

MAPPING ARTIFICIAL INTELLIGENCE RESEARCH IN COLD SPRAY ADDITIVE MANUFACTURING

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Cold Spray Additive Manufacturing (CSAM) is a solid-state process that enables high-rate fabrication and repair of metallic components with low thermal input, making it suitable for heat-sensitive materials. Its wider industrial adoption, however, is constrained by challenges in porosity control, geometric accuracy near edges and concavities, anisotropy, and costs linked to gas use and nozzle wear. Recent research increasingly integrates artificial intelligence (AI) and machine learning (ML) to address these issues. This review analyses how AI/ML is applied to CSAM-specific problems and identifies the model types most commonly used. Based on keyword co-occurrence and clustering, the literature is structured into four themes: design and inverse planning, materials analytics, in situ monitoring and defect analysis, and deposition modelling with AI-enabled optimisation. Dominant approaches include physics-informed surrogate models, active learning for difficult process regions, and uncertainty-aware optimisation. While challenges remain in data availability, transferability, and sensor integration, these methods outline a clear pathway toward robust and scalable AI/ML-enabled CSAM.

KEYWORDS

Additive manufacturing, Cold Spray, Artificial Intelligence, Machine Learning, Co-Occurrence

1 INTRODUCTION

Additive manufacturing (AM) design has progressed from geometry-driven approaches to physics-aware, co-designed workflows that integrate digital modeling, process physics, and data-driven control. This evolution aligns with international standards that emphasize AM's layer-by-layer fabrication and its consequences for tolerancing, process planning, and quality verification [Roshith 2025]. As a fundamentally multidisciplinary domain, AM combines mechanics, materials science, thermal-fluid physics, electronics, robotics, and computer science, meaning that final part quality emerges from the interaction of process parameters, operating conditions, and feedstock characteristics rather than from isolated design choices [Kafle 2024].

Cold Spray Additive Manufacturing (CSAM) is a solid-state AM process in which metal powders are accelerated to supersonic velocities and consolidated through severe plastic deformation without melting, enabling dense deposits and phase retention on temperature-sensitive substrates [Kindermann 2024]. Despite these advantages, CSAM faces limitations related to

porosity control, edge accuracy, helium cost, and nozzle wear, with dimensional accuracy strongly dependent on path planning and process kinematics [Vaz 2023]. As a multi-physics, multi-scale process, CSAM involves coupled gas–particle flow, impact mechanics, and layer build-up, while existing physics-based and computational fluid dynamics (CFD) models remain computationally expensive and difficult to apply for real-time control or inverse design [Perna 2022].

Artificial intelligence (AI) and machine learning (ML) provide effective tools to address current challenges in CSAM by enabling fast surrogate models for track and layer prediction, process parameter optimization, and nozzle design, as well as quality and porosity estimation [Falco 2025]. Recent studies highlight progress toward closed-loop control using laser profilometry, aero-acoustic monitoring, and thermal prediction for adaptive process correction [Bokade 2025]. Nevertheless, most ML applications rely on small, heterogeneous datasets, leading to limited robustness and inflated accuracy from random data splits. Improved validation strategies, uncertainty-aware learning, and hybrid training using both simulations and experiments are therefore required [Perna 2023]. Model transferability across materials, sensors, and process conditions remains challenging, while fragmented sensing systems hinder real-time feedback integration [Savangoudar 2024].

Some of these reports consider that solid-state manufacture, especially CSAM, is becoming an important means of producing light structures. CSAM offers such advantages as low thermal and energy consumption, good material efficiency, the ability to repair and restore the structure, preservation of the properties of the materials, and limited damage to the base material [Yin 2018, Prashar 2021]. Besides CSAM, a number of related processes, such as ultrasonic and friction-based CSAM, further enhance the design freedom and mechanical performance of light structures [Li 2025a]. However, several important challenges still exist. In particular, to date, studies have focused on material and process issues rather than on the integration of optimization and intelligent modeling methods. This leaves a considerable gap in the further development of scalability and efficiency.

