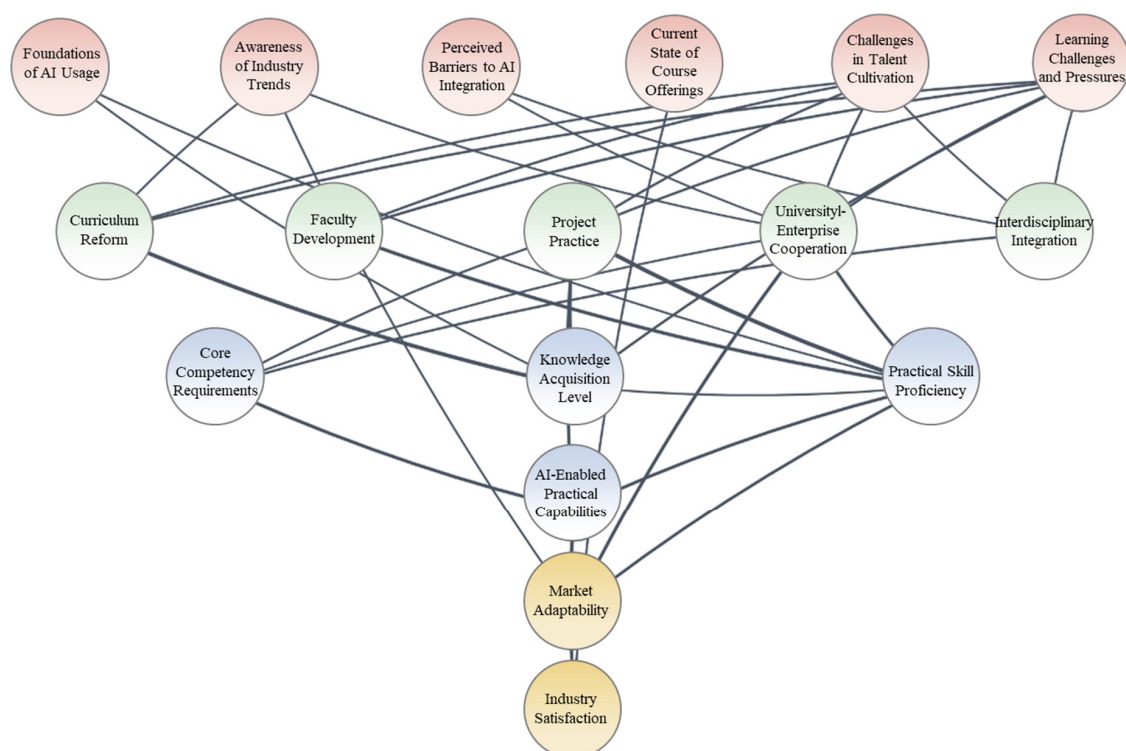


Figure 8. Bayesian Network Structure. The figure illustrates a Bayesian network structured as a directed acyclic graph to map causal interactions among variables. Red nodes signify parent variables (antecedents), while nodes in alternative colors correspond to child variables (consequences) at varying hierarchical tiers. All edges are directed, indicating a unidirectional probability flow from parent to child nodes. Furthermore, edge thickness scales with the strength of conditional dependencies, where bolder arcs denote stronger causal associations.

4.3.1. Prediction Results and Sensitivity Analysis of Alternative Educational Scenarios

Based on the questionnaire design, four educational intervention scenarios (S1–S4) were developed to evaluate the effects of alternative talent cultivation pathways. Scenario 1 (S1) represents the current fragmented training model. Scenario 2 (S2) emphasizes systematic curriculum enhancement. Scenario 3 (S3) extends S2 by incorporating teacher professional development and university–industry collaboration. Scenario 4 (S4) represents a comprehensive collaborative pathway integrating curriculum enhancement, teacher development, university–industry collaboration and project-based practice. For each scenario, the Bayesian network inferred the posterior probability distributions of downstream outcome variables under the specified intervention states. To facilitate comparison across scenarios, the posterior distributions were converted into expected values using a three-level scoring scheme, where low, medium and high were assigned values of 0, 0.5 and 1, respectively (Table 6). The prediction results are presented below (Figure 9a).

Table 6. Evidence states assigned to the educational-input nodes under comparative scenarios S1–S4.

Scenario	Curriculum Reform	Teacher Development	University–Industry Collaboration	Project-Based Practice
S1 Low-input reference	Low	Low	Low	Low
S2 Curriculum-centred	High	Low	Low	Low
S3 Capacity-building	High	High	Medium	Low
S4 Integrated collaboration	High	High	High	High

Note: All remaining nodes were left unobserved and inferred from the network. Low, medium, and high denote sample-relative discretised states. The scenarios represent comparative conditional “what-if” configurations rather than observed longitudinal interventions or causal policy effects.

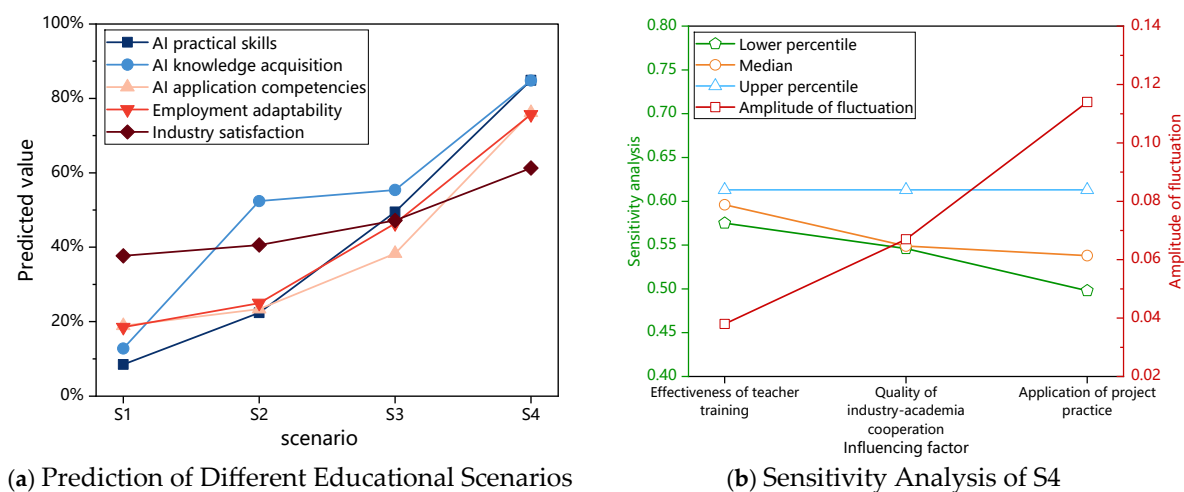


Figure 9. Prediction and sensitivity analysis of different educational scenarios.

Diminishing Marginal Returns of Curriculum Expansion Alone

Compared with S1, S2 increased the predicted level of AI knowledge acquisition by 39.6%. However, the corresponding improvements were substantially smaller for AI practical skills (13.9%) and further declined to 4.5% for AI application competencies. These results indicate that gains in knowledge do not automatically translate into practical skills or application competencies. In the absence of complementary practice-oriented mechanisms, simply expanding AI-related coursework yields diminishing marginal returns, with its effectiveness progressively attenuating along the competency development pathway from classroom learning to practical application.

Teacher Professional Development and University–Industry Collaboration as Key Mediating Mechanisms

Compared with S2, S3 yielded an additional 27.1% increase in AI practical skills and a further 14.9% improvement in AI application competencies, whereas the corresponding gain in AI knowledge acquisition was only 3.0%. This pattern suggests that teacher professional development and university–industry collaboration primarily enhance the translation of knowledge into higher-order competencies, rather than simply increasing knowledge acquisition. In particular, improving teachers' AI literacy and practical experience strengthens the transmission efficiency from knowledge to skills, enabling course content to be more effectively transformed into students' practical competencies.

