Full length article

Socio-technical assessment of generative AI integration in architecture, engineering, and construction (AEC) workflows: An empirical study using O*NET occupational taxonomy

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ABSTRACT

Generative artificial intelligence (GAI) has the potential to reshape workflows across the Architecture, Engineering, and Construction (AEC) sector. While previous research has offered valuable technical demonstrations and conceptual analyses, empirical evidence quantifying GAI-related impacts across AEC occupations and systematic assessment of adoption readiness remain limited. This study develops a domain-specific socio-technical evaluation framework that provides occupational-level analysis of technical capabilities, social risks, and adoption barriers across thirteen O*NET-defined AEC occupations. Data were collected through a six-month survey of 162 AEC professionals, complemented by six expert interviews and a systematic literature review. The findings reveal: (1) *Technical Capability*, measured using exposure scores ranging from −1 (low applicability) to +1 (high applicability), shows moderate applicability in design-oriented roles (e.g., architectural drafters: 0.16) and minimal alignment for site-based and manual activities (e.g., construction laborers: −0.89). (2) *Social Risks*, assessed on a 0–1 scale of concern, identify hallucinations (0.71), data privacy (0.70), and intellectual property issues (0.69) as critical concerns. (3) *Socio-Technical Adoption* highlights limited technical expertise (26.0%) and uncertain return on investment (16.8%) as primary barriers, while respondents emphasized the need for usage guidelines and standards (29.6%) and targeted training (29.2%) to facilitate responsible integration. Based on these findings, the study outlines strategic priorities for responsible GAI deployment, including AEC-specific standards, targeted workforce training, human-in-the-loop validation mechanisms, and domain-tailored digital infrastructure. The framework and empirical evidence provide a foundation for researchers, practitioners, and policymakers seeking to guide the safe and effective integration of GAI into AEC workflows.

1. Introduction

The Architecture, Engineering and Construction (AEC) industry faces persistent challenges, including labor shortages, low productivity, and increasing project complexity [1,2]. Addressing these systemic challenges requires approaches that augment workforce capacity and improve operational efficiency without compromising safety or quality. Generative Artificial Intelligence (GAI) has emerged as a promising technological development with the potential to transform how AEC professionals plan, design, communicate, and deliver projects [3]. By learning from large repositories of design documents, specifications, contracts, and site information, GAI systems can substantially reduce the manual effort required for tasks such as designs, documentation, reporting, and information synthesis [4,5].

Despite this potential, significant gaps remain across technical, social, and socio-technical dimensions that constrain effective and responsible GAI integration. *Technically*, the multi-stakeholder and safety-critical nature of AEC projects creates challenges for deploying GAI in workflows that involve heterogeneous tasks, varied digital maturity, and strict regulatory requirements [5,6]. Much of the existing literature focuses on use-case demonstrations or qualitative analyses, with limited empirical evidence on GAI readiness in specific occupations [7]. *Socially*, GAI adoption introduces significant ethical and social concerns, including risks related to intellectual property (IP) in design, hallucination errors in safety-critical tasks, and potential workforce displacement [8,9]. These issues are particularly consequential in the construction and infrastructure domains, where decisions carry

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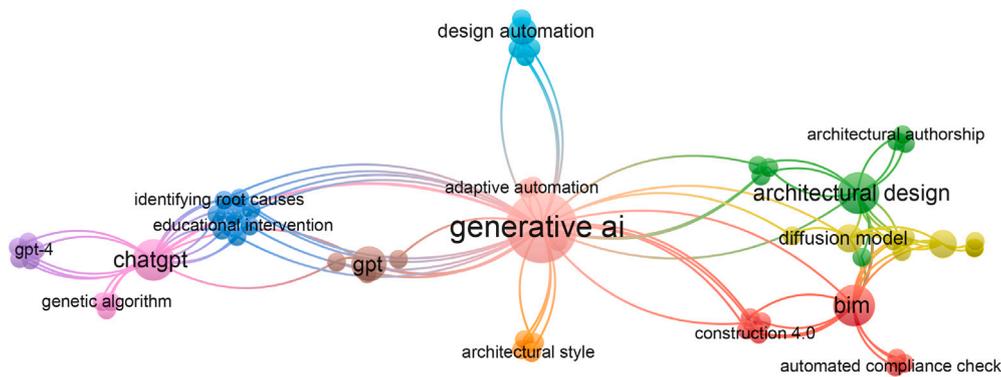*E-mail address:* ptang@andrew.cmu.edu (P. Tang).

Fig. 1. Keyword co-occurrence network of 118 publications on generative AI in AEC. Node sizes reflect keyword frequency; edge thickness represents co-occurrence strength.

long-term public and regulatory implications. From a *socio-technical* perspective, many AEC organizations lack sufficient digital infrastructure, training mechanisms, and governance frameworks to support responsible adoption [10]. Addressing these multidimensional gaps requires systematic evaluation frameworks capable of assessing technical capabilities, ethical and social risks, and organizational readiness.

Existing adoption models, such as Technology Acceptance Models (TAM) [11] and the Technology–Organization–Environment (TOE) framework [12], offer valuable insights into organizational behavior but are not designed to assess GAI's task-level suitability, domain risks, or AEC-specific regulatory constraints [13]. Trustworthy and responsible AI frameworks, such as the EU Ethics Guidelines for Trustworthy AI [14] and the NIST AI Risk Management Framework [15], highlight the importance of reliability, transparency, explainability, and human oversight, but these high-level principles require operationalization within AEC's domain-specific workflows.

Motivated by these gaps, this study develops a socio-technical evaluation framework tailored for GAI integration in AEC. The framework assesses: (1) technical capability readiness using the O*NET [16] task-level descriptors and exposure metrics; (2) social and ethical risks grounded in responsible-AI principles; and (3) socio-technical adoption conditions tailored to AEC workflows, such as organizational barriers, training needs, and governance requirements. Using empirical data from 162 AEC professionals across thirteen occupations, the study quantifies where GAI capabilities align or conflict with AEC work structures, identifies the most salient perceived risks, and reveals organizational needs for responsible adoption. The findings inform a set of actionable sector-level recommendations for standards, workforce development, human-in-the-loop (HITL) validation, and domain-specific digital infrastructure.

The remainder of the paper is organized as follows: Section 2 reviews the state of GAI applications and evaluation methods in AEC. Section 3 details the method design. Section 4 presents empirical findings. Section 5 discusses implications, strategic recommendations, and limitations. Section 6 concludes the study.

2. Literature review

This section reviews current advances in GAI within the AEC industry, within the AEC industry, reviews existing approaches for evaluating GAI systems, and identifies key knowledge gaps that motivate this study.

2.1. Advancements of generative AI in AEC industries

GAI represents a shift from conventional predictive AI toward systems capable of generating novel content such as text, images, 3D representations, and multimodal outputs, by learning from large-scale datasets [17]. These capabilities align with many AEC tasks that rely

on iterative design, technical documentation, and information-intensive decision-making [5].

To characterize emerging research, we conducted a literature search using Scopus and Web of Science with Boolean combinations of GAI-and AEC-related terms. Search terms included "(generative artificial intelligence OR generative AI OR GAI OR large language model OR LLM) AND (AEC OR architectural design OR civil engineering OR construction industry OR building design OR construction management)." After screening, 118 relevant publications were analyzed.

Fig. 1 visualizes the resulting keyword co-occurrence network and reveals three relatively distinct thematic clusters: (1) generative and automated design exploration, (2) BIM-based automation and compliance checking, and (3) LLM-enabled educational and diagnostic applications. The minimal linkage between clusters suggests that research on design generation, BIM reasoning, and human–AI interaction is progressing in parallel rather than converging around shared socio-technical challenges. Notably, keywords related to AI governance, explainability, or responsible AI principles remain sparse, indicating limited attention to safety and ethical considerations.

Table 1 summarizes representative GAI applications across major AEC phases. In design and planning, GAI supports conceptual design, code interpretation, documentation automation, and energy simulation [18,19]. In construction, GAI assists with project document generation, risk identification, specification review, hazard recognition, and schedule analysis [20,21]. In operation and maintenance, applications include building system optimization, predictive maintenance, and knowledge management [22–24]. Collectively, the literature demonstrates rapid expansion of GAI applications, but limited synthesis across technical, ethical, and organizational domains.

2.2. Evaluation of generative AI systems in AEC sectors

The evaluation of GAI systems within AEC remains underdeveloped. Traditional AI evaluation focuses on accuracy-based metrics [40], which are insufficient for generative systems whose output influences design intent, documentation quality, and collaborative workflows [41]. The deployment of GAI in AEC requires consideration of the unique socio-technical conditions of the sector, characterized by physical safety risks, dynamic work environments, regulatory and liability obligations, and sensitive data [4,42]. These conditions require evaluation approaches that extend beyond technical accuracy to ensure reliability, transparency, and responsible use [4].

Responsible and trustworthy AI frameworks offer relevant principles. The EU Ethics Guidelines for Trustworthy AI [14] and the NIST AI Risk Management Framework [15] emphasize reliability, robustness, explainability, and verifiability as core components of trustworthiness, while responsible AI indicates broader considerations such as fairness, accountability, privacy protection, and safe human–AI interaction,

Table 1

Generative AI Applications across different phases of AEC workflows.

