Opportunities and Challenges of the Adoption of Artificial Intelligence in Steel Fabrication for Construction

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Abstract

Steel construction is a widely adopted building method that relies on durable, high-strength materials to achieve efficient and reliable structures. Artificial Intelligence (AI) technologies have the potential to enhance efficiency, precision, safety, and overall productivity within steel fabrication, a process that remains largely dependent on manual operations. Despite promising advancements, the adoption of AI in this domain has been limited by technical, organizational, and workforce-related challenges. This paper explores the opportunities and challenges associated with AI adoption in steel fabrication through a literature review and a focus group study with professionals from U.S.-based steel fabrication companies. The focus group gathered industry perspectives on current and potential AI applications across fabrication processes, including welding, fitting, dimensional inspection, and quality assurance/quality control (QA/QC). Findings indicated that AI can improve precision and efficiency, strengthen defect detection and QA mechanisms, and support more accurate cost estimation and performance prediction. However, some barriers persist, such as robotic limitations for non-repetitive tasks, incomplete design models, high implementation cost, and lack of standardized input data. The study provides insights grounded in both research and practice to inform future efforts toward integrating AI effectively in steel fabrication.

Keywords –
AI; Steel Fabrication; Automation

1 Introduction

Steel construction plays an essential role in modern building practice, offering structural reliability, cost-efficiency, and reduced construction time that continue to influence the built environment [1]. The authors in [2] stated that steel construction is an innovative and future-facing approach that allows structures to be disassembled, reused, and adapted over time. The steel construction depends on steel fabrication, where raw steel is shaped into precise structural components that meet design requirements [3]. The fundamental function of steel fabrication is still based upon human labor, while the advanced automation system remains underutilized [4]. Relying so heavily on manual labor can slow production, increase the likelihood of mistakes, and lead to higher costs and safety risks [5]. Artificial Intelligence (AI) is defined as the ability of machines to exhibit human-like intelligence [6]. As AI continues to advance across a range of industries, its potential to automate and optimize key stages of steel fabrication is becoming increasingly evident. AI is playing a transformative role in how steel structures are analyzed, designed, and managed across multiple dimensions [7]. However, the pace of AI adoption in steel fabrication has been relatively slow. To facilitate broader implementation, it is essential to understand both the opportunities presented by AI and the practical challenges that accompany its deployment. However, existing studies have largely focused on the technical aspects of AI and have paid little attention to the practice-based insights from industry experts in steel fabrication. This study addresses this gap by combining a literature review with industry perspectives gathered through a focus group of eight (8) experts from steel fabrication companies based in the United States. Section 2 provides background information on AI potential for automation in construction, challenges of AI in construction, steel fabrication in construction, opportunities of AI in steel fabrication, and challenges of AI in steel fabrication. Section 3 describes the research methodology, and in Section 4, the findings are present. The discussion is presented in Section 5. Finally, the conclusion is provided in Section 6.

2 Background

2.1 AI Adoption in Construction

AI is increasingly recognized as a driving force of automation in construction due to its ability to provide data-driven solutions to complex operational challenges while reducing reliance on manual processes [8, 9]. By enabling forecasting, optimization, and predictive analytics, AI enhances planning efficiency, risk management, and decision-making in dynamic project environments [10,11]. In combination with robotics, AI can improve productivity and worker safety by automating repetitive and hazardous tasks [12]. Hybrid AI models that combine Machine Learning (ML) with techniques such as fuzzy logic or genetic algorithms are also used to address uncertainty and variability in construction operations [13]. These advancements suggest that AI is not only optimizing existing processes but also reshaping construction automation through generative design, digital twins (DT), and blockchain [14].

Despite its transformative potential, AI adoption in construction is hindered by challenges such as limited data availability, difficulties in interpretation of AI-generated outputs, and ethical concerns [15]. High implementation costs, shortages of skilled personnel, data security risks, non-standardized datasets further limit AI adoption [16]. Additional barriers include interoperability issues with legacy systems and organizational resistance [17, 18]. Other challenges involve limited generalizability, integration of domain knowledge, and regulatory concerns [19]. Furthermore, AI-driven applications such as cost estimation remain dependent on reliable datasets and standardized data structures [20].

