

Identifying the key AI-enabled benefits enhancing 3D printing performance: A DEMATEL based approach

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Abstract: This study aims to investigate the key AI-enabled benefits that enhance the performance of 3D printing technology. Eleven key AI-enabled benefits were identified through extensive literature review and in consultation with expertise in AI, additive manufacturing, industry workers, and higher institution academic staffs. Among the identified enablers, Decision-Making Trial and Evaluation Laboratory (DEMATEL) approach was employed to investigate cause and effect AI-enablers that improve the performance of 3D printing performance. The findings of the study investigate five cause enablers that affect six effect factors, Defect detection and quality monitoring (0.232), Process optimization and intelligent control (0.171), Design optimization and manufacturing flexibility (0.841), Predictive maintenance and predictive analytics (0.916), Human computer interaction and intelligent design support (1.173). This study extends the existing research by identifying the causal relationship and interdependencies among key AI-enabled benefits impacting 3D printing technology. The findings of this study provide both theoretical insights into AI-enabled additive manufacturing and practical guidance for researchers, practitioners, and decision-makers seeking to maximize the value of AI adoption in 3D printing systems.

Key words: AI enabled benefits, 3D printing, DEMATEL approach, cause and effect enablers

1. Introduction

Three-dimensional (3D) printing has emerged as one of the most promising manufacturing technologies for supporting sustainable production and facilitating the adoption of Industry 4.0. This technology offers several advantages, including reduced material waste, improved manufacturing efficiency, design flexibility, and the ability to fabricate products with highly complex geometries directly from digital models [1]. These advantages have encouraged its application across various sectors, including aerospace, healthcare, automotive, and construction.

Despite these benefits, the widespread adoption of 3D printing remains constrained by several technical and operational challenges. According to Altun et al. [2], issues such as poor dimensional accuracy, inadequate surface quality, excessive printing time, and material waste continue to limit the performance and industrial application of 3D printing technologies. In addition, variations in material properties and process parameters often lead to defects such as warping, poor layer adhesion, shrinkage, and inconsistent extrusion, which negatively affect the quality and reliability of printed products. Furthermore, conventional 3D printing technologies have limited capability to fabricate complex multi-material structures or embed electronic components during the printing process, requiring manual assembly and reducing manufacturing efficiency [3].

However, Artificial Intelligence (AI) has recently emerged as a transformative technology capable of overcoming many of these limitations by improving the intelligence, automation, and adaptability of 3D printing systems. AI techniques such as machine learning (ML), deep learning (DL), reinforcement learning (RL), computer vision (CV), artificial neural networks (ANN), generative design (GD), predictive analytics (PA), natural language processing (NLP), large language models (LLMs), digital twins (DT), and robotics and autonomous control (RAC) have been increasingly integrated into additive manufacturing processes. These technologies enable intelligent decision-making throughout the manufacturing lifecycle, from design optimization and process planning to real-time monitoring, quality assurance, predictive maintenance, and automated production [2].

Previous studies have reported numerous benefits arising from AI integration with 3D printing. ML, DL, and RL have been successfully applied to predict printing defects, optimize build orientation, improve surface quality, and reduce manufacturing errors [4]. Computer vision enables automated defect detection and quality monitoring by identifying dimensional inaccuracies caused by shrinkage and calibration errors [5]. Artificial neural networks and generative design contribute to reducing printing time, material consumption, and production costs while improving design optimization [6]. Similarly, predictive analytics and digital twin technologies facilitate real-time monitoring, predictive maintenance, process optimization, and sustainable manufacturing [1, 7]. In addition, natural language processing and large language models simplify 3D modeling, improve human-computer interaction, and enhance intelligent process monitoring, while robotics and autonomous control enable automated assembly and hybrid manufacturing of complex products [3, 8].

Although previous research has demonstrated the effectiveness of individual AI technologies in improving specific aspects of 3D printing, the existing literature remains fragmented. Most studies focus on the technical application of AI methods rather than providing a comprehensive understanding of the broader AI-enabled benefits and their relative importance in improving overall 3D printing performance. Moreover, little attention has been given to understanding how these benefits influence one another or which benefits serve as the primary drivers of enhanced manufacturing performance.

