

(REVIEW ARTICLE)



THE TRANSFORMATION OF RAPID PROTOTYPING IN INDUSTRY 4.0: A SYSTEMATIC REVIEW OF CLOUD-BASED ADDITIVE MANUFACTURING

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ABSTRACT

Industry 4.0 changes the dynamics of how additive manufacturing (AM) is used for product development and rapid prototyping. Cloud computing, Internet of Things (IoT), cyber physical systems (CPS), artificial intelligence (AI) and machine learning (ML) and digital twins are increasingly becoming part of AM, providing enhanced connectivity, flexibility and access to manufacturing resources. However, the more technologies emerge and the greater the number of benefits that are touted, the more difficult it is to assess the extent to which cloud-based additive manufacturing (CBAM) has transformed rapid prototyping—let alone why its popularization remains stymied. This systematic review outlines the changes to rapid prototyping in the context of Industry 4.0 using CBAM. The literature published from 2016 to 2026 was retrieved from Google Scholar, Web of Science, IEEE Xplore and Emerald and screened according to the included and excluded criteria pre-designed, and reported using PRISMA 2020. The review categorises the enabling technologies based on function, data flow, consolidates the reported applications and benefits of the technologies, and identifies technical, operational, economic and organisational barriers to their adoption, specifically considering the needs of small and medium-sized enterprises (SMEs) and developing economies including Zimbabwe. The results demonstrate the potential of CBAM to provide access to manufacturing resources at distance, collaborative and iterative design, distributed manufacturing and stronger integration of digital and physical manufacturing systems. There are still major shortcomings, however, in cybersecurity, interoperability, data handling, network reliability, quality consistency and interoperability with heterogeneous systems. The evidence of technical feasibility is much greater than the evidence of long-term economic gains, industrial scalability and implementation in reality. The review thus suggests more rigorous industrial validation, shared interoperability and security rules, process-parameter knowledge-bases that can be reused and paths towards implementation that are low-cost and incremental for resource-poor manufacturers.

Keywords: Cloud-based additive manufacturing; Rapid prototyping; Industry 4.0; Manufacturing-as-a-Service; Digital twin; Machine learning; SMEs; Systematic review

1 INTRODUCTION

The concept of rapid prototyping has come a long way since the advent of additive manufacturing (AM). Instead of relying primarily on subtractive and formative techniques, designers can now create complex and custom-designed parts directly from digital models. This has made AM a fundamental way of product development and led to applications beyond prototyping (Garden 2016; Dilberoglu et al., 2017; Gibson et al., 2021).

With Industry 4.0, this is taking a step further with the association of AM to the cloud and to the Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), and digital twins (Bănică, Sover and Anghel, 2024; Pant et al., 2024). Cloud-based additive manufacturing (CBAM) in particular enables manufacturing resources and production data to be accessed and shared via the cloud, enabling remote production, collaboration and distributed production (Baumann and Roller, 2017; Wu et al., 2015; Rahman et al., 2022). However, in practice, it is not always easy to see the advantages of such systems.

Limited adoption is threatened by cyber security, interoperability, reliability, cost and quality consistency (Tartici et al., 2023; Kilic and Bartolo, 2023; Gharibvand et al., 2024). The barriers are deeper in the developing economies. A survey of Zimbabwean manufacturers revealed that AM, simulation and mathematical modelling software were among the least adopted Industry 4.0 technologies and that the lack of an Industry 4.0 strategy, the high costs of the solutions, limited government support and fear of cyber-attacks were the main barriers (Muhla et al., 2025a). In the same industrial base, though nearly all companies had access to the Internet, a related study found that rapid prototyping equipment and numerically controlled machine tools were in very short supply (Muhla et al., 2023).

Cloud-based access to AM is therefore especially attractive for companies that do not afford to invest in such equipment, but also has specific risks in the event of low connectivity, low investment capacity and low digital skills. There are already some reviews available that cover different aspects of cloud manufacturing (Gharibvand et al., 2024), Industry 4.0 and monitoring and control in AM (Tartici, Kilic and Bartolo, 2023), digital twins in AM (Tudorache et al., 2025) and ML in AM (Ng et al., 2024). There are not many studies which integrate these aspects around the question of transformation in rapid prototyping, nor are there many which address the implications of this transformation for SMEs in resource-constrained environments. This review is intended to fill that gap. It has three contributions: (i) a taxonomy of the technologies that enable CBAM, categorised by type of function and by the direction of data flow; (ii) a critical synthesis of the reported benefits of rapid prototyping that is able to make a distinction between demonstrated benefits and claimed benefits; and (iii) a research agenda where SMEs and developing economies are made explicit.

2 METHODOLOGY AND SEARCH STRATEGY

2.1 Systematic review approach

The systematic review approach used in this study involved finding, assessing and summarising previous research on the topic of the application of CBAM to transform rapid prototyping. The review covers three closely related areas – additive manufacturing, cloud and digital manufacturing, and Industry 4.0. It was conducted following the stages of a systematic review as described by (Pollock and Berge, 2018) which includes the steps of identifying relevant studies, screening the studies based on inclusion and exclusion criteria, extracting the relevant information and synthesising the results with regard to the research questions. Reporting is based on the statement of PRISMA 2020 (Page et al., 2021). Google Scholar, Web of Science, IEEE Xplore and Emerald were searched to ensure the study was credible and reliable as they had peer-reviewed engineering research.

2.2 Research questions

- RQ1: How has Industry 4.0 transformed rapid prototyping through cloud-based additive manufacturing?
- RQ2: Which technologies enable cloud-based additive manufacturing, and how do they interact?
- RQ3: What benefits and applications does cloud-based additive manufacturing provide compared with conventional, locally operated additive manufacturing?
- RQ4: What technical, operational and organisational challenges limit the adoption of cloud-based additive manufacturing?
- RQ5: What research gaps and future research opportunities exist, particularly for SMEs and developing economies?

2.3 Search strategy

The databases listed above were searched using a structured search. The concepts used for its construction were: additive manufacturing, cloud manufacturing, rapid prototyping and industry 4.0. Boolean operators were used to

connect related terms and synonyms, and AND was used to connect the concepts, OR used to capture alternate wording. The main search term was: The string was used on titles, abstracts and keywords (when the database permitted), and adjusted to the syntax of each database. Further relevant work was identified through backward and forward citation searching of the included studies, which included regionally relevant studies on Industry 4.0 adoption, process optimisation and prototype development that were not included in the major databases in Zimbabwean manufacturing. Works published prior to 2016 are only included for definition or context purposes and were not included in the synthesized corpus.

2.4 Inclusion and exclusion criteria

Table 1 sets out the eligibility criteria applied at every screening stage.

Table 1: Inclusion and exclusion criteria

No.	Criterion	Inclusion criteria	Exclusion criteria
1	Publication period	Published between 2016 and 2026	Published before 2016
2	Language	Written in English	Published in a language other than English
3	Publication type	Peer-reviewed journal articles and relevant conference papers	Editorials, news articles, book reviews, dissertations and other non-eligible publication types
4	Subject focus	Directly addresses additive manufacturing within a cloud-based or Industry 4.0 context	Unrelated to additive manufacturing or rapid prototyping, even if cloud computing is discussed
5	Thematic scope	Addresses rapid prototyping or digital manufacturing	Focuses exclusively on AM materials or processes with no relevance to the review questions
6	Technological context	Situated within an Industry 4.0 or cloud-based manufacturing environment	Unrelated to Industry 4.0 or cloud-based manufacturing
7	Data availability and relevance	Sufficient full text for evaluation and data extraction; relevant to at least one research question	Full text unavailable or insufficient for data extraction; does not address any research question

2.5 Study selection and screening

The records obtained from the database searches were then screened in a staged fashion to filter for adherence to the eligibility criteria established prior to the search. These records were initially culled for duplicates, then title/abstract was checked, and the records that appeared to be relevant to the project went to full-text screening. The same inclusion and exclusion criteria were used throughout, and any studies that did not meet the criteria and/or did not clearly address at least one of the research questions were excluded.

