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PERSPECTIVE ARTICLE

Language models to assess printability in additive manufacturing: a future perspective

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Abstract

Large language models and vision-language models have the potential to change how printability is assessed in additive manufacturing. By learning from the rapidly expanding body of literature, process logs, simulation outputs, and image-based defect data, these models can move printability evaluation from trial-and-error experimentation to scalable, knowledge-rich reasoning across materials and processes. They can classify and explain defects, link them to process–parameter choices, and act as intelligent supervisors that suggest targeted process-variable adjustments while integrating physics-based simulations and specialized machine-learning models. At the same time, realizing this potential requires new multimodal printability datasets, physics-preserving algorithms, rigorous uncertainty quantification, and benchmarking frameworks, as well as exploration of advanced computational infrastructures, including quantum-inspired approaches for high-dimensional optimization. This perspective outlines how language models can capture human expertise, unify heterogeneous data, and enable more reliable, data-driven printability decisions for next-generation metal additive manufacturing.

Keywords: Large language model; Vision-language model; Machine learning; Defects; 3D printing; Quantum computing; Uncertainty quantification

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1. Introduction

Printability in additive manufacturing (AM) refers to the ability of a given material–process combination to produce defect-free, dimensionally accurate, and structurally reliable parts.[1-6] At the most basic level, a material is considered printable if it can be processed into complex geometries with minimum to zero porosity, cracking, distortion, delamination, surface roughness, or balling, without prohibitive process tuning or expensive and time-consuming post-processing.[6] Figure 1 schematically represents these defects e.g., porosity, lack-of-fusion voids, balling and roughness, cracking, distortion and delamination, and composition change—around the central concept of printability. It emphasizes that printability is not a single property but a characteristic of multiple interacting defect-formation mechanisms that span powder handling, melt pool dynamics, solidification, and post-solidification transformations.[7-9] For metallic AM, printability thus represents whether an alloy and process-parameter window can

be found that keeps these defects within tolerable limits for targeted applications, such as fatigue-critical aerospace components or corrosion-resistant energy systems.[10] In this article, printability assessment is defined operationally as a pre-build evaluation of whether a material, machine, and process parameter window can produce parts that meet specified requirements for defects, dimensional accuracy, microstructure, and properties. Therefore, printability assessment aims to identify acceptable processing windows before extensive experimental builds are performed. From a manufacturing science perspective, printability is important because it governs the fabrication of new alloys and complex geometries with acceptable quality, process stability, and cost.

Over the past decade, printability has remained an important research domain in AM literature. Figure 2 illustrates the literature trend from 2016 to 2025, showing an approximately monotonic increase in articles on printability assessment and defect control, reaching several hundred publications per year. This literature indicates several interconnected challenges in printability assessment.[11-17] They span multiple length scales and physical phenomena, making systematic evaluation difficult and costly. At the powder level, factors such as particle size distribution, morphology, flowability, and apparent density critically influence powder spreading and layer formation. These factors must be considered alongside thermophysical properties including thermal conductivity, specific heat capacity, melting point, and laser absorptivity that govern heat transfer and melt pool stability.[18] During the AM process, rapid heating and cooling rates, often on the order of 10^6 K/s in laser powder bed fusion,[2] create complex solidification conditions that determine keyhole or lack-of-fusion porosity, solidification versus liquation cracking, and residual-stress-driven distortion.[2] The resulting as-built microstructure and mechanical properties thus emerge from a tightly coupled interplay among composition, process parameters, thermal history, and solid-state transformations,[19,20] which is difficult to fully capture in simplified printability metrics. Current printability assessment approaches typically rely on iterative experimental trials that systematically vary processing conditions. This methodology is rigorous but time-consuming, material-intensive, and expensive, often stretching over months for a single alloy system.[21] Physics-based models[22] such as finite element thermal–fluid simulations and solidification and grain growth modeling can provide valuable insight into melt pool behavior and microstructure evolution. However, these models demand substantial computational resources and accurate input data (e.g., temperature-dependent material properties, boundary conditions) that may not be available for emerging alloys. Conventional machine learning[23] and deep learning[24] models can also predict defects, process outcomes, or material properties from available AM datasets. However, these models are usually developed for a specific task, material, machine, sensor, or parameter range, and their predictions may not transfer reliably to new alloys, geometries, or AM systems. Physics-informed approaches[25,26] improve physical consistency, but they still require suitable governing models, calibration data, and computational resources. In contrast, large language models (LLMs) and vision-language models (VLMs) can complement these methods by connecting their predictions with unstructured information from literature, material databases, process records, and expert knowledge. This landscape motivates the exploration of language models for printability assessment.

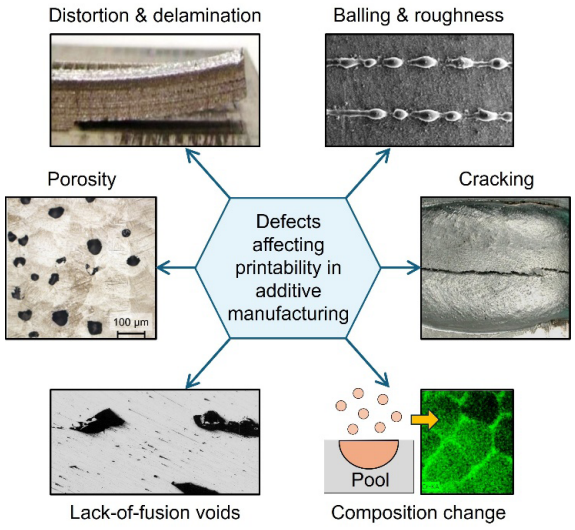


Figure 1. Schematic overview of printability in metallic additive manufacturing, illustrating key defect mechanisms, including porosity, lack-of-fusion voids, balling and surface roughness, cracking, distortion and delamination, and composition change, that collectively determine whether a material–process combination can produce high-quality parts. Sub-figures are modified/reprinted from different sources.[8,11,14-17]

Large language models and VLMs can provide a unique strategy for assessing printability, because they operate on natural language and visual data rather than explicit equations or features.[27-29] As illustrated in Figure 3, an LLM is trained on a large volume of text, books, articles, and websites, and can respond to queries such as "Name a metal printing process" with descriptions of powder bed fusion or directed energy deposition, implicitly drawing on encoded knowledge of processes, materials, and defects.[30] VLMs extend this capability by incorporating a vision