Industry–Education Integration as a Catalyst for AI Competency Development

Compared with S3, S4 yielded the largest improvements across all outcome dimensions: AI application competencies (+37.9 percentage points), AI practical skills (+35.4 percentage points), AI knowledge acquisition (+29.4 percentage points), employment adaptability (+29.3 percentage points) and industry satisfaction (+14.1 percentage points). These findings suggest that university–industry collaboration and authentic project-based learning provide the contextual conditions necessary for translating AI knowledge and skills into workplace competencies. By exposing students to real-world data, authentic engineering problems and professional practice environments, this integrated educational approach bridges the gap between classroom learning and industry needs, thereby accelerating AI competency development. The results further indicate that competency development follows a cumulative pathway rather than a linear accumulation process, highlighting the importance of coordinated educational interventions rather than isolated curriculum expansion.

4.3.2. Sensitivity Analysis

To further evaluate the robustness of the integrated collaborative scenario (S4), sensitivity analysis was performed by independently varying the states of three key intervention nodes—teacher training effectiveness, university–industry collaboration quality and project-based practice implementation—and examining the corresponding changes in the expected value of overall industry satisfaction. It evaluates how the posterior industry-satisfaction estimate responds to changes in selected input-node states within S4; it is not intended as a global sensitivity test of alternative weighting schemes, discretisation rules, association thresholds, parent limits, or network structures.

The results showed that project-based practice implementation exhibited the highest sensitivity, indicating that it exerted the greatest influence on the predicted outcome within the S4. These findings suggest that university–industry collaboration and project-based practice should extend beyond symbolic activities, such as formal partnership agreements, guest lectures, or short-term site visits. Instead, they should be embedded throughout the educational process through the co-design of course-based projects, access to authentic industrial data, joint assessment of student outcomes and sustained industry participation in teaching (Figure 9b).

5. Discussion

5.1. From Tool Adoption to Competency Reconstruction: Rethinking AI-Driven AEC Education

The transformative pressure that AI exerts on AEC education is not technological in a narrow sense; it is epistemological. It demands a broader reconfiguration of what it means to be a competent professional, not merely an update to the toolkit. The prominence accorded to professional foundations is particularly instructive. It runs counter to the

widespread narrative that AI-driven educational reform should focus on students' acquisition of computational skills [78]. Stakeholders appear to regard AI not replacement for professional expertise but as an augmentation technology—one whose effective deployment presupposes, rather than obviates, substantial domain-specific judgment. In architecture and engineering practice, decisions involving safety, constructability, sustainability and regulatory compliance remain irreducibly contextual. AI can inform such decisions, but it cannot ground them. Disciplinary knowledge thus constitutes the necessary foundation upon which AI-enabled competencies must be built, not an obsolescent inheritance to be streamlined away. This interpretation aligns with recent scholarship on human–AI collaboration, which increasingly frames AI's value in terms of collaborative intelligence rather than autonomous decision-making [79]. Under such a paradigm, the professional is positioned not as an operator of AI tools but as a critical integrator—someone who brings domain expertise to bear on data-informed reasoning and who exercises judgment in evaluating AI-generated outputs [80]. It suggests that the central task for AEC education is not to teach students how to use AI technologies, but to cultivate their capacity to collaborate effectively with intelligent systems while maintaining the professional judgment, creativity and ethical responsibility that such collaboration demands. This represents a shift from a knowledge-transmission model toward a competency-centered model—one in which the curriculum is organized not around what students should know about AI, but around what they should be able to do with and through it.

5.2. Divergent Expectations Among Stakeholders: Conflict as a Productive Signal

A second major finding concerns the significant perceptual differences that emerged across stakeholder groups regarding curriculum implementation, faculty development, and the timing of AI adoption. The temptation in applied educational research is to treat such divergence as noise—an impediment to consensus that reform efforts should seek to minimise. This study suggests a different reading. Stakeholder divergence is better understood as a structural feature of the educational ecosystem, reflecting the distinct positionalities, responsibilities, and temporal horizons that different groups bring to the question of AI integration. The sharpest divergence appeared between students and other stakeholder groups on the question of learning challenges. Students expressed stronger concerns about learning difficulties and the need for structured pedagogical guidance throughout the educational process. This finding warrants careful interpretation. Learning AI within AEC contexts requires students to navigate disciplinary knowledge, computational thinking, data literacy and emerging technologies simultaneously. The integration of multiple unfamiliar knowledge domains is likely to increase both intrinsic and extraneous cognitive load, making it difficult for students to establish meaningful connections between AI concepts and professional applications [81,82]. Therefore, curriculum designers should develop student-centered and discipline-specific AI learning pathways that consider the knowledge foundation, learning characteristics, and professional objectives of students from different AEC majors. Universities should establish progressive teaching plans that introduce AI concepts, computational foundations and professional applications according to students' disciplinary backgrounds and learning stages. Such structured learning pathways can reduce cognitive overload, help students progressively connect AI knowledge with professional problems, and enable them to develop AI competencies while maintaining the disciplinary expertise required for future AEC practice.

Differences among faculty members, researchers and practitioners reflect their respective professional priorities. Researchers tend to emphasize innovation-oriented competencies and emerging technological trends, reflecting a future-oriented perspective structurally aligned with the temporal logic of academic research. Faculty members' greater sensitiv-

ity to instructional feasibility, resource constraints and institutional capacity reflects the lived reality of curriculum delivery. Industry practitioners' prioritization of practical AI application within authentic engineering contexts reflects an accountability to immediate professional outcomes. These are not competing truths; they are partial perspectives on a multidimensional problem [83]. To address these divergent needs, AEC education reform should establish sustained collaboration mechanisms bridging academia, industry and research communities. Universities can institutionalize joint curriculum committees, co-design flexible learning platforms and maintain structured communication channels to align academic innovation and pedagogical feasibility with evolving industry demands.

5.3. Systematic Transformation of Curriculum Oriented Towards Artificial Intelligence

The barriers identified in this study could be read as a catalogue of discrete deficiencies requiring targeted remediation. Such a reading would be analytically shallow. These challenges are more accurately understood as symptoms of a deeper structural condition: a misalignment between educational systems designed for an era of disciplinary stability and the emerging realities of AI-mediated professional practice. As AI-enabled practice increasingly depends on collaboration among engineers, data scientists and software developers, the boundaries that have historically organized AEC education—between disciplines, between technical and professional knowledge, between the academy and industry—are becoming less tenable [84]. The problem, therefore, is not the absence of specific AI-related courses. It is the lack of effective alignment among the key components of the educational system: curricula, learning objectives, faculty capacity, institutional incentives and industry relationships. This interpretation resonates with research on digital transformation in higher education, which emphasizes that successful innovation depends less on the introduction of novel content than on the coordinated evolution of institutional arrangements, organizational capabilities, and curriculum ecosystems [85]. For AEC education, the implication is that reform efforts must move beyond the logic of supplementation—adding AI courses to an otherwise unchanged structure—and toward a logic of systemic restructuring. Curricula, faculty development, resource allocation and industry partnerships must be realigned around the integrative competencies that AI-enabled practice demands, rather than being optimized independently within their respective silos.

5.4. Bayesian Networks as an AI-Based Decision-Support Approach: Contributions and Limitations

Traditional educational research relies on static statistical tools like ANOVA and regression analysis. These approaches remain largely explanatory in nature [86]. While effective in revealing which factors are associated with educational performance, they provide limited insight into how different educational interventions interact over time or which reform strategies are most likely to produce desirable outcomes [87]. As educational transformation grows increasingly complex, integrating AI-based analytical approaches into educational research represents an emerging direction for understanding, modelling and supporting decision-making processes.