However, existing studies have not sufficiently consolidated the diverse benefits of AI integration into 3D printing into a comprehensive set of AI-enabled benefits. Moreover, limited attention has been given to the interdependencies among these benefits and to identifying which benefits act as causal drivers and which are primarily influenced by others. Therefore, a systematic analysis of the causal relationships and influence structure among AI-enabled benefits is needed to provide a more comprehensive understanding of how AI can enhance 3D printing performance.

Therefore, this study aims to identify and prioritize the key AI-enabled benefits that enhance 3D printing performance by employing the DEMATEL method. Specifically, the study investigates the causal relationships among AI-enabled benefits to determine the most influential factors that contribute to improved quality, efficiency, automation, sustainability, and overall manufacturing performance. The findings are expected to provide both theoretical insights into AI-enabled additive manufacturing and practical guidance for researchers, practitioners, and decision-makers seeking to maximize the value of AI adoption in 3D printing systems.

1. What are the key AI-enabled benefits that improve 3D printing performance?
2. Which AI-enabled benefits are the most influential in enhancing 3D printing performance?
3. How are the identified AI-enabled benefits causally related to one another?

2. Literature review

2.1 AI-enabled defect detection and quality improvement

One of the most significant contributions of AI to 3D printing is the improvement of print quality through defect prediction and quality monitoring. Machine learning, DL, and RL have been widely employed to predict printing defects, optimize build orientation, and minimize design errors, thereby improving dimensional accuracy and reducing common manufacturing defects such as warping, poor layer adhesion, and surface roughness [4]. Similarly, [9] demonstrated that AI-driven ML and DL models effectively

predict surface roughness and detect printing defects, leading to improved intelligence, accuracy, and efficiency of fused deposition modeling (FDM) systems.

Computer Vision has also become an essential AI technique for quality assurance in additive manufacturing. The study by [5] identified CV algorithms as highly effective for real-time defect detection and quality monitoring. Likewise, Bhandari and Manandhar [10] integrated CV with computer-aided design (CAD) to detect dimensional inaccuracies caused by shrinkage and calibration errors, thereby improving the geometric accuracy of printed components. Recent study by [8] proposed an LLM-based framework capable of detecting printing defects such as inconsistent extrusion, stringing, warping, and poor layer adhesion while identifying the process parameters responsible for these defects. Collectively, these studies indicate that AI substantially enhances product quality by enabling early defect prediction, automated inspection, and intelligent quality assurance.

2.2 AI-enabled process optimization and intelligent control

Another major benefit of AI integration in 3D printing is process optimization through intelligent control and adaptive decision-making. Reinforcement learning has demonstrated significant capability in learning the relationships between process parameters and printing outcomes. Dharmawan et al. [11] developed a model-based reinforcement learning framework for robotic wire arc additive manufacturing that effectively corrected interlayer geometric deviations and improved the quality of manufactured components. Similarly, Mattera et al. [12] reported that reinforcement learning efficiently manages nonlinear and multivariable process interactions, resulting in enhanced tracking performance, robustness, and overall product quality.

Predictive analytics has also contributed significantly to process optimization. The study by Kuldir et al. [1] developed a cyber-physical production system integrating predictive analytics with 3D printing to monitor process parameters, estimate nozzle remaining useful life, identify optimal printing parameters for targeted surface quality, and minimize printing time. These findings demonstrate that AI enables intelligent process control through continuous monitoring, adaptive optimization, and predictive decision-making, thereby improving manufacturing efficiency and reliability.

2.3 AI-enabled resource efficiency and cost reduction

AI technologies also contribute to improving manufacturing efficiency by reducing printing time, material consumption, and production costs. The study by Ahmad [6] employed ANNs and RL to optimize the 3D printing workflow. The proposed framework reduced printing time by 15-25%, decreased material consumption by 10-20%, and lowered defect rates by approximately 30%.

Similarly, GD has emerged as an effective approach for optimizing product design and manufacturing efficiency. Martin and Jozef [13] demonstrated that generative design significantly reduces design time, material usage, and production costs by automatically generating optimized design alternatives based on predefined design constraints. Likewise, the paper by Kim et al. [14] reported that integrating generative AI into 3D modeling and printing facilitates process optimization, enables the creation of complex geometries, and enhances production efficiency. These findings suggest that AI plays an important role in improving resource utilization and achieving cost-effective manufacturing.