2.2 Steel Fabrication in Construction

Steel fabrication is a key stage in construction that transforms raw materials into structural elements; however, it still remains heavily reliant on manual labor and conventional processes, with project control systems often based on slow and error-prone data collection that delay deviation detection, increase costs, and contribute to schedule overruns [3]. In addition, [21] emphasized the need for accurate man-hour estimation because fabrication directly affects both cost and productivity. Similarly, [22] found that scheduling challenges persist because manual fitting and welding stations are highly labor-dependent and prone to bottlenecks. Waste generation is also an emerging concern, with up to 20% of steel produced being scrap, underscoring the need for organized recycling and reuse systems [23]. Fabrication of curved structural components will present additional challenges, due to the potential for cracking, higher energy consumption, and greater costs compared to planer components [24]. As mentioned by [25], the quality issues also remain, with average defect rates reported around 4%, influenced by welder skill, fit-up, joint complexity, and inspection requirements. Furthermore, steel fabrication processes such as layout and fit-up are prone to costly errors and material waste due to their reliance on limited skilled labor [26]. Finally, broader utilization of stainless steel fabrication in building applications is constrained by unstable material costs, relatively low mechanical strength, and limited familiarity with fabrication procedures, all of which restrict adoption despite durability benefits [27].

2.3 AI Opportunities in Steel Fabrication

The study in [28] demonstrated that AI, particularly through ML, deep learning (DL), and decision tree (DT), can advance fabrication processes by enabling real-time monitoring, optimizing parameters, and detecting defects at earlier stages, thereby improving the precision and efficiency of laser cutting, welding, and inspection. The authors in [29] applied support vector machine (SVM), gradient boosting (GB), and DT models to predict the cost performance index (CPI) in off-site steel construction (OSC), showing that such models can accurately forecast project outcomes when trained on key features. The authors in [30] developed modified AlexNet (i.e., a type of DL architecture for image classification) and hybrid DL models for classifying surface defects in hot-rolled steel strips, achieving classification accuracy of up to 100%. These key opportunities are summarized in Table 1, which highlights main areas AI can advance steel fabrication.

Table 1 Key opportunities of AI adoption in steel fabrication

Item	Key Opportunities	Key Literatures
1	Enhancing precision and efficiency	[28,30,32]
2	Supporting accurate prediction of project costs and performance outcomes	[29,32]
3	Strengthening defect detection and quality assurance mechanisms	[30,33]

2.4 AI Challenges in Steel Fabrication

While AI offers promising opportunities for improving efficiency, precision, and decision-making, its integration into steel fabrication also presents notable technical challenges. Based on two plant case studies, the authors in [31] found that efforts to apply ML and AI in steel plants are mainly limited by three factors: data, infrastructure, and talent. Data issues are related to poor specification, traceability, and quality; infrastructure problems come from fragmented systems that are difficult to connect; and talent shortages affect every stage of the ML/AI lifecycle, from building and testing models to deploying and maintaining them.

It was stated in [30] that AI adoption for steel surface-defect detection in steel fabrication is limited by the scarcity of labelled data, high variability in defect characteristics, and reduced model reliability under real operating conditions. The authors in [34] emphasized further obstacles for adopting AI and digital technologies in the steel industry, including concerns about system reliability and data security, the lack of compatible technologies, and broader organizational barriers to digital integration. The study in [33] examined AI-driven surface defect detection in steel manufacturing and emphasized two challenges: the need for models that remain robust under the noisy and variable conditions of industrial environments, and the importance of explainable AI techniques to improve transparency and build user trust in model decisions. These challenges are summarized in Table 2, which outlines the main barriers to effective AI adoption in steel fabrication.

Table 2 Key challenges of AI adoption in steel fabrication

Item	Key Challenges	Key Literatures
1	Non-standardized input data and data collection systems	[30,31]
2	Limited supply-chain integration	[31,34]
3	Lack of AI-skilled workforce	[31]
4	AI reliability limitations and model robustness concerns	[30,33,34]
5	High implementation cost	[34]
6	Limited transparency and explainability of AI models, reducing trust in practical applications	[33]

