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INTELLIGENT CAD/CAM INTEGRATION FOR ADAPTIVE MANUFACTURING: A SYSTEMATIC REVIEW OF AI AND IOT FRAMEWORKS IN INDUSTRY 4.0

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ABSTRACT

The union of Artificial Intelligence and the Internet of Things (IoT) is transforming the way Computer-Aided Design (CAD) and Computer-Aided Manufacturing (CAM) systems are used in the Industry 4.0 production process. Based on the PRISMA 2020 reporting framework (Page et al., 2021), this report is a systematic literature review on the intelligent integration of CAD and CAM technologies in adaptive manufacturing. Based on a structured search of major scientific databases, a curated list of peer-reviewed studies was analysed thematically to address five research questions related to designing with AI, toolpath optimisation using AI, IoT/IIoT architectures for real-time adaptive control, interoperability standards and barriers to AI adoption in specific sectors. AI models, especially deep learning, graph neural networks and reinforcement learning, have led the way in recent research and development on automatic feature recognition and toolpath generation, while digital twins, edge computing and Industrial Internet of Things (IIoT) sensor networks are more and more being used to implement predictive maintenance and closed-loop adaptive control in the shop floor. The design phase is also starting to change with Generative AI to enable manufacturability constraints to be built in earlier in the CAD process. The literature, however, shows that there are still significant gaps that need to be addressed: AI models deployed outside of the simulation environment are not adaptable in real-time, training datasets are not standardized and openly shared, and there are interoperability protocols that are still quite disjointed, and resources for small and medium enterprises (SMEs) looking to use these technologies are still limited. To situate these gaps in a particular developing-economy context, this review is also supplemented by a series of recently published empirical studies. The review suggests that interoperability standards, Human Safety for Industry 5.0 design principles, cybersecurity, and sustainable practice are the key factors that need to be coordinated for the intelligent CAD/CAM-IoT integration to be fully realised, and it presents a roadmap of future research directions for adaptive and connected manufacturing ecosystems.

Keywords: Adaptive Manufacturing, Industry 4.0, CAD/CAM integration, Digital twins.

1 INTRODUCTION

Computer-Aided Design and Computer-Aided Manufacturing (CAD/CAM) systems began to be used in modern manufacturing in the 1970s, first for numerical control programming, and are now part of the current engineering practice as design-to-production pipelines (Reichle, Ellwein and Verl, 2022). These systems have been transformed by the Fourth Industrial Revolution (Industry 4.0), which has facilitated the integration of cyber-physical systems, the Internet of Things (IoT) and data-driven automation with the manufacturing process, enabling for instance real-time monitoring, predictive maintenance and adjustment of manufacturing processes (Cohen et al., 2019).

In this transition, Artificial Intelligence (AI) has become a pivotal element, it takes CAD/CAM from the realm of static, rule-based automation to a new level of intelligent systems that are able to recognize certain features, generate toolpath accordingly and control the process self-improvingly (Simonič, Palčič and Klančnik, 2025). However, there is still a gap between the design intelligence that is in CAD models, and the manufacturing intelligence needed for adaptive and responsive manufacturing. CAD tools provide detailed and accurate geometric models, but a lack of communication between the CAD and CAM systems can also arise – the information is not always transferred seamlessly to instructions for production without rework, delays and only minimal real responsiveness to shop floor conditions (Simonič, Palčič and Klančnik, 2025; Reichle, Ellwein and Verl, 2022).

On the other hand, the digital revolution has given rise to the Internet of Things (IoT) sensor and connectivity technologies that enable the integration of production data into design and production systems in real-time, leading to the technical foundation for digital twin and a closed-loop, AI-DT (digital twin) integration model that is flexible and adapts the CAD/CAM (computer-aided design/computer-aided manufacturing) operations to changing conditions (Sajadieh and Noh, 2025). However, the literature on the incorporation of AI and IoT in CAD/CAM is still fragmented; there are studies focused solely on the individual use of AI for toolpath optimization, digital twin architectures and IoT connectivity, but there are not many that focus on the interplay between the two in an adaptive manufacturing system (Simonič, Palčič and Klančnik, 2025; Odimgbe et al., 2026).

This is complicated by the fact that applications have differential adoption rates across the globe. The adoption of intelligent CAD/CAM workflows has progressed significantly, with intelligent manufacturing being a focus in highly precision-oriented industries like the aerospace and biomedical manufacturing sectors, however SMEs are limited due to resources, infrastructure and skills and have lower rates of adoption (Simonič, Palčič and Klančnik, 2025). Other challenges identified by Odimgbe et al. (2026) that hinder the adoption of AI-driven CAM involve infrastructure gaps, power supply issues, and the lack of technical skill and knowledge in certain areas, such as Sub-Saharan Africa, where significant productivity potential exists. This picture is further supported by empirical evidence from Zimbabwean manufacturing itself; a country-wide study of the implementation of Industry 4.0 in the manufacturing sector revealed that Zimbabwean manufacturing enterprises are constrained by lack of commitment, lack of infrastructure and lack of skilled personnel while the overall technology set that underpins the intelligent CAD/CAM-IoT integration is still progressing globally (Muhla et al., 2025).

Complementary research in the same manufacturing base also indicates that the ability to adapt processes and products to volatile demand, which is highly linked to adaptive manufacturing, is also limited in the region due to slow technology adoption and economic instability (Muhla et al., 2023). Therefore, the technical and developmental needs for Industry 4.0 are about the current applications and impact of the fields of AI and IoT in adaptive manufacturing in CAD/CAM, and to identify research and development gaps. This systematic review aims to fill this gap by summarizing the existing literature on intelligent CAD/CAM integration for adaptive manufacturing, particularly concentrating on the framework of AI and IoT in Industry 4.0. In the context of the systematic review of the CAD/CAM research presented in the aforementioned paper (Simonič, Palčič and Klančnik, 2025) the aim of this paper is to satisfy the following research questions:

- RQ1: How is artificial intelligence being applied to automate and enhance feature recognition and design processes in CAD systems for adaptive manufacturing?
- RQ2: What AI techniques are used to generate and optimise toolpaths in CAM systems, and what benefits do they offer over conventional programming methods?
- RQ3: What IoT and Industrial IoT architectures, including digital twins, edge and cloud computing, and sensor networks, support real-time adaptive control and predictive maintenance in CAD/CAM-driven manufacturing?
- RQ4: What standards and protocols enable interoperability across intelligent CAD/CAM and IoT systems?
- RQ5: What factors shape the adoption of intelligent CAD/CAM-IoT integration across industry sectors, and what specific barriers do SMEs face?

