

PERSPECTIVE ARTICLE

Artificial intelligence and additive manufacturing as a coupled design system: Rethinking inference, manufacturability, and design education

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Abstract

Artificial intelligence (AI) is becoming deeply integrated into additive manufacturing (AM) workflows, reshaping how designers approach geometry, materials, and process constraints. AI holds significant potential by accelerating design exploration, revealing complex patterns in AM behavior, and supporting earlier assessment of manufacturability. At the same time, it introduces new risks related to model transparency, data quality, physical validity, and the potential for overreliance by students and practitioners. This perspective examines these issues through four guiding questions that address the role of AI in AM-enabled design, the gaps that limit or enable AI contribution, the implications for engineering education, and the responsibilities of the research community in ensuring trustworthy and secure AI-AM integration. The main contributions of this perspective include: (i) Highlighting AI and AM as a coupled inference-fabrication system rather than independent tools; (ii) identifying zones of strong interdependence where inference and manufacturability interact; and (iii) articulating implications for design reasoning, education, and responsible research practice.

Keywords: Additive manufacturing; Artificial intelligence-enabled design; Design automation; Artificial intelligence governance

1. Introduction: Design, artificial intelligence (AI), and additive manufacturing (AM)

Engineering design has always been a balancing act between design intent, geometry, material behavior, and manufacturability constraints. Historically, these considerations were often integrated late in development, relying on expert judgment to resolve mismatches between functional goals and manufacturing feasibility, resulting in the common “design–manufacturing mismatch” problem observed in systems engineering and optimal design.^{1,2} AI tools are now helping to reshape this landscape by redistributing reasoning between human designers and computational models, assisting with both sequential and parallel decision-making. In this perspective, we use the term “AI” to include supervised and unsupervised learning, deep learning, surrogate and reduced-order modeling, physics-informed approaches, and large language models when applied to interpret design representations or support analysis tasks. These tools identify relationships in data or simulation and apply them to prediction, generation, or decision support.

AM offers a particularly revealing environment for examining these relationships, since designers using AM must consider geometry, thermal history, microstructure, and mechanical performance. When using AM, designers must account for anisotropy, residual stress, defect formation, melt pool behavior, and post-processing considerations.^{3–7} This coupling (AM–AI) greatly affects the feasible design space, both positively by expanding it and negatively by imposing additional constraints, and increases sensitivity to early decisions. Unlike traditional computer-aided design/computer-aided manufacturing pipelines, where design and manufacturing tools are loosely connected, and information flows primarily in one direction, AI and AM can form a coupled inference–fabrication system, where inference and physical realization continuously shape and constrain each other. The coupling operates along three intertwined dimensions:

- (i) Inference, where AI models shape which regions of the design space are explored.
- (ii) Constraints, where AM physics and manufacturability bounds determine which inferences remain viable.
- (iii) Failure propagation, where small mismatches between model assumptions and process realities amplify into large deviations in realized performance.

The frame of AI and AM in this way emphasizes that design reasoning, process behavior, and manufacturability cannot be cleanly separated once AI participates directly in AM-focused workflows. By focusing on inferences coupled

with manufacturability, rather than evaluating finalized designs, we believe that early-design decision-making will be improved, resulting in lower cost and schedule risk for product and system design. In this conceptualization, AI models reshape the design space by producing predictions of increasing quality as more data are collected, geometric features, or generative outcomes, while AM reshapes the AI learning environment by constraining which predictions remain physically meaningful. This is a key example of a successful application of manufacturability-driven design.^{8,9}

This coupling produces cross-dependence zones, or regions of the design and process spaces where small mismatches between AI assumptions and AM realities can amplify into large deviations in fabricated performance. These zones include regions of high thermal sensitivity, transitions between stable and unstable process–material interactions, and areas where geometric freedom interacts strongly with support generation logic or post-processing requirements. Similarly, AM does not simply benefit from AI; it can also reveal its limitations and failure modes more clearly. These issues extend to engineering education, since students generally encounter AI tools early in their professional training including, but not limited to, large language models often before they have developed the reasoning skills needed to assess manufacturability, uncertainty, and physical validity. This perspective highlights that AI tools and their coupling with AM processes are beneficial only when they support human decision-makers; they should always be used as an aid, not a replacement for human creativity, skill, and experience, or responsible decision-making.