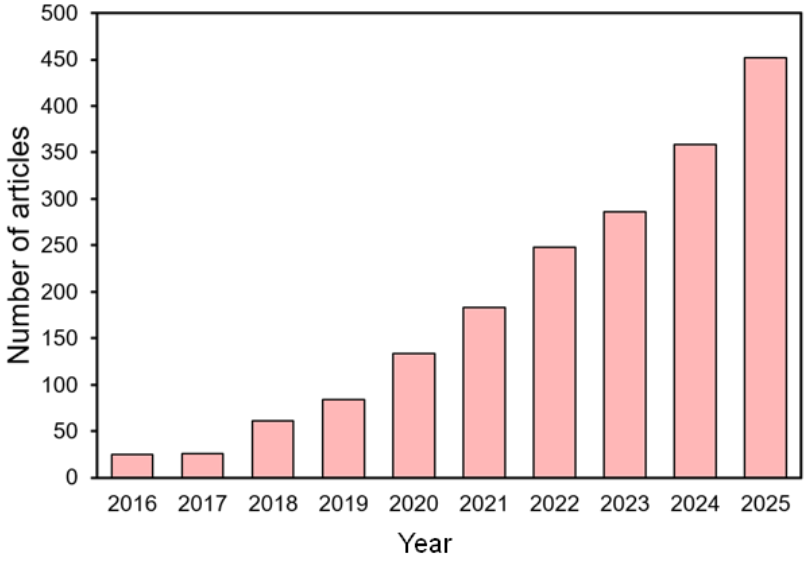


Figure 2. Growth in the number of research articles related to printability from 2016 to 2025. Data were acquired from Web of Science's "all databases," searched using the keywords "printability" and "additive manufacturing" as topics on July 26, 2026.

encoder that allows them to see and interpret images. For example, given a micrograph of a part, a VLM can infer that the image shows a lack-of-fusion defect and describe the associated process conditions in text, leveraging training on paired image-text datasets.[29] LLMs and VLMs both use deep neural networks, understand natural language, and learn from massive datasets, making them well suited to integrating literature, standards, process logs, and image-based inspection data for printability assessment.[31,32] Language models are needed in printability assessment because they can serve as knowledge engines that synthesize scattered information, propose hypotheses about defect origins, and generate process parameter suggestions to avoid defects.[33] Existing machine learning models[34] can predict specific AM outcomes when sufficient, well-labeled data are available, but they often cannot combine information across literature, material databases, process records, simulation results, and expert observations. They also provide limited support for interpreting results, identifying missing information, or transferring knowledge to a new alloy, machine, or process condition outside the original training dataset.[24] Language models can change printability assessment by linking structured numerical data with unstructured scientific knowledge and by providing traceable, human-readable reasoning for pre-build screening, monitoring interpretation, and model selection.[31,32]

Language models can act as knowledge-guided assistants that utilize experimental observations, simulation results, and specialized machine learning models to iteratively develop printable material–process windows. In this perspective, direct applications of LLMs and VLMs to printability assessment include pre-build prediction of likely defect modes and screening of material–process parameter windows. However, data from *in situ* monitoring, post-process characterization, and part testing can further validate the printability prediction and improve the language models. For example, *in situ* monitoring and image-based anomaly detection are treated as supporting technologies because they identify process deviations and provide evidence to validate printability predictions. Post-build defect diagnosis similarly supports assessment by establishing the relationship between predicted and observed quality. Closed-loop parameter optimization is considered an extension of printability assessment because it uses monitoring and prediction to move the process toward a printable operating window.

2. Recent applications of language models to assess printability

Recent work has started to explore how language models can be embedded into AM workflows to classify defects, guide parameter adjustments, and interpret multimodal process data in ways that directly impact printability assessment. Table 1 summarizes a few such selected examples. For clarity, this perspective distinguishes five related but different artificial intelligence (AI) approaches. LLMs process and generate text; VLMs or multimodal

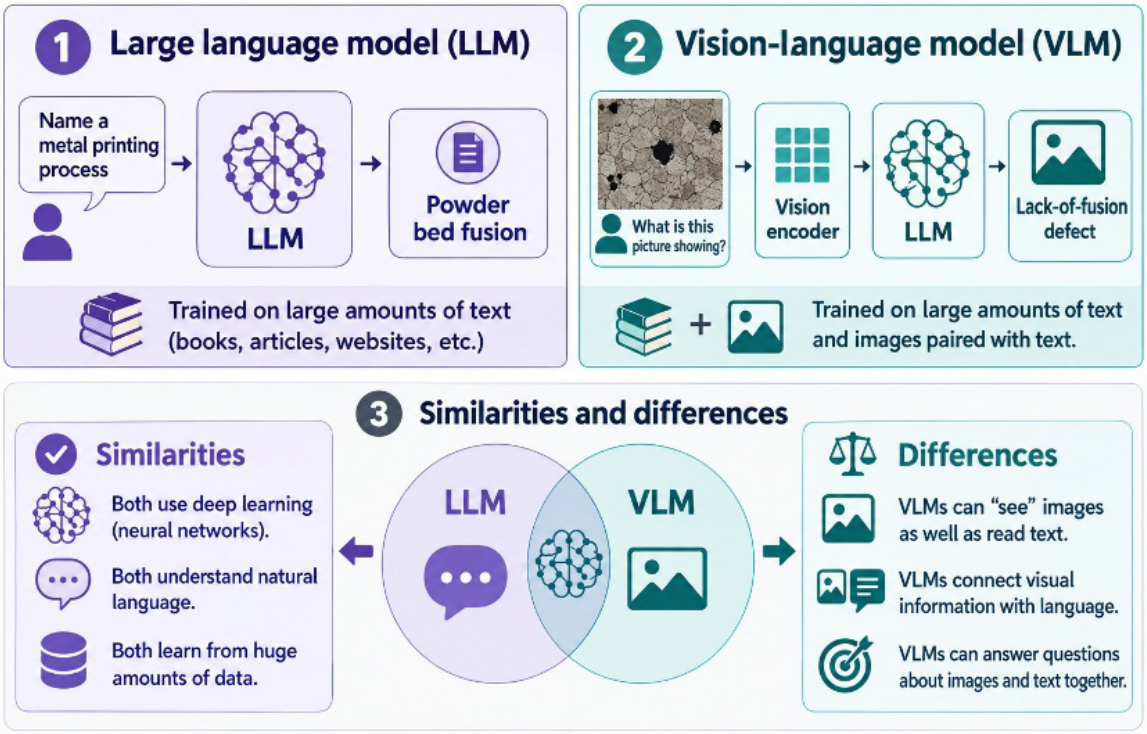


Figure 3. Conceptual illustration of large language models (LLMs) and vision-language models (VLMs) for additive manufacturing (AM), showing how LLMs reason over text (e.g., process descriptions) and VLMs jointly interpret images (e.g., micrographs of defects) and language, and summarizing their shared and distinct capabilities.

LLMs jointly process text and images; vision transformers and foundation vision models analyze images without a language component; conventional multimodal deep learning models combine sensor, image, and process data; and agentic or retrieval-augmented systems use language models to access external information, plan tasks, or interact with computational tools. The examples in Table 1 are classified according to this taxonomy to distinguish demonstrated language-model applications from enabling AI technologies that could later be integrated with LLMs or VLMs.