1.1 Rationale

This review lies at the heart of the artificial intelligence and Internet of Things themes explored that relate to a real and dynamic area of industrial practice. The knowledge of how intelligent CAD/CAM systems are being developed, what still hinders their improvement, and where the research frontier is are relevant to every student and practitioner aiming to prepare for the production environments of the future, where connected machines and data sharing are key elements: both in the large-scale precision sectors and in resource-constrained small and medium manufacturing enterprises. This rationale is reinforced locally. Researches have looked at real-world, resource-limited aspect of this programme, including statistically driven process-parameter optimisation in injection moulding, additive manufacturing and CNC milling processes (Mapindu et al., 2026b), condition-based and predictive maintenance of thermal and metallurgical plant (Senda et al., 2026; Mashava et al., 2026), optimization of welding parameters (Mapindu et al., 2026d) and Industry 4.0 readiness and workplace safety assessments across the sector (Muhla et al., 2025). To contribute to and respond to the surrounding body of work on CAD/CAM-AI-IoT, a review of the engineering-education literature which aims to equip the Southern African engineering graduates for these technologies was conducted (Ndiyamba et al., 2026).

1.2 Industry 4.0 and the Development of Smart Manufacturing

The manufacturing industry has gradually moved from traditional mechanised and automated production to very connected and data-driven manufacturing. This is often referred to as Industry 4.0, a term that denotes the digitalization of manufacturing processes. Industry 4.0 is not just a single technology, it is a series of related technologies such as Internet of Things (IoT), cyber-physical systems (CPS), artificial intelligence (AI), big-data analytics, cloud computing, digital twins and advanced automation.

These technologies provide the capability for manufacturing systems to gather, communicate and process production data in ways not previously realized through traditional automation. Hermann et al. (2016) were able to identify a number of principles underlying Industry 4.0, such as interoperability, information transparency, technical assistance and decentralised decision making. The principles illustrate this that this is not just automation but a transformation to manufacturing systems in which machines, products, information systems and people are able to interact with one another through connected digital environments. Lu (2017) also highlighted the essential role of IoT, cyber-physical systems, data integration and interoperability in Industry 4 manufacturing systems.

With the rise of Industry 4.0 this has led to the change from manufacturing systems mainly following defined instructions towards systems monitoring, analysing and reacting to production conditions. This change sets the technological background for intelligent CAD/CAM integration. However, the rate of this transition is very uneven across economies: a recent evaluation of Industry 4.0 implementation principles in the manufacturing sector of many Zimbabwean firms revealed that the principles are at an early but largely uncoordinated phase of implementation, largely owing to limited capital resources, poor infrastructure conditions and an insufficient pool of digitally skilled staff (Muhla et al., 2025a), which is the type of developing economy in which interpretations of intelligent CAD/CAM-IoT integration research should be approached with caution.

1.3 Computer-Aided Design and Computer-Aided Manufacturing

There are mature digital tools, such as Computer-Aided Design (CAD) and Computer-Aided Manufacturing (CAM), which are being used throughout the product development and manufacturing process. CAD allows engineers and designers to create digital models of products, components and assemblies, and CAM allows it to help plan and schedule manufacturing, define manufacturing processes, and generate manufacturing instructions for machine tools. This integration has traditionally resulted in better accuracy of design, manufacturing planning and production efficiency. But the basic concept of CAD/CAM processes is somewhat more fixed.

After a design has been turned into manufacturing instructions, a change in the manufacturing process can necessitate hand-coded changes to the digital manufacturing instructions. With the advent of Industry 4.0, researchers have begun to question this long-standing dichotomy between the digital design environment and the physical manufacturing process. In a specific systematic review of the use of AI and machine learning for intelligent CAD-CAM integration, Simonič et al. (2025) have identified some of the most common use cases such as feature recognition, adaptive toolpath optimisation and predictive maintenance. Other challenges they identified for intelligent CAD-CAM systems were interoperability, lack of real-time adaptability and lack of training data. Finally, it is important to note that many of the processes and methods used in everyday CAD/CAM practice still depend on traditional (non-AI) design and simulation processes, especially in environments with limited resources, and not on the deep-learning based processes predominant in this review.

This baseline is well illustrated locally with examples produced. To address these issues, Tandi et al. (2025) designed and analysed a PULS for construction workers in the traditional CAD-CAE design workflow, taking advantage of SolidWorks for solid modelling of three design concepts and Ansys finite element analysis to predict the stress, deformation and factor of safety of each concept and select the best-performing design configuration before physical

prototyping. In a more typical yet CAD-CFD coupled approach, Muyambo et al. (2025) created a vertical axis wind turbine (VAWT) for energy harvesting using a slipstream.

The design was repeated using computational fluid dynamics (CFD) analysis and a CAD based approach to aerodynamic and structural-load analysis before prototype testing began. These studies demonstrate that the geometric-modelling and simulation-based design-selection capability that is at the heart of CAD is already firmly entrenched in engineering outside AI-enhanced pipelines and that it would be necessary to incrementally introduce features that can be recognized by AI and generative design (discussed below under RQ1) into such engineering practices. This signifies a shift away from CAD/CAM systems mainly producing manufacturing instructions to systems that have the ability to learn and change manufacturing decisions based on manufacturing data. This is at the heart of the concept of intelligent CAD/CAM integration.

1.4 Artificial Intelligence in Manufacturing

Industry 4.0 manufacturing is an important aspect of Artificial Intelligence (AI) analysis. AI refers to computer-based techniques used to enable systems to make predictions, classify, recognise patterns, optimise and make decisions. In manufacturing applications, AI is often implemented in conjunction with machine learning, deep learning, neural networks, fuzzy logic and optimisation algorithms.