While prior work in design for AM (DFAM), digital twins, and hybrid modeling has addressed aspects of AI-assisted design and process prediction,^{10–14} this perspective proposes a different framing. Specifically, we conceptualize the coupling between inference and fabrication as a primary design driver rather than a background implementation task. The aim of this perspective is therefore not to review AI algorithms or benchmark AM processes, but to articulate how inference, manufacturability, uncertainty, and human judgment become highly coupled once AI participates directly in AM-focused workflows. [Figure 1](#) illustrates the primary couplings, the role of AI, and the limitations of this approach compared with standard DFAM and digital twins.

This perspective offers three major contributions to the discussion regarding AI and AM:

- (i) A conceptual framing of AI and AM as a coupled inference–fabrication system.

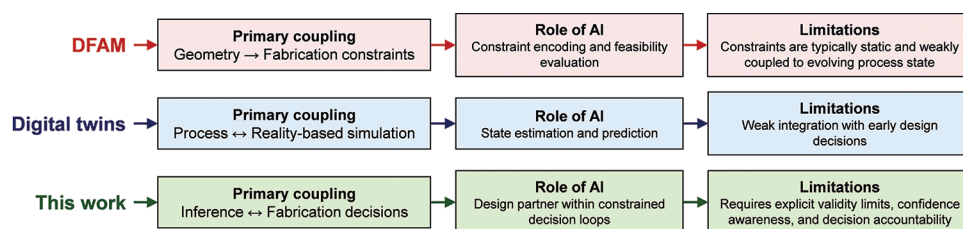


Figure 1. Primarily couplings, the role of artificial intelligence, and limitations of standard design for additive manufacturing and digital twins compared with this perspective. Image created by the authors.

- (ii) Identification of cross-dependence zones where small design or process mismatches can propagate into large performance deviations downstream during the design lifecycle.
- (iii) Discussion of implications for design practice, engineering education, and responsible research.

This framing is intended to guide future methodological development rather than introduce a specific toolset or workflow.

2. AI as a partner in AM-enabled design

The term “AI-enabled design” refers to workflows^{15,16} in which data-driven or physics-assisted models participate in generating, evaluating, or refining design representations or design problem formulations.^{17,18} In contrast, “AM-enabled design” describes workflows^{10,19,20} in which AM capabilities and constraints shape the feasible design space. When these two paradigms are combined, inference and fabrication can no longer be treated as sequential or independent stages. AI outputs directly reshape the space of manufacturable designs, rather than merely evaluating candidate solutions. Within this coupled environment, AI is frequently positioned as an accelerator capable of exploring complex design spaces, predicting failure modes, or recommending process parameters. In practice, this positioning elevates AI from a post-processing aid to a computational partner, whose outputs influence downstream manufacturability, validation burden, and risk exposure.^{12,21,22}

Sparse and heterogeneous data, machine-specific behavior (common with AM processes), and non-linear interactions challenge the mathematical assumptions underlying many AI models. As a result, AI can mistakenly infer correlations rather than physical relationships or generate geometries that violate thermal or mechanical constraints. These breakdowns occur because AM routinely violates the smoothness, stationarity, and data-consistency assumptions on which many AI models implicitly depend. Rather than being exceptional cases, such breakdowns define the conditions under which AI-based inference remains locally useful versus where human oversight and manufacturability-driven reasoning must dominate.

Table 1 provides an overview of the common AM data types and their implications for AI-driven modeling.

Positioning AI tools appropriately requires treating them as computational partners rather than a final decision-maker. This distinction is critical in AM-enabled design, where AI outputs directly influence manufacturability, validation burden, and downstream risk, rather than merely accelerating analysis.^{23,24} In our view, AI in AM-enabled design can be categorized into three major complementary categories as follows (Table 2):

- (i) AI as a predictor uses learned relationships or surrogate models to estimate thermal responses, defect likelihood, distortion, or mechanical performance. These tools improve computational speed but require explicit uncertainty characterization, since the AM process behavior is highly variable. In practice, this implies that predictor models should be used to bound feasible regions of the design space and guide exploration, rather than to certify performance without independent physical validation.
- (ii) AI as a generator proposes geometries, microstructures, or process parameters. These models must explicitly embed manufacturability constraints; otherwise, they risk producing mathematically coherent yet physically unrealizable designs. This is a common risk in generative design and topology optimization tools. When generators operate without embedded process constraints, downstream correction becomes infeasible, and failure risk is merely displaced rather than reduced.
- (iii) AI as an integrator connects information across stages of the AM workflow, linking design, simulation, monitoring, and post-processing. This role remains underdeveloped, but is essential for building coherent, traceable, closed-loop workflows. Integrator models are therefore central to managing uncertainty propagation, model provenance, and decision traceability across the design–fabrication pipeline.