3 Methodology

This study was informed by the literature review presented in Section 2. Relevant studies were identified through keyword-based searches in Web of Science, Scopus, and Google Scholar using terms such as AI, construction, steel fabrication, and automation. The retrieved studies were screened based on their relevance to AI applications and adoption challenges in construction and steel fabrication, and the most relevant publications were combined to create a research background. To further examine and validate both the opportunities and challenges of AI adoption in steel fabrication, this study conducted a virtual focus group with industry professionals. The session involved 8 experts from steel fabrication companies located across the U.S., drawn from a sample of companies that have adopted or plan to adopt AI in steel fabrication. Focus group discussion methodology is widely employed as a qualitative approach for examining not only what people think, but also how and why they hold certain perspectives [35]. In practical terms, the focus groups consist of panels, facilitated by a moderator, where participants share experiences, knowledge, and thoughts on specific themes, generating insights through natural conversation, questioning, and explanation. The participants were recruited through a combination of snowball sampling, consistent with the approved IRB protocol, by inviting professionals from the research team's industry network, identifying steel fabrication professionals on LinkedIn, and then asking potential participants to recommend additional qualified experts. A semi-structured format was used to guide the discussion around the study's research questions, allowing participants to shape the dialogue rather than respond to rigid questioning. The focus group questions are categorized into two parts: (1) demographic questions that gathered information about participants' roles, years of experience, company characteristics, and familiarity with AI; (2) study questions that explored the participants' views on AI, examples of its current or potential use in fabrication processes such as cutting and marking, drilling and punching, dimensional inspection, welding, defect detection, quality assurance/quality control (QA/QC), and surface treatment, as well as the opportunities they observed, challenges encountered, and expectations for the future of AI in steel fabrication. The focus group session lasted about 60 minutes and was conducted virtually using Zoom teleconferencing platform to allow participation from multiple locations. With participants' consent, the session was recorded and transcribed for analysis. The audio-video recording was transcribed using Zoom's auto-generated transcription feature, with additional manual review and correction to ensure accuracy. The transcripts were analyzed using thematic analysis to identify recurring patterns and organize the findings according to the study's objectives on opportunities and challenges of AI adoption in steel fabrication. This approach ensured the results were based on real industry practice and reflected professionals' actual experiences rather than theoretical assumptions. NVivo was used to code, organize, and synthesize the transcript data for thematic analysis. The research protocol was approved by the Virginia Tech Institutional Review Board (IRB) under protocol #25-569.

4 Results

A total of eight (8) industry professionals participated in the focus group. Participants represented two sectors, fabrication shops and engineering firms, and held diverse positions including president, vice president of operations, project engineer, executive or owner, and structural engineer. Professionals from engineering firms were included because they are involved in design modeling and detailing, which influence the fabrication workflows and the use of AI in steel fabrication. Half of the participants (50%, 4 people) were employed in large companies with 251–500 employees, while equal proportions (12.5%, one person each) worked in smaller (11–50 employees), small-to-mid (51–100 employees), mid-sized (101–250 employees), and very large firms with more than 501 employees. The experts were in various U.S. states including Virginia, Delaware, Kentucky, Maryland, North Carolina, and Pennsylvania. Most participants had over 10 years of professional experience in steel fabrication (75%, 6 people), while equal shares (12.5%, 1 person each) had 3–5 years and 6–10 years of experience. Regarding AI familiarity, 37.5% (3 people) of participants reported being very familiar and another 37.5% (3 people) moderately familiar with AI in general, whereas 25% (2 people) indicated slight familiarity. However, familiarity levels decreased when referring specifically to AI applications in steel fabrication, where half of the participants (50%, 4 people) described themselves as moderately familiar and the remaining half (50%, 4 people) as slightly familiar.

4.1 Focus Group Findings

The participants represented diverse roles, experience levels, and organizational contexts, and the discussion produced recurring themes across participants. Table 3 summarizes the opportunities for AI adoption in steel fabrication identified during the focus group and their frequency of mention. In total, 7 main opportunities were identified, 3 of which align closely with the ones discussed in the literature review in Section 2.3.

Table 4 summarizes the key challenges of AI adoption in steel fabrication discussed during the focus group; 10 key challenges were identified, 6 of which are consistent with those identified in literature in Section 2.4.

Table 3 Identified key opportunities

Item	Key Opportunities		Frequency of Mentions
1	Enhancing precision and efficiency in fabrication processes	Robotic welding for repetitive tasks	4
		Robotic welding enhanced by AI visual sensing	2
		Fitting	2
		Surface treatment	1
		Sorting	1
		AI assisted robotic welding programming	1
2	Supporting accurate prediction of project costs and performance outcomes		2
3	Strengthening defect detection and quality assurance mechanisms	Defect detection	3
		QA/QC	2
4	AI integration in girder and beam builder assembly		3
5	Long-term expansion of AI in fabrication processes		2
6	AR-enabled layout and inspection within AI-enabled workflows		2
7	Miscellaneous opportunities (See Section 5)		One for each item