The growing significance of AI in manufacturing is closely connected to the vast amount of data produced by the connected production equipment. Jan et al. (2023) reviewed the application of AI in Industry 4.0 and noted that AI and machine learning are key technologies to leverage manufacturing data and enable smart production. They connect the use of AI tools to technologies like sensor networks, Internet of Things, cloud computing and big data processing. AI can be used in various manufacturing processes such as predictive maintenance, quality control, process optimization, production planning, and monitoring the machining process. One way in which this is used is through the analysis of sensor data from a machine tool using machine-learning algorithms, which can be used to detect patterns related to tool wear or machine degradation.

Then the predicted condition can be used as a basis for maintenance or process adjustment decisions. In a developing-economy plant, Senda et al. (2026) analysed 13 years of monthly operating data from a coal fired thermal power station in Zimbabwe, trained several machine-learning classifiers with the aim of finding the optimal operating point for boiler reliability, and chose a Random Forest model because of its superior predictive performance, for the purpose of optimizing the existing, largely reactive maintenance regime towards a more data-driven preventive regime.

This ability is especially pertinent to CAD/CAM as AI may offer the opportunity to expand CAM beyond the scope of preplanned processes. A production history and real-time production data can be used to optimise the machining parameters or toolpath, not just generate a toolpath from fixed machining parameters in an intelligent CAM system. Similarly, Simonič et al. (2025) have noted that in the past few years, most of the research has focused on AI based approaches, especially in feature recognition, toolpath optimization, and predictive applications involved in intelligent CAD–CAM integration.

1.5 Internet of Things and Industrial Internet of Things

Internet of Things (IoT): The physical devices, objects can communicate through digital networks and exchange information. The concept is often applied to other areas within manufacturing, such as the Industrial Internet of Things (IIoT), which links sensors, machines, controllers and industrial information systems to facilitate production data collection and exchange. The impact of IoT in Industry 4.0 is especially significant since smart decision-making relies on having access to information on the manufacturing floor that is timely and correct.

The sensors can measure the temperature, vibration, cutting force, spindle speed, energy consumption, tool condition, etc. of the machine and other process parameters. Kalsoom et al. (2021) conducted a systematic literature review on application of IoT in Industry 4.0 in manufacturing sector and concluded that IoT is an important enabler of smart manufacturing and also discussed the challenges with implementing IoT.

They found several technological and organisational aspects that affect the implementation of IoT in manufacturing settings. An example of such a sensor-driven enabling layer is described in Mashava et al. (2026) which involves a multi-agent condition-monitoring system for an induction furnace in a copper-cable manufacturer in Zimbabwe, that incorporates a heterogeneous network of sensors, including infrared temperature sensors, electromagnetic flow meters, conductivity transducers and a float sensor, together with a programmable logic controller, to perform autonomous fault detection and notification.

The connection between IoT and intelligent manufacturing can then be expressed as: IoT is not intelligence; it is just the networking and data collection system needed by intelligent manufacturing systems. The data gathered by AI can then be used to detect trends, forecast future state, and aid in manufacturing decisions. Munotyani et al. (2026) show that

the same idea can be applied at "device scale" as they built their prototype of a dual-mode smart wheelchair for users in Zimbabwe, where the ultrasonic distance sensors are connected to an embedded microcontroller that both detects obstacles automatically (via sensor data) and controls the wheelchair via voice commands or joystick input, a scenario in which low-cost sensor- and microcontroller-based architectures can be used to extend IoT-style sensing to assistive product contexts and others that are resource-constrained. This difference is important for the present review as it is essential that the information from the physical production environment can be retrieved to be used in the digital design and manufacturing software.

1.6 Cyber-Physical Systems as an Integration Framework

The concept of cyber-physical systems offers a key theoretical foundation for the digital revolution and its relationship with physical manufacturing. A CPS combines physical devices with computing and communication technologies and allows for monitoring and representation of the state of a physical process in a digital environment. Dafflon et al. (2021) discussed the problems, solutions and technologies of cyber-physical system in manufacturing sector in Industry 4.0.

They present a review which shows that CPS research requires the combination of sensing, communication, computation and physical manufacturing processes. They also outline difficulties in complexity and integration of CPS technologies into manufacturing environments. The CPS concept acts as a valuable link between the digital product model and real-world production processes, serving as a vital step towards intelligent CAD/CAM. CAD model: the product that is intended to be produced, CAM: the process that will be used to manufacture the product, and manufacturing system: the process that will actually be used to manufacture the product. This can be transferred using IoT technologies to the cyber environment, analyzed using AI, and decisions made in the cyber environment that can then impact the physical process.

1.7 Adaptive and Intelligent Manufacturing

Adaptive manufacturing is the capability of a manufacturing system to change its processes, parameters or decisions in response to changes in its operating environment. These changes can be due to tool wear, machine degradation, material variation, product requirements, changes in demand or other production conditions. Industry 4.0 technologies enable the capabilities needed to create this adaptability. According to Davari et al. (2020), a systematic review on smart production planning and control reveals that Industry 4.0 technologies enable capabilities like real-time operation, adaptability, dynamicity, visibility, traceability and autonomy.

The potential capabilities demonstrate the shift from traditional production systems to dynamic manufacturing systems that can adapt. Several technologies are required to make this feedback loop effective. IoT supplies the data, AI analyzes it and forecasts, and CAD/CAM supplies the digital product and manufacturing information to define and modify manufacturing operations. In addition to the machine level of adaptability, there is an organisational level of adaptability as well; Muhla et al. (2023) showed that Zimbabwean manufacturing companies with an agile strategic posture (i.e., re-brand, rejuvenate, and make changes quickly to cope with changing demand) were more likely to be competitive during and after COVID-19, meaning that the technical adaptability discussed in this review should be complemented by comparable organisational agility if adaptive manufacturing gains are to be realised in practice. So adaptive manufacturing is more of an effect of intelligent CAD/CAM integration than a stand-alone technology.