Table 1. Selected examples of language model applications in predicting and controlling defects

Process & materials	Type of defects	LLM/VLM used	Application, model performance, technological maturity	Current barriers & future needs	Reference with status
LPBF; SS316L & Ti-6Al-4V	Lack of fusion	DistilBERT, SciBERT, T5, Llama 3.2	• Predicts defect regimes from LPBF process parameters. • Up to 94.23% accuracy (F1 = 0.906) with Llama 3.2; 82.22% accuracy (F1 = 0.714) with DistilBERT for natural-language prompts. • Validated computationally using experimental and simulation-derived datasets; no real-time hardware control demonstrated. • 2,779 original data points, augmented to 724,764 samples; fine-tuning with a 75%/15%/10% split; external validation not reported.	• Performance decreases with unstructured natural-language inputs and imbalanced/limited datasets. • Diversify materials/process datasets and improve numerical understanding.	Peer-reviewed journal article[28]

(*Cont'd...*)

Table 1. (***Continued***)

Process & materials	Type of defects	LLM/VLM used	Application, model performance, technological maturity	Current barriers & future needs	Status with reference
LPBF; Maraging steel, 17-4 PH SS, Inconel 718	LPBF anomalies	GPT-4o-mini, Qwen2-VL-2B	• Detects and classifies LPBF anomalies using multimodal RAG. • GPT-4o-mini outperformed Qwen2-VL-2B by 34.6%; RAG improved average accuracy by 12%. • Validated on four real LPBF image datasets; no real-time hardware control. • 54 LPBF test images; no additional training/ fine-tuning; evaluated across different printers and materials.	• Limited classification accuracy and black-box behavior. • Improve image retrieval and multimodal generation to increase detection accuracy.	Peer-reviewed journal article[35]
DED-LW; Ti-6Al-4V	Improper bead height, poor bead quality	Gemini 2.0 Flash and Gemma-3 27B. Gemini	• Detects insufficient bead height from cross-sectional images. • Gemini QA-VLM: 96% conclusion correctness; 0.82 validity. • Validated on 24 physical single-bead DED-LW samples; not demonstrated for online process control. • 24 DED-LW samples; no fine-tuning reported; no external validation reported.	• Limited single-bead dataset and dependence on reference/domain knowledge. • Validate across multi-layer/ multi-pass, and broader process/material conditions.	Peer-reviewed journal article[29]
DED; powder-fed 316L and wire-fed IN718	Melt-pool anomalies	AM-VLM (Qwen2.5-VL-7B + dual-index RAG)	• Analyzes *in situ* melt-pool images for anomaly detection and defect diagnosis. • Detection accuracy: 93.3%; F1: 0.934. • Validated on an industrial DED platform, but parameter changes remain human-in-the-loop. • 20 melt-pool datasets; no LLM/VLM fine-tuning reported; no independent external validation reported.	• Limited coverage across alloys and machines, and optical monitoring sensitivity to sensor effects. • Broaden multimodal datasets and enable reliable process control.	SSRN preprint[36]
FFF; PLA, ABS & TPU	Under-extrusion, over-extrusion	CIPHER (E.2 configuration), LLaMA 3.2, and GPT-4o-mini	• Detects under-/over-extrusion, estimates flow rate, and generates corrective G-code. • Flow-rate MAE reduced from 82.92 to 17.62 with the process expert; correction frequency ≈ 2.3 Hz. • Demonstrated autonomous control and executable G-code on physical manufacturing hardware. • 920,000 samples (>5M original images), 80/10/10 split, LoRA fine-tuning, unseen-process generalization tested.	• Numerical uncertainty, limited causal reasoning, and reliability of explanations. • Improve uncertainty quantification, reasoning, causal modeling, and integration with manufacturing standards.	Peer-reviewed journal article[37]
FFF; PLA & ABS	Under-extrusion	LLM-ADAM (Extractor–LLM, Reference–LLM, Judge–LLM)	• Analyzes G-code to detect under-extrusion. • 87.5% overall accuracy; near-ceiling recall for defect classes. • Validated on 200 G-codes/printed parts across two physical printers; no automated correction. • 200 G-code samples; prompt-based LLM inference without reported fine-tuning; external validation not reported.	• Requires printer/material documentation and still needs manual correction. • Automate reference retrieval and safe parameter/G-code correction.	arXiv preprint[38]

(*Cont'd...*)

Table 1. (***Continued***)

Process & materials	Type of defects	LLM/VLM used	Application, model performance, technological maturity	Current barriers & future needs	Reference with status
FFF; plastic filament	Layer shift/ Misalignment	GPT-4o and Gemini-Vision Pro	• Analyzes images of FFF-printed parts to classify layer-shift defects. • Up to 91.42% classification accuracy; only 16.27% localization accuracy. • Experimentally validated on physical FFF prints. • 630 LLM evaluation data points; prompt engineering without fine-tuning; external validation not reported.	• Limited spatial localization and validation on only layer shift/ stringing. • Improve spatial defect localization, prompt engineering, and validation across broader defect types.	Master of Engineering thesis[39]
FDM; plastics	Over-extrusion	LLaVA-IntelliPrint	• Detects over-extrusion and estimates material flow rate from printing images. • 90% extrusion-quality classification accuracy; flow-rate MAE = 12.02%. • Evaluated on real printer-image data; no closed-loop hardware control demonstrated. • Over 500,000 labeled images used; four-stage training approach; external validation not reported.	• Image-quality sensitivity and limited generalization. • Incorporate labeled data, G-code, temperature data, and broader AM datasets.	Master of Philosophy dissertation[40]
Material extrusion; PLA & TPU	Layer separation/ Poor layer adhesion	GPT-4o, GPT-4.1	• Detects defects, identifies causes, and adjusts print parameters. • Significant improvement with a 5.06× increase in peak load capacity. • Closed-loop control on two physical 3D printers. • No domain-specific training dataset; no fine-tuning; cross-platform validation on two printers and testing with PLA/TPU.	• Limited spatial/ thermal context and difficulty in distinguishing some defects. • Integrate multimodal thermal data.	Peer-reviewed journal article[30]
Vat photo-polymerization; resin	Deposition non-uniformity	GPT-4o (in-context learning)	• Classifies resin deposition images as normal or defective. • 96.2% accuracy (F1 = 0.962) using few-shot multimodal context + RQV. • Demonstrated using images captured from a physical vat-photopolymerization printer but not deployed for real-time control. • 10 demonstration images; no fine-tuning; no external validation.	• Prediction inconsistency/ uncertainty and dependence on selected demonstrations and expert context. • Improve demonstrations, uncertainty, and real-time deployment.	Peer-reviewed conference paper[41]

Abbreviations: ABS: Acrylonitrile butadiene styrene; AM: Additive manufacturing; DED: Directed energy deposition; DED-LW: Laser-wire directed energy deposition; FDM: Fused deposition modeling; FFF: Fused filament fabrication; LLM: Large language model; LoRA: Low-rank adaptation; LPBF: Laser powder bed fusion; MAE: Mean absolute error; PLA: Polylactic acid; QA: Quality assessment; RAG: Retrieval-augmented generation; RQV: Repeated query and voting; SSRN: Social Science Research Network; TPU: Thermoplastic polyurethane; VLM: Vision-language model.