Table 4 Identified key challenges

Item	Key Challenges	Frequency of Mentions
1	AI reliability limitations and dependence on training data	4
2	Material or dimensional inconsistencies and tolerance issues	4
3	Lack of standardization in connection design workflow	3
4	Robotic limitations for non-repetitive tasks	3
5	Incomplete design models	2
6	High implementation cost	2
7	Non-standardized data collection system	2
8	Lack of standardized input data	2
9	Limited supply-chain integration	2
10	Miscellaneous challenges (See Section 5)	One for each item

5 Discussion

As discussed in previous section, through the qualitative analysis of the focus group discussion, seven (7) key opportunities and ten (10) key challenges were identified. The key opportunities are discussed as follows:

- ***Enhancing Precision and Efficiency in Fabrication Processes*****:** Participants highlighted that AI can enhance precision and efficiency across several steel fabrication stages, including robotic welding, fitting, dimensional inspection, surface treatment, and sorting. Among these, robotic welding was most frequently cited as an area of significant advancement. Some experts mentioned that AI-driven automation systems, such as the Fanuc R-J3iB robotic welder, are already improving repetitive fabrication operations. However, they noted that these systems still face limitations when applied to complex fabrication tasks. Participants also explained that AI-integrated CAD/CAM machinery is increasingly used in sorting and fitting processes, particularly in large-scale and repetitive production where standardization supports efficient automation.
- ***Supporting Accurate Prediction of Project Costs and Performance Outcomes*****:** Two participants stated that AI-based estimation and cost prediction can streamline the early stages of steel projects. They viewed AI as a valuable advancement for enhancing quantity takeoffs,

sales forecasting, and production tracking across fabrication operations. None of the participants reported having experience with AI-based cost-estimating tools; however, they expressed that other fabricators in the industry have used such tools (e.g., SketchDeck), which may have potential benefits in improving early cost estimation.

- ***Strengthening Defect Detection and QA/QC Mechanisms*:** The focus group participants believed that AI-driven visual perception and image analysis can enable automating detection of defects and inconsistencies, allowing them to adapt their operations in real time. One participant mentioned new software solutions such as STRUMIS that is using AI to streamline steel fabrication processes and defect detection. Therefore, such capabilities can directly strengthen QA/QC mechanisms in steel fabrication.
- ***AI integration in girder and beam builder assembly*:** Some participants stated that "a lot of the major producers of CAD/CAM equipment now have basically girder-builder or beam-builder assembly plants, and it's really impressive the way it's going," highlighting the growing potential of machine-based assembly lines to automate repetitive fabrication tasks. This shows potential for integrating AI within automated girder- and beam-builder systems.
- ***Long-term expansion of AI in fabrication processes*:** Focus group participants highlighted the expected expansion of AI adoption across steel fabrication processes, within "in five to ten years" that is "organically coming… and going to evolve" and "it's going to be a whole new world". One participant emphasized that from the actual making of parts all the way through to the end, most, if not all, aspects of fabrication, especially when it's large-scale replication, can benefit from AI, which makes the fabrication process "limitless", indicating the broad potential of AI.
- ***AR-enabled layout and inspection within AI-enabled workflows*:** Focus group participants also explained the potential of immersive environment technologies that are used frequently in steel fabrication. One participant explained the use of AR technologies for QC, layout, and fitting, using a headset or an iPad "where you're looking at the physical piece and then it's overlaying the information out of the model onto it for a comparison", which can be further enhanced by AI-based techniques such as computer vision for object recognition and alignment, highlighting the potential of immersive technologies for layout and fitting as well as quality control in steel fabrication. They also mentioned this technology, while helpful, it causes safety concerns too.
- ***Miscellaneous Opportunities*:** One of the experts viewed automated shop-drawing generation as an opportunity for applying AI in steel fabrication, highlighting that "we are going to have shop-drawings supplied to us; they will automatically be done once they go to the next stage by the engineer." One of the participants also expressed "robotic machines that can pick up pieces and deliver them to the main member" show the clear potential for AI-assisted material handling in fabrication operations. Another participant suggested that automation is advantageous in large-scale fabrication environments. One expert observed that "they track a lot of different things that AI could make these data make sense to everybody and highlight improvement areas," illustrating an opportunity for AI in steel fabrication. A different expert explained that increased standardization through automation is additional benefit of AI adoption in fabrication. Another participant noted that integration with BIM and 3D models is supported by the observation that "we can get a model from the structural engineer and put that model in our system to drive automated estimating and production."