1.8 Integration of CAD/CAM, AI and IoT

The core of this review is the concept of CAD/CAM, AI and IoT integration within Industry 4.0 manufacturing environment. The combination of these technologies can create a closed loop manufacturing system, but each technology has its own purpose. Typical production process in a traditional manufacturing is that information flows in one way: CAD -> CAM -> CNC -> Product. Recent research on CAD/CAM also shows the integration of these technologies. Simonič et al. (2025) uncovered the growing link between AI driven automation and machine learning capabilities and intelligent CAD-CAM integration, specifically with adaptive toolpath optimisation and predictive maintenance. Their review also found that interoperability challenges still exist with fragmented data models and legacy systems.

2 METHODOLOGY

This research adopts a systematic literature review (SLR) methodology to study, analyse and consolidate existing literature on the intelligent integration of CAD/CAM with AI and IoT frameworks in adaptive production within Industry 4.0. The research covers multiple comparable technology domains such as CAD/CAM and IoT and using multiple SLRs would have increased the chances of subjective/convenient sampling of literature that could have affected the results. The review is based on Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) which focus on transparency when searching, selecting, and synthesising studies in the systematic review process. This section describes the data sources and selection criteria and analytical methods used in this study, so that other authors can replicate and validate this study.

2.1 Search strategy

To ensure academic rigor and reliability, four databases were chosen: Scopus, Web of Science, Google Scholar and ResearchGate. Boolean operators were utilized in order to narrow down results and obtain sound studies. Search strings were composed of terms that referred to CAD/CAM, artificial intelligence in industry, IoT and adaptive manufacturing, for the title, abstract and keywords. The review process consisted of four main stages, which were identification, screening, eligibility and inclusion. Table 1 summarizes the databases searched, the number of records found, and search terms used.

Table 1: Database search strategy and record counts

Database	Records retrieved	Date range applied	Core search string (truncated)
Scopus	312	2016-2025	("artificial intelligence" OR "machine learning") AND ("CAD" OR "CAM") AND ("IoT" OR "Internet of Things") AND ("Industry 4.0" OR "smart manufacturing")
Web of Science	241	2016-2025	TS=((AI OR "machine learning") AND ("CAD/CAM" OR "computer-aided manufacturing") AND (IoT OR "cyber-physical") AND "adaptive manufacturing")
IEEE Xplore	198	2016-2025	((("CAD" OR "CAM") AND ("artificial intelligence" OR "deep learning") AND ("IoT" OR "Industry 4.0"))
Emerald Insight	87	2016-2025	("Industry 4.0" OR "smart manufacturing") AND ("CAD/CAM" OR "digital manufacturing") AND ("adoption" OR "integration framework")

2.1.1 Inclusion and exclusion criteria

To ensure study relevance and maintain focus, the inclusion and exclusion criteria were defined as follows:

2.1.1.1 Inclusion

- Studies published in a peer-reviewed journal and articles indexed in ResearchGate, Web of Science, Scopus and Google Scholar.
- Studies published between 2016 and September 2026.
- Studies that addressed AI and/or IoT applications in relation to smart manufacturing, digital twins, CAD, CAM and had clear relevance to Industry 4.0.
- Studies published in English with full text access.

2.1.1.2 Exclusion

- Studies that were not related to CAD-CAM, AI, IoT, adaptive manufacturing processes (i.e. had no industrial manufacturing applications).
- Non-peer-reviewed studies (e.g. news articles and editorials), lacking sufficient technical evidence and published before 2016.
- Non-English studies that did not report sufficient methodological detail.

2.2 Study selection and synthesis

The process of study selection was done based on the PRISMA 2020 framework suggested by Page et al. (2021). Scopus, Web of Science and Research Gate were chosen as the databases, in addition to Google Scholar, from which records were retrieved. The records were then merged together and any duplicate records were eliminated. The other studies were screened for title and abstract using the predetermined inclusion and exclusion criteria. Records without information regarding the research questions were omitted. Full text assessment was done using the exclusion and inclusion criteria. Finally, another set of eligible papers were extracted for data and synthesized. This process is summarised on the PRISMA flow diagram (Figure 1). As is good practice in a systematic review to base it on a specific implementation context, the critical synthesis in Section 4 also includes a few recent empirical studies, identified explicitly and relevant to the context of our specific implementation, by members of the Department of Industrial and Manufacturing Engineering at NUST, besides the fifty studies retrieved from the databases. These studies, however, were not part of the formal database search and screening process outlined above, and are included with the retrieved studies to illustrate how the themes identified by the SLR related to AI, IoT, and CAD/CAM are manifested in practice within a Southern African manufacturing and engineering-education setting.

3 CRITICAL ANALYSIS AND SYNTHESIS

3.1 Critical Synthesis of Findings

The 50 studies that passed the screening process were synthesized in a critical fashion, organized by the five research questions outlined in Section 1.5, and then brought together in a cross-cutting synthesis that looks at how AI, IoT and CAD/CAM are coming together to create an integrated framework of adaptive manufacturing. However, where relevant, the synthesis also draws on a few empirical studies, explicitly labelled as such, from a small group of complementary studies from a manufacturing-engineering research group in Zimbabwe, as examples of how the global themes manifest themselves in a particular developing-economy context.

3.1.1 RQ1 - AI-Driven Feature Recognition and Design Automation in CAD

One that is common in the literature is Automatic Feature Recognition (AFR): the process of obtaining the machining-appropriate features, like holes, slots, pockets and chamfers, etc., that a CAM system or process planner should operate on, from the CAD geometry represented as boundary-representation (B-Rep) solids.

Rule-based approaches to early recognition of 2D shapes proved to be difficult to implement for overlapping or intersecting features, and also demanded a large amount of manual encoding of geometric rules. These rule-based methods are outperformed by more recent deep learning-based methods, especially in cases of the geometry being complex and intersecting (Ma and Yang, 2024). One of the main challenges found in the literature is the representation, in which many of the deep learning AFR methods transform the CAD model to voxel grids or point clouds, losing valuable topological information from the original B-Rep model.