2.4 AI-enabled intelligent design and human-computer interaction

AI has expanded the accessibility and flexibility of 3D printing by improving the interaction between users and digital design systems. Natural Language Processing enables users without extensive CAD expertise to generate printable 3D models through natural language commands. According to Teshager [15], NLP enhances multimodal 3D interfaces by supporting voice commands, contextual understanding, and language-driven interaction, thereby improving user experience and facilitating more intuitive design workflows.

Furthermore, the study of [8] demonstrated that LLM can assist process monitoring by interpreting printing errors and identifying their underlying causes. In addition to monitoring, LLM simplify the generation of machine instructions (G-code) and supports intelligent communication between users and

manufacturing systems. Consequently, NLP and LLM technologies improve design accessibility, simplify modeling processes, and enhance collaboration between users and intelligent manufacturing systems.

2.5 AI-enabled real-time monitoring, predictive maintenance, and smart manufacturing

Real-time monitoring and predictive maintenance have become essential capabilities of AI-enabled smart manufacturing systems. Digital Twin technology provides real-time digital representations of physical manufacturing systems, enabling continuous monitoring, simulation, and optimization throughout the production lifecycle. Rojek et al. [7] reported that integrating digital twins with AI improves manufacturing performance, system reliability, and profitability through data-driven monitoring and intelligent process optimization.

Similarly, the study by Ritul et al. [16] demonstrated that Digital Twin technology enhances design accuracy, reduces material waste, improves sustainability, and enables adaptive process control through real-time monitoring and predictive analytics. Predictive analytics further complements these capabilities by forecasting equipment conditions and optimizing production parameters [1]. Together, these technologies establish intelligent manufacturing environments capable of continuously improving operational performance while reducing downtime and waste.

2.6 AI-enabled automation and hybrid manufacturing

Automation represents another important benefit achieved through AI integration in 3D printing. Robotics and RAC enable automated assembly during the additive manufacturing process, allowing the fabrication of products that cannot be produced using conventional 3D printing systems. Munguia et al. [3] developed a robotic manufacturing system that combined fused deposition modeling (FDM) with automated pick-and-place assembly, successfully embedding electronic components directly into printed structures. Their findings demonstrate the feasibility of hybrid additive manufacturing, expanding manufacturing flexibility while reducing manual intervention. This advancement illustrates the growing role of AI-driven automation in improving manufacturing capability, productivity, and process integration.

In summary as a research gap, previous studies have demonstrated that AI enhances 3D printing through different benefits, including defect detection and quality monitoring, process optimization, resource efficiency, intelligent design, real-time monitoring, predictive maintenance, and manufacturing automation [4, 6, 7]. However, these studies have primarily investigated individual AI specific applications in isolation, such as machine learning, computer vision, reinforcement learning, digital twins, or large language models, with a focus on technical performance improvements.

Despite these valuable contributions, the existing literature remains fragmented and provides limited understanding of which AI enabled benefits are the most influential in improving overall 3D printing performance. Furthermore, previous studies have not systematically examined the interdependencies and causal relationships among these benefits. Since many AI-enabled benefits reinforce one another, understanding their cause-and-effect relationships is essential for prioritizing investment and implementation strategies. To address this gap, this study employs the DEMATEL method to identify, prioritize, and analyze the causal relationships among the key AI-enabled benefits that enhance 3D printing performance. By revealing the driving and dependent benefits, the study provides a comprehensive framework that supports both researchers and practitioners in making informed decisions regarding AI adoption in 3D printing technology.

Table 1. Summary of AI technology and its enabled benefits

AI technology	AI-enabled Benefits	Sources
ML, DL and RL	Predict print defects, select optimal orientations and minimize design, Predict surface roughness; predict and improve error factors; Improve product quality, Reduce defect rate	[4, 9, 11]
CV	Identify surface defects, monitor quality, improve geometric dimension by improving defects arising from shrinkage and calibration	[5, 6 10]