2.6 Data extraction and synthesis

The relevant information from the studies that fulfilled the criteria was extracted, including information on author, publication year, objectives, enabling technologies, type of study (review study, conceptual framework study, optimisation model study, laboratory platform or industrial case study) and the main results of each study regarding each research question. The data was subsequently analysed in order to identify the common themes, namely, enabling technologies, applications and benefits, challenges and research gaps. The studies were grouped in this way to facilitate the identification of commonalities and differences within the set and to distinguish between studies that have confirmed benefits in the laboratory or field, versus those that have merely been asserted and/or modelled. The themes were then used to answer the research questions.

2.7 PRISMA flow diagram

Figure 1 summarises the flow of records through the identification, screening and inclusion stages, following the PRISMA 2020 template (Page *et al.*, 2021).

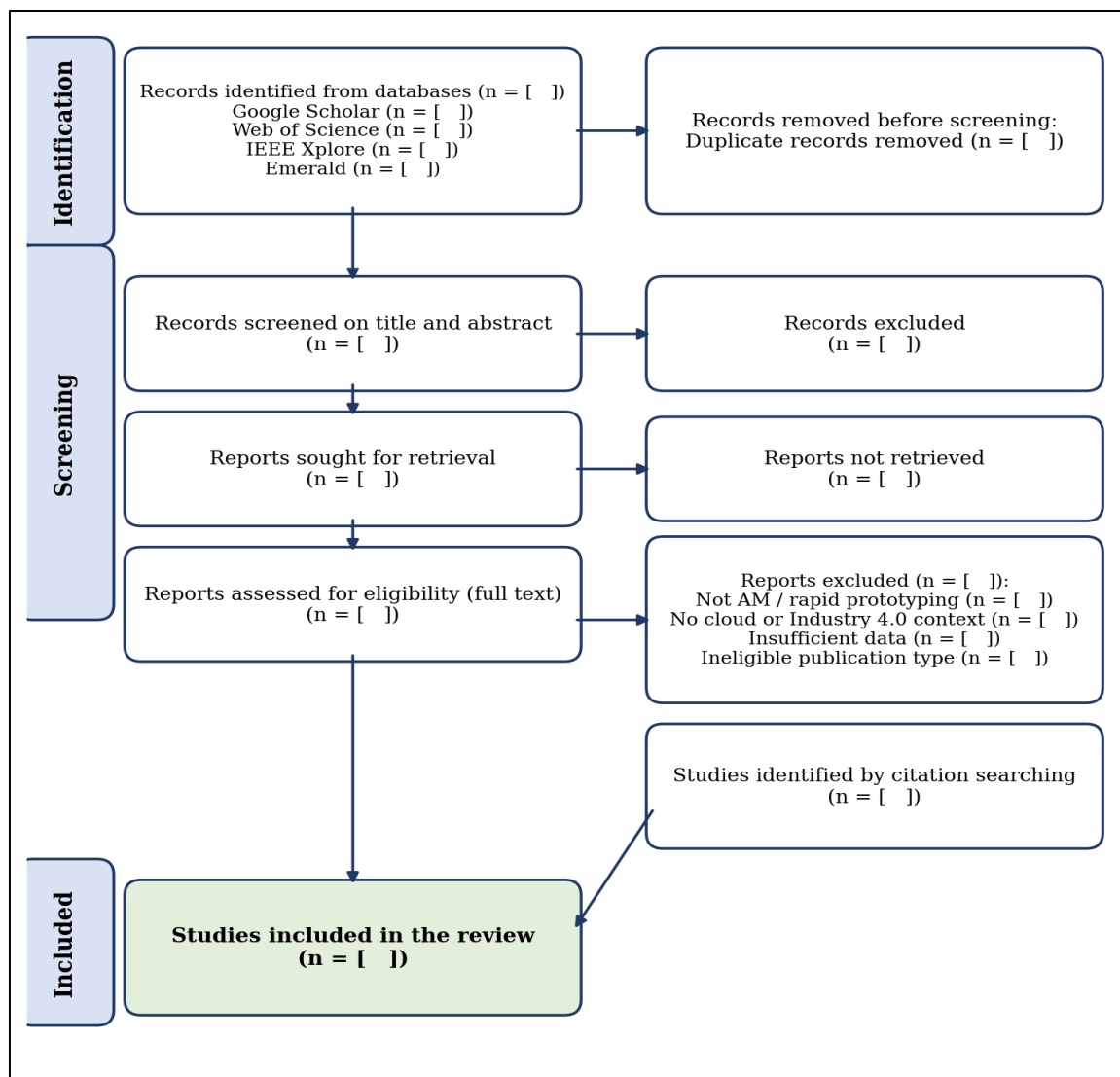


Figure 1: PRISMA 2020 flow diagram of the study selection process (template adapted from Page *et al.*, 2021).

3 BACKGROUND

Rapid prototyping is the process of converting the digital design into a physical model before finalizing the production process. This has been reinforced by AM's ability to fabricate parts layer by layer from a 3D model, making it easier to come up with complex or bespoke geometries without the need for dedicated tools (Gibson *et al.*, 2021; Jiménez *et al.*, 2019). AM is now implemented beyond prototyping and more flexible, low-volume production is now being explored (Dilberoglu *et al.*, 2017; Zhou *et al.*, 2024).

Industry 4.0 is another level. The production data can be more easily collected, shared and acted upon by integrating them with IoT, cyber-physical systems (CPS), cloud computing, AI, ML and digital twins with AM systems (Bănică, Sover and Anghel, 2024). Process data can be analysed using AI/ML, and process monitoring and control (PMC) can be achieved through digital twins (Rahman *et al.*, 2022; Ng *et al.*, 2024; Ahmmed *et al.*, 2025). Cloud manufacturing is important because the manufacturing resources no longer need to be located at one location.

According to Wu *et al.* (2015), cloud-based design and manufacturing is an approach of service-oriented networked design and manufacturing model in which the customer can configure, select and utilize the customized resources required for product realisation as per service needs. Networked platforms enable users to upload designs, to gain access to equipment that is located elsewhere and to coordinate the production of the designs (Baumann and Roller, 2017), which supports collaboration and distributed manufacturing. Initial commentators did not believe that the concept was truly new, but rather a re-branding of previous distributed and networked manufacturing concepts (Wu *et al.*, 2014), while later studies described it as a software-defined approach for Industry 4.0 (Thames and Schaefer, 2016).

Cloud manufacturing is also seen as a key factor in enhanced access and flexibility by Gharibvand et al. (2024). Yet there are still challenges that need to be addressed in practice. There are cybersecurity, data-protection, interoperability and network-reliability challenges involved in CBAM (Gharibvand et al., 2024). Additionally, the evidence of a technology's ability to perform is different from evidence of its ability to demonstrate industrial benefits, meaning the potential and limits of the existing evidence should be considered. This is especially pronounced in developing economies, where the enabling technologies may be available in firms, but are not tightly linked together (Muhla et al., 2023; Muhla et al., 2025).

4 CLASSIFICATION AND TAXONOMY OF ENABLING TECHNOLOGIES

4.1 Introduction to technology integration

Rapid prototyping has undergone a significant transformation in its nature with the advent of Industry 4.0. Industry 4.0 is all about linking machines, products and people together through digital networks to allow the transfer of data between the physical and virtual worlds. In 3D printing, it means that machines will become "intelligent" rather than standalone and will exist in a connected environment. In the literature, five enabling technologies are identified, namely: cloud manufacturing, the Internet of Things, cyber-physical systems, digital twins and artificial intelligence (Tartici, Kilic and Bartolo, 2023; Pant et al., 2024). These are set out below, and summarised in Table 2 and Figure 3.

4.2 Cloud manufacturing and Manufacturing-as-a-Service (MaaS)

Cloud manufacturing offers manufacturing resources on the form of services on the Internet (Baumann and Roller, 2017; Wu et al., 2015). A customer uploads a 3D design to a cloud-based platform that queues the design to an available, appropriately equipped 3D printer. This model is referred to as Manufacturing-as-a-Service (MaaS). In their chapter, Ivkić et al. (2024) discuss how additive manufacturing services (AMaaS) can be used through a cloud platform that connects customers and SMEs equipped with 3D printers, and evaluate the pros and cons. These organizations use application programming interfaces (APIs) and cloud gateways that connect customers to the production resources to enable on-demand production and reduce waiting times. According to others studies, the model can also shorten the lead time and enhance resource utilization (Khan et al., 2022; Xiao et al., 2025).