Ma and Yang (2024) directly tackle this by introducing a graph structured representation, Multidimensional Attributed Face-Edge Graph (MAFEG), and a Graph Neural Network (GNN), Sheet-metalNet to learn from such richer representation. They also introduce a second key limitation of supervised AFR: brittleness, where the model fails to learn a newly introduced feature without being retrained from scratch, by adopting a pretraining and fine-tuning strategy and adding prototype-based replay and knowledge distillation.

While acknowledging what is already there, generative AI is starting to define the nature of the design process itself. Quan, Rosen and Song (2026) go on to analyse their applications in the context of the additive manufacturing design and process pipeline, ranging from generating candidate geometries, predicting build outcomes to knowledge-driven design workflows and more, across the workflow, along with the large language models. Also, generative and topology-optimisation approaches are gaining traction to incorporate manufacturability and material-efficiency requirements as part of the design process, integrating design and process intelligence.

In their more comprehensive study about intelligence in AM and AM-based technologies Rahman et al (2023) also mention that AI and data analytics are increasingly playing a part in enabling collaborative, predictive and decision-oriented design and production environments. In connection with this, it is worth noting that a topology-optimization process has already been applied in the traditional CAD-CAE workflow, but just without any AI. In the passive exoskeleton design, Tandi et al. (2025) used topology optimisation inside Ansys to pare the load of the initial design down to just 2.6 kg, and still maintain the structural performance of the device, demonstrating that manufacturability-aware design refinement is made more easy by generative AI methods, but it can also be done manually using a conservative finite-element method-based iteration.

This implies that in engineering contexts where resources are limited, the use of generative and AI-based design approach is likely to be a gradual step on top of, but not the replacement for, the already established simulation-driven refinement of CAD. Combined, these studies show that instead of being a mere geometric authoring tool, AI is becoming a tool that can interpret, classify and increasingly generate manufacturing-aware design. This is a prerequisite for the adaptive, closed-loop manufacturing systems described in later sections in this section.

3.1.2 RQ2 - AI-Driven Toolpath Generation and Optimisation in CAM

The trial and error method for toolpath generation has been used for many years, where a toolpath is generated, simulated or physically machined, measured and adjusted, - a slow and error prone cycle. One thing that is clearly visible in the literature is the prediction and/or direct generation of a near-optimal tool path strategy from the CAD model itself, which greatly reduces this iteration.

This is illustrated directly by Kukreja and Pande (2023), who design a toolpath analysis module that ranks candidate strategies (adaptive planar, iso-scallop and hybrid) by their surface finish, toolpath length and smoothness, label a large library of CAD models using this module, and then train a convolutional neural network to predict the optimal strategy for a new part, reporting successful prediction of the surface finishing strategy directly from the geometry of a large set

of freeform surface CAD models. This is a transition from simulate & select to predict & generate toolpath planning. Notably, even when these AI-supported CAM methods are commercially proven to be mature and reliable as in the case of adaptive clearing and dynamically adjusted feed rates that respond to real-time spindle load, the literature reviewed and industry commentary consistently depict a human programmer as being 'in the loop', reviewing and approving AI-generated toolpaths before they are posted to a machine. This implies that AI-CAM integration is not fully automatic, but rather a system for supporting and augmenting decision-making, which is a significant qualification if interpreting the number of AI-CAM adoptions as mentioned in RQ5.

In contrast to this AI-driven frontier, the design of experiments (DOE) approach still used extensively in much of the manufacturing base, including Southern Africa, for practical CAM parameter selection is useful. In many multi-response problems, the Taguchi method, often used in conjunction with grey relational analysis (GRA), is still the preferred method of choice for the optimisation of machining and moulding parameters, where a large number of training data might not be available for deep learning. Mapindu et al. (2026b) employed Taguchi L9(3³) orthogonal array to analyze the CNC milling of mild steel, and identified feed rate as the most influential process parameter for surface roughness and spindle speed as the most influential one for flank tool wear.

In order to obtain a compromise optimum among the two conflicting quality characteristics, grey relational analysis was used, and the optimum value for a single process parameter was obtained. Tayisepi et al. (2024) implemented an L16 Taguchi design for the honing of dry cast-iron cylinder relining sleeves in remanufacturing engine blocks for motor-vehicle engines to optimise the surface roughness, cutting power, and total energy input for cutting, while Tayisepi et al. (2023) employed a similar comparative-optimisation framework to determine cutting parameters that optimise both surface quality and energy efficiency when processing teak, saligna and pine wood. In addition to subtractive manufacturing, the same Taguchi-GRA approach has been extended to two other processes of great relevance to CAD/CAM practice, namely, the minimisation of shrinkage and warpage in injection moulded plastic components, by using the Taguchi-GRA method to tune only the melt temperature, mould temperature, injection pressure, and cooling time (Mapindu et al. 2026a), and the minimisation of trade-offs between tensile strength and print time in fused deposition modelling (FDM) additive manufacturing, by tuning only the layer height, infill density, nozzle temperature, and print speed (Mapindu et al. 2026c).

Of these five studies, none uses machine learning, rather, these replace the huge labelled data sets which AI-based toolpath and process-parameter methods require with a statistically efficient, low-computation experimental design. In addition to the AI-driven approaches mentioned above, they suggest that, despite the limitations posed by AI-CAM methods, optimisation based on DOE is still a viable alternative for manufacturers unable to collect the training data required for AI-CAM methods, a topic explored further under RQ5 and discussed as a research gap under SME accessibility.

3.1.3 RQ3 - IoT/IIoT Architectures for Real-Time Adaptive Control

RQ1 and RQ2 consider the intelligence in design and programming while RQ3 considers the intelligence being maintained in the shop floor. Conventional condition monitoring was based on only one localised sensor and interpretation of data offline, which does not work for the data-driven, multi-machine production environment today. In his systematic review of condition-monitoring architectures for CNC machine tools, Hamza (2026) documents new trends in the industry, including distributed cloud, edge-cloud and digital-twin architectures that can collect, process and interpret large amounts of heterogeneous machining data, and how new paradigms like federated learning across machine fleets and edge-cloud collaboration can help to enhance generalisation while minimising latency for data processing in the cloud.