This study presents a systematic literature review that organizes and synthesizes existing research on AI and ML applications in CSAM, following the PRISMA 2020 guidelines and using structured database searches with keyword clustering. Guided by two research questions; (RQ1) which CSAM-related problems are addressed using AI/ML and (RQ2) which AI/ML models are applied review identifies dominant research strategies, including physics-informed, data-driven surrogate models supported by targeted experiments, active learning to explore challenging process regions, uncertainty-aware optimization to ensure feasible solutions, and the offline use of computationally intensive CFD and FEA models combined with lightweight predictors for real-time control. The analysis also highlights important sustainability implications, showing that ML-based approaches can reduce energy consumption, helium usage, consumable wear, and material waste through improved design, monitoring, and process optimization [Falco 2025, Li 2025b]. Despite these advances, a key research gap remains in the development of integrated, fast, and uncertainty-aware closed-loop control systems capable of handling complex CSAM geometries.

2 METHODOLOGY

An extensive systematic literature review combined with text-mining analysis was conducted to identify, evaluate, and synthesize studies applying AI and ML to CSAM up to April 2025. The review followed the PRISMA-2020 guidelines and the structured systematic review procedure proposed by [Page 2021], including the formulation of research questions, comprehensive literature retrieval, and critical screening. Peer-reviewed English-language publications addressing AI/ML applications in CSAM were included, with no restrictions on publication year or access. Studies were excluded if they did not involve AI/ML methods, focused on non-CSAM processes, or were published in languages other than English. For the final set of eligible studies, keyword co-occurrence and clustering analyses were performed using Vosviewer, following established bibliometric methods [Nguyen 2024].

This approach enabled the identification of dominant research themes, methodological trends, and knowledge structures within AI/ML-driven CSAM research. A structured Boolean search was conducted in the Scopus database to identify studies at the intersection of CSAM and AI/ML, covering publications from 2020 to 2025. The search string combined CSAM-related terms with AI/ML methodologies using Boolean operators: ("cold spray additive manufacturing" OR "cold spray 3D printing" OR "CSAM") AND ("artificial intelligence" OR "machine learning" OR "deep learning" OR "reinforcement learning" OR "neural network*" OR "physics-informed" OR "surrogate model*" OR "data-driven").

The initial search yielded 149 records, of which duplicates were removed. Title, abstract, and keyword screening excluded 13 records, leaving 136 articles for full-text assessment. Based on clearly defined CSAM problems and justified application of AI/ML, 53 studies were further excluded due to process mismatch, absence of AI/ML methods, or language limitations, resulting in a final set of 83 primary studies included for synthesis.

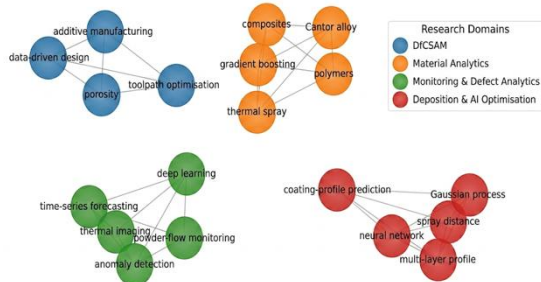


Figure 1. Keyword Co-occurrence Clustering of AI/ML Research in CSAM

3 CHAPTER RESULTS AND DISCUSSION

3.1 Cluster AI/ML applications in CSAM

Analysing how specific keywords appear together in the literature provides a practical means of identifying dominant themes within a research field [Lee 2010]. Based on the keyword co-occurrence analysis of the 83 studies that met the inclusion criteria, four distinct research clusters emerge, representing the principal directions of AI/ML applications in CSAM. Keyword frequency reflects their prominence in the literature, while the proximity between keywords indicates how often they co-occur, allowing closely related concepts to form coherent thematic groups. These clusters align well with major phases of the CSAM

workflow, from design to in-process monitoring and deposition optimization, as shown in Figure 1.