Several emerging frameworks further extend these roles by positioning AI systems as participants in formal decision-making loops, particularly in narrowly scoped,

Table 1. Common additive manufacturing data types and their implications for artificial intelligence modeling

AM data type	Characteristics and challenges	Implications for AI models
Toolpath and G-code	Structured, layer-wise, and discontinuous, reflects machine-specific conventions and support-generation logic	Violates smoothness assumptions and introduces path-dependent behavior related to feature extraction and sequence modeling
Thermal history data	Sparse, noisy, highly sensitive to scan or deposition strategy and material properties, difficult to measure with consistent spatial resolution.	Limits surrogate-model accuracy, reduces generalization across builds, and amplifies dataset bias
Process monitoring	High-frequency, multimodal (optical, infrared, coaxial), and sensor-specific, prone to drift and domain shift	Requires robust pre-processing and domain adaptation. Models must handle non-stationarity and abrupt temporal changes
Microstructure data	Expensive to obtain, limited sampling, strongly condition-dependent. Often paired with expensive, destructive testing	Restricts dataset size for supervised learning and motivates hybrid or physics-informed modeling strategies
Mechanical test data	Low-volume, protocol-dependent, and influenced by build parameters, orientation, and post-processing	Creates bias in learned structure-property relationships, prevents naive transfer learning across materials and processes

Abbreviations: AI: Artificial intelligence; AM: Additive manufacturing.

Table 2. Roles of artificial intelligence in additive manufacturing-enabled workflows, associated failure modes, and safeguards (predictor, generator, and integrator)

AI role	Typical use in AM	Common failure modes	Required safeguards
Predictor	Thermal response prediction, distortion estimation, defect likelihood assessment	Distribution shift, extrapolation beyond training data	Validity limits, confidence awareness
Generator	Geometry generation, process parameter recommendation	Constraint violation, physically unrealistic designs	Manufacturability constraints, human review
Integrator	Workflow linking, data fusion, and traceability across design and fabrication stages	Misaligned data streams, loss of provenance	Traceability, uncertainty propagation

Abbreviations: AI: Artificial intelligence; AM: Additive manufacturing.

highly automated manufacturing contexts. From a technical standpoint, such formulations require well-characterized process windows, validated uncertainty bounds, stable sensor feedback, and decision policies that can be formally verified against physical and safety constraints. At present, implementation of AM processes remains challenging, but we anticipate improvements in the future and are actively working toward this goal. We therefore view fully autonomous AI-driven decision-making in AM as a future research direction rather than a current design paradigm for AM-enabled systems, and argue that final decision authority should remain with human designers until these technical pre-conditions are reliably met across machines, materials, and deployment contexts.

Because AM workflows are fragmented, integrator models are the least mature but represent the greatest opportunity to advance reliable AI-AM co-design. Hybrid

workflows that combine AI inference with physics-based reasoning and human oversight are clearly necessary. Figure 2 illustrates a conceptual view of this coupling. Specifically, it illustrates how AI-based inference interacts with AM process constraints across the design, fabrication, and validation stages, and highlights regions where inference errors and manufacturability constraints strongly interact. In practice, this coupling depends on integrating heterogeneous AM data types, including geometric representations, process parameters, *in situ* sensor streams, and post-build inspection data, into a coherent inference-decision loop. Breakdowns in this integration tend to occur in cross-dependence zones, where small mismatches in assumptions or data fidelity can amplify into large deviations in fabricated outcomes.