The digital twin concept, an ongoing virtual copy of a physical machine or process that is continually updated with live information from the machine, is a recurring theme in this literature as the organisation of adaptive control. When comparing the live behaviour of a machine with the digital twin, deviations are detected in time, such as abnormal vibration, thermal drift or tool wear, and process parameters can be adjusted in time so that a defect does not occur, but only reacted to after it has occurred.

This architecture is demonstrated in two Zimbabwean case studies, but not in CNC machine tools themselves. With a heterogeneous sensor network reporting to an Siemens S7-1200 programmable logic controller, a FIPA-compliant JADE multi-agent platform, a multi-agent, self-diagnostic condition-monitoring framework was implemented for induction furnace equipment at a copper-cable manufacturer, in which four specialised software agents (for diagnosis, decision, database logging, and notifications) were used for the detection of fault conditions such as refractory overheating and cooling-water flow degradation, and for the generation of automatic notifications, effectively implementing a lightweight, rule-based digital-twin style monitoring loop without requiring a full commercial digital-twin platform.

For generation-side plant, Senda et al. (2026) developed a preventive-maintenance model using a random forest algorithm using 13 years of operating data for a thermal power station in Zimbabwe; the model was used to determine

an optimum reliability operating condition which the current, largely reactive maintenance approach was not meeting, and tested against 16 weeks of future operating data.

In both studies, the authors found that condition monitoring and predictive maintenance, typical components of the IIoT, can be realized in a resource-constrained industrial environment with relatively low-cost sensor and controller hardware and either rule-based multi-agent reasoning or standard machine learning classifiers, in contrast to the larger and more complex cloud-edge-digital-twin stacks that are usually used in the case studies found in the broader literature, mostly from the aerospace and automotive sectors.

In summary, all these studies suggest that the architecture is moving toward a layered approach for IIoT systems where the edge devices make decisions that require low latency, the cloud systems manage the large-scale analysis and cross-machine learning, and the digital twin is the common reference point, linking cloud systems and edge devices to CAD/CAM systems that created the initial design and process plan.

3.1.4 RQ4 - Interoperability Standards and Protocols

One of the common themes in the literature is the tendency to design and test intelligent CAD/CAM and IIoT parts separately with varying data formats, communication protocols, and machine interfaces, thus preventing complete plug-and-play operation in the field. Limited progress in the field of interoperability based on STEP-NC and the lack of standardised data-exchange protocols are among the most significant gaps identified by Simonič, Palčič and Klančnik (2025) that currently hinder the uniform integration of CAD/CAM systems into larger Industry 4.0 and Industry 5.0 infrastructure.

Of particular importance here is the feature-based, machine-neutral CNC programming standard known as STEP-NC: In principle, the same information on the machining features recognised by the AFR techniques discussed in RQ1 can be transferred to the CAM and machine controller without having to re-encode it for each proprietary system. There is a growing convergence in both the literature and industry toward two complementary protocols at the communications layer. OPC-UA (IEC 62541) is now the preferred standard for structured and secure, semantically rich data exchange between the shop floor and higher level IT and cloud based systems and forms the basis for reference architectures like RAMI 4.0 and the Industrial Internet Reference Architecture (IIRA) to describe the relationship between the communication, information and functional layer. MQTT, in contrast, is a lightweight publish-subscribe protocol that works well for constrained IIoT sensor devices with limited bandwidth and processing capacity, and is increasingly used in combination with OPC-UA information models, with the models being transported on top of the MQTT protocol, rather than having to redesign the underlying data model to fit the compute and bandwidth constraints of lightweight sensor devices.

These protocols, along with fifth-generation (5G) connectivity, are at the heart of the performance and decision-making gains well-implemented IIoT systems deliver, and, as Qiu et al. (2025) point out, security is a requirement that must be taken care of as well as interoperability if IIoT adoption is to be widespread and sustainable.

The furnace condition-monitoring system of Mashava et al. (2026) is a clear example, albeit relatively small, of the interoperability layer in action: the OPC server is explicitly employed to provide a channel between the Siemens PLC's proprietary control environment and the FIPA-ACL messaging protocol used by the JADE multi-agent platform, enabling the sensor data collected at the field level to be transferred in a vendor-neutral format to the diagnostic and decision-making software agents. This follows at a much more modest and limited level the OPC-UA-centred interoperability architectures that are considered best practice in the broader CAD/CAM-IIoT literature, and implies that interoperability based on the OPC bridge is a viable interoperability approach even if a full STEP-NC or RAMI 4.0-compliant deployment is not yet achievable.

3.1.5 RQ5 - Sector Adoption Patterns and SME Barriers

The level of intelligent CAD/CAM-IIoT integration is not the same across all industries. A high precision, high-value sector such as the manufacture of aerospace and biomedical devices leads the way in terms of the adoption of AI/IoT, as its benefits offer the highest precision, traceability and scrap reduction that justify the investment. Small and medium enterprises (SMEs) are often mentioned as being held back by resource issues, including capital costs of sensorising machines (especially older and legacy equipment that is more difficult to make work with sensors), software licensing and the expertise required to install and maintain these systems.

This view is echoed by Barua, Sami and Barua (2025): although technical arguments in favour of AI adoption in smart production management abound, their survey and interviews revealed that technical, employee resistance and other ethical issues remain obstacles that are organisational as well as human. Qiu et al. (2025) emphasize that unaddressed security concerns with networked IIoT systems are another, often understated obstacle to the increased adoption of

integrated manufacturing, as manufacturers may not want to put their manufacturing processes at risk by exposing them to the connectivity that adaptive, data-driven manufacturing demands.

The results will have a direct impact on production environments, including significant numbers of small and medium sized enterprises (SMEs) which form an important component of the industrial base in much of the Southern African region. The findings of Zimbabwean evidence collected outside the SLR search project closely mirror this pattern: Muhla et al. (2025a) demonstrated that the main challenges to the adoption of Industry 4.0 in Zimbabwean manufacturing industries were the lack of commitment, weak infrastructure, and lack of skilled personnel, in line with other findings reported across the international literature for SMEs generally in relation to resource constraints. In a related investigation of occupational safety in the same industrial sector, it was revealed that the deficiencies in the application of safety regulations and lack of training and consistency in adherence to them are prevalent, as well as the more basic issues of the lack of safety and poor operational performance of the machinery (Muhla et al., 2025b), thereby highlighting that the barriers to the adoption of any new production technology, including AI and IoT, is further complicated in this context by the more fundamental problems of operations and safety which would need to be resolved in addition to any other digitalization process.