Cluster 1 represents Design-for-CSAM (DfCSAM), grouping design-stage concepts such as additive manufacturing, toolpath optimisation, porosity, and data-driven methods. Cluster 2 corresponds to Material Analytics, comprising materials-oriented terms that include Cantor alloy, composites, polymers, thermal spray, metal deposition, and gradient boosting. Cluster 3 reflects Real-Time Monitoring and Defect Analytics, characterised by keywords such as anomaly detection, powder-flow monitoring, thermal imaging, deep learning, and time-series forecasting. Cluster 4 covers Deposition and AI Optimisation, focusing on multilayer profile prediction, spray distance, geometric overlap, Gaussian processes, and neural networks. Collectively, these clusters illustrate how AI/ML research in CSAM spans the full process chain while concentrating on a small number of tightly connected thematic domains.

Keyword statistics supporting these thematic patterns are summarized in Table 1. The term cold spray appears most frequently with 11 occurrences and shows the highest total link strength of 51, confirming that Cluster 3 represents a central research focus. Among the 75 high-frequency keywords, Cluster 4 is the most prominent, accounting for 28 occurrences with a cumulative link strength of 155. Representative keywords include neural network with 5 occurrences and 25 links, model with 3 occurrences and 19 links, and geometry-related terms such as profile and spray angle, each with 2 occurrences and 14 links. Notably, single-occurrence terms such as data-efficient, limited data, geometry, and trajectory still exhibit relatively high link strengths of 9, indicating sustained interest in predictive models under data-scarce conditions.

In contrast, Cluster 1 comprises 11 keyword occurrences with an aggregate link strength of 49, while Cluster 2 comprises 14 occurrences with an aggregate link strength of 62. Overall, Clusters 3 and 4 together account for 50 keyword occurrences and a combined link strength of 249, demonstrating a strong emphasis on in-process monitoring and AI-driven deposition optimisation, whereas AI-enabled design integration and alloy development remain comparatively underexplored.

In terms of overall findings, the research activity in CSAM is strongly concentrated in Cluster 3 and Cluster 4, which together account for the majority of high-frequency keywords, reflecting a dominant focus on real-time monitoring, in-process quality assurance and data-driven parameter optimisation. In contrast, design-oriented Cluster 1 and materials-focused Cluster 2 receive substantially less attention, revealing clear research gaps in part-level design methodologies and alloy development for CSAM. Furthermore, recent studies prioritize sensing, prediction and optimization during deposition, whereas systematic integration of machine learning into design guidelines and data-driven alloy discovery remains in an early and fragmented stage.

Addressing RQ1, existing studies cluster AI/ML applications in CSAM into four main clusters. Design-for-CSAM uses predictive and inverse models to estimate track and layer geometry, support edge compensation, and enable path planning under spray footprint and access constraints. Material analytics links process and feedstock parameters to porosity, adhesion, and mechanical properties, with image-based learning supporting microstructural and defect analysis. In-situ monitoring and defect analytics apply thermal, acoustic, laser, and vision data to detect process drift, identify defects, and enable early layer-wise

correction. Deposition modelling and optimization integrate ML with CFD and analytical models to accelerate nozzle design solver-in-the-loop planning.

3.2 AI/ML-Driven results in CSAM

Table 2 shows that AI/ML research in CSAM is dominated by prediction tasks, particularly for geometry, porosity, and particle-scale impact behaviour, often reporting very high accuracy ($R^2 > 0.90$). Detection studies are less prevalent and mainly use thermal or vision-based data; despite strong classification performance, their integration into closed-loop control remains limited. Optimisation efforts typically combine surround gate models with evolutionary algorithms, emphasising computational efficiency rather than explicit accuracy metrics, resulting in prediction, detection, and optimisation being treated largely as separate tasks.

Prediction studies primarily use neural-network surrogates for forward and inverse modelling, achieving high accuracy but remaining sensitive to sparse data at off normal spray angles [Savangouder 2024]. Physics-based and analytical models are increasingly employed to generate synthetic data for rapid shape prediction [Falco 2025], while optimisation relies on surrogate-assisted evolutionary strategies for nozzle design and porosity control [Perna 2022]. Neural-network-based methods dominate CSAM research due to their flexibility in regression and classification, with feed-forward and convolutional architectures most common and increasing use of autoencoders and LSTM-based models for real time monitoring, defect detection, and deposition modelling from image, thermal, acoustic, and geometric data. Design-oriented studies and materials analytics remain constrained by sparse and heterogeneous datasets, motivating physics-informed and hybrid ML approaches that embed process knowledge and multi-source data for more robust integration.