Cloud platforms don't have to be solely additive processes. Qian et al. (2019) introduced an additive subtractive manufacturing cloud service platform for enhancing resource utilization, enabling the printing and machining of a part. For hybrid platforms, reliable knowledge of processes for each route is necessary. For CNC milling, Taguchi and grey relational analysis (GRA) study have revealed that feed rate is the major contribution to surface roughness (82.81%) while spindle speed is the major contribution to flank wear (Mapindu et al., 2026b). This kind of knowledge could be captured in a hybrid cloud system to determine the production and completion of a prototype feature.

4.3 Internet of Things (IoT) and cyber-physical systems (CPS)

To make a 3D printer work with the cloud, the 3D printer should be able to communicate with the cloud, which is possible via IoT sensors and CPS. Real-time data including temperature and vibration, and melt-pool behaviour (Rahman et al., 2022) are collected by sensors and a CPS connects these sensors to software, typically via a low cost single board computer like the Raspberry Pi. This enables users to track and manage the printer from afar. For instance, an ML model can be used to predict the optimized printing parameters and communicate them to the printer automatically (Rahman et al., 2022; Ahmmed et al., 2025).

From the industrial experience in developing economies, there are examples of the feasibility and limitations of such data pipelines. Mashava et al. (2026) created a multi-agent condition-monitoring system for an induction furnace that has sensors connected to a programmable logic controller (PLC), which transmits information to agents for diagnosis, decision-making, storage and notification via an OPC server. The system has performed well, with no false positives in detecting all injected faults after 72 hours on a hardware-in-the-loop testbed, and OPC data update within 500ms.

The authors suggest that migration to MQTT, cloud analytics and ML based anomaly detection are next, and that there may be a risk of relying on a single OPC node. Likewise, a low cost dual mode smart wheelchair prototype was designed by incorporating a microcontroller, ultrasonic obstacle sensors, voice control and cloud based voice service and remote monitoring was suggested as future enhancement (Munotyaani et al., 2026). Reliable communication between AM equipment and cloud services is thus primarily dependent on standardisation (Ji and Xu, 2025), e.g., using OPC UA.

4.4 Digital twins

A digital twin is a virtual copy of a physical object or activity that is continuously updated with information about that object or activity. It is used in 3D printing to simulate and enhance the printing process (Tudorache et al., 2025). It is essential to have an understanding of the distinctions between a digital model, a digital shadow and a true digital twin

(Ehteshamfar, Xu and Yang, 2026). A digital model can't automatically share information with its physical counterpart; and a digital shadow only gets data from the printer, not from the computer. A digital twin is one that can share data between the physical printer and virtual model, including control of the physical printer from the virtual model. In fact, most existing AM systems are essentially "broadcast" systems (Ehteshamfar, Xu and Yang, 2026) with only one-way communication. This is starting to be addressed in standards: Cabral, Álvares and Caribé de Carvalho (2024) introduced a digital twin for an AM robotic cell from the framework of the ISO 23247, and Rodriguez and Alvares (2025) proposed a standards-based digital thread to link digital twins throughout the AM lifecycle.

4.5 Artificial intelligence (AI) and machine learning (ML)

The cloud-based 3D printing system with its associated sensor and process data creates a large amount of data that must be processed with AI and ML (Ng et al., 2024). Defects can be detected by analysing images of printed layers with algorithms such as convolutional neural networks (CNNs). Reinforcement learning (RL) algorithm was applied to control the printing process: Using RL, the algorithm first explored different parameters of the printing process, including the laser power or scan speed, in a simulation to learn an optimal policy before moving to the real printing process (Ng et al., 2024; Ahmmed et al., 2025).

Furthermore, deep learning has been integrated with cloud manufacturing and reverse engineering to enable the transformation of 2D images into 3D designs and models that can be modified (Huang et al., 2023). However, ML models are only as accurate as the data they are trained on and currently there is little data available, and it is still somewhat heterogeneous and poorly annotated, making it difficult to adopt in industry (Safdar, Xie and Zhao, 2025). An important and, often, overlooked source of such data is the structured design of experiments (DOE) study. Mapindu et al. (2026c) used a replicated Taguchi L9 orthogonal array for fused deposition modelling (FDM) and managed to reduce the number of experimental runs from 81 to 9 combinations of the parameters, which showed that the infill density had the largest effect on tensile strength (68.99%) and the layer height on print time (51.77%). They then applied GRA to reconcile both conflicting responses to one compromise response. Similarly, Taguchi–ANOVA–GRA studies of injection moulding revealed that injection pressure was the dominant factor for shrinkage (67.25%) and warpage (60.55%) (Mapindu et al., 2026a).

Cloud-based ML models and parameter-recommendation services require such replicated and analysed data sets for training and validation. From the perspective of the maintenance engineering, experience demonstrates the possibility of providing the models of decision-making in the field of maintenance in the form of light-weight Web services. Senda et al. (2026) used 13 years of boiler operating data to train several classifiers, they chose Random Forest and deployed it through a Streamlit Web Application. They emphasized that models need to be tested with real results, retrained with changes in circumstances, and put to work in work-management procedures if they are to result in real improvements. AI services on CBAM platforms are no exception.

4.6 Summary of enabling technologies

To organise these technologies, Table 2 groups them by function and by the direction in which data move, and Figure 3 places them within a layered architecture for CBAM.

Table 2: Classification of enabling technologies for cloud-based additive manufacturing

Technology	Main function	Data direction	Use in AM / rapid prototyping	Representative sources
Cloud manufacturing (MaaS)	Manages and brokers shared resources	Two-way	Connects customers to 3D printing services; queues and schedules jobs	Wang <i>et al.</i> (2019); Ivkić <i>et al.</i> (2024)
IoT and sensors	Collects process data	One-way (printer to cloud)	Monitors temperature, vibration and melt-pool behaviour	Rahman <i>et al.</i> (2022); Mashava <i>et al.</i> (2026)
Cyber-physical systems (CPS)	Connects physical and software systems	Two-way	Remote control of printers via gateways (e.g. Raspberry Pi, PLC, OPC UA)	Rahman <i>et al.</i> (2022); Ji and Xu (2025)
Digital twins	Simulates, monitors and improves	Two-way (true twin); one-way (shadow)	Tests designs and process settings virtually before printing	Tudorache <i>et al.</i> (2025); Cabral, Álvares and Caribé de Carvalho (2024)

AI and machine learning	Makes and supports decisions	Data processing	Detects defects and predicts suitable process parameters	Ng <i>et al.</i> (2024); Mapindu <i>et al.</i> (2026c); Senda <i>et al.</i> (2026)
Blockchain	Secures data and transactions	Permanent, tamper-evident record	Protects designs and tracks data provenance	Ahmmed <i>et al.</i> (2025); Pant <i>et al.</i> (2024)

Figure 2 illustrates how a cloud-based AM platform supports the full rapid product-development loop, from product design and process design through material processing and component manufacture, with feedback from consumers and prosumers driving redesign, reconfiguration, repair and recycling.

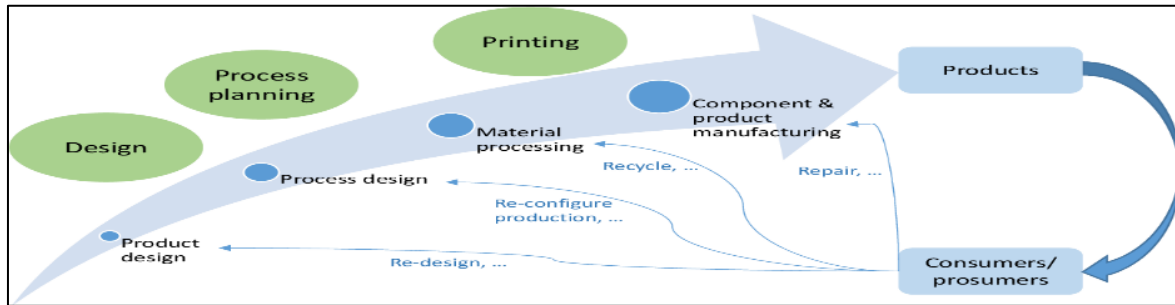


Figure 2: Product development process supported by a cloud-based additive manufacturing platform. Source: Wang *et al.* (2019).