The wider engineering skills pipeline is also a limiting factor on the demand side: according to Ndiyamba et al. (2026) southern African engineering education has not kept up with the adoption of intelligent CAD/CAM-IoT, as graduates are lacking in hands-on, industry-relevant experience, and argues that a network of learning-factories, similar to the existing installations in South Africa, should be established throughout the region to develop the practical AI, IoT and automation skills necessary for the adoption.

A staged adoption pathway that starts with lower-cost, high-value applications like vibration or temperature based condition monitoring and predictive-maintenance dashboards on existing machines is more likely to be a realistic option for such enterprises than the shift to more comprehensive digital-twin or closed-loop adaptive systems that generally require a certain degree of sensorisation, connectivity and in-house data-analysis ability that many SMEs currently lack. The case studies from the three countries reviewed under RQ2 and RQ3 – Taguchi-GRa process optimisation, machine-learning based preventive maintenance, or multi-agent condition monitoring based on relatively low-cost sensors and controllers – collectively show how such a staged pathway can play out in practice: namely, statistically driven, low computation optimisation and rule-based monitoring first, followed by the progressive adoption of full AI- and IoT-native systems as data becomes available, connectivity evolves, and skills develop.

3.1.6 Cross-Cutting Synthesis: Toward an Integrated AI-IoT-CAD/CAM Framework

When reading the results from RQ1 to RQ5, a coherent architecture of adaptive manufacturing can be observed, also referred to in literature as an AIoT system (AI plus IoT) (Qiu et al., 2025). These can be divided into three layers: Design-intelligence layer, in which AI recognises features directly on CAD models, becoming more and more generative; Process-intelligence layer, where AI generates and optimises the toolpaths that CAM systems feed to the machine tool; Execution-and-monitoring layer, where IIoT sensors, digital twins and edge/cloud analytics monitor the actual machining process and alert when things have gone wrong.

These three layers are connected by information flows based on standards like STEP-NC, OPC-UA and MQTT, which when applied appropriately, serve as the mule that carries information from one layer to another rather than keeping it isolated in each one (RQ4).

Table 2 summarizes the above mapping of the principal AI and IoT techniques surveyed in this review to the three layers, providing also as representative examples sources to illustrate each, and also provides, in an additional rightmost column, the mapping of the above Zimbabwean case studies to each layer, as largely non-AI, non-Africa but developing-economy examples of each.

Table 2: Mapping of AI and IoT techniques to the design, process and execution layers of an integrated adaptive manufacturing framework, with illustrative developing-economy analogues.

Layer	Representative AI/IoT technique	Function	Key source(s)	Zimbabwean/NUST analogue
Design intelligence (CAD)	Graph neural network-based automatic feature recognition; incremental learning	Converts raw geometry into machining-relevant features; adapts to new feature types over time	Ma and Yang (2024)	Conventional CAD-CAE design iteration and topology optimisation (Tandi et al., 2025)
Design intelligence (CAD)	Generative AI (GANs, diffusion models, LLMs)	Generates and screens candidate designs against manufacturability and performance targets	Quan, Rosen and Song (2026); Rahman et al. (2023)	CAD-CFD integrated aerodynamic/structural design iteration (Muyambo et al., 2025)
Process intelligence (CAM)	CNN-based toolpath-strategy prediction	Predicts the best toolpath strategy directly from CAD geometry	Kukreja and Pande (2023)	Taguchi-GRA milling and honing parameter optimisation (Mapindu et al., 2026b; Tayisepi et al., 2024)
Process intelligence (CAM)	Agent-based deep learning with metaheuristic path smoothing	Recognises trajectory features in G-code and removes path discontinuities	Li et al. (2024)	Taguchi-GRA injection moulding and FDM parameter optimisation (Mapindu et al., 2026a; Mapindu et al., 2026c)
Process intelligence (CAM)	Deep reinforcement learning with graph neural networks	Adaptively optimises toolpaths for complex, freeform parts	Simonič, Palčič and Klančnik (2025)	Comparative cutting-parameter optimisation for wood machining (Tayisepi et al., 2023)
Execution and monitoring (IIoT)	Digital twins; edge-cloud condition monitoring	Synchronises a virtual model with live sensor data to detect deviations and enable predictive maintenance	Hamza (2026)	Multi-agent induction-furnace condition monitoring (Mashava et al., 2026)
Execution and monitoring (IIoT)	Big-data analytics and anomaly detection	Anticipates failures and flags abnormal process behaviour in real time	Qiu et al. (2025); Barua, Sami and Barua (2025)	Random Forest boiler-reliability preventive maintenance (Senda et al., 2026)
Interoperability	STEP-NC; OPC-UA; MQTT; RAMI 4.0/IIRA	Carries feature and process data between CAD, CAM and IIoT layers using shared, machine-neutral formats	Simonič, Palčič and Klančnik (2025); Qiu et al. (2025)	PLC-OPC-JADE multi-agent bridging (Mashava et al., 2026)

This layered view also explains why research gaps in each of the studies listed in Section 5 appear in so many different contexts: The three layers are still largely developed and validated separately, and weaknesses in one layer, such as the absence of a common feature-recognition dataset in the design layer, or the lack of coherent communication protocols in the interoperability layer, constrain the extent to which intelligence in each can translate into truly closed-loop, adaptive manufacturing on the ground. As each layer already has a working prototype, albeit in a less sophisticated or demanding application, in a developing economy, as highlighted in the right-most column of Table 2, the hurdle to achieving fuller integration of AI/IoT applications in such settings is not so much conceptual as it is related to data availability, connectivity investment, and skills development, the themes that are directly addressed in the research gaps and future directions presented next.

4 RESEARCH GAPS AND FUTURE DIRECTIONS

Drawing on the synthesis, eight interlinked research gaps stand out across the reviewed literature. Each is presented below with a corresponding direction for future research.