Figure 4 shows a vision-based *in situ* monitoring framework for fused filament fabrication (FFF) AM, which uses transformer-based models to recognize printing quality from camera images and infer the presence of defects such as under-extrusion, over-extrusion, warping, and cracking.[42] The setup includes a camera capturing images of the filament, print head, liquefier, and nozzle as the material is deposited layer by layer. A large, unlabeled dataset of images is first used to pretrain a base model such as DINOv2 through unsupervised learning,[43] enabling the network to extract robust visual features related to specific defect types. A domain-specific dataset with labeled examples of good quality, under-extrusion, over-extrusion, and other defect modes is then employed to fine-tune the model, adapting it to the particular visual signatures of FFF.[42] The system learns to classify images into print-quality categories and accumulates information about local anomalies, distinguishing inner-plane defects (e.g., under-/over-extrusion within a layer) from inter-plane defects (e.g., warping, cracking between layers). Methodologically, this example is a vision transformer/foundation vision model application rather than an LLM or VLM application, because DINOv2 processes images without using a language input or generating language output. It demonstrates image-based defect recognition through pretraining and fine-tuning. It is included as an enabling computer-vision technology that could be combined with an LLM or VLM for language-based explanation, process reasoning, or human interaction. In addition, Figure 4 demonstrates vision-based quality recognition in polymer FFF, not metallic AM. It demonstrates the ability to classify visible polymer-printing defects after model pretraining and domain-specific fine-tuning. Adapting this approach to metal AM is a future opportunity, but it requires metal-specific training data, validation against metallographic and *in situ* measurements, and testing across alloys and machine platforms. However, the model identifies associations between visual features and defect classes rather than establishing the physical causes of those defects. Therefore, its predictions should be interpreted as

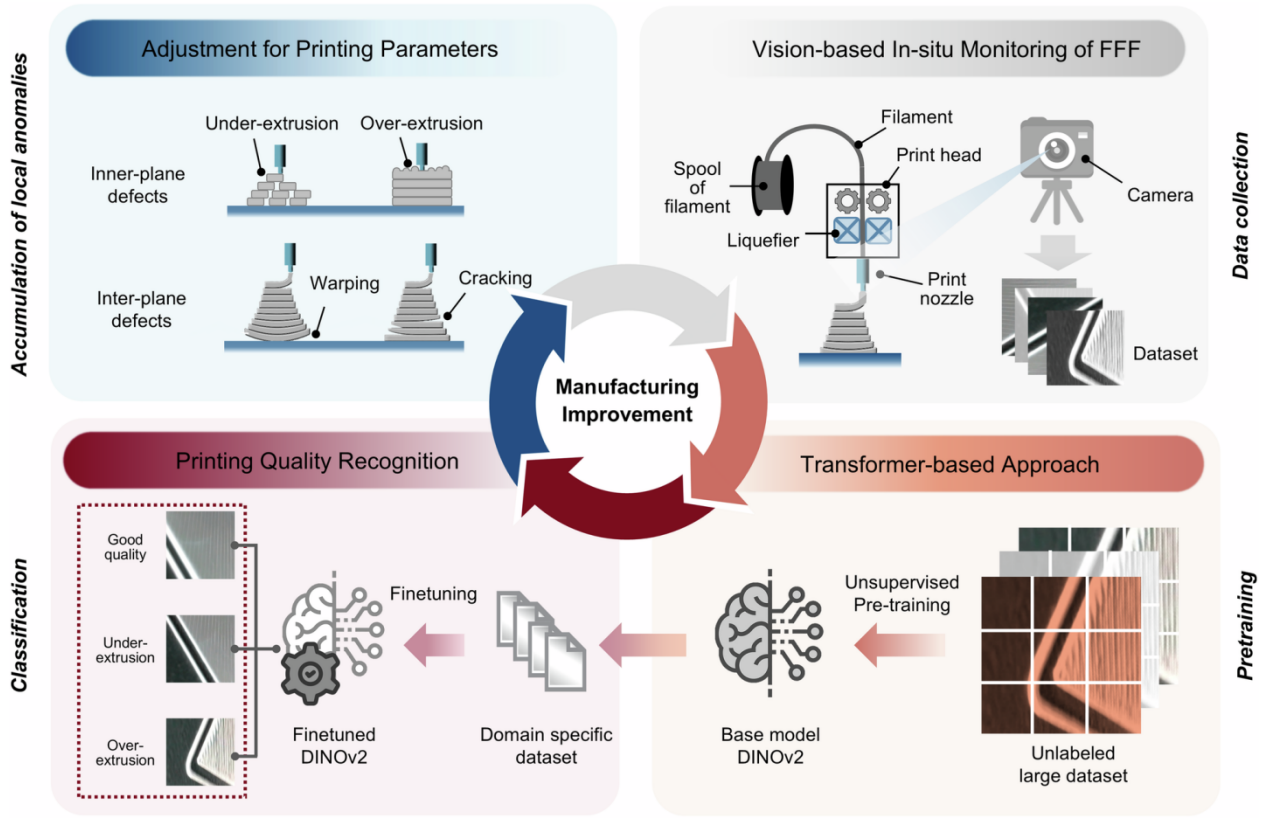


Figure 4. Vision-based *in situ* monitoring framework for fused filament fabrication (FFF), in which transformer-based models trained via unsupervised pretraining and domain-specific fine-tuning classify camera images into printing quality categories (good, under-extrusion, over-extrusion, warping, cracking) to support manufacturing process improvement. This polymer printing example is provided as an analog transferable to metal printing in the future. Reprinted from Wang *et al.*[42]

evidence-linked classifications, and their reliability and reproducibility should be verified across datasets, printing conditions, and model versions before broader application.

Figure 5 demonstrates the use of LLMs as annotation and reasoning engines for AM defect datasets during laser powder bed fusion of stainless steel 316L.[28] It depends on a process parameter–defect dataset that includes laser power, scan speed, material, hatch spacing, layer height, and beam diameter, along with experimentally measured and simulated melt-pool dimensions (depth, length, width).[44] Defect criteria are then defined using simple geometric relationships.[28] Keyhole porosity is associated with a melt pool width-to-depth ratio greater than 1.5, lack-of-fusion porosity arises when the combination of hatch spacing and layer height relative to melt pool width and depth satisfies a specific inequality, and balling porosity is linked to a melt pool length-to-width ratio below π. These criteria encode domain knowledge about how process parameters and melt-pool geometry drive different porosity mechanisms.[20,45,46] An LLM is used to process natural language prompts that describe process conditions and generate textual descriptions of likely defects.[28] These LLM responses can be mapped to defect labels and compared against the geometric criteria, enabling automated or semi-automated dataset labeling, consistency checks, and knowledge extraction. In effect, the LLM acts as a classifier that translates process conditions into defect probabilities, which can be used to guide parameter screening for printability and highlight regimes where empirical criteria may be incomplete. Figure 5 is a direct LLM application because the model receives process information in natural-language form and generates defect-related responses in text. However, the defect labels are also informed by predefined melt-pool geometric criteria; thus, the LLM is used together with physics-based or rule-based defect definitions rather than serving as an independent physical model. This example is best classified as an LLM-assisted, knowledge-guided defect prediction and dataset annotation approach. The LLM-generated defect assessment should therefore be treated as an evidence-linked prediction rather than an independently validated causal explanation, since the defect labels are grounded in predefined melt-pool criteria. Reproducibility should also be evaluated across model versions using consistent prompts and test cases to determine whether the same process conditions lead to comparable defect predictions.