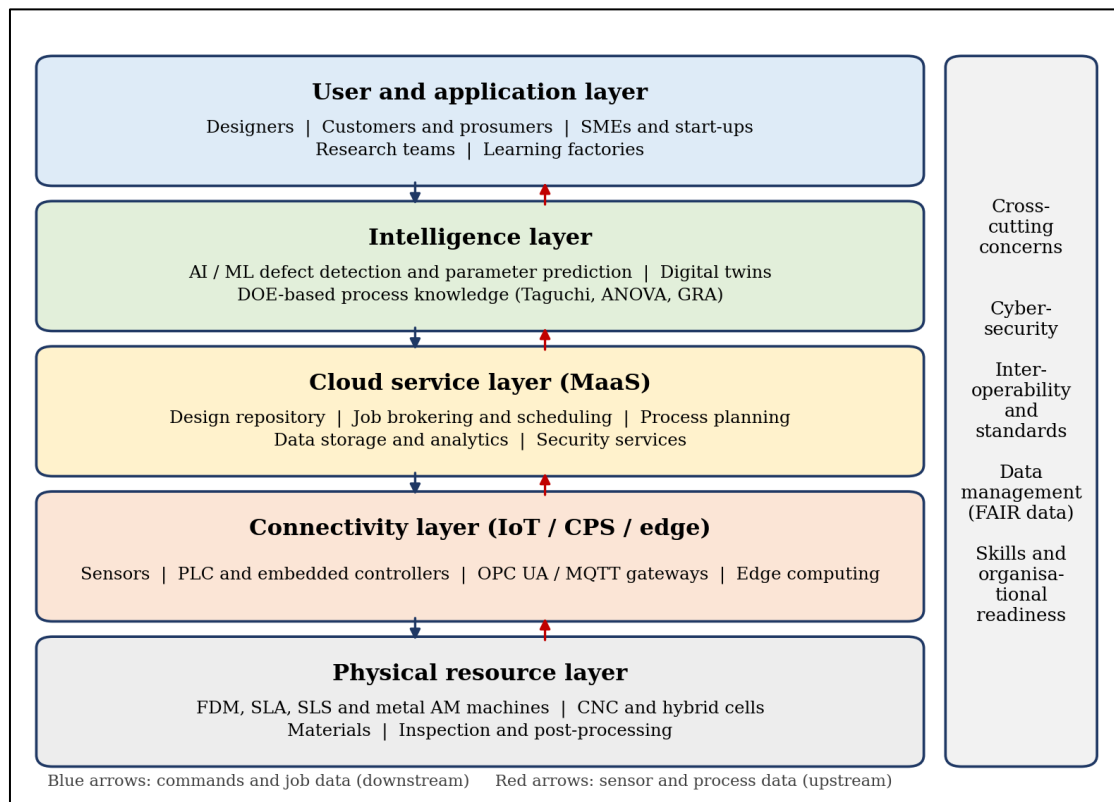


Figure 3: Conceptual layered architecture of cloud-based additive manufacturing for rapid prototyping, synthesised by the authors from the reviewed literature.

5 APPLICATION, IMPACT AND BENEFITS OF CLOUD-BASED ADDITIVE MANUFACTURING ON RAPID PROTOTYPING

CBAM is shifting from prototyping as a task which is predominantly local and uses machines towards prototyping that is more distributed and digitally connected. This is shown by Wang *et al.* (2019) with an IoT-based platform that

connects printers and materials to design knowledge and process-planning data and test results, and enables remote observation and management. Pant et al. (2024) locate the same trend as a component of a larger trend from production-oriented to service-oriented manufacturing, where the use of equipment and expertise is contingent on the user's needs. The ramifications of this are real: If the designer, manufacturing resource and monitoring system aren't in physical proximity, they don't have to be either if they are digitally connected.

5.1 Product-development speed, design iteration and collaboration

Pros often mentioned in the literature is that it will help to reduce product development time. AI-assisted defect detection gets problems identified sooner and combining design, process planning, printing, and monitoring in a single environment saves on development time and eliminates needless design/print cycles, Wang et al. (2019) argue.

Rahman et al. (2022) propose a more automated process in which online customer input is processed by Microsoft Azure and an ML model, and finally printed with an FDM printer. Similarly, Huang et al. (2023) integrate cloud manufacturing with deep learning and reverse engineering, and report that it takes about 60 seconds to convert 2D to 3D before the model is edited and printed, in their case study.

The majority of the time saved is due to virtual iteration prior to printing. Three concepts were modelled using SolidWorks, followed by those designs being evaluated using finite element analysis (FEA) in ANSYS, and finally optimizing the design using topology optimisation, which reduced the mass of the selected design to 2.6 kg before specifying 3D printing and CNC for prototype manufacture (Tandi et al., 2025). The same process was applied to a Vertical-axis wind turbine where analytical design, computational fluid dynamics (CFD) simulation, fabrication, and testing of a physical prototype followed. The same process was adopted with a vertical-axis wind turbine, in which analytical design and computational fluid dynamics (CFD) simulation were followed by fabrication and testing of a physical prototype (Muyambo et al., 2025).

Cloud platforms that bring simulation, optimisation and printing services into one environment may further shorten these design–simulate–print cycles; and let distributed teams collaborate on the same digital design. These studies all have the same conclusion: CBAM can reduce the work that goes into printing and also the actual printing process, particularly in the area of design preparation, information transfer, process selection and redesign. But the evidence is more robust with regard to technical feasibility than measured lead-time reduction in industry. For example, Wang et al. (2019) acknowledge that their platform was still in its prototype phase and should undergo additional testing in the real world. The human role does not go away, it changes: the engineer plays less and less the role of manually operating every step of the process, and more the role of understanding and evaluating the data, verifying the automated suggestions and taking the decisions for design.

5.2 Access to equipment, geographical flexibility and resource utilisation

CBAM can help eliminate the need to purchase equipment. Wang et al (2019) note that distributed AM resources are available online without the need for users to purchase each machine they require. It is a distributed system where the orders are distributed among the providers according to capability, cost, availability and delivery requirements, and a large order is divided between several manufacturers when one has limited capacity, as described by Framiman, Perez-Gonzalez and Fernandez-Viagas (2023). Kucuc (2024) extends this, demonstrating that geographically distributed AM machines can be scheduled, taking into consideration production costs, transport costs and carbon emissions.

The results of these studies suggest improved resource sharing and scalability, especially for smaller firms, start-ups and research teams that might not be able to afford specialized equipment. The argument is particularly applicable in Zimbabwe where there is limited availability of rapid prototyping equipment and funding and working capital are significant constraints on technology adoption (Muhla et al., 2023).

The benefit is still subject to careful reading. Many of the findings on the increase in utilisation are not based on commercial networks in operation for many years, but on optimisation models and experimental platforms. The other issue with cloud access is that it doesn't eliminate the capital expenditure, it simply moves it to the cloud provider, who still needs to invest in the machines, keep them maintained and operating. Geographical limits are Not gone, but cut down: digital files are sent almost immediately but the final product could be sent to the customer.

5.3 Customisation and transition from prototype to production

The studies also show increased linkage between what customers demand and production. Rahman et al. (2022) present a production workflow in the cloud, and feed customer data directly into it, and Huang et al (2023) demonstrate the ability to reconstruct, modify and produce personalised products. Tartici, Kilic and Bartolo (2023) also consider AM as suitable for low volume, customer-oriented manufacturing. This is in line with findings that customer-oriented and customised products are essential conditions for achieving manufacturing agility in markets with changing demand

(Muhla et al., 2023), and that design integration with production is a vital factor in manufacturing agility in such markets (Muhla et al., 2016). It helps to establish the transition from rapid prototyping and internal design checks to rapid and customer driven production.