In this study, Bayesian Network modelling was introduced as an AI-based analytical approach to examine the complex relationships underlying AI-oriented AEC talent development. Bayesian Networks combine data-driven learning with probabilistic reasoning, allowing researchers to represent interactions among multiple influencing factors and to explore possible changes under different intervention conditions [88]. This capability is particularly valuable for educational reform, where decisions must often be made before long-term effects can be directly observed. From this perspective, AI-based analytical methods may contribute to a transition from retrospective evaluation toward more proac-

tive and evidence-informed educational decision-making. The contribution of Bayesian Networks is not to replace conventional educational analysis methods, but to provide an additional analytical perspective for investigating complex and uncertain educational systems. Therefore, the significance of Bayesian Networks in this study lies not in demonstrating the superiority of a particular algorithm, but in illustrating how AI-based analytical approaches can expand the methodological toolkit for educational transformation research. Future studies may further integrate longitudinal data, multi-source evidence and expert knowledge to enhance the robustness and generalizability of AI-supported educational decision frameworks.

5.5. Practical Recommendations for AI-Oriented AEC Education Transformation

Based on the competency development pathway identified in this study, four practical strategies are proposed to support AI-oriented transformation in AEC education.

(1) Establish a progressive AI curriculum pathway supported by continuously updated teaching resources.

① AI education should be introduced in accordance with students' learning stages and disciplinary development, not as isolated technical content. At the early undergraduate stage, the priority is to foster general AI literacy rather than to cultivate specialized algorithm developers. Foundational courses, such as Introduction to Artificial Intelligence, Computational Thinking, Basic Programming and Data Literacy, can help students grasp fundamental AI principles, data processing methods and the potential applications and limitations of AI within the built environment.

② At the intermediate and advanced undergraduate levels, AI education should pivot from foundational comprehension toward applied professional practice. Higher education institutions ought to embed computational and AI-driven methodologies into core architectural, urban planning, civil engineering and construction management curricula through an "AI + Professional Practice" framework. Specialized domain modules—such as AI in Architectural Design, Spatial Analytics in Urban Planning and Smart Construction Systems—equip students to contextualize, adapt and leverage AI models within their respective professional contexts. Crucially, curriculum redesign must account for the diverse roles, disciplinary backgrounds and career trajectories of different stakeholders, avoiding a one-size-fits-all training paradigm.

③ Where resources permit, AI may be offered as secondary major, minor program or interdisciplinary certificate, allowing interested students to develop deeper AI capabilities while maintaining their primary disciplinary identity. Universities should move beyond traditional departmental boundaries to facilitate the interdisciplinary collaboration that AI-enabled professional practice demands [89]. Interdepartmental teaching initiatives, shared laboratory platforms, project-based learning environments and structured university–industry partnership programs can promote knowledge integration and competency development across disciplines—outcomes that isolated departmental efforts cannot achieve.

④ To support this transformation, universities must develop dynamic AI-AEC teaching resources, including regularly updated professional cases, real-world datasets and practical application scenarios. These resources should demonstrate not only successful AI applications but also the limitations, uncertainties, and potential risks of AI, enabling students to develop a comprehensive understanding of appropriate AI use within professional contexts.

(2) Strengthen practice-oriented learning and university–industry collaboration.

The core competencies required for AI-enabled AEC professionals are developed through engagement with complex, real-world problems. Therefore, universities should

strengthen AI-integrated practical learning through design studios, engineering projects, industry-supported courses and interdisciplinary innovation activities. Industry partners, including architectural firms, engineering companies and construction enterprises, can provide authentic engineering problems, professional datasets and practical application scenarios to ensure that AI education remains aligned with evolving professional practices. Through authentic project-based learning, students can experience the complete process: identifying professional problems, selecting appropriate AI methods, applying AI tools, interpreting AI-generated outputs and making informed professional decisions. Such practice-oriented environments are essential for transforming AI knowledge into professional competence and for improving students' readiness for AI-enabled AEC practice.

(3) Enhance faculty development for AI-integrated teaching.

The successful implementation of AI-oriented AEC education hinges on faculty readiness to integrate AI into existing teaching practices. This transformation does not, however, require every AEC educator to become an AI specialist or software developer. Instead, faculty development should focus on enabling educators to understand fundamental AI concepts, identify appropriate AI applications within their professional courses, redesign AI-supported teaching activities and evaluate AI-assisted student work. Universities can support this development through AI teaching workshops, interdisciplinary collaboration between AEC and AI-related disciplines, and the establishment of shared teaching resources and case databases. Such efforts help educators transition from knowledge transmitters to learning designers who guide students in collaborating effectively with AI.

(4) Adapt assessment methods to evaluate AI-enabled professional competencies.

Traditional assessment methods, which focus primarily on final products or theoretical knowledge, may not adequately capture students' ability to work with AI in professional contexts. Therefore, evaluation methods should consider students' abilities to identify appropriate AI applications, interpret AI-generated results, integrate AI outputs with disciplinary knowledge and make informed professional decisions. Project-based assessment, interdisciplinary collaboration evaluation and industry participation in assessment can together provide more comprehensive evaluations of students' readiness for AI-enabled professional practice.

Figure 10 presents a dynamic competency reconstruction framework for cultivating AI-empowered future AEC innovators. Driven by the AI revolution, digital transformation, Industry 5.0 and smart construction, evolving professional tasks redefine competency requirements across the AEC lifecycle. Accordingly, the framework proposes a four-level developmental pathway—from professional foundation through AI augmentation and system integration to collaborative innovation—supported by coordinated reforms in curriculum, pedagogy, assessment and university–industry collaboration. The framework incorporates a continuous feedback loop. As AI-ready graduates enter professional practice, their competencies and performance shape emerging industry expectations and societal needs. These evolving demands, together with ongoing technological advances, in turn redefine competency requirements and drive further educational reform. Through this iterative cycle—linking technology evolution, industry transformation, talent cultivation and educational reconstruction—the framework remains responsive to future AI-driven disruptions. Longitudinal studies are therefore needed to evaluate and refine the framework as technologies, industry requirements and educational practices co-evolve.