Phases	Examples of GAI applications	References
Design & Planing	Structure design; Conceptual design; Architectural design; Construction planning; BIM information search; Design review; Compliance checking; Building energy simulation	[18,19,25–33]
Construction	Project document creation; Contract risk identification; Specification review; Safety report analysis; Hazard recognition; Construction scheduling	[20,21,34–39]
Operation & Maintenance (O&M)	Building system operation control; Predictive maintenance; Documentation and knowledge management	[22–24]

Table 2

Summary of existing evaluations of GAI in the AEC industry. Note: ✓ = addressed; ✗ = not addressed.

Reference	Year	Domain	Methods	Technical		Social	Socio-Technical	Analysis
				Application	Capability	Risk/Harm	Barriers/Support	
[4]	2024	AEC	Scoping Review	✓	✗	✗	✗	Qualitative
[5]	2023	AEC	Scoping Review	✓	✗	✗	✓	Qualitative
[50]	2024	AEC	Scoping Review	✓	✗	✗	✓	Qualitative
[51]	2024	Construction	Scoping Review	✓	✗	✗	✓	Qualitative
[52]	2024	Construction	Scoping Review	✓	✗	✗	✗	Qualitative
[53]	2024	Architecture	Scoping Review	✓	✗	✗	✗	Qualitative
[54]	2023	Construction	Scoping Review	✓	✗	✗	✗	Qualitative
This study	**2025**	**AEC**	**Mixed Method**	✓	✓	✓	✓	**Quantitative**

often supported through mechanisms like human oversight [43]. However, these high-level frameworks require contextualization for AEC workflows, where errors can have operational, contractual, or safety implications.

Technology adoption models, such as the technology–organization–environment (TOE) framework [12] and technology acceptance model (TAM) [44], offer well-established perspectives for analyzing digital transformation and information-systems adoption [45]. These models identify the organizational, technological, and individual factors that shape the adoption decisions [46]. However, their primary emphasis on the adoption determinants provides limited guidance for evaluating how GAI interacts with the structure of work, risk sources, and system-level interdependencies that characterize AEC tasks [13,47].

Given these limitations, sector-specific evaluation requires a broader socio-technical lens. Socio-technical systems theory conceptualizes technology use as emerging from the interplay among technical capabilities, human behavior, organizational norms, and institutional constraints [48,49]. This perspective aligns closely with AEC workflows, where technical coordination, safety considerations, and sensitive information sharing intersect [4]. A socio-technical framework provides a more comprehensive foundation for evaluating the implications of GAI across diverse occupational roles and project environments.

Table 2 compares existing AEC GAI evaluations. Most studies rely on qualitative scoping reviews and address only subsets of relevant dimensions. Few provide quantitative assessments of capability readiness, structured risk evaluation, or systematic analysis of organizational adoption barriers. This gap highlights the need for comprehensive and empirically grounded evaluation approaches.

2.3. Research gaps and contributions

Despite growing interest in GAI integration within the AEC industry, three critical research gaps remain.

- (*Technical Dimension*) Most studies focus on conceptual discussions or specific use cases rather than task-level or occupation-level evaluations. There is little empirical evidence showing where GAI aligns (or misaligns) with the cognitive, analytical, or physical demands of AEC tasks.

- (*Social Dimension*) Although issues such as hallucination, IP protection, data privacy, and workforce impacts are frequently acknowledged, they are seldom examined through quantitative methods. This limits the development of domain-specific governance mechanisms.
- (*Socio-Technical Systems Dimension*) Digital maturity, training availability, regulatory uncertainty, and workforce readiness vary widely across AEC organizations. However, the sector lacks empirical assessments of which barriers are most important and what types of support practitioners require.

This study addresses these gaps and provides three key contributions to advance understanding of GAI integration in AEC workflows.

- The study introduces a domain-specific socio-technical evaluation framework that extends existing models by integrating responsible-AI principles with occupation- and task-level descriptors from the O*NET taxonomy. The framework examines how GAI interacts with the specialized work activities and organizational contexts of AEC practice.
- The study quantifies variation in task-level applicability, perceived risks, and adoption constraints based on survey data from 162 professionals across thirteen AEC occupations. This constitutes the empirical mapping of where GAI capabilities, social concerns, and support needs converge or diverge across the AEC workforce.
- The study synthesizes the empirical findings to identify sector-level implications for standards development, governance mechanisms, workforce training, and organizational readiness. These insights advance the evidence-base needed to guide responsible and scalable GAI adoption in the AEC sector.

3. Research methodology and data collection

This study employs a four-phase research design to develop and apply a socio-technical evaluation framework for GAI integration in AEC workflows (Fig. 2). The phases include: (1) framework development through literature synthesis and expert interviews, (2) survey operationalization, (3) empirical data collection, and (4) synthesis of findings into sector-level implications.
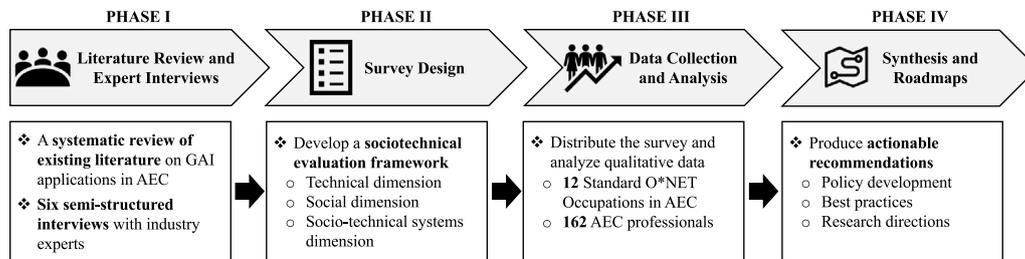
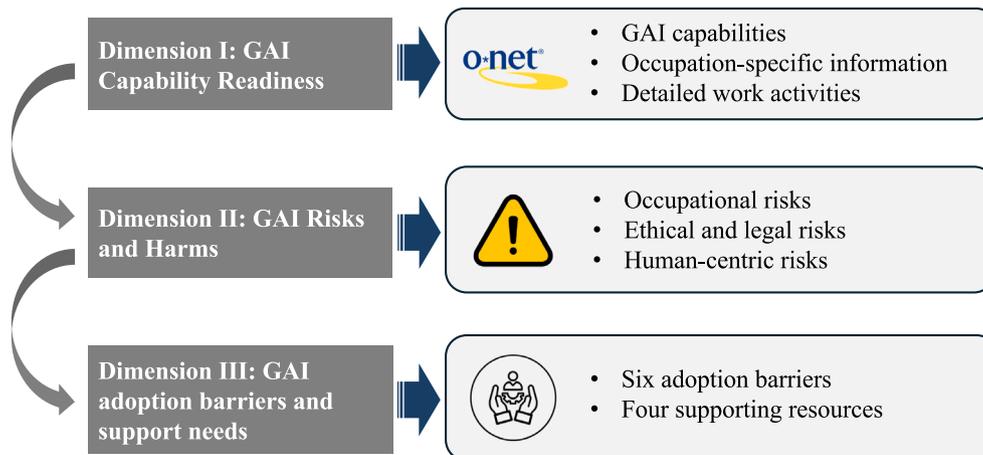**Fig. 2.** Methodology framework for GAI evaluation in AEC workflows.

Fig. 3. A socio-technical evaluation framework for GAI integration.

3.1. Socio-technical evaluation framework

The framework integrates insights from a systematic literature review and six semi-structured interviews with experienced AEC professionals, including architects, engineers, construction managers, and technology consultants. The review established theoretical foundations based on responsible AI and socio-technical systems principles, while interviews grounded the framework in practical challenges related to workflow design, risk sources, and organizational readiness. The resulting framework comprises three interconnected dimensions (Fig. 3):

- *Technical Dimension (GAI Capability Readiness):* This dimension assesses the technical feasibility of GAI adoption by focusing on its capabilities, applicability to specific occupations, and detailed work activities.
- *Social Dimension (GAI Risks and Harms):* This dimension examines perceived risks related to accuracy, hallucinations, IP and privacy concerns, human oversight, bias, and workforce impacts.
- *Socio-Technical Systems Dimension (GAI Adoption Barriers and Support Needs):* This dimension evaluates organizational barriers (e.g., expertise, cost, regulatory compliance), governance needs, and support mechanisms such as training and guidelines.

3.1.1. Dimension I: GAI occupational capability readiness assessment

This dimension examines the extent to which GAI is prepared to support specific occupational tasks within AEC workflows. To assess this readiness, this study: (1) identifies key AEC occupations and associated tasks, (2) maps these tasks to the functional capabilities of GAI, and (3) evaluates and scores the potential impact and feasibility of GAI adoption for each occupation and task.

AEC Occupation and Task Identification The O*NET database [16], developed by the U.S. Department of Labor, provides standardized descriptors for U.S. occupations, including work activities, detailed work activities (DWAs), and required competencies in more than 1000 occupations. This study focuses on 13 AEC-related occupations, including (1) Architects; (2) Architectural and Civil Drafters; (3) Budget Analysts; (4) Civil Engineers; (5) Civil Engineering Researchers; (6) Civil Engineering Technologists and Technicians; (7) Compliance Managers; (8) Construction Laborer; (9) Construction Managers; (10) Construction and Building Inspectors; (11) Cost Estimators; (12) Facilities Managers; and (13) Project Management Specialists.