AI can add value when it strengthens human design thinking driven by manufacturability and can decrease value when it obscures physical constraints or encourages overconfidence in incomplete models. These roles map directly onto AM constraint pathways, with predictors tied to process physics, generators tied to geometry and material behavior, and integrators tied to workflow traceability. Integrator models are particularly sensitive to gaps or inconsistencies in these data flows, as missing provenance or uncertainty information can propagate errors across the design-fabrication pipeline. Operationally, identifying these high-sensitivity regions early becomes a design objective, informing where additional validation, sensing, or human oversight is required. The same AI-AM coupling logic extends naturally to adjacent domains, such as industrial automation, where AM-enabled components, robotic deposition systems, and offline programming workflows introduce similar inference-realization feedback loops. In these contexts, AI-enhanced digital twins and surrogate models can accelerate automation system design and commissioning, but only when they

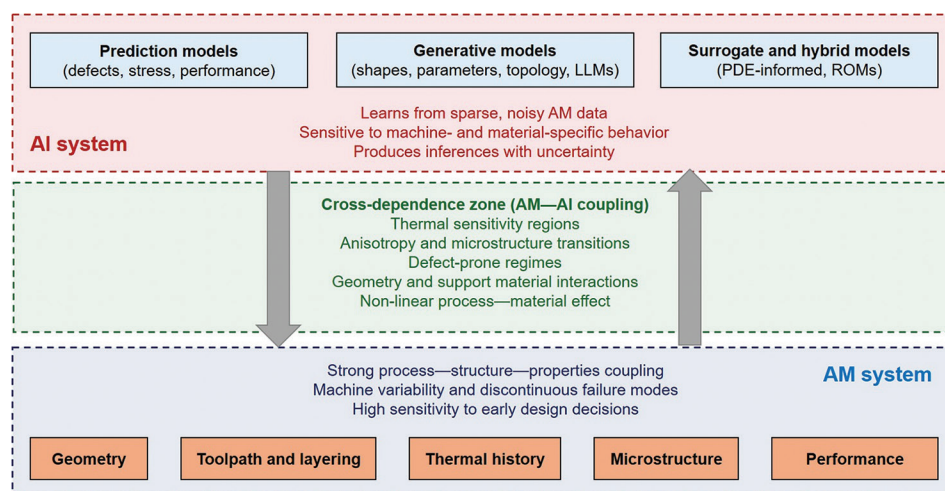


Figure 2. Conceptual illustration of AI and AM as a coupled inference–fabrication system, highlighting AI model roles, the AM process chain, and the cross-dependence zone. Image created by the authors.

Abbreviations: AI: Artificial intelligence; AM: Additive manufacturing; LLM: Large language model; PDE: Partial differential equations; ROM: Reduced order model.

remain grounded in the physical constraints, assembly logic, and control realities of the deployed manufacturing systems.

3. AM workflows: Opportunities and limitations for AI

AM introduces several gaps that simultaneously create opportunities for AI and constraints that limit its reliability. This section synthesizes these gaps into a small number of recurring failure mechanisms that arise specifically from the coupling between inference and fabrication, rather than from AI or AM in isolation. The primary gap (which we consider the most important) is data quality, since data from the AM process are often sparse, noisy, and inconsistently recorded across machines and facilities. The fact that almost all AM processes operate with open-loop control systems is a major reason for these data issues. Toolpaths, thermal histories, consolidation and layering artifacts, and meso/microstructural behavior vary between builds and even between nominally identical machines in the same operating environments. AM also produces data types that are far more complex than those found in conventional processes, including thermal fields, scan vector time series, melt pool signatures, defect-localization maps, and geometry-linked toolpath encodings. These datasets vary between machines and materials and often contain noise, missing information, or inconsistent spatial and temporal resolution.^{25,26}

As a result, AI models trained on nominal datasets are frequently exposed to distribution shifts that are difficult to detect before fabrication.²⁷ AM physics violates several

assumptions underlying common AI models non-linear thermal behavior, path-dependent melt dynamics, and abrupt transitions between stable and unstable regimes violate smoothness and stationarity assumptions used in many learning algorithms. As a result, AI models may infer relationships that are only locally valid and fail unpredictably under modest changes in geometry, scan strategy, or process conditions. These failures are rarely catastrophic on their own but become consequential when embedded in coupled design–fabrication workflows.