NN	Reduce printing time and material consumption	
GD	Save design process time and material consumption by creating cost effective production methods, optimizing designs and process, creating complicated, innovative shapes, and securing efficiency in every part of the process	[13, 14]
PA	Predict remaining life of tools, find optimum printing parameter for the target surface quality	[1]
LLM and NLP	Identify printing errors, effectively determine the parameters causing inconsistent extrusion, stringing, warping, and layer adhesion; Improve human computer interaction, support more accessible and efficient design workflows, simplify modeling, create simple machine instructions	[8, 15]
DT	Through monitoring, simulating and optimizing, improve performance, reliability and profitability. It enables real-time monitoring, predictive analytics, and adaptive control in building processes, enhances design accuracy, reduces waste, and improves sustainability.	[7, 16]
RAC	Fabricate an object that cannot be fabricated with traditional 3D printers due to the drawback of lacking a more diverse set of materials	[3]

3. Materials and methods

3.1 Research procedure

As part of the study, an extensive literature review was conducted to identify the key AI-enablers that enhance 3D printing technology. A panel of 20 experts from manufacturing industries and higher education institutions, with relevant expertise in AI, additive manufacturing, industrial engineering, and smart manufacturing, assessed the identified enablers for content validity using a three-point scale: (1) essential, (2) important but not essential, and (3) not necessary. Lawshe Content Validity Ratio (CVR) was used to evaluate the content validity of each enabler, and the retained enablers were subsequently used for further analysis. Based on consultations with the experts, contextual relationships among the retained enablers were established, and the DEMATEL method was applied to construct the total relation matrix and identify cause-and-effect relationships among the enablers.

3.2 Content validity of the constructs

According to Yusoff [17], content validity refers to how well a measurement tool captures the construct being tested. It is seen as crucial proof that a measurement tool, such a research questionnaire, is legitimate. Content validation should be carried out methodically based on the available data and industry best practices, since it is essential to ensuring overall authenticity. Based on best practices and available data, content validity was assessed using the CVR, because CVR is specifically an index for evaluating the necessity of individual items as shown in Eq. (1). The equation for CVR is given below.

$$CVR = \frac{(N_e - \frac{N}{2})}{\frac{N}{2}} \quad (1)$$

Where, N_e = the number of experts indicating “essential” and N = the total number of experts.

3.3 DEMATEL procedures

Step 1: Formation of a matrix of direct relationships (DRM) (e) Using the linguistic scale, n AI enablers and L experts have shared their opinions regarding the relationships and level of correlation between the enablers. In this study five degrees of influence are used as shown in Table 2. After collecting all of the

expert's responses, the (n × n) matrix for individual expert is created using the Mathematical formulation shown in Eq. (2).

$$e = \begin{pmatrix} 0 & e_{12} & \cdot & e_{1(n-1)} & e_{1n} \\ e_{21} & 0 & \cdot & e_{2(n-1)} & e_{2n} \\ \cdot & \cdot & 0 & \cdot & \cdot \\ \cdot & \cdot & \cdot & 0 & \cdot \\ e_{(n-1)1} & e_{(n-1)2} & \cdot & \cdot & e_{(n-1)n} \\ e_{n1} & e_{n2} & \cdot & e_{n(n-1)} & 0 \end{pmatrix} \quad (2)$$

Table 2. Five levels of influence

The influence of enablers on another	Related number
No influence	0
low influence	1
Medium influence	2
High influence	3
Very high influence	4

Step 2: Calculating average of DRM (a) After forming a direct relationship matrix (e) as shown in Eq. (2) for individual 20 experts, the average direct relationship matrix (a) was developed using Eq. (3).

$$a = \frac{1}{L} \sum_L^n e_{ij} \quad (3)$$

$$g = \frac{1}{\text{Max } 1 \leq i \leq n \sum_{j=1}^n e_{ij}} \quad (4)$$

Step 3: Normalizing matrix of direct relationships (H) Normalized DRM (H) was obtained by multiplying equations 3 and 4 (a × g)

Step 4: Calculate or Development of Total Relationship Matrix (S)

$$S = H (I - H)^{-1} \quad (5)$$

Where I is n × n identity matrix

Step 5: Obtain sum of raw and column or Calculation of Causal Parameters Equation (5) and (6) were used to obtain the sum of raw and column from the total relationship matrix.

$$SR = \sum_{i=1}^n e_{ij} \quad (6)$$

$$SC = \sum_{j=1}^n e_{ij} \quad (7)$$

Step 6: Computing threshold value (α)

By utilizing Equation (8), the threshold value (α) is calculated by averaging the components in matrix T. With this computation, the elements with values less than threshold value are removed while conducting (drawing) cause effect diagram.

$$\alpha = \frac{\sum_{i=1}^n e_{ij} \sum_{j=1}^n e_{ij}}{N} \quad (8)$$

where N is the total number of elements in the matrix T.