An alternative, locally designed prototype can even be more cost-effective than imports; the dual-mode smart wheelchair for users in Zimbabwe was estimated at a cost of 60–70% cheaper than the similar commercial wheelchair (Munotyaani et al., 2026) and the passive exoskeleton was estimated at \$387 (Tandi et al., 2025). However, the successful manufacture of individual customised parts does not mean large quantities of individual orders can be managed economically and greater customisation also results in increased difficulties in order scheduling, quality control and data management. Prototyping is also becoming more indistinguishable from the actual production.

Alabtah et al. (2026) took an old industrial pump gear, reverse engineered it, redesigned, and simulated it, created new gear parts by AM of metal, tested the gears, and installed one of the additively manufactured pump gears in an operating pump. It wasn't actually a full cloud-manufacturing implementation, but it indicates that a digital AM process can take a part beyond the prototype phase to a fully functional industrial part. This is the type of production that could be distributed across multiple facilities in the future with cloud platforms.

5.4 Critical analysis and synthesis

Overall, the literature agrees that CBAM can link designers, customers, manufacturing resources and process information across distances. The firmest practical evidence relates to remote communication, monitoring and customer-driven workflows: Wang *et al.* (2019), Rahman *et al.* (2022) and Cabral, Álvares and Caribé de Carvalho (2024) each demonstrate working elements of connected AM systems. Direct contradictions are rare. The more meaningful tension lies between the benefits claimed and the level at which those benefits have been verified (Table 3). Remote access and digital connectivity have been shown experimentally, whereas claims about substantial cost savings, improved long-term machine utilisation and industrial-scale scalability rely more on prototypes, simulations and optimisation models.

Table 3: Representative studies and the level at which cloud-AM benefits have been verified

Study	Focus	Main contribution to rapid prototyping	Evidence type
Wang <i>et al.</i> (2019)	IoT-enabled cloud AM platform	Integrates design, process planning, printing and monitoring; ANN-based quality assessment	Laboratory platform prototype
Rahman <i>et al.</i> (2022)	Cloud-based CPS for remote AM	Online customer input processed in the cloud and sent to an FDM printer	Experimental implementation
Huang <i>et al.</i> (2023)	P2P cloud manufacturing with deep learning	2D-to-3D reconstruction for personalised products in about 60 s	Exploratory case study
Framinan, Perez-Gonzalez and Fernandez-Viagas (2023)	Operations research in AM	Order allocation and scheduling across distributed providers	Review
Kucukkoc (2024)	Distributed AM scheduling	Scheduling of dispersed machines considering carbon emissions	Optimisation model
Ivkić <i>et al.</i> (2024)	AM as a service	Cost-benefit perspective on brokering jobs to printer-owning SMEs	Conceptual / cost analysis
Cabral, Álvares and Caribé de Carvalho (2024)	Digital twin of AM robotic cell	ISO 23247-based twin with cloud data storage	Laboratory implementation
Xiao <i>et al.</i> (2025)	AM lifecycle in the cloud	Distributed manufacturing through to post-processing	Review
Alabtah <i>et al.</i> (2026)	AM of critical spare parts	Reverse-engineered pump gear installed in a working pump	Industrial case

Mapindu <i>et al.</i> (2026c)	FDM process optimisation	Taguchi-ANOVA-GRA compromise between strength and print time with 9 of 81 runs	Replicated experiment
Mashava <i>et al.</i> (2026)	Multi-agent condition monitoring	Sensor-PLC-OPC-agent pipeline for real-time diagnosis	Hardware-in-the-loop testbed
Muhla <i>et al.</i> (2025a)	Industry 4.0 adoption in Zimbabwe	Low AM uptake; strategy, cost and cybersecurity barriers	Industry survey

The aggregate picture, then, is that research has progressed further in showing that CBAM technologies can work than in proving that they reliably deliver better economic performance at scale. Tartici, Kilic and Bartolo (2023) also note the relatively thin body of work on cost-effective Industry 4.0 solutions for SMEs. CBAM is best seen as an evolving manufacturing model: the shift from local prototyping to digitally integrated, distributed manufacturing is clearly under way, but economic validation and large-scale industrial uptake are still catching up.

6 CHALLENGES, RESEARCH GAPS AND FUTURE DIRECTIONS

While CBAM offers the above benefits, it also presents technical, organisational and economic challenges that intensify with the dissemination of manufacturing resources over networks. Cybersecurity, interoperability, infrastructure, scalability, and reliability and system complexity remain thus as the major challenges for implementation of cloud manufacturing, as reviewed (Gharibvand *et al.*, 2024). Increased connectivity and the sharing of resources bring opportunities for collaboration, but they also increase demands for the security of data, integration of compatible systems and reliability of digital infrastructure.

6.1 Cybersecurity, interoperability and data management

The key issues that half of all companies are worried about are cybersecurity and intellectual property protection, as CBAM must be able to share CAD models, material specifications, process parameters, machine settings and production data between customers, cloud platforms and manufacturing equipment. Milaat and Lubell (2024) suggest layered security guidelines on how to secure AM data assets, and Gharibvand *et al.* (2024) identify security and privacy as two of the ongoing challenges in cloud-manufacturing, while Ahmmed *et al.* (2025) explore cybersecurity in the context of digital twins and AI in AM.

The risk extends beyond leaked design information: The physical product being built could be different if the design parameter or process is changed in an unauthorised manner. This is not just a theory for adopters but one of the major challenges for Zimbabwean manufacturers is fear of cyber-attacks (Muhla *et al.*, 2025a). The closely related problem of interoperability is also a problem. In cloud environments, machines, sensors, software and information systems are typically of diverse vendors and have different interfaces and data structures. Interoperability is one key challenge with heterogeneous manufacturing resources needing to seamlessly operate through a single platform (Wang and Xu 2013) and cloud manufacturing and CPS need to be better integrated: OPC UA is one way forward (Ji and Xu 2025).

Kim *et al.* (2015) urge the need for a systems approach for streamlining the AM digital spectrum, while Li *et al.* (2023) advocate for findable, accessible, interoperable and reusable (FAIR) AM data infrastructure. Field implementations show that the architecture of gateways is significant: A vulnerability of relying on a single OPC node in an industrial condition monitoring system (Mashava *et al.*, 2026) was identified. All the above studies suggest that a consistent digital thread from design to production to inspection is hard to maintain from one heterogeneous system to another.

6.2 Reliability, quality and organisational adoption

Dependence on networks brings operational risk. Stable connectivity, ample bandwidth and responsive cloud services are prerequisites for real-time monitoring, scheduling and control. Scalability, reliability and infrastructure are also continuing issues, as cited by Gharibvand *et al.* (2024), and a failure of the internet can lead to financial losses and a shutdown of production, as pointed out by Rahman *et al.* (2022). The more machines, users, and jobs that are added to a platform, the more complex becomes the service composition and scheduling (Liu *et al.*, 2019), as there are varying machine build volumes, materials, accuracy, speed and cost (Kucukkoc, 2024; Xiao *et al.*, 2025).

Another factor in equipment reliability is maintenance discipline. For a thermal power station, corrective work made up approximately 72% of the maintenance strategy mix, thus reducing asset reliability (Senda *et al.*, 2026). Unless condition monitoring and predictive maintenance are incorporated into the development of distributed AM networks, they will be equally at risk (Mashava *et al.*, 2026). Quality assurance is also more challenging in a distributed production. Different physical results may be achieved from the same digital file, depending on the machines, materials,

environments or process conditions. However, the lack of material and process qualification, and the lack of standardisation, are still important challenges for the broader adoption of industrial AM (Seifi et al., 2016; Kim et al., 2015).

Experimental research confirms this: While the value of a certain parameter may be recommended in a specific study, or even found in a standard database, this is not sufficient to choose it for a particular material or printer without re-optimisation, as shown in the previous studies (Mapindu et al., 2026c). When using cloud access for a machine, there is no guarantee of the same results from all service providers. At the organisational level, adoption requires investment in networking, sensors, cyber security, data systems and training staff. These include data analysis and cybersecurity and connected manufacturing skills, requiring extra resources for engineers and operators, especially for small companies.