Some of the major interactions that we have observed in our previous studies and literature reviews are shown in Table 3. Although this perspective primarily refers to metal powder bed and extrusion-based processes as canonical examples, the coupling phenomena described here extend to polymer, composite, ceramic, binder jet, and large-format AM processes, each with its own characteristic data structures and process–geometry interactions. Table 3 summarizes these interactions by explicitly showing how AM characteristics shape AI behavior and how AI, in turn, reshapes AM workflows.

However, these same limitations create opportunities for hybrid modeling, as combining sparse experimental data with physics-informed or simulation-trained surrogate models can improve predictive reliability. AI can also detect patterns in multi-sensor monitoring data that are difficult to identify manually, supporting early detection of overheating, void formation, or mechanical collisions or interferences during processing. The same mechanisms that enable these benefits also define characteristic failure modes when assumptions are violated or uncertainty

Table 3. Key two-way interactions between artificial intelligence and AM in coupled inference–fabrication workflows

Coupling dimension	How AM shapes AI	How AI shapes AM
Data characteristics	Sparse, noisy, and machine-specific AM data challenge generalization and stability in learned models; unmodeled physics creates discontinuities.	AI improves data usability by filtering noise, creating surrogates, integrating multi-sensor streams, and forming structure–process–property links
Constraint representation	AM imposes geometric, thermal, and process constraints that limit which AI-generated designs are physically meaningful	AI enables early constraint evaluation, manufacturability indices, and real-time assessment of geometric or thermal feasibility
Failure modes and uncertainty	Process variability, anisotropy, and defect formation expose weaknesses in AI prediction and amplify extrapolation risks	AI assists in predicting failure modes, propagating uncertainty, and identifying vulnerable regions in design or process spaces
Workflow integration	Fragmented AM workflows with disconnected data streams restrict the impact of AI models	AI can unify stages through closed-loop reasoning, cross-stage feedback, and adaptive process control
Human decision-making	AM requires designers to maintain physical intuition, making AI hallucinations or misleading correlations more dangerous	AI augments human reasoning by exploring complex design spaces, automating routine tasks, and highlighting non-intuitive patterns

Abbreviations: AI: Artificial intelligence; AM: Additive manufacturing.

is ignored. AM also introduces distinct AI failure modes compared with those observed in conventional manufacturing. In general, the failure modes observed in both the literature and in our own research work can be categorized into four major categories:^{24,28}

- (i) Data failure modes arise when models trained on one machine or material are applied elsewhere, violating assumptions of stationarity for the AI models. These failures are often subtle and hard to observe early, as degraded prediction confidence or inconsistent trends, rather than obvious errors.
- (ii) Constraint failure modes occur when AI-generated geometries violate support generation logic, produce thermally unstable regions, or create shapes incompatible with process mechanics or post-processing requirements. It is commonly thought that AM processes have few, if any, geometric restrictions, but this is far from true. The process constraints are different from those seen in subtractive or formative manufacturing, but they certainly exist. Such failures are especially difficult to detect when AI-generated outputs appear visually plausible but are physically unrealizable.
- (iii) Semantic failure modes emerge when AI treats geometry as an abstract representation rather than a sliced, toolpath-dependent entity. In these cases, models may optimize nominal geometry while inadvertently degrading manufacturability or process stability.
- (iv) Workflow failure modes occur when timestamps, sensor streams, or intermediate representations are misaligned across tools, leading to incorrect inferences (such as predictions about performance) or lost provenance. These failures are amplified in fragmented workflows where assumptions and uncertainty are not explicitly carried across stages.

Identifying and naming these modes is essential for developing validation strategies, benchmarking AI behavior, and training students to detect unrealistic output before fabrication. As a group, these categories provide a compact framework for reasoning about where AI–AM coupling is most vulnerable and where additional validation effort should be focused. This leads to another major gap: Workflow fragmentation and interpretability. AM workflows typically separate design, slicing, simulation, monitoring, and post-processing, with limited continuity of data or uncertainty information. AI introduced in one stage of the design process cannot compensate for missing or incompatible information from earlier stages. Meaningful integration, therefore, requires redesigning workflows around traceability, uncertainty propagation, and cross-stage feedback. Designers must understand not only what a model predicts, but why it predicts it, and how sensitive the prediction is to uncertainty. Without such interpretability, AI accelerates error propagation rather than mitigating it, particularly in cross-dependence zones identified earlier.