Step 7: Obtaining or calculation of prominence and cause-effect

Cause-effect is computed by subtracting SC from SR, whereas prominence is computed by adding the causal parameters SR and SC. It is said that the cause component is positive SR-SC and the impact component is negative SR-SC.

4. Results and findings

4.1 Content validity test results

For calculating CVR values for each AI enablers Lawsh CVR excel worksheets were used and the results were reported in Table 3. The findings indicated that all the identified enablers obtained positive CVR value ranges from 0.655 to 1, which fulfills the minimum cut of CVR value 0.42 as recommended by Robert et al. [17]. The highest CVR value was obtained for AIE10, with a CVR of 1.000, indicating strong agreement among experts regarding its relevance to AI-enabled 3D printing. This was followed by AIE9 with a CVR of 0.975 and AIE11 with a CVR of 0.961. The lowest CVR was observed for AIE5, with a value of 0.655. Nevertheless, this value remained above the adopted acceptance criterion, indicating that the experts considered the factor sufficiently relevant to the study. This result revealed that the identified enablers from literature review and experts' opinion were correctly identified and explains AI enablers that enhance 3D printing technology.

Table 3. Content validity test result

AI Factors	Coding	CVR – Value
Defect detection and quality monitoring	AIE1	0.70
Surface quality and dimensional accuracy improvement	AIE2	0.90
Process optimization and intelligent control	AIE3	0.70
Printing time reduction	AIE4	0.90
Material consumption and waste reduction	AIE5	0.70
Design optimization and manufacturing flexibility	AIE6	0.90
Predictive maintenance and predictive analytics	AIE7	0.80
Real-time monitoring and adaptive control	AIE8	0.80
Human computer interaction and intelligent design support	AIE9	1.00
Automation and autonomous manufacturing	AIE10	1.00
Sustainability and resource efficiency	AIE11	1.00

4.2 Average direct - relation, normalizing, total - relation matrix results

In this study, the interrelationships between the identified eleven AI enablers were determined (identified) using the DEMATEL approach. The average direct relation, normalizing, and total-relation results were obtained by using Eq. (2) to Eq. (8) and their outcomes were summarized in Table 4 to 6. From Table 6 Causal Parameters (SR and SC) of the enablers were calculated to identify the cause-and-effect factors and the results are illustrated in Table 7.

The findings presented in Table 4 (average direct-relation matrix) indicate that the experts perceived different levels of influence ranged from 0 to 4, representing no influence to very high influence, respectively. The normalized direct-relation matrix in Table 5 presents the standardized direct influences among the AI enablers after normalization. The values range from 0 to 0.128, with the normalized values preserving the relative pattern of direct influence observed in the average direct-relation matrix. The normalization facilitates the subsequent calculation of the total-relation matrix and ensures that the influence relationships can be appropriately incorporated into the DEMATEL analysis. In addition, the finding in Table 6 provides a more comprehensive representation of the influence structure within AI enabled 3D printing. The result indicated that most of AI enabled benefits have substantial overall influence on other factors. These results confirmed that AI enabled benefits do not operate independently within 3D printing systems. Instead, improvements in one benefit can influence several other benefits through direct and indirect pathways. This finding supports the use of DEMATEL because a simple ranking approach would not adequately capture these interconnected relationships. The threshold value was calculated as approximately 0.149 by averaging the elements of the total-relation matrix. Relationships with values below this threshold were excluded from the cause-effect diagram to improve the clarity of the influence structure.