Figure 6 illustrates an LLM serving as a supervisor that monitors process observations, gathers relevant information, and proposes parameter adjustments to mitigate defects in filament-based printing.[30] The workflow begins with monitoring and evaluation of the printing process, where visual signs such as visible stringing and inconsistent extrusion are identified as failure modes, including stringing and poor wall adhesion. An LLM is placed in the loop as a supervisor that plans and solves based on these observations, interacting with control variables such as retraction rate, feed rate, and extruder temperature.[30] The LLM can be prompted with structured descriptions of the current state and asked to suggest modifications to process parameters aimed at reducing stringing or improving adhesion. By iteratively gathering information (e.g., asking for additional sensor data or context) and evaluating outcomes, the LLM can converge on parameter sets that produce more stable printing behavior, as indicated by the comparison between "Baseline" and "Optimized" conditions in the figure.[30] The application demonstrated in Figure 6 is limited to filament-based printing, where the LLM recommends adjustments to retraction rate, feed rate, and extruder temperature. Applying an LLM supervisor to metal AM process variables, such as laser power, scan speed, hatch spacing, preheat temperature, or shielding-gas conditions, remains a future research direction. Such systems would require metal-specific datasets, physics-based constraints, safe operating limits, and experimental validation before they can be used for process recommendations. Given a set of observed defects (porosity, cracking, distortion) and known process conditions, an LLM could analyze past literature and datasets to recommend adjustments in process conditions, explaining the rationale in terms of known defect mechanisms.[47] Such supervisory control links printability assessment directly to process optimization, turning assessment from a passive diagnostic into a proactive, language-guided search in parameter space. Figure 6 is an agentic LLM application because the language model acts as a supervisor that interprets observations, gathers additional information, and recommends actions. The demonstrated system operates in filament-based printing and uses language-based planning and decision support rather than a stand-alone computer-vision classifier. Its extension to metallic AM remains conceptual and would require integration with metal-specific sensing, validated process models, and safety constraints. Accordingly, parameter recommendations and their accompanying explanations should be viewed as source- or evidence-linked mechanistic hypotheses rather than validated causal relationships unless they are confirmed experimentally or by validated physical models. Their reliability should also be tested across model versions to determine whether similar observations produce consistent and safe parameter recommendations.

Figure 7 demonstrates a multimodal, AI-driven defect-detection architecture for metal AM that integrates

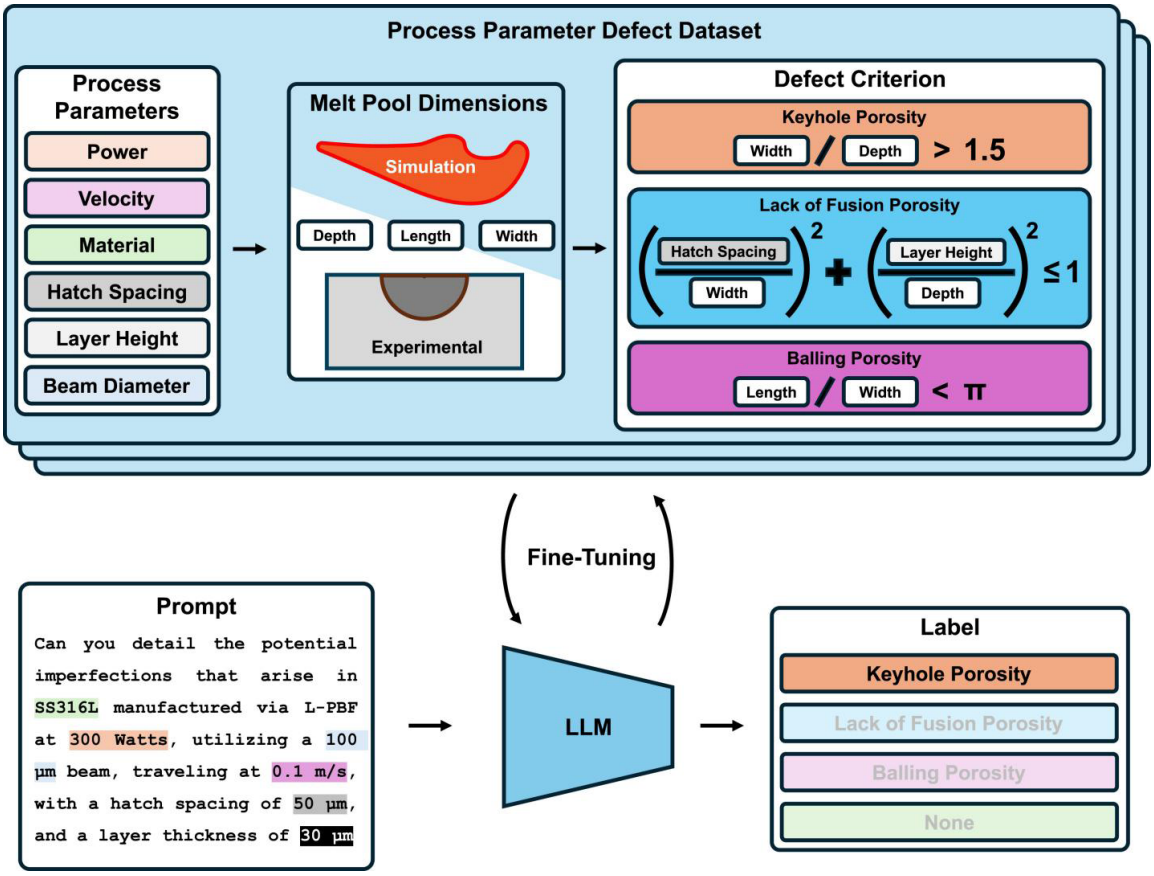


Figure 5. Process-parameter-defect dataset for laser powder bed fusion of stainless steel 316L, combining melt-pool geometry (depth, length, width) and simple geometric defect criteria to label keyhole, lack-of-fusion, and balling porosity, and demonstrating how a large language model (LLM) can map natural-language process descriptions to defect labels. Reprinted from Pak and Farimani.[28]

acoustic signals,[48] temperature data, pyrometer readings, and camera-based images (visible and near-infrared) to identify a broad range of defect types.[43] The input consists of *in situ* sensor data, such as acoustic voltage traces over time, frequency-domain representations with stored-energy evolution, thermal histories from pyrometers, and simultaneous melt-pool images captured in different spectral bands. These signals are fed into a deep neural network architecture with input, hidden, and output layers, potentially enhanced with reinforcement learning to improve defect classification over successive builds.[43] The output includes detailed defect labels spanning recoater hopping, recoater streaking, incomplete spreading, soot, super-elevation, porosity of various sizes at different energy densities, part damage, swelling, debris, spatter, jet misfire, misprint, and broader categories of spreading defects and dimensional/surface irregularities. The concept of defect definition and identification in Figure 7 highlights the complexity of printability as experienced in real manufacturing environments and the need for models that can jointly interpret diverse signals.[43] In the context of language models, such multimodal architectures can be extended by coupling sensor-level AI models with LLMs or VLMs that describe, summarize, and reason about detected defects in natural language, linking them to causal hypotheses and mitigation strategies. For example, a VLM could analyze melt pool images and acoustic spectrograms, identify a pattern indicative of keyhole instability, and then use an LLM component to explain that excessive energy density and insufficient scan speed are likely drivers, suggest parameter reductions, and reference relevant studies.