The selection of the 13 occupations for this study is guided by defined inclusion and exclusion criteria. The inclusion criteria were designed to ensure that the selected occupations reflect core functions, sector diversity, and the potential for GAI integration: (1) *Relevance to AEC workflows:* Occupations were chosen for their alignment with key phases of the AEC project lifecycle, including design and planning (e.g., architects, civil engineers), construction management and execution (e.g., construction managers), and operations (e.g., facilities managers); (2) *Diversity across AEC sectors:* Selected occupations represent a range of AEC sectors, including architect design, construction management, and facility operations, ensuring comprehensive coverage; and (3) *Potential for GAI integration:* Roles involving tasks that can be augmented using GAI, such as design optimization and data analysis, were prioritized.

To maintain focus and generalizability, the study excluded occupations falling into the following categories: (1) *Irrelevance to AEC industry:* Roles unrelated to AEC workflows, such as those in healthcare or financial services, were excluded; and (2) *Highly specialized roles:* Occupations with narrowly defined responsibilities, such as exclusive equipment maintenance technicians, were excluded to ensure that the findings remain broadly applicable in the AEC sector.

Table 3 presents examples of these AEC occupations, their associated work activities, DWAs, and task descriptions from the O*NET database.

Mapping Tasks to GAI Capabilities General work activities represent general job behaviors shared across various occupations. This study uses the O*NET taxonomy [16] to organize work activities into

Table 3

Examples of occupations, work activities, and Detailed Work Activities (DWAs) from the O*NET database.

O*NET Code	Occupation title	Work activities	Detailed Work Activities (DWAs)	Description
11-3013.00	Facilities Managers	Coordinating, developing, managing, and advising	Monitor facilities or operational systems	Plan, direct, or coordinate operations and functionalities of facilities and buildings
13-1051.00	Cost Estimators	Information and data processing	Estimate costs of goods or services	Prepare cost estimates for product manufacturing, construction projects, or services to aid management in bidding on or determining price of product or service
47-4011.00	Construction and Building Inspectors	Getting information	Looking for and receiving job-related information	Inspect structures using engineering skills to determine structural soundness and compliance with specifications, building codes, and other regulations
47-2061.00	Construction Laborers	Performing physical and manual work activities	Position structural components	Perform tasks involving physical labor at construction sites

four functional categories: Information Input (*E1*), Interacting with Others (*E2*), Mental Processes (*E3*), and Work Output (*E4*). Table A.1 (in the Appendix) provides an overview of these categories, linking them to their associated activities and illustrative tasks.

Within these categories, we analyzed nine general work activities: (1) Identifying and Evaluating Job-Relevant Information (*W1*); (2) Looking for and Receiving Job-Related Information (*W2*); (3) Administering (*W3*); (4) Communicating and Interacting (*W4*); (5) Coordinating, Developing, Managing, and Advising (*W5*); (6) Information and Data Processing (*W6*); (7) Reasoning and Decision Making (*W7*); (8) Performing Complex and Technical Activities (*W8*); and (9) Performing Physical and Manual Work Activities (*W9*).

Occupation- and Task-Level GAI Exposure Metrics To quantify GAI suitability, we constructed two exposure metrics consistent with established AI-exposure research [55–57]. All readiness and risk-perception items were rated on a five-point Likert scale. Table A.2 (in the Appendix) summarizes the response categories and their numerical encoding. Readiness ratings were rescaled to the interval $[-1, 1]$, which provides a symmetric representation of perceived suitability and enables comparability between exposure metrics.

Occupation GAI Exposure Score (E_{occ}). Respondents rated GAI suitability for each DWA associated with their occupation using a five-point Likert scale. The score is computed as the weighted mean of DWA-level readiness values:

$$E_{occ} = \frac{\sum_{k=1}^{N} w_k \left(\frac{1}{S_k} \sum_{j=1}^{S_k} R_{k,j} \right)}{\sum_{k=1}^{N} w_k} \quad (1)$$

where

- $R_{k,j}$ is the subjective readiness rating provided by respondent j for DWA k,
- S_k is the number of respondents who rated DWA k,
- N is the total number of DWAs associated with the occupation, and
- w_k is the weighting factor for DWA k, which may encode task relevance and importance.

In our analysis, we set $w_k = 1$ for all DWAs, giving each task equal weight within an occupation. This follows prior AI-exposure studies [57] and is consistent with the treatment of O*NET work activities as parallel and atomic units.

Task GAI Exposure Score (E_{task}). To estimate the cross-occupational suitability of GAI for broader work functions, E_{task} aggregates readiness ratings for each general work activity across occupations. Following prior AI-exposure studies [55,56], each occupation contributes equally to the task-level estimate to avoid dominance by larger subsamples.

$$E_{task} = \frac{1}{M} \sum_{j=1}^{M} \left(\frac{1}{S_j} \sum_{i=1}^{S_j} R_{j,i} \right) \quad (2)$$

where

- $R_{j,i}$ is the normalized readiness rating for the activity provided by respondent i in occupation j,
- S_j is the number of respondents in occupation j who rated the activity, and
- M is the total number of occupations for which the work activity is relevant and was rated.

3.1.2. Dimension II: GAI risk and harm evaluation

Integrating GAI into AEC workflows introduces potential risks and harms that require careful assessment. Informed by existing literature [58,59] and expert insights, this study categorized these risks into three main categories: operational risks (*R1*), ethical and legal risks (*R2*), and human-centric risks (*R3*). These risks are contextualized with practical examples to demonstrate their implications in real-world AEC scenarios, as summarized in Table 4.

To quantify respondents' perceptions of GAI-related harms, this study defines a *GAI Risk Score* (H_i, $i = 1, \ldots, 6$) for each risk dimension. Likert-scale responses (*Strongly Disagree* to *Strongly Agree*) were linearly rescaled to the interval $[0, 1]$ to reflect risk as a nonnegative construct and to ensure comparability between heterogeneous risk types. This normalization follows established practices in risk-perception research [66,67]. The mapping from Likert categories to normalized values is provided in Table A.2 in Appendix.

3.1.3. Dimension III: GAI adoption barriers and support needs

Organizational barriers were identified through literature review and interviews and categorized into six types (*B1–B6*) [68,69], as summarized in Table A.3 in Appendix. Financial challenges, such as uncertain ROI (*B1*) and high implementation costs (*B2*), were especially prominent, as many organizations remain hesitant to invest without clear evidence of economic benefit [70]. Technical barriers, such as the lack of reliable vendors (*B3*) and the lack of technical expertise within organizations (*B4*), underscore the need for stronger technical support and capacity-building. Regulatory challenges, including compliance with data protection laws and IP rights (*B5*), further complicate adoption [71]. Organizational resistance to change (*B6*), driven by skepticism about GAI's value and concerns.

To address these barriers, this study identified four key support mechanisms (*S1–S4*) to facilitate GAI adoption based on literature review and expert interviews [68,72], as summarized in Table A.4. Technical training and support (*S1*) are essential to close skill gaps and enable effective implementation [4]. Industry-wide guidelines and

Table 4

Classification of risks associated with GAI integration in AEC.

Risk category	Specific risks and harms	Examples in AEC context
Operational Risks (*R1*)	Made-up Facts and Hallucinations (*H1*) Loss of Human Oversight (*H2*)	GAI generate incorrect technical specifications for building components [60]. GAI alters project schedules without human approval [61].
Ethical and Legal Risks (*R2*)	Intellectual Property (IP) Concerns (*H3*) Data Privacy and Security (*H4*)	Disputes over ownership of GAI-generated designs [62]. Exposure of confidential project data due to inadequate security [63].
Human-Centric Risks (*R3*)	Job Displacement (*H5*) Bias in Decision-Making (*H6*)	AI automates tasks, reducing the need for human drafters [64]. GAI favors certain construction methods based on biased data [65].

standards (*S2*) can help organizations navigate regulatory requirements and ensure responsible GAI use [51]. Financial incentives (*S3*), such as grants or subsidies, can reduce cost-related barriers and encourage investment [51]. Finally, enhanced stakeholder collaboration through knowledge-sharing platforms and partnerships (*S4*) can improve vendor reliability, spread best practices, and support innovation in GAI adoption [72].

3.2. Survey distribution and collection

The survey was used as the primary data collection instrument to assess GAI capabilities, risks, and adoption factors in the AEC roles. The following provides additional details on the sampling approach and recruitment procedures, as well as the ethical protocols and data handling processes applied throughout the study.

3.2.1. Sampling strategy and recruitment procedures

To ensure adequate coverage across AEC occupational domains, this study used a purpose-sampling strategy targeting professionals who self-identified with one of the targeted occupations for analysis. This sampling approach is appropriate for exploratory studies in which the target population has specialized domain knowledge [73]. Recruitment was carried out over a six-month period from May 2024 to November 2024 through multiple channels, including professional associations (e.g., ASCE working groups), LinkedIn outreach, academic and industry webinars, and conference communications. These channels were selected to reach the respondents across various types of organizations and project environments.