A comparison of the focus group results with the identified opportunities in literature shows clear areas of alignment. Both sources consistently emphasize that AI can improve precision, increase efficiency, strengthen defect detection, and support more accurate cost and performance prediction across fabrication workflows. These themes appear repeatedly in the reviewed studies in literature, particularly in the research on laser processing, welding automation, and AI-driven inspection. The focus group confirmed these opportunities while adding several that the literature mentions only briefly or not at all. Participants described the growing interest in integrating AI into girder and beam builder assembly lines, the use of VR and AR for layout and inspection, and the value of AI-assisted material handling and automated shop-drawing generation. They also highlighted the broader potential of data analytics for process improvement and the role of increased standardization in enabling automation. These practice-based insights point to emerging applications that have not yet been fully captured in academic work.

In what follows, the key identified challenges are discussed:

- ***AI Reliability Limitations and Dependence on Training Data*:** Some participants expressed uncertainty about the reliability of AI systems. They explained "the reliability of AI is based off of how well you train" the AI model. Two focus group participants referred to the example of robotic welding where if there is "3.16 to an inch weld and there is a gap there the robot will not understand that" and in that instance it is an American Welding Society (AWS) criteria but "a human will know I can add an extra pass to fill the gap … [to] close that gap and but the AI hasn't". This highlighted that the accuracy and quality of training data directly influences AI performance in steel fabrication.

- ***Material or Dimensional Inconsistencies and Tolerance* Issues:** Focus group participants explained that a major barrier to implementing technology in steel fabrication is due to the shape inconsistency and dimensional inconsistency from the mills. They expressed that "the tolerances within ASTM A6 need to be tightened up" for "the material we're getting from the mills". ASTM A6 is a standard for rolled structural steels that ensures all structural steel products from different manufacturers meet the same baseline quality and dimensions. One of the experts explained that the accuracy of robotic operations in steel fabrication is constrained by inconsistent mill tolerances. For instance, if a plate is not cut precisely to its specified dimensions, the robotic welder may fail to detect and fill the gaps resulting from these tolerances; however, a human welder can visually identify the gaps and fill them through manual welding.
- ***Lack of Standardization in Connection Design Workflow*:** Participants pointed out that connection design varies widely across projects and fabrication shops. One noted that "connection design preferences were driven by the equipment we had on the shop floor," and explained how robotic fitting has affected connection design from bolted clip angle to flat plate work "because the robotic arm handles flat plates". Participants remarked that "in the bridge work, you don't delegate connections." And there is a different avenue for that. These differences illustrate the broader lack of a standardized connection design workflow. This lack of standardization limits the applicability of AI, as data-driven models require consistent design patterns and structured inputs to perform reliably across projects.
- ***Robotic Limitations for Non-Repetitive Tasks*:** Focus group extensively elaborated that current robotic systems perform efficiently on repetitive fabrication tasks but face difficulties when dealing with variable geometries and unique structural configurations. Participants also specified that there are some challenges in working with complex geometries. As a result, AI-driven robots still lack the adaptability required for non-repetitive fabrication tasks and when using AI-enabled robots in "fabricating items that are very different from each other, it actually takes longer".
- ***Incomplete Design Models*:** One of the participants emphasized the importance of 3D models in some projects that the clients, such as Department of Transportation (DOT), require the models as "legal document", and noted that in some projects, such as bridges, there is no delegated connection design, and everything is based on the model. Also, the experts noted that many design models prepared by engineers lack sufficient details and "aren't complete enough … to a high enough level of development to have everything in it". As a result, AI-based estimation cannot fully rely on existing design models due to their limited completeness and level of development.
- ***High Implementation Cost*:** Participants noted that the high implementation cost is one of the major barriers to AI adoption in steel fabrication. They agreed that companies will adopt AI when it demonstrates measurable savings, reinforcing the need for cost-benefit justification.
- ***Non-Standardized Data Collection System*:** One participant explained that the industry collects data in many ways, which creates major inconsistencies. As one explained, "we do it by person by shop by location by different types, so all this data is available," while another added that "the way that we collect that data is not easily integrated into the current way that some of these AI's work." Together, these points indicate that the challenge lies not in data availability but in the lack of a standardized data collection system.
- ***Lack of Standardized Input Data*:** Participants noted that the main difficulty lies in inconsistent data formats rather than data quantity or availability. One participant explained that "the format of the data and the way it is set up is the real challenge," and identified that "where most people are going to struggle is how [to] use the data they have" and another added that when older or differently detailed drawings are uploaded, "the model will see the differences and will not know how to interpret them". These comments highlight a clear lack of standardized input data. Participants explained to mitigate this challenge is "systematically setting up their data so it is able to be ingested into the model or in or used by" the AI models.
- ***Limited Supply-Chain Integration*:** Experts noted that poor digital coordination among mills, fabricators, and contractors, such as inconsistent barcoding, limits the integration of AI across the supply chain.
- ***Miscellaneous Challenges*:** One of the experts viewed data cleaning as one of the major barriers to AI adoption in fabrication. One participant also expressed most workers often are reluctant in AI adoption because of limited digital skills and noted that "they would be pretty hesitant to adapt to using it, to learning it, or to engaging with things of that nature." Another participant explained that many companies lack personnel with the technical expertise to implement AI, highlighting a broader shortage of skilled workforce and he emphasized that "having someone capable of implementing AI is often just a coincidence, and companies usually need to hire people who can work with AI if it is going to save the company's money".