Table 4. Direct relationship matrix (Average)

	AIE1	AIE2	AIE3	AIE4	AIE5	AIE6	AIE7	AIE8	AIE9	AIE10	AIE11
AIE1	0.000	3.950	1.950	0.950	3.950	0.000	2.000	3.100	1.000	1.000	3.150
AIE2	3.050	0.000	1.050	0.950	0.000	1.950	3.050	1.000	0.000	1.950	4.000
AIE3	4.000	3.950	0.000	4.000	3.950	1.000	0.000	3.000	1.050	2.000	0.000
AIE4	0.000	1.000	3.000	0.000	2.000	1.150	0.000	2.000	1.000	2.000	4.000
AIE5	0.000	1.950	3.050	1.000	0.000	0.000	2.000	3.050	2.000	1.000	4.000
AIE6	1.000	4.000	1.950	4.000	3.050	0.000	1.000	1.900	0.000	2.000	4.000
AIE7	3.050	1.050	2.050	4.000	1.000	1.950	0.000	3.000	1.950	3.000	4.000
AIE8	4.000	3.050	0.000	1.000	1.900	0.000	3.050	0.000	1.050	4.000	2.000
AIE9	2.000	1.000	4.000	3.050	4.000	3.950	0.000	1.000	0.000	4.000	2.150
AIE10	0.000	1.100	3.000	3.950	4.000	1.050	1.900	1.000	0.000	0.000	4.000
AIE11	1.050	0.000	1.000	2.000	1.100	1.150	0.000	3.000	1.900	1.000	0.000

Table 5. Normalized relationship matrix (H)

	AIE1	AIE2	AIE3	AIE4	AIE5	AIE6	AIE7	AIE8	AIE9	AIE10	AIE11
AIE1	0.000	0.126	0.062	0.030	0.126	0.000	0.064	0.099	0.032	0.032	0.101
AIE2	0.097	0.000	0.034	0.030	0.000	0.062	0.097	0.032	0.000	0.062	0.128
AIE3	0.128	0.126	0.000	0.128	0.126	0.032	0.000	0.096	0.034	0.064	0.000
AIE4	0.000	0.032	0.096	0.000	0.064	0.037	0.000	0.064	0.032	0.064	0.128
AIE5	0.000	0.062	0.097	0.032	0.000	0.000	0.064	0.097	0.064	0.032	0.128
AIE6	0.032	0.128	0.062	0.128	0.097	0.000	0.032	0.061	0.000	0.064	0.128
AIE7	0.097	0.034	0.065	0.128	0.032	0.062	0.000	0.096	0.062	0.096	0.128
AIE8	0.128	0.097	0.000	0.032	0.061	0.000	0.097	0.000	0.034	0.128	0.064
AIE9	0.064	0.032	0.128	0.097	0.128	0.126	0.000	0.032	0.000	0.128	0.069
AIE10	0.000	0.035	0.096	0.126	0.128	0.034	0.061	0.032	0.000	0.000	0.128
AIE11	0.034	0.000	0.032	0.064	0.035	0.037	0.000	0.096	0.061	0.032	0.000

Table 6. Total relationship matrix (S)

	AIE1	AIE2	AIE3	AIE4	AIE5	AIE6	AIE7	AIE8	AIE9	AIE10	AIE11
AIE1	0.097	0.217	0.156	0.140	0.227	0.057	0.136	0.209	0.090	0.138	0.247
AIE2	0.166	0.083	0.113	0.130	0.099	0.105	0.147	0.130	0.048	0.143	0.247

AIE3	0.215	0.235	0.113	0.235	0.247	0.088	0.087	0.214	0.091	0.174	0.178
AIE4	0.071	0.108	0.166	0.092	0.153	0.078	0.050	0.149	0.075	0.140	0.229
AIE5	0.090	0.144	0.177	0.136	0.102	0.054	0.119	0.192	0.112	0.129	0.244
AIE6	0.122	0.220	0.163	0.237	0.207	0.058	0.104	0.179	0.060	0.167	0.283
AIE7	0.195	0.153	0.184	0.259	0.179	0.126	0.078	0.226	0.125	0.216	0.300
AIE8	0.204	0.186	0.103	0.145	0.173	0.057	0.166	0.112	0.087	0.219	0.218
AIE9	0.160	0.162	0.249	0.240	0.273	0.183	0.081	0.171	0.065	0.240	0.251
AIE10	0.081	0.124	0.186	0.227	0.225	0.083	0.115	0.144	0.058	0.094	0.260
AIE11	0.088	0.066	0.095	0.131	0.112	0.070	0.043	0.158	0.092	0.100	0.092