Participation eligibility required that respondents: (1) currently work or have worked in one of the thirteen target occupations, and (2) possess professional experience in design, engineering, construction management, field operations, or facility roles. No geographic restrictions were applied. Although participation was not evenly distributed across all occupations, recruitment was monitored throughout the data collection period to avoid single-occupation dominance and ensure representation across all investigated occupational categories.

To reduce potential response bias and improve construct validity, the survey instrument was designed using neutral language, and response options were randomized where applicable to minimize order effects. All task-level questions were anchored to the O*NET framework to ensure that respondents evaluated standardized task descriptions. The survey was subjected to a pilot test with six professionals (two architecture professionals, three construction professionals, and one information systems and public policy professional) to ensure clarity, interpretability, and consistent understanding in all domains. Feedback from the pilot test was used to refine task descriptions and adjust item wording to reduce ambiguity and enhance construct validity.

A total of 254 responses were received. After excluding incomplete responses and entries lacking required occupational identifiers, 162 valid responses remained for analysis. Based on the Cochran sample size formula [74], this sample produces an estimated error margin of approximately ±7.7% at a confidence level of 95%, meeting common standards for exploratory technology-adoption research [75]. As the study used purpose-sampling and participation levels varied between occupational groups, the authors acknowledge that the results should be interpreted within the context of the sampled population; further considerations regarding scope are discussed in the limitations section.

3.2.2. Ethics, data handling, and confidentiality

This study was reviewed and approved by the Carnegie Mellon University Institutional Review Board (IRB #IRB00000603). Participation was fully voluntary, and respondents were informed about the study's purpose, the anonymous nature of their involvement, and their right to withdraw at any time. To ensure privacy, no personally identifiable information was requested or recorded, including names, email addresses, employer information, or device metadata.

All data were collected anonymously and stored on secure, access-restricted university servers in accordance with institutional data-protection protocols. Only the research team had access to the dataset. Data handling followed the principles of minimal collection, secure retention, and proper disposal. These measures ensured that individual respondents could not be identified and that all processing aligned with IRB-approved protocols and ethical guidelines on privacy and responsible use of human-subject data.

4. Results

This section presents characteristics of the respondents and reports findings for the three evaluation dimensions: (1) technical capability exposure, (2) social and ethical risks, and (3) socio-technical adoption and organizational readiness.

4.1. Respondent demographics and occupational characteristics

Fig. 4 summarizes respondents' project experience and occupational affiliations. Respondents represent a broad cross-section of the AEC sector, including design professionals (architects, drafters), engineering roles (civil engineers, engineering technologists), analytical roles (cost estimators, budget analysts), construction management and inspection roles, and field-oriented occupations (construction laborers). In particular, civil engineering researchers (27.8%), architects (25.9%), and civil engineers (24.1%) constitute the largest groups in the sample. This mix ensures inputs from technical, analytical, and managerial roles relevant to GAI use cases across the project lifecycle. Respondents reported experience in multiple project types. Residential buildings were the most common (63.0%), followed by commercial buildings (41.4%), infrastructure projects (30.9%), and industrial facilities (25.9%). These distributions indicate exposure to a range of project environments with varied complexity and regulatory conditions.

Respondents' professional experience is shown in Fig. 5. One-third (32.7%) have more than ten years of experience, and an equal proportion (32.7%) have one to five y. Another 23.1% fall within six to ten years, while 9.0% have less than one year. Only 2.6% did not report experience. The distribution provides balanced insights from both early-career and senior professionals.

Patterns of GAI usage are presented in Fig. 6. ChatGPT is the most widely used tool, followed by Midjourney, DALL-E, and GitHub Copilot. Regarding usage frequency, 28.8% report using GAI tools a few times per week, and 27.5% report regular or daily use. Weekly use accounts for 11.1%, while 25.5% use such tools rarely, and 7.2% indicate no usage. These patterns indicate growing, but still uneven, adoption across the sector.
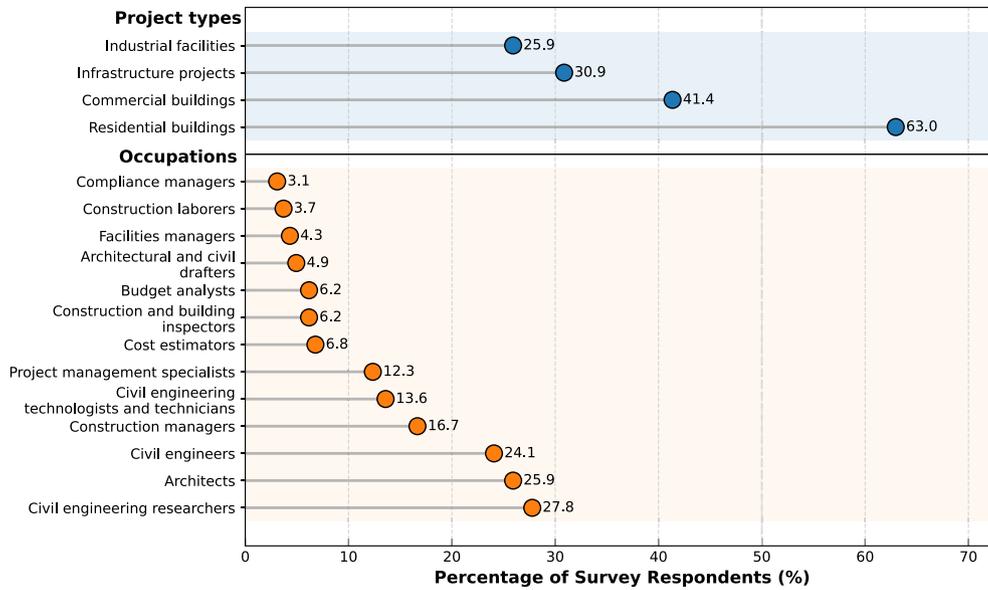
Fig. 4. Respondents' occupation affiliation and project experience (multiple selections allowed).
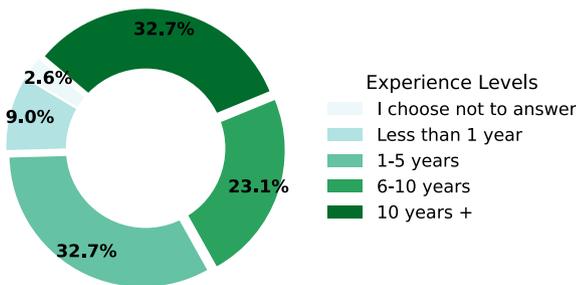

Fig. 5. Distribution of respondents' years of experience in the AEC industry.

4.2. Technical dimension: Capability exposure across occupations and work activities

The technical dimension examines how strongly GAI aligns with occupational tasks using exposure scores that range from –1 (no exposure) to 1 (full exposure).

4.2.1. Occupational-level capability exposure

Fig. 7(a) presents exposure scores for thirteen AEC occupations. Compliance managers show the highest exposure (0.22), reflecting the alignment between GAI capabilities and tasks that involve regulatory documentation and procedural review [50]. Architectural and civil drafters also show notable exposure (0.16), consistent with the growing role of generative models in design documentation [53]. Civil engineering researchers, budget analysts, and construction managers have moderate exposure (0.12). In contrast, construction and building inspectors (−0.31), along with construction laborers (−0.89), exhibit negative exposure, reflecting the limited relevance of GAI tools to tasks requiring physical skill, embodied perception, and real-time contextual judgment [76].

4.2.2. Work-activity-level exposure

Work-activity exposure patterns (Fig. 7(b)) further illustrate how GAI's technical strengths map onto specific AEC activities. The highest exposure occurs in information and data processing (0.26), followed by reasoning and decision-making (0.19) and communication activities

(0.15). These tasks align with GAI capabilities in data synthesis, pattern identification, structured reasoning, and the generation of context-appropriate text or visual content [53]. In contrast, activities requiring situational judgment, causal reasoning, dynamic coordination, or embodied perception show negative scores. Physical tasks reach exposure scores as low as −1.00, highlighting persistent limitations of current GAI models [76].

Fig. 8 compares DWAs for compliance managers and construction laborers. Compliance managers show positive exposure in most DWAs, with values reaching 0.50 in tasks such as risk analysis and audit preparation. Conversely, construction laborers show predominantly negative exposure, with physical tasks consistently scoring −1.00. Only limited coordination tasks, such as blueprint review or signaling equipment operators, generate positive exposure values (up to 0.33).

4.3. Social dimension: Ethical and social risks of GAI integration

Fig. 9 presents levels of agreement with GAI-related risks. Hallucinations and made-up facts received the greatest concern, with 31.5% strongly agreeing and 35.4% agreeing. Only 2.4% strongly disagreed, indicating a broad recognition that GAI-generated inaccuracies could undermine reliability in AEC workflows. Data privacy and security risks showed a similar pattern, with 34.4% strongly agreeing and 31.2% agreeing, reflecting the sensitivity of project information and client data. Opinions on job displacement were more divided. Although 14.2% strongly agreed and 30.7% agreed that GAI poses a threat to jobs, 9.4% strongly disagreed, suggesting variation between occupational groups. Concerns related to IP and loss of human oversight also received substantial agreement, with 28.9% and 22.3% strongly agreeing, respectively.