Figure 7 represents conventional multimodal deep learning with reinforcement learning, rather than a demonstrated LLM or VLM system. It combines acoustic, thermal, pyrometer, and imaging data to detect defects, but it does not inherently use natural-language understanding or generation. It is included as an enabling

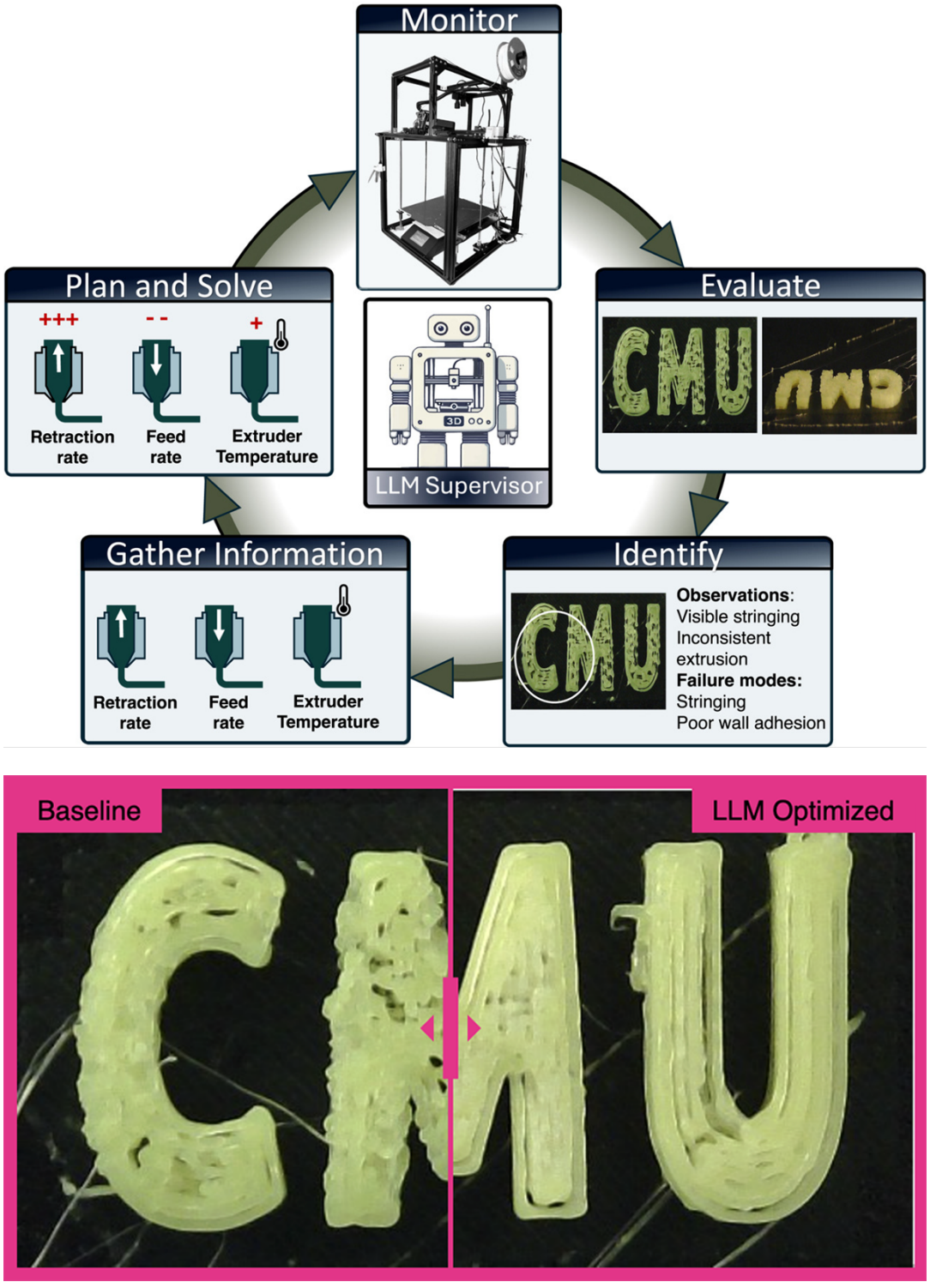


Figure 6. Large language model (LLM) acting as an intelligent supervisor for filament-based printing, monitoring observable failure modes (e.g., stringing, poor wall adhesion), gathering information on control variables (retraction rate, feed rate, temperature), and proposing optimized parameter adjustments relative to a baseline condition. The LLM-optimized conditions successfully printed better quality parts. This polymer printing example is provided as an analog transferable to metal printing in future. Reprinted from Jadhav *et al.*[30]

multimodal sensing framework that could be coupled with an LLM or VLM in the future to provide language-based interpretation, traceable reasoning, and decision support. When coupled with an LLM or VLM, these multimodal signals could support evidence-linked explanations or mechanistic hypotheses about defect formation, but such interpretations should not be considered causal unless independently validated by experiments or physical models. Reproducibility across model versions should also be assessed to ensure that the same multimodal evidence produces consistent defect interpretations and process guidance. The aforementioned examples of demonstrated LLM and VLM applications (Figures 4–6), as well as supporting multimodal AI architectures (Figure 7), indicate that such models can contribute to printability assessment by classifying defects, labeling datasets, supervising process tuning, and integrating multimodal in-situ data into human-readable assessments of process health.

3. Research needs

A comprehensive assessment of printability requires connecting process conditions with the resulting thermal history, microstructure, defects, material properties, and component performance. This is because the thermal history during AM is known to govern the formation of defects.[1-6] Improper microstructure can lead to defects.[1-6] For example, long columnar grains are known to cause solidification cracking.[23] Internal cracks and pores are detrimental to the mechanical properties, such as tensile strength and fatigue.[1-6] Language models could support these connections by integrating process and experimental data with microstructural information, material properties, and predictions from computational models, extending printability assessment beyond defect prediction and process parameter selection. Despite recent progress discussed in Section 2, realizing these aforementioned effects of language models requires targeted research in five main areas (Figure 8).