It has been found that even when management is involved, and awareness has been created, resistance to change and the lack of sufficient training are major constraints to even established human-factors interventions in the Zimbabwean manufacturing sector (Muhla et al., 2025b), while the absence of a strategy for Industry 4.0 is a major constraint in digital transformation (Muhla et al., 2025a). The graduates have low levels of proficiency with IoT, automation, AI, big data and cyber security, the very field that CBAM demands. Overall, graduates in Southern Africa demonstrate limited expertise with IoT, automation, AI, big data and cyber security – the very field that CBAM demands.

6.3 Research gaps and future directions

This literature review identified a number of gaps in research. First, CBAM must have integrated security solutions that will safeguard the entire digital supply chain, not just the parts: authentication and access control, encryption and protection of intellectual property in cloud, edge and machine environments.

Second, there must be a shift towards the adoption of common standards for AM data, machine interfaces and cloud-service communications so that equipment from various vendors can communicate with each other without significant proprietary changes to the data (Li et al., 2023; Rodriguez and Alvares, 2025).

Third, there is a need for additional research into cloud–edge architectures that determine how functions are distributed between cloud and edge environments, and how to safely deploy functions to the cloud with measurable performance metrics, including latency and machine availability (downtime).

Fourth, CBAM platforms require process knowledge that can be reused. Replicated DOE studies provide statistical analysed data of high quality at low experimental costs for optimisation of FDM (Mapindu et al., 2026c), injection moulding (Mapindu et al., 2026a), CNC milling (Mapindu et al., 2026b), honing (Tayisepi et al., 2024), wood machining (Tayisepi et al., 2023), optimization of welding parameters for weld strength (Mapindu et al., 2026d) and for industrial processes (Jansen et al., 2025).

Future work should investigate the ability to pool such results into common machine readable knowledge bases that can be used to power cloud-hosted ML models and optimisation services for parameter recommendations, and the influence of energy use, as several of these studies have already explored, as an objective to be optimised for distributed AM. Economics and context, too. While it is often complex combinations of IoT, AI, digital twins and cloud computing are demonstrated in existing projects, affordable solutions for SMEs are still less mature.

There is also limited specific attention in the reviewed literature to the adoption of CBAM in developing economies and other resource-constrained environments, where the availability of reliable connectivity, investments, skills, and digital infrastructure may pose risks to assumptions that are incorporated into CBAM architectures. Experience in Zimbabwe indicates that the technologies tend to be available within firms but not connected, and prioritisation of technologies, assessment of risks, assessment of workforce and scale-up through pilot projects and gradual scale-up is recommended (Muhla et al., 2023; Muhla et al., 2025a).

Learning factories with realistic production environments for Industry-4.0 skills could be used as testbeds and shared facilities for such incremental CBAM implementation at regional level (Ndiyamba et al., 2026). Future research should thus evaluate lower-cost incremental implementations and determine the extent to which it is possible to actually gain accessibility benefits in various industrial and geographic settings.

Last, the field must be supported by more comprehensive manufacturing life cycles, and actual factories. Xiao et al. (2025) urge for optimisation throughout the entire lifecycle of products, from design to material selection, scheduling, inspection to post-processing, and Gharibvand et al. (2024) reinforce the continuing industrial challenge. Moving forward, validation should go beyond a laboratory demonstration and report quantifiable metrics like lead time, machine utilisation, downtime, quality consistency, energy consumption, implementation cost, cybersecurity

performance, etc. This would enable the field to determine whether, and when and under what circumstances, CBAM is practically worthwhile as well as technically possible.

7 CONCLUSION

The aim of this systematic review was to explore the transformation of rapid prototyping by cloud-based additive manufacturing in the context of Industry 4.0. The adoption of IoT, CPS, digital twins and AI in conjunction with the cloud is also accelerating in the progression of AM from individual machines to an intelligent, connected and distributed manufacturing network, as outlined in the literature, and the taxonomy presented here helps to explain the role and data flow of each of these enabling technologies.

The reviewed papers reveal very clear technical benefits, such as remote monitoring, improved design management, on-demand production and sharing resources, which could enable smaller companies to access the advanced manufacturing equipment without purchasing the equipment. However, careful scrutiny of the evidence shows that there is a clear gap between academic demonstration and industry adoption.

While there is a wealth of research demonstrating the benefits of CBAM in controlled settings, there is limited evidence to date of substantial economic benefits at the industrial level. However, issues of cybersecurity, integration with a variety of systems, network reliability, quality uniformity and implementing the system remain as obstacles to widespread use. In brief, CBAM is technically possible, but not yet an alternative to traditional manufacturing. Future studies should not only prove the feasibility problems but more importantly they should be directed towards secure, standardised and cost-effective solutions, with re-usable process-parameter knowledge, and be validated by industrial case-studies reporting measurable results.

This is particularly relevant to the SMEs, comprising a large proportion of the manufacturing sector, but often starved of resources to implement such digital systems and to developing economies like Zimbabwe where incremental and skills-led systems of digital pathways are likely to be more realistic than wholesale digital transformation. It's important to address these challenges in practice to make CBAM a reality in the industry.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

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REFERENCES

- [1] Ahmmed, M.S., Khan, L., Mahmood, M.A. and Liou, F. (2025) 'Digital twins, AI, and cybersecurity in additive manufacturing: A comprehensive review of current trends and challenges', *Machines*, 13(8), p. 691. Available at: <https://doi.org/10.3390/machines13080691>.
- [2] Alabtah, F.G., Chihi, M., Mohammed, A., Khan, N., Al Hamidi, Y., Albakri, M. and Khraisheh, M. (2026) 'Toward resilient energy assets: comparative evaluation of additive manufacturing technologies for critical spare parts', *Rapid Prototyping Journal*, 32(11), pp. 94–113. Available at: <https://doi.org/10.1108/RPJ-12-2025-0648>.
- [3] Bănică, C.-F., Sover, A. and Anghel, D.-C. (2024) 'Printing the future layer by layer: A comprehensive exploration of additive manufacturing in the era of Industry 4.0', *Applied Sciences*, 14(21), p. 9919. Available at: <https://doi.org/10.3390/app14219919>.
- [4] Baumann, F.W. and Roller, D. (2017) 'Additive manufacturing, cloud-based 3D printing and associated services—Overview', *Journal of Manufacturing and Materials Processing*, 1(2), p. 15. Available at: <https://doi.org/10.3390/jmmp1020015>.
- [5] Cabral, J.V.A., Álvares, A.J. and Caribé de Carvalho, G. (2024) 'Digital twin implementation for an additive manufacturing robotic cell based on the ISO 23247 standard', *IEEE Latin America Transactions*, 22(8), pp. 651–658. Available at: <https://doi.org/10.1109/TLA.2024.10620386>.