The normalized risk scores in Fig. 10 reinforce these patterns. Hallucinations (0.71) and data privacy and security (0.70) represent the highest perceived risks. IP issues (0.69) and loss of human oversight (0.66) constitute moderate-to-high risks, reflecting concerns about ownership, accountability, and control during decision-making processes. Bias in decision-making scored 0.61, indicating awareness of fairness and reliability issues arising from training data limitations. Job displacement received the lowest score (0.55), suggesting that automation-related concerns are perceived as less immediate than risks associated with accuracy, data governance, and human oversight.
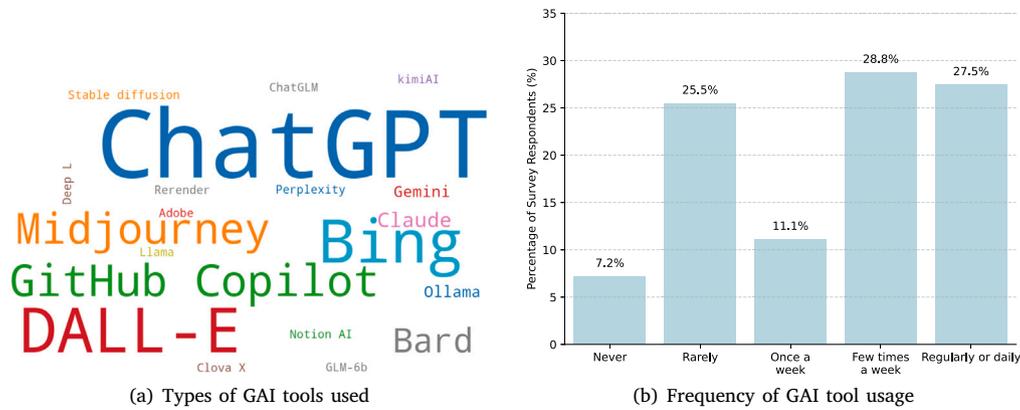
(a) Types of GAI tools used

(b) Frequency of GAI tool usage

Fig. 6. Types and frequency of GAI tool usage.

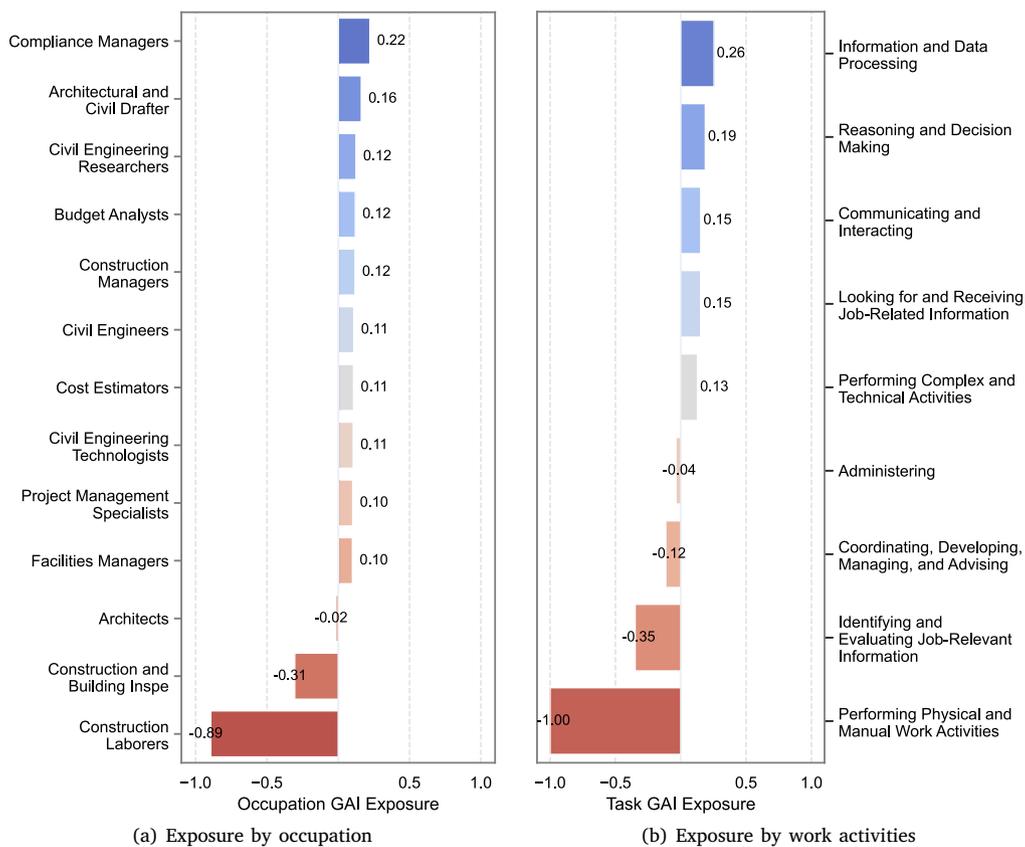(a) Exposure by occupation

(b) Exposure by work activities

Fig. 7. GAI exposure scores for AEC occupations and work activities.

4.4. Socio-technical dimension: Adoption barriers, support requirements, training, and regulation

Fig. 11(a) presents the main barriers to GAI adoption reported by the respondents. The lack of technical expertise is the most frequently cited barrier (26.0%), indicating that many organizations do not yet possess the skills needed to implement and manage GAI systems effectively. Uncertain return on investment (ROI) (16.8%) and regulatory or compliance concerns (16.1%) represent the next most prominent barriers. High implementation costs (14.4%) and organizational resistance (14.4%) were also identified as notable constraints, suggesting that both financial and cultural factors influence adoption readiness.

The support requirements shown in Fig. 11(b) closely correspond to these barriers. Respondents most frequently identified the need for guidelines and standards for GAI usage (29.6%), followed by technical training and support resources (29.2%). These findings indicate that practitioners seek competency-building and well-defined expectations for responsible use. Collaboration opportunities and financial incentives were also reported, suggesting that shared knowledge networks and funding mechanisms could accelerate organizational adoption.

Training availability within organizations remains inconsistent. As shown in Fig. 12, 39.9% of the respondents report that their organizations do not provide any GAI-related training resources. Among those that do, online courses are the most common format (27.6%), followed by in-house workshops (20.2%). Only 12.3% provide formal structured training programs, indicating a gap between the existing workforce needs and institutional support for ongoing skill development.
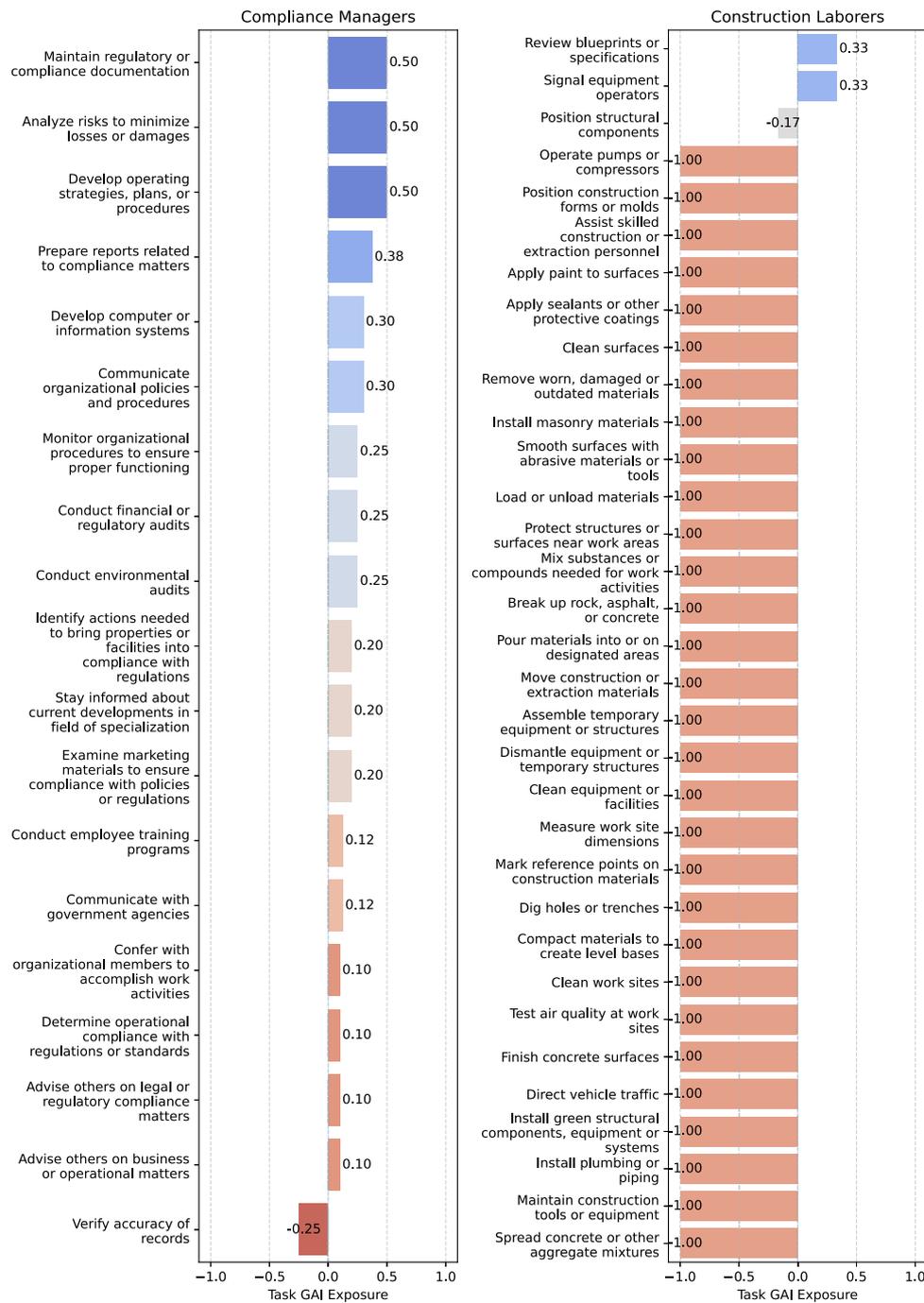
Fig. 8. GAI exposure scores for compliance managers and construction laborers across detailed work activities.