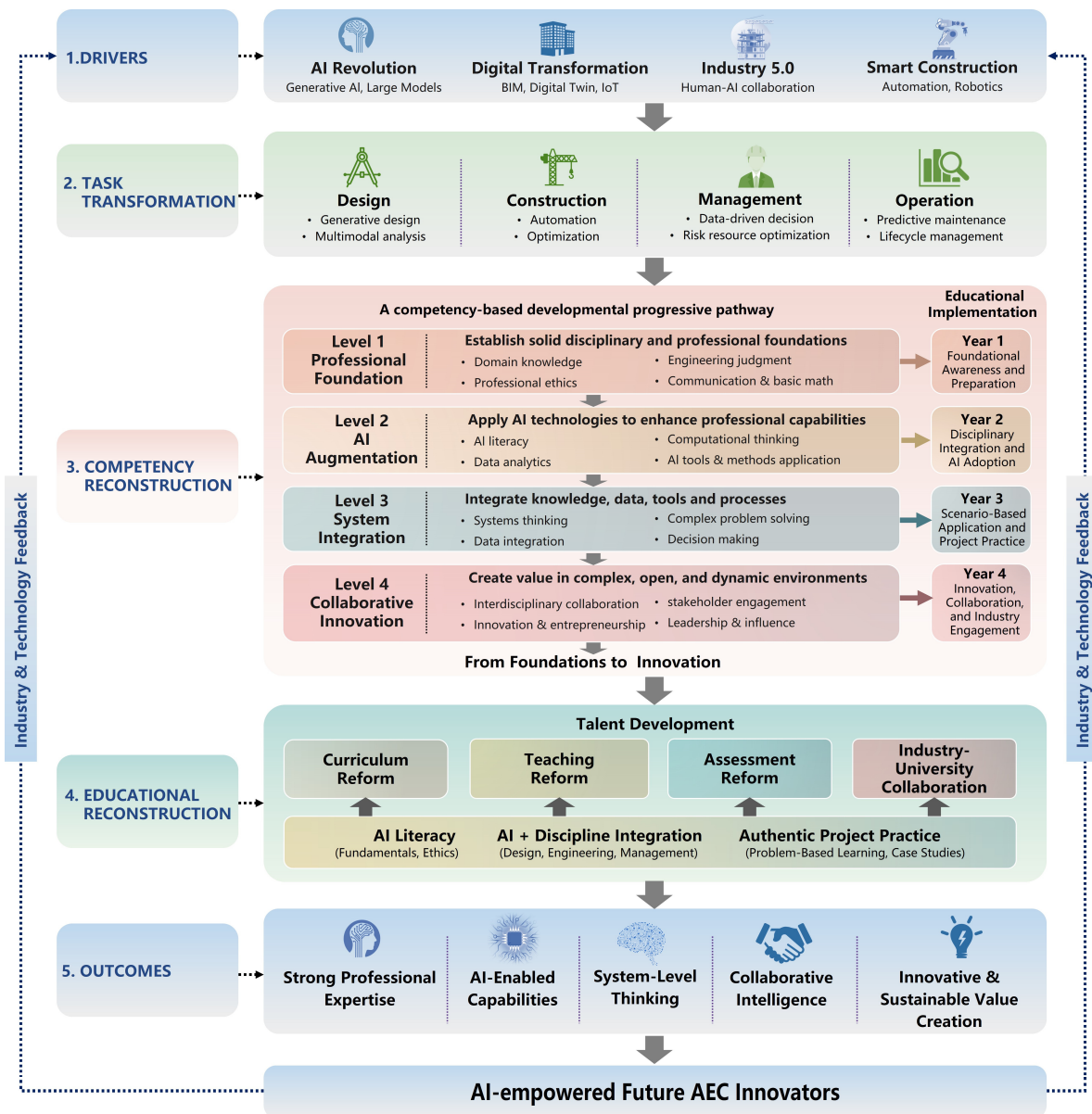


Figure 10. Competency Reconstruction Framework for AI-enabled AEC Education.

Overall, AI transformation in AEC education should move beyond “AI tool adoption” toward “AI-enabled competency development.” The aim is not to replace disciplinary expertise with AI technologies, but to cultivate professionals who can collaborate with AI while maintaining creativity, critical thinking and professional judgment.

5.6. International Implications for Global AEC Education

Although this study draws its evidence from Chinese higher education institutions, its implications should be understood within the broader global transition toward AI-enabled higher education. The emergence of AI is challenging underlying assumptions about how future architects, engineers and built-environment professionals should be educated. Across educational systems worldwide, the central question is shifting from whether AI should be incorporated into curricula toward how higher education can be fundamentally reconfigured to cultivate human–AI collaborative capabilities while preserving disciplinary identity and professional judgment.

One critical issue is the persistence of technological fragmentation, wherein AI is positioned as an independent technical subject rather than an integrated capability embedded within disciplinary knowledge systems [90]. Standalone AI courses may enhance technological awareness, yet they risk unintentionally reinforcing the separation between computational knowledge and professional practice. At the same time, the rapid diffusion of generative AI is fundamentally reshaping the relationship between technological efficiency and professional expertise [91]. While AI has significantly expanded the capacity for rapid visualization, simulation and information generation, it has also intensified concerns regarding the potential weakening of critical thinking, design reasoning and professional accountability [92].

The findings of this study contribute to this international debate by demonstrating that stakeholders do not perceive AI literacy as a substitute for disciplinary expertise. Instead, they emphasize the complementary relationship between professional foundations and computational capabilities. From a global perspective, the future of AI education in AEC requires moving beyond tool-oriented training toward the integration of AI into authentic design exploration, engineering analysis and complex decision-making processes. This perspective reinforces an emerging global consensus that future professionals should be trained not merely as AI users, but as critical interpreters, responsible collaborators and informed decision-makers capable of evaluating and contextualizing AI-generated outcomes [93,94].

Moreover, the global transformation of AI education highlights the persistent tension between universal competency expectations and contextual diversity. Although AI literacy has become a shared priority across higher education systems, the meaning and application of AI competencies vary significantly among disciplines, institutions and regions [95,96]. Within AEC education, different professional domains require distinct combinations of computational thinking, interdisciplinary integration, creative exploration and domain-specific judgment. Global AI education reform should therefore avoid pursuing a single standardized model and instead promote adaptable, context-sensitive approaches that respond to diverse professional and cultural environments.

Beyond the AEC domain, the theoretical insights generated by this study may contribute to broader debates on AI-driven transformation in higher education. Although the empirical investigation is situated within AEC education, the underlying principles identified—competency reconstruction, progressive capability development, differentiated learning pathways, human–AI collaboration and multi-stakeholder governance—represent challenges shared by many professional disciplines undergoing digital transformation. These principles resonate with the emerging educational frameworks promoted by international bodies including UNESCO, the OECD and the World Economic Forum, which advocate a transition from technology-centered adoption toward human-centered AI education emphasizing adaptability, critical thinking, interdisciplinary competence and responsible innovation [97–99].

By connecting these global perspectives with empirical evidence from a specific professional field, this study provides a more fine-grained understanding of how AI-oriented educational transformation can be operationalized in practice. The proposed framework should therefore be regarded not as a universal curriculum prescription, but as a transferable conceptual reference that can be adapted to different disciplinary traditions, institutional structures, accreditation systems and socio-economic contexts.

5.7. Limitations

Several limitations bound the scope and generalizability of this study.

First, although the sample included students, faculty members, industry practitioners and researchers, students constituted the largest proportion of respondents. This imbalance may have amplified student-centric perspectives in the aggregate results; the comparatively smaller representation of industry and research stakeholders warrants caution when interpreting group-level comparisons.

Second, the study relied on cross-sectional data, capturing perceptions at a single moment within a rapidly evolving technological landscape. As AI capabilities advance and industry adoption patterns shift, the competency priorities identified here may themselves require revision—a dynamism that a snapshot design cannot fully accommodate.

Third, the educational framework proposed in this study remains conceptual and policy-oriented. It has not yet been subjected to validation through long-term curriculum implementation or comparative institutional evaluation.

Fourth, although Bayesian Networks offer probabilistic causal inference and scenario simulation, the network structure was partially informed by theoretical assumptions and cross-sectional data. Model outcomes depend on the quality and representativeness of the input data. Accordingly, the Bayesian Network should be interpreted as a theory-weighted probabilistic scenario-analysis tool that compares conditional posterior patterns under specified educational-input configurations. Because the downstream nodes were constructed from the same cross-sectional questionnaire using fixed theory-informed weights, the resulting estimates do not constitute evidence of causal effects, individual-level forecasting, or out-of-sample predictive performance. External validation will require longitudinal or independent data containing objectively observed educational and employment outcomes.

Future research should integrate longitudinal educational data, dynamic Bayesian networks and causal discovery algorithms to enhance predictive accuracy. It should also employ cross-institutional comparisons and quasi-experimental or design-based approaches to examine how competency demands evolve, how educational contexts moderate AI integration, and how curriculum transformation affects student competencies, employability and innovation outcomes.