- [6] Dilberoglu, U.M., Gharehpapagh, B., Yaman, U. and Dolen, M. (2017) 'The role of additive manufacturing in the era of Industry 4.0', *Procedia Manufacturing*, 11, pp. 545–554. Available at: <https://doi.org/10.1016/j.promfg.2017.07.148>.
- [7] Ehteshamfar, M.V., Xu, X. and Yang, S. (2026) 'Quality-centric digital twins in additive manufacturing: a review of the state-of-the-art, challenges, and future directions', *Digital Twin*, 3(2), p. 2613469. Available at: <https://doi.org/10.1080/27525783.2026.2613469>.
- [8] Framinan, J.M., Perez-Gonzalez, P. and Fernandez-Viagas, V. (2023) 'An overview on the use of operations research in additive manufacturing', *Annals of Operations Research*, 322(1), pp. 5–40. Available at: <https://doi.org/10.1007/s10479-022-05040-4>.
- [9] Gardan, J. (2016) 'Additive manufacturing technologies: state of the art and trends', *International Journal of Production Research*, 54(10), pp. 3118–3132. Available at: <https://doi.org/10.1080/00207543.2015.1115909>.
- [10] Gharibvand, V., Kolamroudi, M.K., Zeeshan, Q., Çınar, Z.M., Sahmani, S., Asmael, M. and Safaei, B. (2024) 'Cloud based manufacturing: A review of recent developments in architectures, technologies, infrastructures, platforms and associated challenges', *The International Journal of Advanced Manufacturing Technology*, 131(1), pp. 93–123. Available at: <https://doi.org/10.1007/s00170-024-12989-y>.
- [11] Gibson, I., Rosen, D., Stucker, B. and Khorasani, M. (2021) *Additive manufacturing technologies*. 3rd edn. Cham: Springer. Available at: <https://doi.org/10.1007/978-3-030-56127-7>.
- [12] Guo, L., He, Y., Wan, C., Li, Y. and Luo, L. (2024) 'From cloud manufacturing to cloud-edge collaborative manufacturing', *Robotics and Computer-Integrated Manufacturing*, 90, p. 102790. Available at: <https://doi.org/10.1016/j.rcim.2024.102790>.
- [13] Huang, D., Li, M., Fu, J., Ding, X., Luo, W. and Zhu, X. (2023) 'P2P cloud manufacturing based on a customized business model: An exploratory study', *Sensors*, 23(6), p. 3129. Available at: <https://doi.org/10.3390/s23063129>.
- [14] Ivkić, I., Buhmann, T., List, B. and Gnauer, C. (2024) 'Towards a cost-benefit analysis of additive manufacturing as a service', in *Proceedings of the 14th International Conference on Cloud Computing and Services Science (CLOSER 2024)*. Setúbal: SciTePress, pp. 338–345. Available at: <https://doi.org/10.5220/0012733500003711>.
- [15] Jansen, K.C., Mapindu, I., Muhla, T.M., Kanyemba, G. and Mashava, D. (2025) 'Optimization of edible oil quality through vacuum bleaching: An experimental design and analysis study', *Open Access Research Journal of Science and Technology*, 13(2), pp. 68–78. Available at: <https://doi.org/10.53022/oarjst.2025.13.2.0051>.
- [16] Ji, T. and Xu, X. (2025) 'Exploring the integration of cloud manufacturing and cyber-physical systems in the era of Industry 4.0 – An OPC UA approach', *Robotics and Computer-Integrated Manufacturing*, 93, p. 102927. Available at: <https://doi.org/10.1016/j.rcim.2024.102927>.
- [17] Jiménez, M., Romero, L., Domínguez, I.A., Espinosa, M.M. and Domínguez, M. (2019) 'Additive manufacturing technologies: An overview about 3D printing methods and future prospects', *Complexity*, 2019, p. 9656938. Available at: <https://doi.org/10.1155/2019/9656938>.
- [18] Khan, S.A., Arora, R., Kumar, H. and Arora, P.K. (2022) 'A perspective on advances in cloud-based additive manufacturing', *EVERGREEN: Joint Journal of Novel Carbon Resource Sciences & Green Asia Strategy*, 9(3), pp. 861–869. Available at: <https://doi.org/10.5109/4843119>.
- [19] Kim, D.B., Witherell, P., Lipman, R. and Feng, S.C. (2015) 'Streamlining the additive manufacturing digital spectrum: A systems approach', *Additive Manufacturing*, 5, pp. 20–30. Available at: <https://doi.org/10.1016/j.addma.2014.10.004>.
- [20] Kucukkoc, I. (2024) 'Scheduling of distributed additive manufacturing machines considering carbon emissions', *An International Journal of Optimization and Control: Theories & Applications (IJOCTA)*, 14(1), pp. 20–31. Available at: <https://doi.org/10.11121/ijocta.1444>.
- [21] Li, S., Lu, Y., Aggour, K., Coutts, P., Harris, B., Kitt, A., Lupulescu, A., Mohr, L. and Vasquez, M. (2023) *Enabling FAIR data in additive manufacturing to accelerate industrialization*. NIST Advanced Manufacturing Series 500-1. Gaithersburg, MD: National Institute of Standards and Technology. Available at: <https://doi.org/10.6028/NIST.AMS.500-1>.
- [22] Liu, Y., Wang, L., Wang, X.V., Xu, X. and Zhang, L. (2019) 'Scheduling in cloud manufacturing: state-of-the-art and research challenges', *International Journal of Production Research*, 57(15–16), pp. 4854–4879. Available at: <https://doi.org/10.1080/00207543.2018.1449978>.
- [23] Mapindu, I., Foya, A., Muhla, T.M., Chinguwo, K.N. and Kanyemba, G. (2026a) 'Minimizing defects in injection molding using the Taguchi method', *World Journal of Advanced Engineering Technology and Sciences*, 20(2), pp. 240–252. Available at: <https://doi.org/10.30574/wjaets.2026.20.2.0419>.

- [24] Mapindu, I., Munhuwamambo, G., Mashava, D. and Ngwenya, L. (2026b) 'Optimization of cutting parameters in CNC milling using the Taguchi method', *Global Journal of Engineering and Technology Advances*, 28(2), pp. 149–162. Available at: <https://doi.org/10.30574/gjeta.2026.28.2.0223>.
- [25] Mapindu, I., Muhla, T.M., Chinguwo, K.N. and Foya, A. (2026c) 'Process parameter optimization for 3D printing using the Taguchi method', *Open Access Research Journal of Science and Technology*, 18(1), pp. 34–45. Available at: <https://doi.org/10.53022/oarjst.2026.18.1.0082>.
- [26] Mapindu, I., Mashava D., Shangwa, V., Chigavazira-Gwara, T.T., Munhuwamambo, G (2026d) 'Taguchi-based optimization of GMAW welding parameters for joint strength,' *World Journal of Advanced Engineering Technology and Sciences*, 20(3), pp. 206-219. Available at: <https://doi.org/10.30574/wjaets.2026.20.3.0448>
- [27] Mashava, D., Muhla, T.M., Munhuwamambo, G., Mapindu, I., Chinguwo, K.N. and Wachenuka, T. (2026) 'A multi-agent system framework for real-time self-diagnostic condition monitoring of induction furnace equipment in developing industrial economies', *Open Access Research Journal of Science and Technology*, 17(2), pp. 28–43. Available at: <https://doi.org/10.53022/oarjst.2026.17.2.0071>.
- [28] Milaat, F. and Lubell, J. (2024) 'Layered security guidance for data asset management in additive manufacturing', *Journal of Computing and Information Science in Engineering*, 24(7), p. 071001. Available at: <https://doi.org/10.1115/1.4064128>.
- [29] Muhla, T., Mapindu, I., Munyau, M., Mashava, D., Mhlanga, S. and Goriwondo, W. (2023) 'Agility as a strategy in Zimbabwean manufacturing industries', *Zimbabwe Journal of Science and Technology*, 18(1), pp. 1–11. Available at: <https://www.ajol.info/index.php/zjst/article/view/271920> (Accessed: 25 September 2026).
- [30] Muhla, T.M., Mashava, D., Kanyemba, G., Mapindu, I. and Goriwondo, W.M. (2025a) 'An assessment of the implementation of Industry 4.0 in Zimbabwean manufacturing industries', *World Journal of Advanced Engineering Technology and Sciences*, 15(2), pp. 970–984. Available at: <https://doi.org/10.30574/wjaets.2025.15.2.0653>.
- [31] Muhla, T., Kanyemba, G., Mapindu, I., Chinguwo, N., Mashava, D. and Goriwondo, W. (2025b) 'Enhancing safety in Zimbabwean manufacturing industry: The role of human factors engineering in reducing workplace accidents', *Open Access Research Journal of Science and Technology*, 13(2), pp. 19–30. Available at: <https://doi.org/10.53022/oarjst.2025.13.2.0037>.
- [32] Munotyaaani, S., Bawono, N.M.H., Tayisepi, N., Mapindu, I., Anggoro, P.W., Bawono, B., Pamosoaji, A.K. and Adi, A.Y.N.M.P. (2026) 'Design and development of a dual-mode smart wheelchair prototype with obstacle detection for Zimbabwe', *Jurnal Rekayasa Mesin*, 21(1), pp. 51–66. Available at: <https://doi.org/10.32497/jrm.v21i1.6954>.
- [33] Muyambo, R.D., Muhla, T., Kanyemba, G., Mashava, D., Munhuwamambo, G. and Mapindu, I. (2025) 'Design and development of a vertical axis wind turbine for slip stream energy harvesting', *Global Journal of Engineering and Technology Advances*, 23(3), pp. 10–20. Available at: <https://doi.org/10.30574/gjeta.2025.23.3.0166>.
- [34] Ndiyamba, D., Murena, E., Kasukusa, S., Mafuratidze, F., Nenzhelele, T., Mpofu, K. and Mapindu, I. (2026) 'Learning factories as a catalyst for innovation in Southern African engineering education', in *CLF 2026 Book of Short Papers on Learning Factories: Proceedings of the 16th Conference on Learning Factories (CLF 2026)*, Bolzano, Italy, 5–7 May 2026. Bolzano: Free University of Bozen-Bolzano, pp. 93–99. Available at: <https://doi.org/10.5281/zenodo.20780648>.
- [35] Ng, W.L., Goh, G.L., Goh, G.D., Ten, J.S.J. and Yeong, W.Y. (2024) 'Progress and opportunities for machine learning in materials and processes of additive manufacturing', *Advanced Materials*, 36(34), p. 2310006. Available at: <https://doi.org/10.1002/adma.202310006>.
- [36] Page, M.J., McKenzie, J.E., Bossuyt, P.M., Boutron, I., Hoffmann, T.C., Mulrow, C.D. *et al.* (2021) 'The PRISMA 2020 statement: an updated guideline for reporting systematic reviews', *BMJ*, 372, p. n71. Available at: <https://doi.org/10.1136/bmj.n71>.
- [37] Pant, R., Singh, R., Gehlot, A., Akram, S.V., Gupta, L.R. and Thakur, A.K. (2024) 'A systematic review of additive manufacturing solutions using machine learning, Internet of Things, big data, digital twins and blockchain technologies: A technological perspective towards sustainability', *Archives of Computational Methods in Engineering*, 31(8), pp. 4601–4616. Available at: <https://doi.org/10.1007/s11831-024-10116-4>.
- [38] Pollock, A. and Berge, E. (2018) 'How to do a systematic review', *International Journal of Stroke*, 13(2), pp. 138–156. Available at: <https://doi.org/10.1177/1747493017743796>.
- [39] Qian, C., Zhang, Y., Liu, Y. and Wang, Z. (2019) 'A cloud service platform integrating additive and subtractive manufacturing with high resource efficiency', *Journal of Cleaner Production*, 241, p. 118379. Available at: <https://doi.org/10.1016/j.jclepro.2019.118379>.