Regulatory preparedness exhibits a similar early-stage pattern of organizational development. Fig. 13 shows that 50.8% of the respondents report no GAI-specific policies within their organizations. However, 25.4% indicate that such policies are already in place and 16.9% report planned development efforts. An additional 6.9% note the presence of broader technology or data governance frameworks. These results suggest that while formalized GAI governance remains limited across the sector, institutional awareness is increasing and policy formation processes are beginning to take shape.

4.5. Measurement validation and inferential analysis

To assess the quality of the measurement instruments, three analyses were conducted: an internal consistency check for the risk scale, a construct-validity assessment of the exposure metrics, and a correlation analysis examining the relationship between exposure and perceived risk.

4.5.1. Internal consistency of perceived-risk scale

The six Likert-type items assessing respondents' perceptions of risks associated with GAI were designed to reflect a single underlying construct. Cronbach's alpha was computed to examine internal consistency. The resulting coefficient of $\alpha = 0.801$ indicates good internal consistency based on commonly accepted thresholds (i.e., $\alpha \geq 0.70$). This finding supports the interpretation of the items as measuring a coherent underlying dimension of perceived risk.
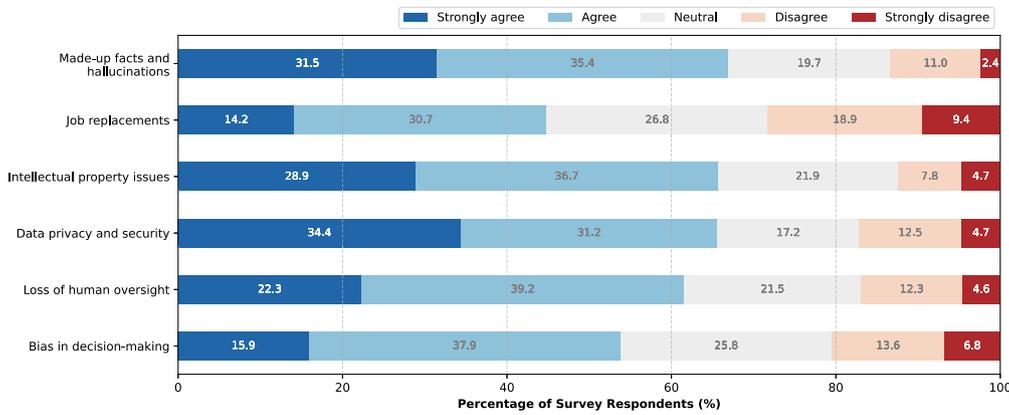
Fig. 9. Levels of agreement with ethical and social concerns associated with GAI integration.
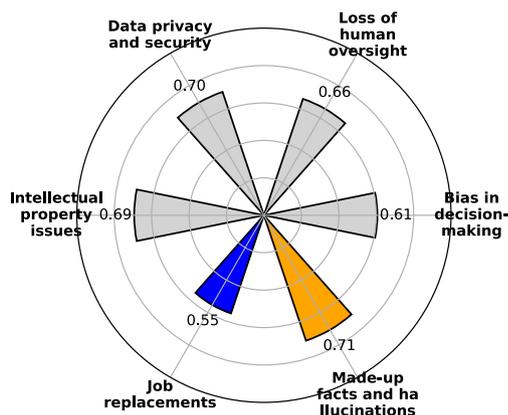

Fig. 10. Normalized risk scores for GAI integration in AEC workflows (0–1 scale; higher indicates greater perceived risk).

4.5.2. Construct validation of exposure metrics

Construct validity of the occupational exposure metrics was examined using known-group comparisons. Consistent with previous studies [13,53], design- and documentation-oriented occupations (e.g., architects, drafters, engineers) showed systematically higher exposure scores than field-focused roles such as inspection and site management. The observed patterns confirm that exposure metrics function conceptually coherent and empirically stable [76,77].

4.5.3. Association between occupational exposure and perceived risk

To assess whether occupational exposure to GAI capabilities corresponds to practitioners' perceptions of risk, we computed a Spearman rank-order correlation between the exposure index and the perceived-risk index (Fig. 14). The correlation coefficient was $\rho = 0.184$ ($p = 0.548$), indicating no statistically significant association between the two measures. This lack of correlation suggests that perceived risks are not primarily shaped by the functional suitability of GAI for specific occupational tasks. Instead, risk perceptions appear to be influenced by broader contextual and organizational considerations, including data-governance protocols and concerns about ethical and legal accountability [78,79].

5. Discussion

This section synthesizes the empirical findings in the three dimensions of the socio-technical framework and examines their implications for AEC practice, organizational strategy, and policy development.

5.1. GAI adoption: Varied impacts across AEC workflows

Recent studies indicate that GAI primarily affects the information-intensive phases of AEC projects, including design development, technical documentation, and analytical reasoning tasks [53,77]. Our empirical results substantiate this trend: occupations centered on structured information, such as architects, engineers, drafters, and researchers, exhibit the highest exposure scores for information processing (0.26) and reasoning (0.19). These patterns confirm GAI's role as a cognitive augmentation tool that accelerates design iteration, supports multi-source analysis, and reduces repetitive documentation tasks [76].

The heterogeneity observed across occupations reflects the fundamental division of labor in AEC. Field-centered roles depend on embodied perception, dynamic spatial awareness, and context-sensitive judgment within environments that lack stable, machine-readable representations. These requirements explain the markedly negative exposure scores for construction laborers (−0.89) and other site-intensive occupations. The results offer quantitative evidence of the current mismatch between GAI capabilities and the requirements of physical, adaptive work, suggesting that meaningful progress in field support will depend on advances in robotics, sensing infrastructure, and multimodal AI systems capable of grounding reasoning in real-world context [64].

Our findings refine broad claims about sector-wide AI-driven transformation by identifying where early transformations are most plausible: tasks involving interpretation of drawings, specifications, and codes [77]. In contrast, field operations are likely to remain less affected until GAI becomes more tightly integrated with robotics, sensing technologies, and immersive systems capable of providing context-aware decision support.

5.2. Policy and regulatory implications

Survey responses reveal strong concerns about hallucinations (0.71), data privacy (0.70), and IP stewardship (0.69). These empirical patterns align with previous studies that emphasize trustworthiness and accountability as prerequisites for AI deployment in safety-critical domains [5]. In AEC, however, their implications are amplified by the sector's reliance on contractual documentation, multi-party data exchange, and regulatory compliance.

Hallucinations pose particular risks because design documentation, technical specifications, and code interpretations serve as authoritative references in permitting, procurement, and construction [76]. Erroneous AI-generated content can propagate across BIM coordination, submittal reviews, and contractual documents, potentially leading to rework, schedule delays, cost escalation, or regulatory non-compliance [50]. These risks explain respondents' strong concerns about accuracy, reliability, and verification. Privacy risks reflect the sensitivity of project information, including proprietary BIM models,
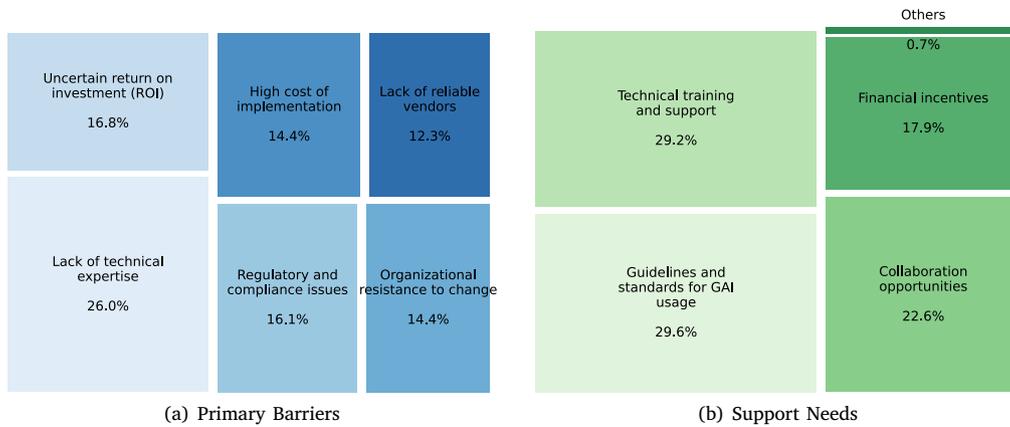
(a) Primary Barriers
(b) Support Needs