6. Conclusions

Four main conclusions emerge from this study. First, future AEC education should cultivate integrated competencies—professional expertise, systems thinking, interdisciplinary collaboration and AI-enabled problem-solving—rather than prioritising AI tool proficiency in isolation. Second, the major barriers to AI-oriented education reflect a structural misalignment between existing educational systems and the competency demands of AI-enabled professional practice, highlighting the need for coordinated reform across curriculum, institutional structures and industry engagement. Third, the significant differences observed among stakeholder groups and disciplines indicate that AI-oriented curricula must adopt differentiated yet coherent competency-development pathways, resisting the temptation of a one-size-fits-all model. Fourth, Bayesian Network modelling extends conventional statistical analysis by enabling probabilistic reasoning and scenario evaluation, thereby providing evidence-based support for curriculum planning and educational decision-making.

Based on these findings, the study proposes a competency-oriented educational framework that progresses from disciplinary foundations through AI augmentation and systems integration to collaborative innovation. Rather than recommending isolated curriculum improvements, the proposed framework systematically links competency requirements, curriculum restructuring, faculty development, interdisciplinary integration and practice-oriented learning, providing a coherent roadmap for AI-oriented educational transformation. This study extends existing research on AI-in-engineering-education in three important ways. First, while previous studies have focused on identifying AI-related

competencies or integrating AI tools into individual courses, this study develops a four-stage competency reconstruction pathway that explains how future AEC professionals progressively develop the competencies required for AI-enabled practice. Second, in place of fragmented curriculum reforms, this study establishes an integrated educational transformation framework that connects technological evolution, professional task transformation, competency development and educational reform, offering a systematic perspective on AI-oriented talent cultivation. Third, recognizing that existing studies mainly evaluate current educational conditions, this study combines empirical survey data with Bayesian Network modelling to simulate alternative reform pathways and predict their potential impacts on competency development. This shifts educational research from explaining current challenges toward supporting future-oriented educational planning and evidence-based decision-making.

Although the proposed framework is grounded in the Chinese higher education context, the challenges it addresses are common to engineering education worldwide. By shifting the emphasis from technology-oriented curriculum reform to competency-oriented educational transformation, the framework provides a transferable conceptual foundation for redesigning engineering education to respond to the continuous co-evolution of artificial intelligence, professional practice and competency requirements.

Author Contributions: P.W., Z.H. and D.W. conceived the concept and designed the study. D.W. and Z.H. performed the simulations and theoretical calculations and wrote the original draft. P.W. and Z.L. contributed to enhancing the conceptual design and improving the manuscript. All authors have read and agreed to the published version of the manuscript.

Funding: The authors are grateful for the financial support for this work from the Higher Education Teaching Reform Research Project of Jiangsu Province, China (Grant No. 2025JGYB285).

Institutional Review Board Statement: The research project has been reviewed by the Institutional Ethics Committee of Jinling Institute of Technology in accordance with the ethical guidelines for human subject research. The study involves an anonymous, multi-stakeholder questionnaire survey targeting students, faculty members, industry practitioners, and researchers in the Architecture, Engineering, and Construction (AEC) sector. The primary goal is to collect perceptual data on competency requirements and curriculum needs for AI integration in AEC education, which will be analyzed using descriptive statistics and inferential method as described in the study protocol. The Committee is satisfied that the rights and welfare of the participants are adequately protected.

Informed Consent Statement: Due to the anonymous and minimal-risk nature of this educational survey, the requirement for written informed consent has been waived.

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

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

References

1. Gabsi, A.E.H. Integrating artificial intelligence in industry 4.0: Insights, challenges, and future prospects—a literature review. *Ann. Oper. Res.* **2024**, *341*, 1343. [[CrossRef](#)]
2. Rashid, A.B.; Kausik, M.A.K. AI Revolutionizing Industries Worldwide: A Comprehensive Overview of Its Diverse Applications. *Hybrid Adv.* **2024**, *7*, 100277. [[CrossRef](#)]
3. Zhang, Z.; Fort, J.M.; Mateus, L.G. Exploring the Potential of Artificial Intelligence as a Tool for Architectural Design: A Perception Study Using Gaudí's Works. *Buildings* **2023**, *13*, 1863. [[CrossRef](#)]
4. Jia, M.; Komeily, A.; Wang, Y.; Srinivasan, R.S. Adopting Internet of Things for the Development of Smart Buildings: A Review of Enabling Technologies and Applications. *Autom. Constr.* **2019**, *101*, 111–126. [[CrossRef](#)]