The coupling of AI inference and AM has direct implications for certification, qualification, and regulatory acceptance of AM components, particularly in safety-critical or high-consequence applications. In contrast to conventional qualification approaches, AI-assisted AM workflows increasingly rely on adaptive models whose predictions may evolve with data, architectures, or operating conditions. Within this context, AI offers clear potential value for defect detection, process monitoring, and traceability. Models applied to *in situ* sensor data, post-build inspection results, and process logs can assist in identifying defects, unstable process regimes, or anomalous behavior that may be difficult to detect manually. When coupled with appropriate provenance tracking, such

approaches can strengthen traceability by linking observed defects or performance deviations to specific toolpaths, process parameters, or design decisions. Integrated digital records that capture model versions, process histories, sensor data, and post-processing steps can further support regulatory confidence by enabling auditors to reconstruct how a component was produced and evaluated. However, the reliability of these approaches depends critically on the quality of data, sensor calibration, and the consistency of data representations across machines, materials, and builds.^{25,26}

Uncertainty quantification and risk awareness play a central role in determining whether AI outputs can meaningfully support certification decisions. Predictions of defect likelihood, material properties, or geometric distortion are only actionable for qualification if their associated uncertainty bounds are interpretable and defensible. In the absence of robust uncertainty estimation, AI models risk providing overconfident predictions that obscure extrapolation or process variability, undermining certification rather than supporting it. These risks are amplified in safety-critical contexts, where distribution shifts (similar to those seen in statistical quality control), hidden biases in training data, or limited model explainability may lead to unpredictable failure modes. As emphasized in trusted AI frameworks, certification strategies must therefore bound the scope of AI autonomy, rely on human oversight for critical decisions, and ensure that failure modes are detectable before fabrication or deployment. In this sense, AI should be viewed as an augmentative tool that supports qualification and compliance workflows rather than as a substitute for established certification practices. Responsible integration requires aligning AI capabilities with physical grounding, traceability, and accountability, consistent with the coupled inference–fabrication framing advanced in our perspective discussed here.^{7,29}

4. Supporting responsible and effective design education

AI-enabled tools allow students to generate and refine AM designs early in their training, but this can widen the gap between what students can produce digitally and what they can justify or fabricate.³⁰ This gap represents a central educational risk of uncritical AI adoption: Students may produce outputs that appear sophisticated without developing the underlying physical or manufacturing reasoning needed to assess their validity. Engineering education must therefore shift from teaching tool operation to teaching reasoning with and about AI systems. Students must learn to interrogate AI outputs, evaluate

uncertainty, and recognize when a model is extrapolating beyond reliable data or is clearly physically unrealistic. Without these skills, AI tools risk accelerating superficial competence rather than deep engineering understanding. This mirrors the principles of manufacturability-driven design discussed above, in which students learn to treat physical feasibility as a primary design constraint rather than a late-stage check. To support this shift, students need a core set of AI-informed design competencies.

Table 4 presents an overview of major core competencies expected from engineering students using AI–AM workflows, which we recommend integrating into engineering curricula. These include interpreting model outputs in the context of AM process physics, assessing uncertainty, sensitivity, and data relevance, recognizing when AI-generated suggestions violate manufacturability constraints, and tracing how design choices propagate forward into thermal behavior, defect risk, and post-processing requirements.

Importantly, these competencies emphasize judgment and interpretation rather than optimization or automation. This requires instruction in manufacturability reasoning, sensitivity analysis, constraint interpretation, and physical drivers of AM behavior, such as thermal gradients, anisotropy, void formation, and heat accumulation. This instruction does not have to focus on deep and complex mathematical formulations, but can be integrated as a concept into coursework to help students develop practical intuition. An overemphasis on algorithmic sophistication without corresponding physical grounding risks reinforcing misplaced confidence in AI-generated results. This could range from introductory courses such as a first computer-aided design course or lower-level survey courses on design and manufacturing to capstone projects and professional development courses for practicing engineers.