The comparison of challenges reveals substantial overlap between literature and the focus group, particularly regarding non-standardized input data and data collection systems, limited supply-chain integration, shortages of skilled personnel, concerns about the robustness and reliability of AI models in real operating environments, and high implementation cost. When the literature-based challenges in Table 2 are compared with the focus-group findings in Table 4, five direct correspondences become clear. Item 1 in Table 2 aligns with Item 7 in Table 4, as both refer to non-standardized data collection systems. Item 2 in Table 2 is consistent with Item 9 in Table 4, which identifies limited supply-chain integration. Item 3 in Table 2 corresponds to Item 10, the lack of AI-skilled workforce noted as a miscellaneous challenge in Table 4. Item 4 in Table 2 aligns with Item 1 in Table 4, where participants emphasized AI reliability limitations. Finally, Item 5 in Table 2 is consistent with Item 6 in Table 4, reflecting shared concerns about high implementation cost. These issues are widely documented in literature and were strongly reinforced by the study participants. In addition, the focus group introduced challenges rooted in daily fabrication practice that are not well reflected in the literature. Participants emphasized inconsistent mill tolerances, lack of a standardized connection design workflow, and practical difficulty robots face when dealing with non-repetitive fabrication tasks, incomplete design models, workforce resistance toward automation, and data cleaning problems. These observations highlight operational and organizational barriers beyond the technical limitations identified in previous research.

6 Conclusion

This paper provided in-depth insight into the opportunities and challenges of adopting AI in steel fabrication within the construction industry. A focus group study was conducted with eight (8) professionals from U.S.-based steel fabrication companies to identify key opportunities and challenges of AI application in steel fabrication. As a result, seven (7) opportunities and ten (10) challenges were identified. Among the top-ranked opportunities, AI was found to improve precision and efficiency across fabrication stages such as robotic welding, fitting, etc. Conversely, the most significant challenges of AI adoption in steel fabrication included AI reliability limitations and dependence on training data, material or dimensional inconsistencies and tolerance issues, lack of standardization in connection design workflow, and the limited adaptability of robots to non-repetitive tasks. While these challenges illustrate the complexity of integrating AI into existing fabrication workflows, the findings also suggest that the steel fabrication industry is gradually advancing toward broader AI adoption, especially as the economic and operational benefits become more apparent. Although this study may not encompass all possible advantages or limitations of AI in steel fabrication, it offers practice-based insights to guide future research. Future research should administer a survey questionnaire to validate the findings of this focus group research with a larger population. Future research can identify how AI models in steel fabrication are trained, especially when training data remain limited, inconsistent, or incomplete. Also, challenges related to incomplete design models, non-standardized input data and data collection systems, as well as the high cost of implementation need further investigation; the future research should focus on improving the completeness of design models, developing standardized input data and data collection frameworks, and evaluating cost-effective strategies for AI implementation in steel fabrication. An additional question about the limited transparency of AI and its effect on participants’ trust in it was not included in this study, as it was considered too technical for this focus group discussion, but it could represent a viable direction for future research especially when AI gains more maturity in the domain of steel fabrication in the construction industry. This study has limitations, including the relatively small number of participants and the potential influence of participant bias or dominant viewpoints in group discussions. In addition, the qualitative nature of the focus group limits the generalizability of the findings; therefore, the findings should be interpreted as exploratory.

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