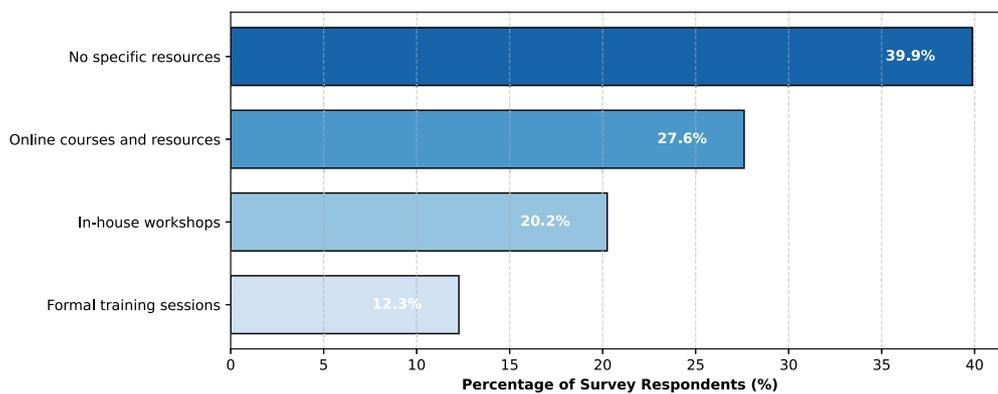**Fig. 11.** Primary barriers and support needs for GAI integration in AEC organizations.

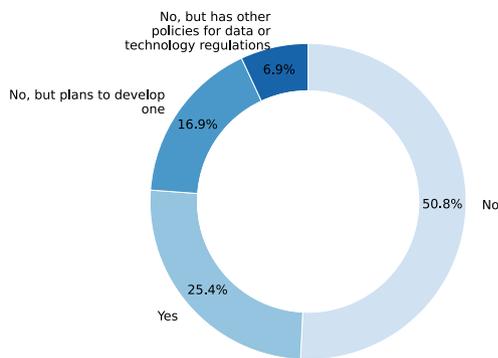**Fig. 12.** Training resources for learning GAI provided by AEC organizations.

Fig. 13. Regulatory preparedness for GAI integration in AEC organizations.

client data, subcontractor pricing, and georeferenced site imagery [9]. Reliance on cloud-based GAI systems often introduces uncertainty regarding data retention, access control, auditability, and model training residence, thereby intensifying perceived vulnerabilities [4]. IP concerns pertain to authorship, attribution, and the ownership of AI-assisted design outputs, as well as the reuse of stylistic or technical elements embedded in training data [62]. These issues intersect with long-standing legal responsibilities in architecture and engineering, where liability and authorship carry explicit contractual and regulatory [80].

A review of current AI-related policies (Table 5) highlights notable regulatory gaps. Although frameworks such as the NIST AI Management Framework and the EU AI Act provide high-level principles for responsible AI use, they offer limited guidance for AEC-specific

workflows where AI-assisted decisions may affect public safety, infrastructure performance, or contractual accountability. Given the sector's dependence on accurate documentation, secure data management, and regulatory compliance [4], the findings indicate a need for clearer, domain-tailored oversight mechanisms. Analogous to the aviation sector's interim GAI policy [81], AEC-specific guidelines could help define responsible use cases, verification requirements, and standards for human oversight.

5.3. Strategic recommendations for GAI integration in AEC workflows

The empirical results reveal uneven technical readiness, persistent concerns about hallucinations, data governance, and IP risks, and limited organizational capacity for AI adoption. Fig. 15 maps these gaps to four actionable priorities.

5.3.1. Goal 1: Establish AEC-specific GAI guidelines and standards

Exposure patterns indicate the need for task-specific standards to govern the integration of AI-generated content into regulated AEC workflows. In high-exposure domains (e.g., design, analysis, documentation), verification protocols should specify how AI-generated drawings, narratives, and code interpretations are validated prior to inclusion in construction documents. Embedding verification checkpoints in BIM authoring tools and common data environments would preserve traceability and ensure continuity with existing approval workflows.

In moderately exposed coordination tasks, structured review protocols are needed to govern AI-assisted meeting summaries, scheduling rationales, and submittal analyzes, reducing the risk of propagating inconsistent or hallucinated content. High levels of concern regarding privacy and IP additionally highlight the need for governance

Fig. 14. Relationship between occupational GAI exposure and perceived risk across AEC roles.

Table 5
Overview of GAI-related policies and regulations across sectors.

| Sector	Policy	Policy type	Focus areas	Limitations/challenges
Government	NIST AI Risk Management Framework [15]	Risk Management Framework	AI safety, privacy, transparency, secure data usage	Lacks sector-specific regulations for AEC.
Government	EU AI Act [82]	Legislative Act	Regulating high-risk AI systems, ensuring transparency, preventing harmful AI applications	Does not address construction-specific needs like safety and infrastructure management.
Government	Interim Administrative Measures for Generative AI Services (CAC) [83]	Interim Measures	Transparency, content moderation, privacy protection, and IP	Lacks provisions for critical infrastructure management.
Industry	FAA Generative AI Interim Policy [81]	Interim Policy	Responsible use of GAI in aviation, focusing on operational reliability and safety	Aviation-focused; lacks applicability to construction.
Academia (Higher Education)	Various Institutions' Guideline on GAI in Education [84,85]	Guideline	Ethical AI use, fairness in automated educational tools	Focused on education, not applicable to sectors requiring physical safety.
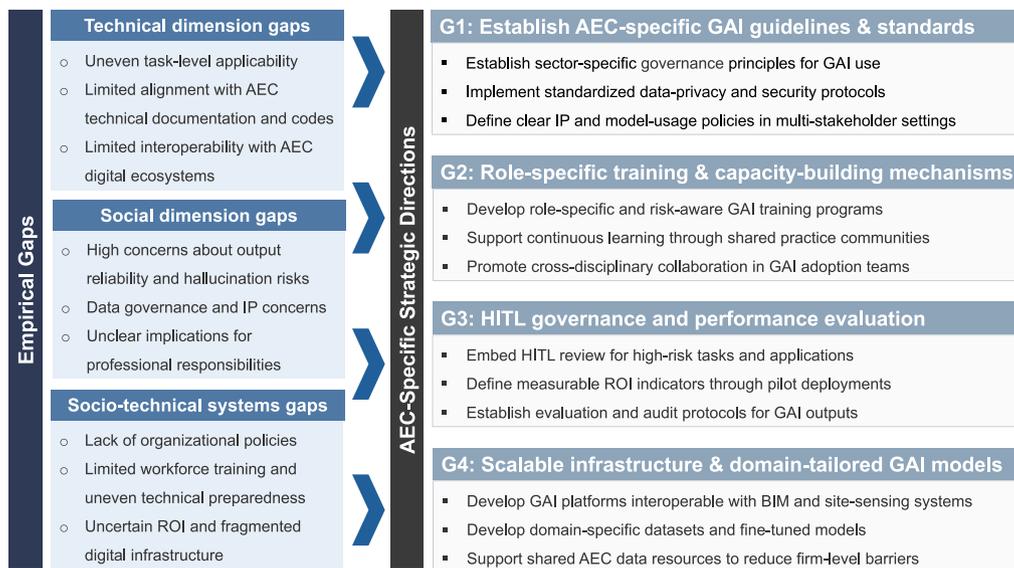
Fig. 15. Strategic recommendations for GAI integration in AEC workflows.

mechanisms specifying how project data may be used for model inputs, requirements for anonymization, and constraints on processing proprietary information.

5.3.2. Goal 2: Develop role-specific training and capacity-building mechanisms

The lack of formal GAI training reported by nearly 40% of respondents, combined with substantial differences in exposure scores, demonstrates that workforce preparation is uneven across occupational groups. For design-oriented professionals, training should emphasize the critical evaluation of AI-generated analytical reasoning, specification text, and code-related explanations. These competencies are necessary to ensure that GAI output can be reliably incorporated into design coordination and permitting workflows.

For coordinators and project managers whose work involves synthesizing information from various sources, capacity building should focus on evaluating AI-generated summaries, schedule analyzes, and risk assessments. The high concern regarding the reliability of textual output suggests that these roles require particular expertise in validation and cross-checking.

Although field roles currently exhibit low exposure, the anticipated expansion of multimodal GAI, incorporating imagery, sensor data, and AR/VR interfaces, indicates future training needs for competencies related to AI-assisted inspections, progress assessments, and safety observations.

5.3.3. Goal 3: Integrate human-in-the-loop governance and performance evaluation

High perceived risks related to hallucinations and data governance issues highlight the need for structured human oversight within GAI-augmented workflows. HITL mechanisms should be incorporated into the established digital pathways through which design and construction information is generated, reviewed, and authorized. Within design development, HITL review can be integrated into existing version-control and approval procedures in BIM authoring environments, allowing engineers and architects to evaluate AI-generated drawings, narratives, and code interpretations prior to their inclusion in contractual deliverables. In regulatory and permitting contexts, digital submission systems can incorporate verification checkpoints that require human confirmation of AI-assisted calculations or explanatory text. For field operations, mobile inspection platforms that present dual human–AI annotations enable a systematic comparison of machine-generated observations with practitioner judgment.