3.1. Integration of language models with computational tools

Most language model applications in AM operate as stand-alone assistants or classifiers, but the true potential lies in using them along with simulations, experiments, and data repositories to establish process–structure–property relationships.[49] An LLM could help define simulation setups (finite element, finite volume, discrete element, phase-field, thermodynamic[50] and kinetic, and data-driven

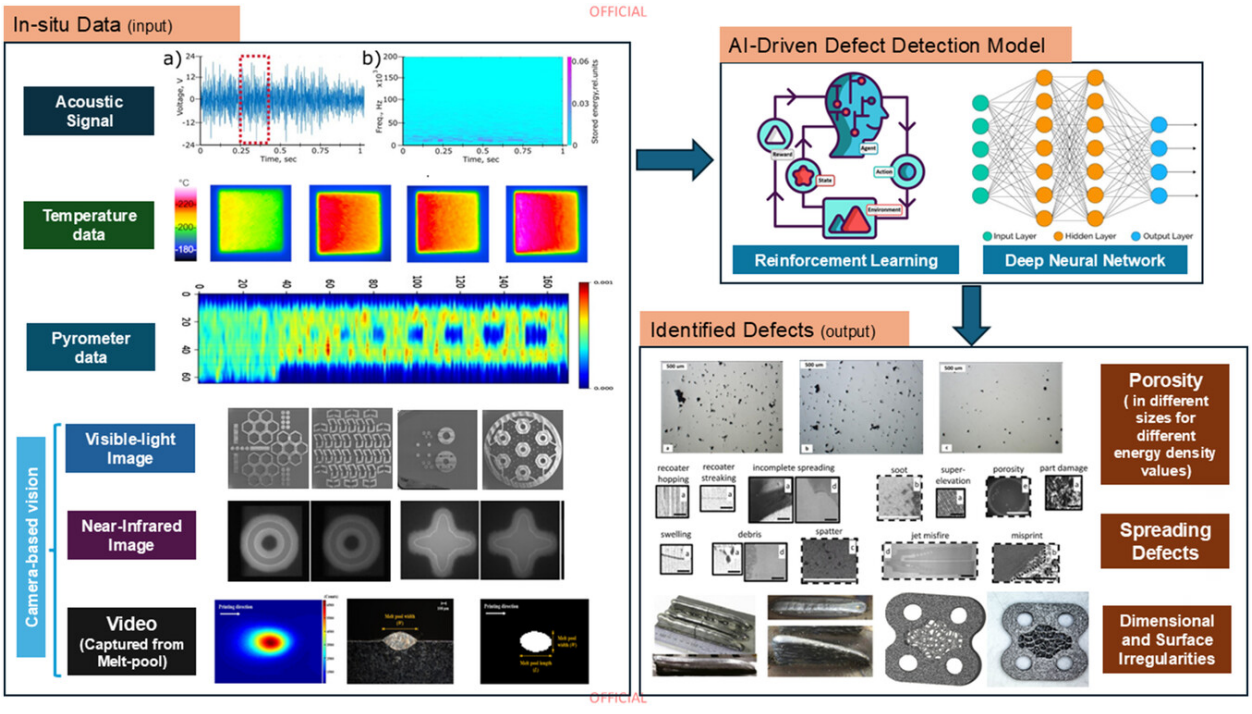


Figure 7. Multimodal artificial intelligence (AI)-driven defect detection architecture for metal additive manufacturing (AM), integrating acoustic, thermal, pyrometer, and visible/near-infrared camera data into a deep neural network and reinforcement learning framework to identify a wide range of spreading, porosity, dimensional, and surface defects/ Reprinted from Zolfagharian *et al.*[43]

surrogate models) by translating high-level printability questions, such as "Will this new alloy crack under these process conditions?" into specific model parameters, boundary conditions, mesh resolutions, and material model selections, while also pulling relevant property data and literature on similar alloys.[51-53] Recent studies demonstrate the feasibility of such integration, where LLM-based frameworks have been used to support thermodynamic model development through data optimization, automate finite element workflows from problem formulation to numerical solutions, and develop surrogate models through automated model selection, training, and evaluation.[54-56] These computational tools could provide complementary information on melt-pool behavior, thermal history, phase stability and transformations, microstructure evolution, residual stress, and other factors that influence printability. Digital twins could further connect computational predictions with continuously updated process and sensor data, while experimental databases could provide additional information for comparison and validation.[1] By combining these sources, an LLM could identify discrepancies between predicted and experimentally observed behavior, link changes in processing conditions to resulting structure and properties, and suggest additional physical mechanisms to improve model predictions.[57] Such integration is particularly important because printability depends on multiple interacting physical processes that cannot be adequately captured by a single model or dataset. A similar application has been recently performed for fusion welding[58] and has potential to be implemented for AM.

3.2. Potential use of quantum computing for language models

Quantum computing has the potential to enable LLM inference, which could be used for data training toward printability assessment.[59,60] Evaluating printability across many alloys, process windows, and geometries requires a high-dimensional decision space, and language models that operate over this space must process extensive textual and visual data, including material datasheets, process logs, micrographs, videos, simulation outputs, and inspection reports. We anticipate that quantum computing can offer a path to accelerate certain sub-tasks,[61,62] such as optimization over large combinatorial parameter spaces or sampling from complex probability distributions.[63,64] High-fidelity melt-pool simulations require solving coupled Navier–Stokes, heat-transfer, and mass-transfer equations under rapidly changing free-surface and phase-change conditions. These calculations can become computationally expensive for high-resolution simulations across many parameter sets, alloys, and geometries. Recent quantum approaches for Navier–Stokes flows[65-67] suggest that quantum algorithms may eventually provide computational advantages for selected nonlinear flow problems. However, such advantages have not yet been demonstrated for melt-pool simulations or for LLM-enabled printability workflows. Progress in this field requires interdisciplinary research spanning quantum information science, machine learning, and manufacturing, including standards that compare classical and quantum-enhanced language-model workflows for multi-objective optimization of printability metrics. The

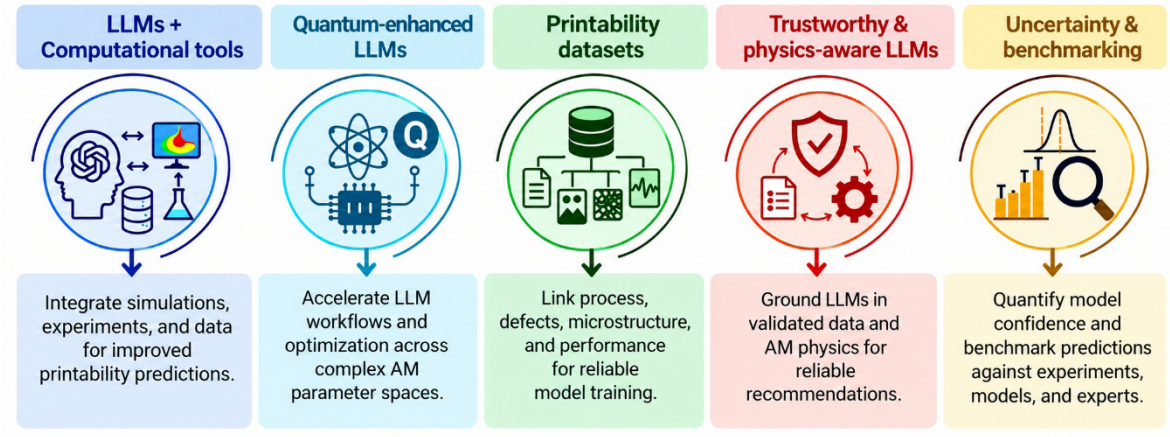


Figure 8. Five main research directions to realize the full impact of language models (e.g., large language models [LLMs] on printability assessment in additive manufacturing [AM])

existing literature indicates that most quantum–LLM/VLM research is currently concentrated on quantum circuit design, reasoning, and optimization rather than manufacturing applications, as summarized in Table 2, strongly emphasizing the potential of this field.