- [40] Rahman, M.A., Shakur, M.S., Ahamed, M.S., Hasan, S., Rashid, A.A., Islam, M.A., Haque, M.S.S. and Ahmed, A. (2022) 'A cloud-based cyber-physical system with Industry 4.0: Remote and digitized additive manufacturing', *Automation*, 3(3), pp. 400–425. Available at: <https://doi.org/10.3390/automation3030021>.
- [41] Rodriguez, E. and Alvares, A.J. (2025) 'Toward a digital ecosystem for additive manufacturing driven by standards-based digital thread and digital twins', *IEEE Access*, 13, pp. 207776–207807. Available at: <https://doi.org/10.1109/ACCESS.2025.3641205>.
- [42] Safdar, M., Xie, J. and Zhao, Y.F. (2025) 'Advancing machine learning in additive manufacturing: Perspectives on data challenges, model development, and industrial adoption', *Engineering Science in Additive Manufacturing*, 1(1), p. 025040004. Available at: <https://doi.org/10.36922/ESAM025040004>.
- [43] Seifi, M., Salem, A., Beuth, J., Harrysson, O. and Lewandowski, J.J. (2016) 'Overview of materials qualification needs for metal additive manufacturing', *JOM*, 68(3), pp. 747–764. Available at: <https://doi.org/10.1007/s11837-015-1810-0>.
- [44] Senda, S., Muhla, T.M., Mapindu, I., Ngwenya, L., Mushangure, R.O. and Mashava, D. (2026) 'Machine learning enabled preventive maintenance strategy for improving boiler reliability of a thermal power station', *Open Access Research Journal of Science and Technology*, 17(2), pp. 18–27. Available at: <https://doi.org/10.53022/oarjst.2026.17.2.0070>.
- [45] Tandi, O., Mapindu, I., Muhla, T.M., Chinguwo, N.K. and Tayisepi, N. (2025) 'Design and analysis of a passive upper limb exoskeleton for augmented construction worker strength', *Open Access Research Journal of Science and Technology*, 13(2), pp. 79–88. Available at: <https://doi.org/10.53022/oarjst.2025.13.2.0050>.
- [46] Tartici, I., Kilic, Z.M. and Bartolo, P. (2023) 'A systematic literature review: Industry 4.0 based monitoring and control systems in additive manufacturing', *Machines*, 11(7), p. 712. Available at: <https://doi.org/10.3390/machines11070712>.
- [47] Tayisepi, N., Svosve, R., Tigere, G., Mnkandla, A.N. and Mapindu, I. (2023) 'Comparative optimisation of the cutting parameters for surface quality and energy efficiency during the machining manufacturing of teak, saligna and pine wood materials', *Journal of Engineering Research and Reports*, 25(11), pp. 73–87. Available at: <https://doi.org/10.9734/JERR/2023/v25i111023>.
- [48] Tayisepi, N., Mugwagwa, L., Mnkandla, A.N., Mapindu, I. and Muhla, T.M. (2024) 'Experimental investigation and simultaneous optimisation of honing parameters of dry cast iron cylinder relining sleeves of motor vehicle engine blocks for surface finish and energy use', *Computational Engineering and Physical Modeling*, 7(4), pp. 88–103. Available at: <https://doi.org/10.22115/cepm.2024.473138.1324>.
- [49] Thames, L. and Schaefer, D. (2016) 'Software-defined cloud manufacturing for Industry 4.0', *Procedia CIRP*, 52, pp. 12–17. Available at: <https://doi.org/10.1016/j.procir.2016.07.041>.
- [50] Tudorache, L., Babur, Ö., Lucas, S.S. and van den Brand, M.G.J. (2025) 'Current approaches to digital twins in additive manufacturing: a systematic literature review', *Progress in Additive Manufacturing*, 10(12), pp. 10819–10853. Available at: <https://doi.org/10.1007/s40964-025-01262-7>.
- [51] Wang, X.V. and Xu, X.W. (2013) 'An interoperable solution for Cloud manufacturing', *Robotics and Computer-Integrated Manufacturing*, 29(4), pp. 232–247. Available at: <https://doi.org/10.1016/j.rcim.2013.01.005>.
- [52] Wang, Y., Lin, Y., Zhong, R.Y. and Xu, X. (2019) 'IoT-enabled cloud-based additive manufacturing platform to support rapid product development', *International Journal of Production Research*, 57(12), pp. 3975–3991. Available at: <https://doi.org/10.1080/00207543.2018.1516905>.
- [53] Wu, D., Rosen, D.W., Wang, L. and Schaefer, D. (2014) 'Cloud-based manufacturing: Old wine in new bottles?', *Procedia CIRP*, 17, pp. 94–99. Available at: <https://doi.org/10.1016/j.procir.2014.01.035>.
- [54] Wu, D., Rosen, D.W., Wang, L. and Schaefer, D. (2015) 'Cloud-based design and manufacturing: A new paradigm in digital manufacturing and design innovation', *Computer-Aided Design*, 59, pp. 1–14. Available at: <https://doi.org/10.1016/j.cad.2014.07.006>.
- [55] Xiao, X., Fu, G., Song, P., Peng, Q., He, N., Mo, T. and Zhang, Z. (2025) 'Comprehensive review of additive manufacturing lifecycle optimization in a cloud environment: from distributed manufacturing to postprocessing', *Rapid Prototyping Journal*, 31(3), pp. 505–521. Available at: <https://doi.org/10.1108/RPJ-04-2024-0182>.
- [56] Zhou, L., Miller, J., Vezza, J., Mayster, M., Raffay, M., Justice, Q., Al Tamimi, Z., Hansotte, G., Sunkara, L.D. and Bernat, J. (2024) 'Additive manufacturing: A comprehensive review', *Sensors*, 24(9), p. 2668. Available at: <https://doi.org/10.3390/s24092668>.