Bridging the gap between K–12 education and engineering increasingly requires hands-on learning experiences that emphasize physical reasoning alongside computational tools. While many AI learning kits rely primarily on programming-based instruction, an important challenge is developing educational platforms that expose students to physical AI systems whose outputs are constrained by fabrication, sensing, and performance limits.^{31,32} Several studies have shown that customizable and open-source platforms can introduce AI concepts through actual physical systems (with and without the use of AM) rather than abstract code alone.³³ However, previous studies have also noted challenges related to educator preparation and curricular alignment, reinforcing the need for educational pathways that explicitly connect inference,

Table 4. Core competencies for engineering students working with artificial intelligence- and additive manufacturing-enabled design

Competency area	Skills needed	Why does it matter?
Interrogate AI outputs	Assess uncertainty, interpret model limits, and identify when AI tools are extrapolating or producing unreliable recommendations	Prevents uncritical acceptance of predictions that may violate AM physics or fall outside the model's training regime
Connect AI predictions to physical drivers	Relate AI-generated insights to thermal behavior, anisotropy, defect formation, and distortion mechanisms	Ensures students ground digital suggestions in the physical realities of AM processes
Evaluate manufacturability early	Apply manufacturability-driven design reasoning and minimally restrictive constraints during concept development	Reduces late-stage mismatch between AI-generated concepts and feasible AM fabrication
Diagnose AI failure modes	Recognize data, constraint, semantic, and workflow failures when using AI in AM contexts	Builds engineering judgment by helping students identify and correct sources of misalignment between inference and fabrication
Interpret AM data structures	Understand toolpaths, layer-based geometry, monitoring signals, and microstructure data	Enables correct model selection, reduces data misuse, and supports reliable AI integration
Work in integrated workflows	Maintain provenance, track design-to-build decisions, and link computer-aided design, slicing, simulation, and inspection data	Reflects real AM practice and supports trustworthy, traceable AI-enabled design
Ethical and security awareness	Identify risks related to data integrity, malicious model manipulation, and intellectual property leakage	Protects against vulnerabilities in increasingly digital and AI-assisted AM pipelines
Understand AI models and their applications	Understand the underlying assumptions, applications, advantages, and limitations of different AI algorithms	Prevent the implementation of incorrect models where they are not applicable and ensure the application of only relevant models

Abbreviations: AI: Artificial intelligence; AM: Additive manufacturing.

uncertainty, and physical constraints rather than treating AI as a standalone capability.³⁴

Students must also understand the reciprocal nature of AI and AM. AI-generated geometries must be assessed for process compatibility, and AM data used for AI training must be evaluated for quality and relevance. Explicitly teaching this reciprocity helps counter the misconception that AI outputs are inherently authoritative or universally transferable. Purposefully examining AI system failures such as incorrect overhang predictions, unrealistic support structures, or unstable scan strategies builds essential engineering judgment rather than tool dependence. This approach directly addresses the risk of cognitive offloading, where students may otherwise bypass rigorous analysis by accepting AI outputs as authoritative rather than provisional. Cognitive offloading is particularly problematic in AM contexts, where fabrication costs and failure consequences are non-trivial. AM-specific instructional strategies can strengthen student competency, such as assignments that require a side-by-side comparison of AI predictions with finite element simulations or fabricated outcomes, helping students diagnose why models fail. Structured “AI failure audits,” in which students analyze distorted or defective prints, encourage critical thinking about model assumptions and data quality.^{35,36}

By requiring students to articulate why an AI-generated optimization succeeds or fails, these activities reinforce

reflective skepticism and self-regulation as core engineering skills. Courses can also integrate AI-generated manufacturability indices, requiring students to justify whether such indices align with physical principles. This emphasis on justification rather than acceptance reframes AI as a support for engineering reasoning rather than a substitute for it. This also helps students learn important intuitive reasoning about engineering models, viewing them not as design products or final artifacts in themselves but rather as imperfect but useful representations of reality that support human judgment and decision-making. Assessment and grading frameworks should evaluate not only student output, but also their reasoning processes, including how they validated AI suggestions and reconciled them with known manufacturability constraints. Explicit evaluation of reasoning quality discourages performative optimization and reinforces accountability for manufacturability-aware decisions.