4.1 Limited real-time adaptability

Many of the AI models reviewed, particularly for toolpath generation and generative design, are validated in simulation or in controlled laboratory case studies rather than deployed as live, closed-loop controllers on production machines (Simonič, Palčič and Klančnik, 2025). Future work should prioritise industrial-scale, real-time deployment studies that report not only accuracy but also latency, robustness to sensor noise, and behaviour under genuine shop-floor disturbances.

4.2 Insufficient and non-standardised training data

The availability of large and diverse CAD datasets with accurate labels is limited, and they are often proprietary or hard to access, or lack coverage of geometric features and concepts (Ma and Yang, 2024). There are incremental and few shot learning approaches like the strategy proposed by Ma and Yang, 2024, that offer a direction for future work, but more comprehensive, publicly available benchmark datasets that cover a wider variety of part families and manufacturing processes are required to enable comparison of the methods.

4.3 Interoperability and protocol fragmentation

STEP-NC, OPC-UA, MQTT and many proprietary CAM data formats are still coexisting, which slows down the plug and play integration between design, process-planning and IIoT systems (Simonič, Palčič and Klančnik, 2025). Future research should include reference implementations and case studies that illustrate end-to-end data flow from CAD to CAM to IIoT monitoring with a single and standardised information model that would build on the work reported by Mashava et al. (2026) of bridging a PLC and a multi-agent platform with OPC.

4.4 Accessibility and cost for SMEs

The initial investment for the sensor installation, software licensing and expertise to handle intelligent CAD/CAM-IIoT systems are still high hurdles for SMEs, which constitute a significant portion of the manufacturing workforce in many economies (Simonič, Palčič and Klančnik, 2025; Barua, Sami and Barua, 2025). Additional research on lightweight low-cost sensing and open-source analytics pipelines tailored for resource-constrained manufacturers could help fill this gap. The studies of RQ2 (Mapindu et al., 2026a; Mapindu et al., 2026b; Mapindu et al., 2026c; Tayisepi et al., 2023; Tayisepi et al., 2024) and the low cost, sensor and microcontroller-based sensing architecture demonstrated by Munotyaani et al. (2026) both suggest a pragmatic, near-term strategy: layering statistically efficient, low computation methods with layers of light machine learning as a step towards AI-driven CAD/CAM for enterprises that may not have the capacity to build large training datasets from the get-go.

4.5 Human-AI collaboration and Industry 5.0

The literature reviewed is focused mainly on the purely technical aspects of the performance, whereas human-centered and socio-technical approaches, which are an integral part of the emerging paradigm of Industry 5.0, are still underrepresented (Simonič, Palčič and Klančnik, 2025). In future studies, the relationship between operators, programmers, and process engineers to the adoption of AI-generated design and toolpath recommendations should be explored, and the trust and trustworthiness of the AI should be studied, as well as how AI is used and misused in their work. In the context of manufacturing in Zimbabwe, evidence presented by Muhla et al. (2025b) demonstrates that addressing human-factors engineering aspects, such as ergonomic design or training operators for safety culture, can significantly improve workplace safety outcomes in terms of human factors-related accidents, thus highlighting the need to integrate these aspects when considering the transition of similar contexts to AI-based, adaptive shop-floor systems.

4.6 Explainability and trust in safety-critical decisions

Deep neural network (DNN) models for feature-recognition and toolpath-generation are typically "black-box" models, posing questions relating to verification and accountability if they are used to control physical machining operations. The combination of incremental learning and better traceability in decision making, as done in the graph-based representation in Ma and Yang (2024) provides a starting point, but explainable-AI approaches specifically tailored to CAD/CAM decision making has not been developed.

4.7 Cybersecurity of connected CAD/CAM-IIoT pipelines

The threat surface of industrial systems increases with the tighter integration of CAD/CAM systems into IIoT sensor networks and cloud infrastructure, as addressed explicitly by Qiu et al. (2025) with respect to more widespread IIoT adoption. The principles of security-by-design, which consider cybersecurity as a separate and downstream IT issue, should be addressed through future work, specifically for AI-enabled CAD/CAM-IIoT pipelines.

4.8 Sustainability of adaptive manufacturing

The reviewed literature shows that while there is potential for using AI in adaptive control to reduce material waste, energy consumption and machining time, the adoption of AI for sustainability-oriented aims appears to be slower than the adoption for pure productivity and quality objectives (Simonič, Palčič and Klančnik, 2025). The environment and energy efficiency effects of intelligent CAD/CAM-IIoT systems need to be explicitly considered in future research in addition to the productivity. It is worth noting that the energy-efficiency machining optimization studies reviewed under RQ2 (honing-energy study of Tayisepi et al. (2024) and wood-machining energy-efficiency study of Tayisepi et al. (2023)) already focus on sustainability goals using conventional DOE methodology, and building on these energy-aware objective functions into AI-based toolpath-generation and generative-design methods is a concrete and yet underutilised research direction.

5 CONCLUSION

AI and IoT-based intelligent CAD/CAM integration is a paradigm shift in Industry 4.0 towards adaptive manufacturing. These technologies offer the potential for unprecedented efficiencies, flexibility, and resilience in manufacturing processes, allowing for real-time monitoring, predictive analytics, and flexible production systems. The systematic review found that despite the progress, the lack of standardization, interoperability issues, cyber security concerns and difficulties in access for SMEs are holding back implementation. Furthermore, sustainability and human-machine cooperation are still under-explored aspects which are crucial for the long-term success of adaptive manufacturing. The review's core finding, that a staged adoption pathway, starting with the low-computation and easy-to-access optimisation and rule-based monitoring that are described throughout this review and moving incrementally toward full engagement with the intelligent CAD/CAM-IIoT integrated environment as described, is the most realistic path by which developing-economy manufacturers can participate in, and eventually benefit from fully, from the intelligent CAD/CAM-IIoT integration discussed throughout this review, is further reinforced by the complementary evidence provided by a manufacturing-engineering research group in Zimbabwe, detailed throughout the review, which includes conventional CAD-CAE design practice (Tandi et al., 2025)

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

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