5. Syarifudin, I.; Prabawasari, V.W.; Nugroho, A. Studi Komparasi Penggunaan Tools Cahaya Omni Sebagai Pendukung Cahaya Spotlight Pada Render Exterior Dengan Software Rendering Lumion 11, Enscape 3.4 Dan Twinmotion Edu 2022. *J. Tek. Dan Sci.* **2023**, *2*, 61–71. [\[CrossRef\]](#)
6. Emad, S.; Abounaga, M.; Wanas, A.; Abouaiana, A. The Role of Artificial Intelligence in Developing the Tall Buildings of Tomorrow. *Buildings* **2025**, *15*, 749. [\[CrossRef\]](#)
7. Royal Institution of Chartered Surveyors (RICS). *The AI in Construction 2025 Report 2025*; Royal Institution of Chartered Surveyors (RICS): London, UK, 2025.
8. U.S. Department of Education. *Artificial Intelligence and the Future of Teaching and Learning: Insights and Recommendations*; Office of Educational Technology: Washington, DC, USA, 2023.
9. European School Education Platform. Preparing Teacher Education for a Future with AI. Europa.eu 2024. Available online: <https://school-education.ec.europa.eu/en/discover/news/preparing-teacher-education-future-ai> (accessed on 10 January 2026).
10. Yiannoudes, S. Shaping Architecture with Generative Artificial Intelligence: Deep Learning Models in Architectural Design Workflow. *Architecture* **2025**, *5*, 94. [\[CrossRef\]](#)
11. Lystbæk, M.S. Machine Learning-Driven Processes in Architectural Building Design. *Autom. Constr.* **2025**, *178*, 106379. [\[CrossRef\]](#)
12. Jin, S.T.; Tu, H.J.; Li, J.F.; Fang, Y.W.; Qu, Z.; Xu, F.; Liu, K.; Lin, Y.Q. Enhancing Architectural Education through Artificial Intelligence: A Case Study of an AI-Assisted Architectural Programming and Design Course. *Buildings* **2024**, *14*, 1613. [\[CrossRef\]](#)
13. Khan, A.; Chang, S.; Chang, H. Generative AI Approaches for Architectural Design Automation. *Autom. Constr.* **2025**, *180*, 106506. [\[CrossRef\]](#)
14. Özorhon, G.; Gelirli, D.N.; Lekesiz, G.; Müezzinoğlu, C. AI-assisted architectural design studio (AI-a-ADS): How artificial intelligence join the architectural design studio? *Int. J. Technol. Des. Educ.* **2025**, *35*, 1999–2023. [\[CrossRef\]](#)
15. Shin, Y.J.; Park, E.J.; Kang, E. Cultivating reflective designers: Process-oriented pedagogies for harnessing AI's creative unpredictability in architectural studios. *J. Asian Archit. Build. Eng.* 2026, early access. [\[CrossRef\]](#)
16. Hikmet, S.; Ozay, N. Human-AI Collaboration in Architectural Design Education: Towards a Conceptual Framework. *Buildings* **2026**, *16*, 1097. [\[CrossRef\]](#)
17. Stanimirovic, M.; Petronijevic, A.M.; Stoiljkovic, B.; Kondic, S.; Nikolic, B. AI Sparring in Conceptual Architectural Design: A Systematic Review of Generative AI as a Pedagogical Partner (2015–2025). *Buildings* **2026**, *16*, 488. [\[CrossRef\]](#)
18. Crawford, J.; Cowling, M.; Kelly-Ann, A. Leadership Is Needed for Ethical ChatGPT: Character, Assessment, and Learning Using Artificial Intelligence. *J. Univ. Teach. Learn. Pract.* **2023**, *20*, 2. [\[CrossRef\]](#)
19. Holmes, W.; Bialik, M.; Fadel, C. *Artificial Intelligence in Education: Promises and Implications for Teaching and Learning*; Centre for Curriculum Redesign: Boston, MA, USA, 2019. [\[CrossRef\]](#)
20. Zhang, C.; Lu, Y. Study on Artificial Intelligence: The State of the Art and Future Prospects. *J. Ind. Inf. Integr.* **2021**, *23*, 100224. [\[CrossRef\]](#)
21. Xu, L. Special Issue on System Research on Artificial Intelligence. *Syst. Res. Behav. Sci.* **2021**, *38*, 187. [\[CrossRef\]](#)
22. Qu, J.; Zhao, Y.; Xie, Y. Artificial Intelligence Leads the Reform of Education Models. *Syst. Res. Behav. Sci.* **2022**, *39*, 581–588. [\[CrossRef\]](#)
23. Liu, X.K.; Chiang, F.K.; Tan, Y.Q.; Wu, X.-Y.; Cha, Y.-Y.; Lim, C.-P. Leveraging Genai Tool in Design Drawing: A Case Study of an Architecture Course in Chinese University. *Int. J. Artif. Intell. Educ.* **2025**, *35*, 3529–3558. [\[CrossRef\]](#)
24. Alamasi, R.; Asfour, O.S.; Ashmeel, R. The Impact of Generative AI on Architectural Design Education: Insights from Hands-on Experience with Architecture Students. *Ain Shams Eng. J.* **2026**, *17*, 103879. [\[CrossRef\]](#)
25. Labib, W.; Abdelsattar, A.; Abowardah, E.; Abdelalim, M.; Mahmoud, H. The Role of Generative AI in Architecture Education from Students' Perspectives—A Cross-Sectional Descriptive and Correlational Study. *Sustainability* **2025**, *17*, 10029. [\[CrossRef\]](#)
26. Aycı, H.; Kinaci, E.B.; Avinç, G.M.; Taş, A. Artificial Intelligence in Architecture Education: Reflections through Structural Equation Modeling. *J. Asian Archit. Build. Eng.* 2026, early access. [\[CrossRef\]](#)
27. Lee, S.; Kang, S. The Influence of Generative AI with Prompt Engineering on Creative Design in Architectural Education. *J. Asian Archit. Build. Eng.* 2025, early Access. [\[CrossRef\]](#)
28. Holstein, K.; McLaren, B.M.; Aleven, V. Co-Designing a Real-Time Classroom Orchestration Tool to Support Teacher-AI Complementarity. *J. Learn. Anal.* **2019**, *6*, 27–52. [\[CrossRef\]](#)
29. Komatina, D.; Miletić, M.; Mosurović Ružičić, M. Embracing Artificial Intelligence (AI) in Architectural Education: A Step towards Sustainable Practice? *Buildings* **2024**, *14*, 2578. [\[CrossRef\]](#)
30. Alnaser, A.A.; Binabid, J.; Sepasgozar, S.M.E. Transforming Architectural Programs to Meet Industry 4.0 Demands: SWOT Analysis and Insights for Achieving Saudi Arabia's Strategic Vision. *Buildings* **2024**, *14*, 4005. [\[CrossRef\]](#)
31. Wang, C.L.; Chen, X.J.; Yu, T.; Liu, Y.D.; Jing, Y.H. Education reform and change driven by digital technology: A bibliometric study from a global perspective. *Humanit. Soc. Sci. Commun.* **2024**, *11*, 256. [\[CrossRef\]](#)
32. Isabel Schorr, I.; Bardach, L.; Bühler, B.; Kasneci, E. Learning-to-learn in the age of generative AI: A scoping review and conceptual framework. *Comput. Educ. Artif. Intell.* **2026**, *10*, 100575. [\[CrossRef\]](#)