5. Community responsibilities

Because AI–AM systems couple inference and fabrication in ways that amplify error, responsibility in this context is not abstract or ethical alone, but also directly technical and procedural. The research community is central to ensuring that AI–AM integration advances engineering practice and that concepts and workflows it develops eventually become useful engineering tools with an ultimately positive social

impact. Trustworthy integration requires shared standards, transparent workflows, responsible data practices, and realistic communication about model limitations.³⁷ In our view, there are five key ways that fellow design, AI, and manufacturing researchers can positively contribute to this development:

- (i) Researchers must work to improve data quality, quantity, accessibility, and traceability. Standardized representations of toolpaths, thermal histories, sensor signatures, and defect data are essential for reproducible research. Shared ontologies and benchmark datasets enable meaningful cross-machine evaluation.
- (ii) Hybrid modeling approaches that integrate physical models with learned or formulated design representations are crucial. Purely data-driven models are rarely sufficient for AM due to non-linear process physics, machine-specific behavior, and sensitivity to initial conditions.
- (iii) Interpretability and validation/verification frameworks must be established. AI tools used for AM must explain why they propose certain geometries or process parameters and must quantify uncertainty in ways compatible with engineering decision-making. Validation should consider robustness, physical plausibility, and sensitivity, not just prediction accuracy.
- (iv) Secure and reliable digital workflows are required. Compromised training data, corrupted model files, or manipulated design representations can produce unsafe results. Secure pipelines, provenance tracking systems, and verification tools are essential for a trustworthy integration and proper physical and cyber security.
- (v) Researchers must communicate realistic expectations. The overstatement of AI capabilities encourages inappropriate use, while the understatement discourages meaningful innovation. Clear communication supports responsible adoption across education and industry. It is important to recognize that these efforts should ultimately serve broader societal benefit.

If these directions are adopted, we can define a clear research agenda for AI-AM integration, one that centers on physically grounded models, standardized representations, secure workflows, and interpretable methods capable of supporting reliable design decision-making. These responsibilities emerge directly from the coupled inference-fabrication framing in this perspective and are therefore essential for ensuring that AI strengthens rather than undermines manufacturability-aware design.

6. Call to action: Building a responsible framework

The integration of AI and AM marks a pivotal transition in design practice, not because either technology is new, but because together they reshape how inference, manufacturability, and physical realization interact. In summary, this perspective argues that the primary challenge is not whether AI can be applied to AM, but how inference and fabrication are coupled, validated, and governed as unified design systems. The central contribution of this work is the framing of AI and AM as a coupled inference-fabrication system, in which uncertainty, manufacturability constraints, and human judgment are inseparable.³⁸ The needs surrounding this integration can be organized into a four-pillar framework for responsible AI-AM integration:

- (i) Transparency requires that models reveal their assumptions, uncertainty, and decision pathways.
- (ii) Traceability ensures that model lineage, design histories, and data sources remain connected throughout the entire workflow.
- (iii) Physical grounding embeds AM process physics, constraints, and invariants directly into the model structure.
- (iv) Education and readiness for the workforce ensure that engineers and designers develop the judgment needed to responsibly evaluate and guide AI behavior.

Reliable AI deployment requires workflows designed for standardized data exchange, uncertainty propagation, and cross-stage verification. AM workflows must evolve from fragmented tool chains into integrated systems where decisions and model versions can be traced, interrogated, and validated. Engineering programs must prepare students not only to operate AI tools, but also to critique them, recognize and diagnose failure modes, and compare algorithmic suggestions against physical reasoning. At the research level, the community must advance hybrid modeling approaches, develop rigorous validation and interpretability frameworks, and establish cybersecurity practices that protect increasingly digital AM ecosystems. These responsibilities include creating benchmark datasets, articulating model limitations, and developing open standards that support trustworthy AI-AM integration. From this perspective, several urgent research challenges emerge that must be addressed to enable responsible and reliable AI-AM systems, including:^{7,23}

- (i) Formal representation and propagation of uncertainty across coupled AI-AM workflows, rather than reporting uncertainty at isolated stages.
- (ii) Robust generalization of AI models across machines, materials, and operating regimes, in the presence of sparse and non-stationary AM data.

- (iii) Verification and validation of AI-assisted design decisions in workflows where inference directly constrains fabrication outcomes.
- (iv) Development of educational and institutional practices that prevent uncritical AI adoption while preserving human accountability for manufacturability-aware decisions.

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