Table 2. Recent applications integrating quantum computing algorithms with LLMs and VLMs

Quantum computing algorithm used	LLM/VLM used	Application domain	Description and advantages	Ref.
Quantum annealing	GPT-4o-mini	Flexible manufacturing system scheduling	• Uses an LLM to select solvers and optimize two-machine production scheduling. • Optimal results for ($n \leq 15$) hybrid quantum runtime ~5 s, while the traditional heuristic algorithm required ~30 s.	68
Bias-field digitized counterdiabatic quantum optimizer (BF-DCQO)	GPT-4o, DeepSeek V1, LLaMA 3.1	LLM reasoning optimization	• Uses IBM quantum hardware to select LLM reasoning fragments and improve reasoning accuracy. • Slightly higher accuracy than traditional probabilistic algorithms.	69
Quantum gate synthesis	Gemini 2.0, Claude 3, GPT 4o-mini, Gemma 3, DeepSeek V3, Wolfram LLM	Quantum operation generation	• Benchmarks six LLMs for generating quantum gate designs and evaluates execution time and code compilation success. • Gemini 2.0 Flash generated quantum gate designs fastest (2.67 s average), 40.8% error-free program execution.	70
Grover algorithm	GroverGPT+ (LLaMA-3)	Symbolic analysis of quantum circuits	• Uses quantum-native tokenization and chain-of-thought reasoning to interpret Grover circuits and explain their algorithmic logic. • Shows sub-linear inference-time growth over 2–9 qubits by using symbolic analysis instead of full state-vector simulation.	71
VQE, quantum kernel method	GPT-5 series, o3-deep-research	Autonomous quantum circuit design	• Uses LLM agents to automatically design and improve quantum circuits for QML and VQE. • Achieved up to 97.72% accuracy and outperformed classical radial basis function.	72
Variational Quantum Circuit (VQC)	Contrastive language-image pretraining	Few-shot image classification	• Uses quantum circuits to improve visual-text features for fine-grained image classification. • Improved few-shot classification accuracy by up to 3.75 percentage points over the corresponding classical VLM baseline.	73
VQE, QAOA, Grover, Shor	Gemini 2.5 Flash, GPT-oss-120B	Qiskit code assistance	• Fine-tunes a VLM to understand quantum visualizations and generate Qiskit code. • Achieved more than a 17 percentage-point gain over the base VLM.	74
VQC	Contrastive language-image pretraining	Image–text compositional generalization	• Uses quantum circuits with CLIP image features to match images with their correct captions. • Achieved 50.31% test accuracy vs. 0% for the classical DisCoCat model.	75
QAOA, VQE, Adaptive VQE	Qwen 2.5 Instruct	Quantum circuit generation & optimization	• Uses a fine-tuned LLM to design and optimize quantum circuits for various optimization tasks. • Achieved 29.5% lower divergence than random parameter initialization.	76

Abbreviations: CLIP: Contrastive language-image pretraining; LLM: Large language model; QAOA: Quantum Approximate Optimization Algorithm; QML: Quantum machine learning; VLM: Vision-language model; VQC: Variational quantum circuit; VQE: Variational quantum eigensolver.

3.3. New printability datasets to train language models

There is a need for standardized printability datasets tailored for language model applications, including both textual and visual data and covering diverse materials and AM processes.[30] Existing datasets (such as in Figures 5 and 7) capture process parameters, melt-pool dimensions, defect criteria, and *in situ* signals, but they are not always organized in forms that language models can easily analyze. A dedicated printability dataset for LLMs and VLMs would include[77,78] structured records combining natural-language descriptions of process setups, quantitative parameter values, simulation outputs, microstructural images, defect labels, and downstream performance metrics (e.g., mechanical strength, fatigue life, corrosion resistance). Such a dataset could be designed to encode relationships between defect modes (porosity, cracking, distortion, composition change), process parameters (power, speed, hatch spacing, layer height, preheat temperature), material properties, and printability outcomes across many alloy–process combinations. Creating this dataset requires careful attention to annotation standards, including consistent defect definitions and clear documentation of how labels are assigned (e.g., geometric criteria, destructive testing, expert judgment). Research is needed to design data schemas, privacy and intellectual-property protocols, and open standards that make these datasets widely usable while maintaining proprietary constraints.

3.4. Need for trustworthy, reliable, and physics-preserving algorithms

Language models must provide credible information and process recommendations before they can be used for printability assessment. Hallucination[79] is a major obstacle because it causes models to produce seemingly plausible results that are not borne out by actual experiments or academic research. This problem can be partially mitigated with retrieval-augmented generation,[80] which links language models to validated AM literature, material databases, and experimental data so that their answers can be tracked to sources. The domain knowledge and specificity of language-model answers can be enhanced using retrieval-based techniques, according to recent AM-specific experiments.[81] The physical suitability of a given material, machine, or AM process may still determine whether a data-supported recommendation is suitable. Because defect generation depends on the combined effects of material properties, process parameters, thermal behavior, and processing conditions, this is especially significant for printability.[25] To keep the suggested processing conditions within physically valid limits, future language models should relate to known AM physics and process-defect correlations. Further investigation is required to ascertain the behavior of these models when confronted with non-data-represented materials, machines, or processing circumstances. By integrating physical knowledge, human expert review, and verifiable information, language models can improve the reliability and transferability of printability assessments, all while ensuring that process recommendations are made under safe processing settings.[82,83]

3.5. Uncertainty quantification and benchmarking

Robust uncertainty quantification and benchmarking frameworks are essential to ensure that language model–based printability assessments are trustworthy and comparable across AM systems, materials, and use cases.[84] Because printability decisions affect material selection, cost, and safety, it is not sufficient for language models to provide qualitative judgments. Their outputs must be accompanied by estimates of confidence, sensitivity to input perturbations, and explicit acknowledgment of knowledge gaps.[85] Uncertainty quantification in this context could involve assessing how LLM answers change under different prompt formulations, how VLM defect classifications vary with image quality and viewpoint, and how model predictions compare with ground-truth experimental data across diverse defect types and alloy–process combinations.[4] Benchmarking requires comparing language model–based workflows with traditional approaches (manual expert assessment, purely physics-based simulations, or specialized machine learning models). These comparisons are needed to quantify gains in speed, coverage, and explanatory power, while highlighting situations where language models may over-generalize or misinterpret domain-specific nuances. In addition, since many of the existing language models (Table 1) have not been rigorously tested across multiple domains, cross-material, cross-machine, and cross-process validation is needed for benchmarking.

4. Concluding remarks

If these aforementioned research directions are pursued, language models can move from being interesting demos to becoming practical tools for assessing and improving printability in metal AM. As they are connected more closely with simulations, sensors, and well-organized datasets, they can support faster, clearer, and more reliable printability decisions. In the long run, this could significantly reduce the time, cost, and effort needed to go from a new alloy design to a qualified printed part.

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As this is a perspective article, no primary research results, data, software, or code have been included.

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The authors used Grammarly AI to fix grammar, spelling, and sentence construction issues. After using the AI tool, the authors carefully checked the manuscript, ensuring the accuracy of the text. In addition, color rendering in Figures 3 and 8 was performed using GPT-2.0. The authors confirm that no AI tools were used to generate the scientific content of this manuscript.

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