33. Roberts, H.; Cowls, J.; Morley, J.; Taddeo, M.; Wang, V.; Floridi, L. The Chinese Approach to Artificial Intelligence: An Analysis of Policy, Ethics, and Regulation. *AI Soc.* **2021**, *36*, 59–77. [[CrossRef](#)]
34. Wu, F.; Lu, C.; Zhu, M.J.; Chen, H.; Zhu, J.; Yu, K.; Li, L.; Li, M.; Chen, Q.F.; Li, X.; et al. Towards a New Generation of Artificial Intelligence in China. *Nat. Mach. Intell.* **2020**, *2*, 312. [[CrossRef](#)]
35. Abioye, S.O.; Oyedele, L.O.; Akanbi, L.; Ajayi, A.; Delgado, J.M.D.; Bilal, M.; Akinade, O.O.; Ahmed, A. Artificial Intelligence in the Construction Industry: A Review of Present Status, Opportunities and Future Challenges. *J. Build. Eng.* **2021**, *44*, 103299. [[CrossRef](#)]
36. Tricco, A.C.; Lillie, E.; Zarin, W.; O'Brien, K.K.; Colquhoun, H.; Levac, D.; Moher, D.; Peters, M.D.J.; Horsley, T.; Weeks, L.; et al. PRISMA Extension for Scoping Reviews (PRISMA-ScR): Checklist and Explanation. *Ann. Intern. Med.* **2018**, *169*, 467–473. [[CrossRef](#)] [[PubMed](#)]
37. Fu, Z.L.; Cao, C.; Gao, F. Current Status, Problems and Promotion Strategies of AI Application in Industrial Energy Management: A Case Study from China. *J. Clean. Prod.* **2025**, *506*, 145533. [[CrossRef](#)]
38. Liu, Z.S.; Lin, S. Digital Twin Model and Its Establishment Method for Steel Structure Construction Processes. *Buildings* **2024**, *14*, 1043. [[CrossRef](#)]
39. Ivanova, S.; Kuznetsov, A.; Zverev, R.; Rada, A. Artificial Intelligence Methods for the Construction and Management of Buildings. *Sensors* **2023**, *23*, 8740. [[CrossRef](#)] [[PubMed](#)]
40. Luo, S.Z.; Wang, H. Digital Twin Research on Masonry–Timber Architectural Heritage Pathology Cracks Using 3D Laser Scanning and Deep Learning Model. *Buildings* **2024**, *14*, 1129. [[CrossRef](#)]
41. Wang, Y.; Ye, H.; Xiong, J.; Nie, Y.; Jiang, L.; Zhang, A.J. Digitization Impact on Future Housing Building Industry Mode. *J. Build. Eng.* **2024**, *96*, 110202. [[CrossRef](#)]
42. Uysal, M.P.; Mergen, A.E. Smart Manufacturing in Intelligent Digital Mesh: Integration of Enterprise Architecture and Software Product Line Engineering. *J. Ind. Inf. Integr.* **2021**, *22*, 100202. [[CrossRef](#)]
43. Jang, S.; Roh, H.; Lee, G. Generative AI in architectural design: Application, data, and evaluation methods. *Autom. Constr.* **2025**, *174*, 106174. [[CrossRef](#)]
44. El Moussaoui, M. Architectural Practice Process and Artificial Intelligence—An Evolving Practice. *Open Eng.* **2025**, *15*, 20240098. [[CrossRef](#)]
45. Sacks, R.; Girolami, M.; Brilakis, I. Building Information Modelling, Artificial Intelligence and Construction Tech. *Dev. Built Environ.* **2020**, *4*, 100011. [[CrossRef](#)]
46. Chen, J.; Wang, D.; Shao, Z.; Zhang, X.; Ruan, M.; Li, H.; Li, J. Using Artificial Intelligence to Generate Master-Quality Architectural Designs from Text Descriptions. *Buildings* **2023**, *13*, 2285. [[CrossRef](#)]
47. Rosłon, J. Materials and Technology Selection for Construction Projects Supported with the Use of Artificial Intelligence. *Materials* **2022**, *15*, 1282. [[CrossRef](#)] [[PubMed](#)]
48. Hua, J.; Wang, R.; Hu, Y.; Chen, Z.; Chen, L.; Osman, A.I.; Farghali, M.; Huang, L.; Feng, J.; Wang, J.; et al. Artificial Intelligence for Calculating and Predicting Building Carbon Emissions: A Review. *Environ. Chem. Lett.* **2025**, *23*, 783–816. [[CrossRef](#)]
49. Lu, Y.; Yuan, W.; Wang, M.; Wang, P.; Wu, S.; Wu, J.; Xing, W.; Xie, W.; Yu, F. Multi-Agent Collaborative Pathways for Chinese Traditional Architectural Image Generation. *Sci. Rep.* **2025**, *15*, 34596. [[CrossRef](#)] [[PubMed](#)]
50. Croce, V.; Caroti, G.; Piemonte, A.; De Luca, L.; Véron, P. H-BIM and Artificial Intelligence: Classification of Architectural Heritage for Semi-Automatic Scan-to-BIM Reconstruction. *Sensors* **2023**, *23*, 2497. [[CrossRef](#)] [[PubMed](#)]
51. Qin, S.Z.; Guan, H.; Liao, W.J.; Gu, Y.; Zheng, Z.; Xue, H.J.; Lu, X.Z. Intelligent design and optimization system for shear wall structures based on large language models and generative artificial intelligence. *J. Build. Eng.* **2024**, *95*, 109996. [[CrossRef](#)]
52. García-González, M.S.; Paniagua-Arís, E.; Martínez-Béjar, R.; López-Caballero, J.A.; Gasparetto, A. An Artificial Intelligence-Based Model for Knowledge Evaluation and Integration in Public Organizations. *Appl. Sci.* **2023**, *13*, 11796. [[CrossRef](#)]
53. Zhang, B.Z.; Mo, Y.C.; Li, B. Reimagining synergy between architects and computational systems: Insights from web-based generative design applications. *Front. Archit. Res.* **2026**, *15*, 795–805. [[CrossRef](#)]
54. Cao, Y.; Gao, X.; Yin, H.; Yu, K.; Zhou, D. Reimagining Tradition: A Comparative Study of Artificial Intelligence and Virtual Reality in Sustainable Architecture Education. *Sustainability* **2024**, *16*, 11135. [[CrossRef](#)]
55. Wang, S.N.; Fan, H.J.; Zheng, H.; Xia, X.Y.; Xu, H.; Li, S.; Shen, C. Integrating education 4.0 and digital turns in architectural pedagogy: Case studies of undergraduate design and build projects. *Int. J. Technol. Des. Educ.* **2026**, *36*, 1829–1855. [[CrossRef](#)]
56. Bian, Y.J.; Xie, L.; Li, J.Q. Research on Influencing Factors of Artificial Intelligence Multi-Cloud Scheduling Applied Talent Training Based on DEMATEL-TAISM. *J. Cloud Comput.* **2022**, *11*, 35. [[CrossRef](#)]
57. Bian, Y.; Lu, Y.; Li, J. Research on an Artificial Intelligence-Based Professional Ability Evaluation System from the Perspective of Industry-Education Integration. *Sci. Program.* **2022**, *2022*, 4478115. [[CrossRef](#)]
58. Kim, J.; Park, S.; Moukhliiss, S.; Song, K.; Koo, D. Perceptions of Artificial Intelligence (AI) in the Construction Industry Among Undergraduate Construction Management Students: Case Study-A Study of Future Leaders. *Buildings* **2025**, *15*, 1095. [[CrossRef](#)]