4.3 Prominence and net causal analysis results

This study identified Prominence (SR + SC) and net causal factors (SR - SC) and the results are reported in Table 7. SR + SC value indicates the overall importance and degree of interaction of the enablers within the system, whereas the SR - SC value determines whether a factor belongs to the cause or effect group. A positive SR - SC value indicates that a factor exerts greater influence on other factors than it receives from them and is therefore classified as a cause factor. Conversely, a negative value indicates that a factor receives greater influence than it exerts and is therefore classified as an effect factor. The findings of this study as shown in Table 7 identified five cause AI enabler (AIE1, AIE3, AIE6, AIE7 and AIE9) and six effect factors (AIE2, AIE4, AIE5, AIE8, AIE10 and AIE11). This result confirmed that AIE9 (1.173) is the strongest driving factor within the identified AI- causal enabled benefit system. On the other hand, AIE7 (0.916), AIE6 (0.841), AIE1 (0.232) and AIE3 (0.171) have ranked from second to fifth causal factors respectively.

This result confirmed that improved interaction between users and intelligent 3D printing systems can contribute to improvements in several other areas, including process optimization, printing time reduction, material efficiency, design flexibility, and automation. This indicates that predictive capabilities can act as an important driver of 3D printing performance. By predicting equipment conditions, identifying potential failures, and supporting parameter optimization, predictive analytics can influence process reliability, printing time, monitoring, automation, and sustainability. This finding demonstrates that AI-supported design optimization is not merely an outcome of intelligent manufacturing but also a driver of other performance benefits. Optimized designs can reduce material requirements, improve manufacturability, reduce production time, and increase the ability of 3D printing systems to produce complex and customized products. In addition, the finding of this study suggests that AI-based defect detection can contribute to downstream improvements in product quality, process control, and manufacturing reliability. Although AIE3 had the lowest positive causal value among the five cause factors, it remains an important driver because intelligent control can influence printing time, material consumption, quality, monitoring, and other operational outcomes.

On the other hand, among the effect factors AIE11 exhibited the most negative causal value (-1.501). The second strongest effect factor is AIE4, with a net causal value of -0.661. Similarly, the remaining effect factors AIE5 (-0.500), AIE2 (-0.287), AIE8 (-0.216), and AIE10 (-0.163) ranked from third to six net causal values respectively. This indicates that sustainability and resource efficiency are strongly influenced by the other AI-enabled benefits rather than acting primarily as independent driving factors. In other words, improvements in intelligent design, predictive maintenance, process optimization, defect detection, and human-computer interaction can collectively contribute to improved sustainability and resource efficiency. This suggests that reductions in printing time are largely achieved because of improvements in other AI-enabled capabilities, particularly process optimization, predictive analytics, intelligent design, and automation. This indicates that material efficiency is substantially influenced by upstream AI-enabled improvements such as design optimization, defect detection, process optimization, and predictive analytics. These findings suggest that these outcomes are influenced by the broader AI-enabled system rather than acting as primary causal drivers.

Table 7. Significant and Relationship Results

	SR	SC	SR+SC	SR-SC	Cause/effect groups based on SR-SC
AIE1	1.715	1.483	3.198	0.232	Cause
AIE2	1.411	1.698	3.109	-0.287	Effect
AIE3	1.876	1.705	3.581	0.171	Cause
AIE4	1.312	1.973	3.285	-0.661	Effect
AIE5	1.500	2.000	3.500	-0.500	Effect
AIE6	1.800	0.959	2.759	0.841	Cause
AIE7	2.041	1.125	3.166	0.916	Cause
AIE8	1.670	1.886	3.556	-0.216	Effect
AIE9	2.074	0.901	2.975	1.173	Cause
AIE10	1.597	1.760	3.357	-0.163	Effect
AIE11	1.047	2.548	3.595	-1.501	Effect

5. Discussion

The findings of this study confirmed that AI-enabled benefits in 3D printing are highly interconnected rather than operating as isolated improvements. Among these, human-computer interaction and intelligent design support showed the strongest causal influence, followed by predictive maintenance and predictive analytics and design optimization and manufacturing flexibility. This indicates that AI-supported decision-making, intelligent design, and predictive capabilities can act as important drivers of broader 3D printing performance improvements.