At the particle scale, hybrid models trained on combined FEM and experimental data reduce data requirements for predicting flattening and penetration but remain sensitive to simulation-experiment bias and missing descriptors [Perna 2023, Perna 2024]. CSAM is a solid-state process in which high-velocity particles bond through severe plastic deformation, producing dense deposits at low temperatures with minimal oxidation; bonding depends on material-specific critical velocity and particle size, influenced by morphology and oxide state [Ghasemi 2024]. Although post-deposition heat treatment improves inter-particle bonding and ductility, it cannot fully eliminate porosity, underscoring the importance of primary process control [Az 2025]. Multi-scale anisotropy arising from splat interactions and scan strategy further affects CSAM design, while emerging non-destructive evaluation and ML-based tools for defect and property prediction remain limited by data scarcity, integration challenges, and interpretability concerns [Janovska 2025].

Addressing RQ2, CSAM research uses both classical ML and neural models, often combined with physics guidance. The base methods of linear models, SVMs, and Gaussian process regression remain effective for small or heterogeneous datasets, with GPR valued for uncertainty-aware, physics-informed prediction. Neural approaches include compact feed-forward networks, CNNs for layer quality, autoencoders for anomaly detection, and time-series models for monitoring. Hybrid and multi-fidelity strategies that blend analytical or CFD features with learned surrogates are increasingly adopted to improve stability and reduce simulation-to-experiment gaps. Although focused on CSAM, these challenges limited data, domain shift, fragmented sensing, and weak validation are common across all

AM categories defined in ISO/ASTM 52900:2021 [BS EN ISO/ASTM 52900 2022]. Addressing data standards, grouped validation, uncertainty-aware multi-fidelity learning, and robust closed-loop control is therefore broadly transferable across AM processes Sani 2024].

3.3 Challenges and Opportunities

Despite growing interest in AI and ML for CSAM, most studies remain constrained by limited and heterogeneous data. Models are commonly trained on small, single-system datasets or literature mined collections with inconsistent labels and measurement protocols, which can lead to overly optimistic performance under random validation and poor generalisation in practice. Ongoing challenges include data sparsity, domain shift, limited uncertainty quantification, and weak closed-loop integration, underscoring the need for hybrid physics-data models and active learning approaches [Ikeuchi 2024, Ikeuchi 2021]. Inverse models often appear effective within narrow process windows but exhibit weak parameter identifiability and unquantified uncertainty, particularly for standoff distance and edge conditions [Savangouder 2024]. Hybrid simulation experiment surrogates and synthetic data help reduce experimental cost, yet domain mismatch and solver bias remain significant challenges unless explicitly addressed [Perna 2024]. Progress therefore depends less on new model architectures than on improved data practices, including grouped validation, uncertainty aware modelling, and active learning focused on difficult regimes.

At the same time, CSAM offers clear opportunities for AI/ML integration. Modern systems generate rich multi-sensor data streams that support layer-wise monitoring and control when properly synchronised and linked to physically meaningful labels [Falco 2025, Li 2025b]. Physics-guided features, multi-fidelity learning, and compact surrogate models enable efficient prediction and real-time deployment, while active learning supports purposeful data expansion. Together, these approaches provide a practical path toward reliable AI/ML-assisted design, monitoring, optimisation, and improved sustainability in CSAM.