Although financial data are not available for formal cost–benefit modeling, exposure patterns suggest several performance indicators for evaluating the impact of GAI integration. Documentation-intensive activities, such as reviewing submittal and drafting technical reports, represent plausible areas for efficiency gains. Reductions in revision cycles or inconsistencies between coordinated documents may serve as additional evidence of improved accuracy. These indicators reflect the types of tasks for which the empirical results suggest the strongest technical alignment with current GAI capabilities.

5.3.4. Goal 4: Build scalable digital infrastructure and domain-tailored GAI models

Limited GAI applicability to field-intensive tasks reflects technological constraints and inadequate digital infrastructure. Many site activities lack reliable digital representations, and existing GAI systems do not incorporate domain-specific knowledge, such as construction sequencing logic, local code requirements, or material system constraints, necessary for contextually valid outputs.

Expanding the scope of GAI in AEC practice requires the development of integrated digital infrastructures that connect BIM, scheduling systems, contract documentation, and site-sensing technologies. Such integration would provide the contextual grounding necessary for more advanced forms of AI-supported reasoning. Parallel efforts to develop domain-tailored datasets and fine-tuned models would help mitigate hallucination risks and improve the reliability of AI-generated technical information.

5.4. Limitations and future work

While this study provides a comprehensive socio-technical assessment of GAI readiness in AEC, several limitations should be acknowledged. First, although the dataset contains 162 valid responses across thirteen O*NET occupations, representation is uneven, particularly among compliance managers and site-based roles, which may influence exposure estimates and risk profiles for these groups. Future studies should incorporate larger and more balanced samples, ideally with broader geographic coverage.

Second, the study also relies on self-reported exposure assessments, perceived risk severity, and alignment between occupational tasks and GAI capabilities. Perceptual constructs are commonly used in established technology-adoption models [11,12]. However, self-reported measures may diverge from actual task performance or behavioral interaction with AI-assisted workflows. However, the consistent relative patterns observed across occupational groups remain informative for characterizing sector-level trends. Future research can strengthen construct validity by integrating controlled experiments, workflow-tracking data, digital interaction logs, and mixed-methods, including interviews and cognitive walkthroughs.

Third, the demographic variables collected, such as occupation, project experience, and GAI usage patterns, capture several important dimensions of respondent diversity but do not include potentially influential factors such as firm size or organizational specialization. The respondent pool is predominantly U.S.-based, which introduces the possibility of cross-cultural bias. AEC practices vary widely across countries with respect to regulatory oversight, procurement systems, data-governance requirements, contractual liability structures, and workforce organization. These institutional differences may shape practitioners' assessments of task-level GAI applicability, perceived risk severity, and organizational readiness. Consequently, the socio-technical patterns observed here may not generalize to regions with distinct regulatory or market conditions. Future studies incorporating geographically stratified samples or parallel multinational surveys would help generalize the observed patterns globally.

Finally, the empirical assessment focuses on GAI systems currently deployed in industry, including models capable of processing text and images. The analysis does not examine technological evolution or future model trajectories, and the findings should therefore be interpreted within the boundaries of the present system capabilities. Exposure patterns indicate limited relevance for field-centered tasks, reflecting persistent challenges in the digital representation of dynamic site environments and the restricted contextual grounding of existing multimodal systems. Investigations of robotics-assisted workflows, drone-enabled inspection pipelines, and AR/VR-based visualization processes can represent promising avenues to understand how advancing technologies can influence task applicability, verification requirements, and human–AI collaboration in field environments [86].

6. Conclusion

This study advances the understanding of GAI integration in the AEC sector by providing a sector-wide socio-technical assessment across thirteen O*NET-defined occupations. The findings demonstrate that GAI readiness is highly varied across the workforce: design- and analysis-oriented roles exhibit moderate capability exposure, while site-based and manual occupations show negative readiness scores, indicating limited applicability under current technological conditions. These disparities suggest that GAI is more likely to augment knowledge-intensive workflows than physical or field-execution tasks in the near term.

Risk assessments reveal great concern regarding hallucinations, data privacy, and IP stewardship, underscoring the need for robust governance, verification mechanisms, and secure data-management protocols. Although job-displacement concerns were moderate overall, the

Table A.1

Categorization of work activities across occupations based on the O*NET taxonomy.

Category	Work activities	Example tasks
Information Input (*E1*)	Identifying and evaluating job-relevant information (*W1*)	Inspecting equipment, structures, or materials
	Looking for and receiving job-related information (*W2*)	Monitoring processes, materials, or surroundings
Interacting with Others (*E2*)	Administering (*W3*)	Performing administrative activities
	Communicating and interacting (*W4*)	Communicating with supervisors, peers, or subordinates
	Coordinating, developing, managing, advising (*W5*)	Coordinating work and activities of others
Mental Processes (*E3*)	Information and data processing (*W6*)	Analyzing data or information
	Reasoning and decision making (*W7*)	Developing objectives and strategies
Work Output (*E4*)	Performing complex and technical activities (*W8*)	Operating or working with computers
	Performing physical and manual activities (*W9*)	Performing general physical activities

Table A.2

Likert scale used for assessing GAI capability readiness and perceived risk.

Response	Readiness description	Score	Risk description	Score
Strongly Disagree	Not at all suitable for this activity	−1.0	Minimal risk; occurrence unlikely with negligible impacts	0.0
Disagree	Generally not suitable for this activity	−0.5	Low risk with limited and manageable impacts	0.25
Neutral	Mixed or uncertain assessment of suitability	0.0	Moderate risk with uncertainty in likelihood and severity	0.50
Agree	Generally suitable for this activity	0.5	High risk likely to affect workflows or outcomes	0.75
Strongly Agree	Highly suitable for this activity	1.0	Severe risk; highly probable occurrence with major consequences	1.0

distribution of perceived vulnerability indicates uneven impacts across occupation types, reinforcing the need for equitable workforce planning and role-specific training.

The study contributes three major aspects. First, the occupation-level exposure metric provides a structured baseline for comparing how current GAI capabilities align with task demands across AEC roles. Second, risk and harm assessment offers an evidence-based foundation for developing mitigation strategies consistent with ethical and legal expectations. Third, the analysis of adoption barriers and support requirements translates workforce concerns into actionable priorities for industry organizations, training providers, and policymakers.

This study has several limitations. The sample, though spanning thirteen occupations, is uneven across roles and largely U.S.-based, limiting generalizability across organizational and international contexts. The reliance on self-reported assessments may also diverge from actual task performance. Future work should draw on larger and more geographically diverse samples and incorporate objective evidence through experiments, workflow-tracking data, and mixed-method evaluations. Finally, the analysis reflects current text- and image-based GAI capabilities; research on emerging multimodal models, robotics-assisted workflows, drone-based inspection, and AR/VR-supported processes is needed to assess how advancing technologies may expand GAI applicability in field environments.

CRediT authorship contribution statement

Ruoxin Xiong: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yael Netser:** Writing – review & editing, Validation, Methodology, Investigation, Data curation, Conceptualization. **Pingbo Tang:** Writing – review & editing, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization. **Beibei Li:** Writing – review & editing, Project administration, Methodology, Funding acquisition, Conceptualization. **Joonsun Hwang:** Writing – review & editing, Investigation, Data curation.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Pingbo Tang reports financial support was provided by Block Center for Technology and Society at Carnegie Mellon University. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix. Measurement scales, taxonomies, and coding schemes

*A.1. Categorization of work activities based on o*net taxonomy*

See Table A.1.

A.2. Likert scales for GAI capability readiness and perceived risk

See Table A.2.

A.3. Barriers to GAI adoption in the AEC industry

See Table A.3.

A.4. Support needs for facilitating GAI adoption

See Table A.4.

Data availability

Data will be made available on request.

Table A.3

Primary barriers to GAI adoption in the AEC industry.

Barrier code	Description	Examples
Uncertain ROI (*B1*)	Difficulty assessing financial benefits of GAI	Hesitance to invest without demonstrable ROI
High Cost of Implementation (*B2*)	Financial burden of integrating GAI systems	Expenses for software licenses, hardware, and infrastructure
Lack of Reliable Vendors (*B3*)	Limited availability of trustworthy GAI solution providers	Few domain-appropriate tools with proven performance
Lack of Technical Expertise (*B4*)	Insufficient internal capacity to implement GAI	Need for training, upskilling, or new technical hires
Regulatory and Compliance Issues (*B5*)	Legal and regulatory constraints	Requirements related to data protection, liability, and IP
Organizational Resistance to Change (*B6*)	Hesitance to adopt new digital technologies	Concerns about job displacement or skepticism toward benefits

Table A.4

Support needs to facilitate GAI adoption in the AEC industry.

Support code	Description	Examples
Technical Training and Support (*S1*)	Educational resources for GAI technologies	Training programs to reduce skill gaps
Guidelines and Standards (*S2*)	Industry-wide protocols for GAI implementation	Standards supporting compliance, documentation, and governance
Financial Incentives (*S3*)	Economic support for GAI adoption	Grants , subsidies, or tax incentives
Collaboration Opportunities (*S4*)	Platforms for knowledge-sharing and cooperation	Consortia, industry partnerships, and research collaborations

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