The six effect factors sustainability and resource efficiency, printing time reduction, material consumption and waste reduction, surface quality and dimensional accuracy improvement, real-time monitoring and adaptive control, and automation and autonomous manufacturing are largely influenced by these causal factors. In particular, sustainability and resource efficiency had the strongest negative causal value, suggesting that sustainability performance is an important downstream outcome of improvements in other AI-enabled capabilities. These findings are consistent with previous studies reporting that AI-based optimization; predictive analytics, computer vision, generative design, and digital twins can improve quality, efficiency, resource utilization, and process reliability in additive manufacturing [1, 2, 7].

The results also extend previous research by moving beyond the assessment of individual AI technologies and demonstrating the causal structure among AI-enabled benefits. This provides a more comprehensive basis for prioritizing AI adoption in 3D printing. Rather than investing equally in all potential benefits, practitioners should initially strengthen the causal factors because improvements in these areas can generate cascading effects across other performance dimensions.

6. Proposed conceptual framework for future research study

This study developed and proposed causal conceptual frame work based on the outcomes of DEMATEL analysis for future study. The developed framework identifies five AI enabled causal factor as the primary driving capabilities of AI-enabled 3D printing. These causal factors are expected to influence downstream 3D printing performance outcomes that include six factors. The framework therefore proposes that strengthening the causal AI capabilities can generate cascading improvements across multiple dimensions of 3D printing performance, consistent with the interconnected relationships identified through DEMATEL. As future study the developed framework should be statistically test using structural equation modeling (SEM). However, the stability of the cause-effect classification under alternative threshold values was not assessed in this study. Future research should conduct sensitivity analysis to examine the robustness of the identified relationships and validate the proposed framework empirically.

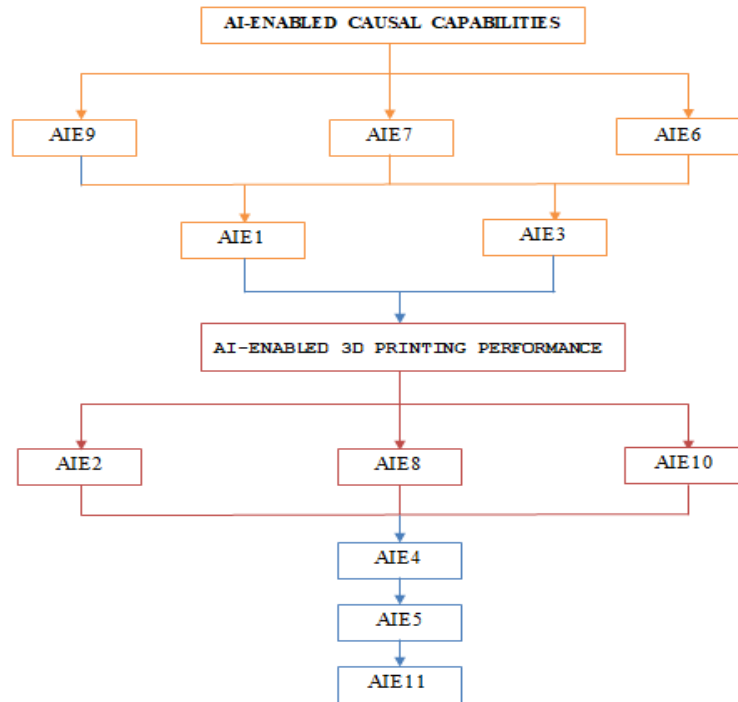


Figure 1. DEMATEL-informed conceptual framework of AI-enabled benefits for enhancing 3D printing performance

7. Conclusion

This study identified and analyzed eleven key AI-enabled benefits associated with improved 3D printing performance using the DEMATEL method. The results classified five benefits as causal factors and six as effect factors. Human-computer interaction and intelligent design support emerged as the strongest causal factor, while sustainability and resource efficiency was identified as the strongest effect factor. The findings indicate that AI can improve 3D printing performance through interconnected pathways involving intelligent design, predictive analytics, defect detection, process optimization, quality improvement, resource efficiency, automation, and sustainability. The main contribution of the study is the development of a causal perspective that helps explain how different AI-enabled benefits influence one another.

Practically, the findings suggest that organizations should prioritize AI-enabled design optimization, predictive maintenance and analytics, intelligent human-computer interaction, defect detection, and process optimization as strategic areas for improving overall 3D printing performance. Future research can validate the identified causal relationships using empirical data from industrial 3D printing applications and investigate the influence of different AI technologies across specific additive manufacturing processes.

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