59. Tusquellas, N.; Santiago, R.; Palau, R. Professional Development Analytics: A Smart Model for Industry 5.0. *Appl. Sci.* **2025**, *15*, 2057. [\[CrossRef\]](#)
60. Fehrenbach, H.; Huisman, J. A Systematic Literature Review of Transnational Alliances in Higher Education: The Gaps in Strategic Perspectives. *J. Stud. Int. Educ.* **2024**, *28*, 33–51. [\[CrossRef\]](#)
61. Xie, H.; Ge, Y.; Yi, J. Cost Control Analysis of Construction Projects Based on Wireless Communication and Artificial Intelligence Decisions. *Wirel. Commun. Mob. Comput.* **2022**, *2022*, 8505922. [\[CrossRef\]](#)
62. Xie, X.; Gu, S.; Gao, X.; Xu, Y.; Yuan, P.F. Vision-Guided Autonomous Drone Construction System for Standardized Bricklaying. *Autom. Constr.* **2025**, *180*, 106525. [\[CrossRef\]](#)
63. Lai, J.; Wan, R.; Chong, H.-Y.; Liao, X. Digital Intelligence in Building Lifecycle Management: A Mixed-Methods Approach. *Sustainability* **2025**, *17*, 5121. [\[CrossRef\]](#)
64. Agri, M.E.; Le, A.; Phung, Q. AI Integration in Architectural Design and Management: Professionals' Perspectives. *Archit. Eng. Des. Manag.* **2026**, *22*, 67–82. [\[CrossRef\]](#)
65. Zhang, J.; Jiang, S. Review of Artificial Intelligence Applications in Construction Management Over the Last Five Years. *Eng. Constr. Archit. Manag.* **2026**, *33*, 1361–1379. [\[CrossRef\]](#)
66. Liu, B.; Li, Q.; Zheng, Z.; Huang, Y.; Deng, S.; Huang, Q.; Liu, W. A Review of Multi-Source Data Fusion and Analysis Algorithms in Smart City Construction: Facilitating Real Estate Management and Urban Optimization. *Algorithms* **2025**, *18*, 30. [\[CrossRef\]](#)
67. Li, Y.; Chen, H.; Yu, P.; Yang, L. A Review of Artificial Intelligence in Enhancing Architectural Design Efficiency. *Appl. Sci.* **2025**, *15*, 1476. [\[CrossRef\]](#)
68. Cheng, S.; Yin, X.; Gao, F.; Pan, Y. Surrounding Rock Squeezing Classification in Underground Engineering Using a Hybrid Paradigm of Generative Artificial Intelligence and Deep Ensemble Learning. *Mathematics* **2024**, *12*, 3832. [\[CrossRef\]](#)
69. Lee, J.; Cho, W.; Kang, D.; Lee, J. Simplified Methods for Generative Design That Combine Evaluation Techniques for Automated Conceptual Building Design. *Appl. Sci.* **2023**, *13*, 12856. [\[CrossRef\]](#)
70. Wang, G.; Zhou, Y.; Cao, D. Artificial Intelligence in Construction: Topic-Based Technology Mapping Based on Patent Data. *Autom. Constr.* **2025**, *172*, 106073. [\[CrossRef\]](#)
71. Chen, X.; Gao, W.; Chu, Y.; Song, Y. Enhancing Interaction in Virtual-Real Architectural Environments: A Comparative Analysis of Generative AI-Driven Reality Approaches. *Build. Environ.* **2024**, *266*, 112113. [\[CrossRef\]](#)
72. Castro Pena, M.L.; Carballal, A.; Rodríguez-Fernández, N.; Santos, I.; Romero, J. Artificial Intelligence Applied to Conceptual Design: A Review of Its Use in Architecture. *Autom. Constr.* **2021**, *124*, 103550. [\[CrossRef\]](#)
73. Hamidavi, T.; Abrishami, S.; Hosseini, M.R. Towards Intelligent Structural Design of Buildings: A BIM-Based Solution. *J. Build. Eng.* **2020**, *32*, 101685. [\[CrossRef\]](#)
74. Jing, X.; Zhu, R.; Lin, J.; Yu, B.; Lu, M. Education Sustainability for Intelligent Manufacturing in the Context of the New Generation of Artificial Intelligence. *Sustainability* **2022**, *14*, 14148. [\[CrossRef\]](#)
75. Del Savio, A.A.; Torres, A.L.; Cárdenas Salas, D.; Vergara Olivera, M.A.; Urdy Ibarra, G.T. Detection and Evaluation of Construction Cracks through Image Analysis Using Computer Vision. *Appl. Sci.* **2023**, *13*, 9662. [\[CrossRef\]](#)
76. Feng, K.L.; Lu, W.Z.; Wang, Y.W. Assessing environmental performance in early building design stage: An integrated parametric design and machine learning method. *Sustain. Cities Soc.* **2019**, *50*, 101596. [\[CrossRef\]](#)
77. Wafudu, S.J.; Kamin, Y.B.; Marcel, D. Validity and reliability of a questionnaire developed to explore quality assurance components for teaching and learning in vocational and technical education. *Humanit. Soc. Sci. Commun.* **2022**, *9*, 303. [\[CrossRef\]](#)
78. Ng, D.T.K.; Leung, J.K.L.; Su, J.H.; Ng, R.C.W.; Chu, S.K.W. Teachers' AI Digital Competencies and Twenty-First Century Skills in the Post-Pandemic World. *Educ. Technol. Res. Dev.* **2023**, *71*, 137–161. [\[CrossRef\]](#) [\[PubMed\]](#)
79. Kaur, R.; Mwambelele, B.J.; Abraham, A.G.; Basheer, S.A.; Garia, S.A. Comprehensive Review on Building Information Modelling (BIM), Its Implementations and Applications. *Discov. Civ. Eng.* **2025**, *2*, 177. [\[CrossRef\]](#)
80. Storey, V.C.; Yue, W.T.; Zhao, J.L.; Lukyanenko, R. Generative Artificial Intelligence: Evolving Technology, Growing Societal Impact, and Opportunities for Information Systems Research. *Inf. Syst. Front.* **2025**, *27*, 2081–2102. [\[CrossRef\]](#)
81. Alwashah, Z.; Xiao, B.; Liu, H.; Mueller, S.T.; Shao, X. Generative Artificial Intelligence for Construction: Use Cases, Trends, Challenges, and Opportunities. *J. Build. Eng.* **2025**, *112*, 113802. [\[CrossRef\]](#)
82. Zhao, T.; Lin, C.; Qian, C.; Zhang, X. Empowering Teaching in Higher Education Through Artificial Intelligence: A Multidimensional Exploration. *Sustainability* **2026**, *18*, 147. [\[CrossRef\]](#)
83. Oliveira, S.; Olsen, L.; Malki-Epshtein, L.; Mumovic, D.; D'Ayala, D. Transcending Disciplines in Architecture, Structural and Building Services Engineering: A New Multidisciplinary Educational Approach. *Int. J. Technol. Des. Educ.* **2022**, *32*, 1247–1265. [\[CrossRef\]](#)
84. Ali, A.K. A case study in developing an interdisciplinary learning experiment between architecture, building construction, and construction engineering and management education. *Eng. Constr. Archit. Manag.* **2019**, *26*, 2040–2059. [\[CrossRef\]](#)
85. Rahmadi, I.F. Research on Digital Transformation in Higher Education: Present Concerns and Future Endeavours. *TechTrends* **2024**, *68*, 647–660. [\[CrossRef\]](#)

86. Yue, C.; Xu, X. Review of Quantitative Methods Used in Chinese Educational Research, 1978–2018. *ECNU Rev. Educ.* **2019**, *2*, 515–543. [[CrossRef](#)]
87. Lindl, A.; Krauss, S.; Schilcher, A.; Hilbert, S. Statistical Methods in Transdisciplinary Educational Research. *Front. Educ.* **2020**, *5*, 97. [[CrossRef](#)]
88. Mihaljevic, B.; Bielza, C.; Larrañaga, P. Bayesian networks for interpretable machine learning and optimization. *Neurocomputing* **2021**, *456*, 648–665. [[CrossRef](#)]
89. Weichert, J.; Eldardiry, H. Scoping the AI Curriculum: Key Competencies for Future AI Practitioners. *AI Ethics* **2026**, *6*, 173. [[CrossRef](#)]
90. Zhong, M.; Wei, L.; Mo, H. Enhancing Graduate AI Education Through Practical and Values-Driven Curriculum Integration. *Front. Educ.* **2025**, *10*, 1630073. [[CrossRef](#)]
91. Liu, X.; Fang, Y.; Lan, X. Regulations, Technology Policies and Universities' Attitudes to Artificial Intelligence in China. *High. Educ. Q.* **2025**, *79*, e70055. [[CrossRef](#)]
92. Manorat, P.; Tuarob, S.; Pongpaichet, S. Artificial Intelligence in Computer Programming Education: A Systematic Literature Review. *Comput. Educ. Artif. Intell.* **2025**, *8*, 100403. [[CrossRef](#)]
93. Chen, X.; Chang-Richards, A.; Ling, F.Y.; Yiu, T.W.; Pelosi, A.; Yang, N. Digital Technologies in the AEC Sector: A Comparative Study of Digital Competence Among Industry Practitioners. *Int. J. Constr. Manag.* **2025**, *25*, 63–76. [[CrossRef](#)]
94. Zhai, C.; Wibowo, S.; Li, L.D. The Effects of Over-Reliance on AI Dialogue Systems on Students' Cognitive Abilities: A Systematic Review. *Smart Learn. Environ.* **2024**, *11*, 28. [[CrossRef](#)]
95. Tian, J.; Zhang, R. Learners' AI Dependence and Critical Thinking: The Psychological Mechanism of Fatigue and the Social Buffering Role of AI Literacy. *Acta Psychol.* **2025**, *260*, 105725. [[CrossRef](#)] [[PubMed](#)]
96. Elfert, M.; Ydesen, C. UNESCO, the OECD and the World Bank: A Global Governance Perspective. In *Global Governance of Education, Educational Governance 24*; Springer: Cham, Switzerland, 2023. [[CrossRef](#)]
97. Noroozi, O.; Khalil, M.; Banihashem, S.K. Artificial Intelligence in Higher Education: Impact Depends on Support, Pedagogy, Human Agency, and Purpose. *Innov. Educ. Teach. Int.* **2025**, *62*, 1425–1430. [[CrossRef](#)]
98. Yang, H.; Xu, J.; Zeng, X.; Gu, X. Comparing AI Literacy Policies in the European Union, the United States, India, and China. *Telecommun. Policy* **2026**, *50*, 103142. [[CrossRef](#)]
99. Chiu, T.K.F. AI Literacy and Competency: Definitions, Frameworks, Development and Future Research Directions. *Interact. Learn. Environ.* **2025**, *33*, 3225–3229. [[CrossRef](#)]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.