4 CONCLUSIONS

Integrating AI/ML into CSAM is steadily shifting the field from empirical trial-and-error toward data-driven, physics-based production. This review organised recent research into four interconnected clusters: design and inverse planning, materials analytics and characterisation, in situ monitoring and defect analysis, and deposition modelling with AI-enabled optimisation. Across these areas, physics-guided ML has shown clear benefits in improving jet behaviour, nozzle design, and deposit quality, while physics-informed surrogates enable rapid track and layer level prediction for inverse design and path correction. Performance, however, still degrades in complex regions such as edges, concavities, and high spray angles, mainly due to limited data, weak parameter identifiability, simplified jet models, and insufficient sensor fusion. Progress toward reliable industrial deployment, therefore depends on tightly coupling physics-based models with robust materials characterisation, multi-sensor monitoring, and timely feedback control. When integrated within uncertainty-aware ML frameworks, these elements can move CSAM from laboratory demonstrations to repeatable, industrial-scale manufacturing.

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Keyword	Occurrences	Total Link Strength
<i>Design-for-CSAM (Cluster 1)</i> Additive manufacturing Data-driven	7 2	35 7
<i>Material Analytics (Cluster 2)</i> Machine learning Thermal spray	5 3	26 12
<i>Real-Time Monitoring and Defect Analytics (Cluster 3)</i> Cold spray Deep learning Multi-stage model	11 4 1	51 14 5
<i>Deposition & AI Optimisation (Cluster 4)</i> Neural network Model Profile Spray angle Trajectory Data-efficient Geometry Limited data	5 3 2 2 2 1 1 1	25 19 14 14 9 9 9 9

Table 1. Keyword clustering co-occurrence analysis by research clusters

Research Target	ML/AI Models	Material	Accuracy
Single-particle penetration and flattening [Perna 2022]	Linear regression, theory-guided ML	Cu particles on fibre reinforced PEEK	$\theta_0 = 0$, $\theta_1 = 0.95$, RMSE = 0.2713 (penetration); $\theta_0 = 0$, $\theta_1 = 0.83$, RMSE = 1.0206 (flattening)
Thermal anomaly detection during cold spray [Bokade 2025]	ThermoAnoNet (DL time-series)	Cu powder on Cu substrate	Accuracy = 90%, F1 = 0.94
Particle flattening and penetration depth for coating adhesion [Perna 2023]	Linear regression, GPR, neural networks	Cu, Al, 316L powders on PEEK and ABS	$R^2 = 0.96$ (penetration), $R^2 = 0.90$ (flattening)
Inverse spray-parameter estimation from single-track geometry [Savangoudar 2024]	Hybrid PSO–MLP	Generic metallic powders	MAE = 0.009 - 0.013 mm (forward); MAE = 0.059 mm (inverse)
Coating porosity from spray and material parameters [Roy 2022]	Decision tree, RF, XGBoost, LightGBM	Generic metal and alloy powders	MAE = 2.93 mm, $R^2 = 0.75$
Powder-flow anomaly detection during spraying [Lee 2024]	CNN, convolutional autoencoder	Tin powder on aluminium substrate	Accuracy = 96.7%
Porosity prediction across multiple materials [Eberle 2024]	RF, XGBoost, Cat Boost	CP-Ti, Ti–6Al–4V, Cu, stainless steels	RMSE < 2% for 12 models
Particle flattening and penetration depth [Perna 2024]	GA-designed deep neural networks	Cu, Al, steel, Ti on polymer substrates	$R^2 = 0.92$ (flattening); $R^2 = 0.60$ (penetration)
Overlapping-track geometry prediction [Ikeuchi 2024]	Physics-informed GPR	Grade-2 Ti powder and substrate	$R^2 = 0.9988$
Full single-track geometry prediction [Ikeuchi 2021]	Hybrid NN + Gaussian regression	Grade-2 CP-Ti powder	MAPE = 1.23%, $R^2 = 0.9988$
Multi-layer deposition profile prediction [Liu 2021]	Feed-forward ANN	Cu powder on aluminium substrate	RMSE = 0.022 mm, $R^2 = 0.9957$

Layer-wise trajectory generation with shape compensation [Li 2024]	Clustering and Rapidly Exploring Random tree path planning	Al and Cu powders on Al substrate	absolute error = 0.8–1.2 mm
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Table 2. Key AI/ML results in CSAM across research themes

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