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Review

A Systematic Literature Review: Industry 4.0 Based Monitoring and Control Systems in Additive Manufacturing

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Abstract: Three-dimensional printing, also referred to as additive manufacturing, offers a wide range of product diversity, design flexibility, and competitive product costs, making it a key technology in the Industry 4.0 era. With a growing demand for customer-oriented manufacturing strategies in the industry, 3D printing holds the potential to revolutionize traditional manufacturing systems by enabling the production of high-value-added complex products at reduced costs. This systematic literature review paper aims to analyze the ongoing research on Industry 4.0-based digital solutions in the field of monitoring and control to facilitate the adoption of 3D technologies. The study utilizes a systematic literature review method to provide detailed analyses. Specific keywords and a comprehensive database are employed for this study. Furthermore, the paper surveys the existing advancements in 3D printing machinery, focusing on process monitoring and control methods, as well as their impact on sustainability. The discussion section evaluates the literature review results for potential implementation in small and medium-sized enterprises.

Keywords: 3D printing; monitoring; control; Industry 4.0; digital technology; additive manufacturing

Citation: Tartici, I.; Kilic, Z.M.; Bartolo, P. A Systematic Literature Review: Industry 4.0 Based Monitoring and Control Systems in Additive Manufacturing. *Machines* **2023**, *11*, 712. https://doi.org/10.3390/machines11070712

Academic Editor: Panagiotis Kyratsis

Received: 6 June 2023
Revised: 22 June 2023
Accepted: 2 July 2023
Published: 4 July 2023

1. Introduction

The term “Industry 4.0” was initially coined at the Hannover Fair in Germany in 2011. Later, the term was used in different versions in different regions of the world such as “Productivity 4.0”, “Made in China 2025”, and “Society 5.0 (Super-smart society)” [1]. The basic definition of Industry 4.0 is the digital transformation of traditional manufacturing methods with the help of computers and data-based control, monitoring, and management, along with the emergence of new manufacturing methods driven by advancing technology.

Industry 4.0 (I4.0) technologies encompass various components, including the Internet of Things (IoT), big data and analytics, artificial intelligence (AI), cybersecurity (CS), cloud computing (CC), augmented and virtual reality (AR/VR), advanced robotics, digital twin, and additive manufacturing (AM). Among them, AM has the most potential to create new methods and innovate manufacturing processes.

Additive manufacturing (AM) is a technique to produce parts by depositing material layer-by-layer according to the three-dimensional computer model. Compared to traditional subtractive manufacturing methods, AM gets particular attention due to its ability to minimize material waste while producing intricately shaped and multi-material components. In addition to its advantages in rapid prototyping, AM enables low-batch, customer-centric mass manufacturing by facilitating quick responses to changes in customer requirements. With its numerous benefits, the AM method finds extensive application in diverse industries ranging from aerospace to biomanufacturing.

Although more than a decade has passed since the term Industry 4.0 appeared, the implementation of these technologies has been predominantly carried out by larger companies with the financial resources and expertise required to operate them. However, the characteristics of large companies, such as mass production, complex decision systems, and high levels of automation, suggest that AM may not be the most suitable method for producing parts within their context. On the other hand, previous literature reviews have indicated that AM is a promising I4.0 technology for small and medium-sized enterprises (SMEs) [2–4]. However, SMEs struggle to adapt AM and other I4.0 technologies because of insufficient funds and knowledge. Considering that they represent 90% of the companies and provide two out of three jobs, supporting SMEs to resolve their challenges will impact the industry positively [5].

In light of technological opportunities and known challenges, the primary objective of this paper is to analyze ongoing research efforts in the field of AM, specifically focusing on monitoring and control of the systems based on I4.0 technologies. The listed literature will then be examined within the scope of sustainability, cost-effective digital solutions and the applicability of research findings in the industry, particularly SMEs. The main goal is to highlight the relevant monitoring and control systems based on I4.0 technologies to enhance the process efficiency and capacity of AM. Considering the significant presence of SMEs in the industry, this study also includes easily applicable digital solutions that have the potential to contribute to the sustainability of manufacturing processes.

This paper is divided into five sections: Section 1 is the introduction that explains the research concept and limitations; Section 2 defines the methodology of the research while summarizing related research questions and details about the article selection process; Section 3 shows the detailed results of the literature review and grouping them in different implementations and field of applications; Section 4 discusses the research results based on used I4.0 technologies, application fields, provided low-cost and sustainability solutions; and the last section summarizes the research findings and concludes with future work.

2. Materials and Methods

Essential requirements of a research study are its reproducibility and transparency, as well as its reliability and evaluability [6,7]. In this regard, the systematic literature review (SLR) satisfies the essential requirements [8], hence it is selected as the method for this review paper. SLR involves searching literature on a specific topic using clearly defined research questions and encompasses several stages, outlined as follows:

⇒ Stage 1: Defining the research aims/questions.
⇒ Stage 2: Planning the research.
⇒ Stage 3: Searching the literature.
⇒ Stage 4: Evaluating the results.
⇒ Stage 5: Finalizing the review with obtained results.

In Stage 1, the research objectives are established, and clear research questions are defined. In Stage 2, a suitable database is constructed, taking into account the keywords derived from the research questions as well as the limitations of the research objectives. Stage 3 involves compiling initial results and conducting a skim-reading of the abstracts. The subsequent stage entails a comprehensive analysis of the listed research articles to derive detailed evaluation results. The final stage of the systematic literature review (SLR) involves summarizing the research findings.

Stage 1 involved the formulation of the following research questions (RQ) based on the research objectives outlined in the introduction (Section 1):

- RQ1: Which I4.0 technologies drive monitoring and control of AM systems?
- RQ2: What are the implementations of AM systems' monitoring and control?
- RQ3: Which industry area uses monitoring and control of AM systems?
- RQ4: What is the impact of AM monitoring and control on sustainability?
- RQ5: Are the provided digital monitoring and control solutions applicable for SMEs when the financial implications are concerned?

As discussed in Section 1, this review paper primarily focuses on additive manufacturing (AM) as the main research field. Previous search results have indicated that addressing the challenges related to monitoring and control in the AM process would enhance productivity and optimize processing conditions [9].

Also, in accordance with the principles of Industry 4.0 (I4.0) and smart manufacturing, optimizing the processing conditions is essential. Furthermore, the manufacturing industry aims to enhance process sustainability through monitoring and control at both the process and system levels. The systematic literature review (SLR) was designed to analyze recent studies in the literature and provide guidance for future research. Hence, Stage 2 was initiated by establishing the following keywords for the research:

("3D print*" OR "Additive manufactur*" OR "rapid prototyp*") AND ("industry 4.0" OR "I4.0" OR "smart manufactur*") AND ("monitor*" OR "control*")

The star symbol (*) allows for searching words in all possible variations, such as "manufacture" or "manufacturing". The keywords were selected based on their usage as synonyms in relevant fields. For example, the term "additive manufacturing" can also be referred to as "3D printing" or "rapid prototyping" in related fields. Similarly, "Industry 4.0" can be referred to as "I4.0" or termed "smart manufacturing".

The review data were collected on 6 October 2022, utilizing the Scopus database. As shown in Figure 1, the initial data collection process yielded 310 documents. Then, the results were constrained by factors such as the time frame, language, resource type, and document type.

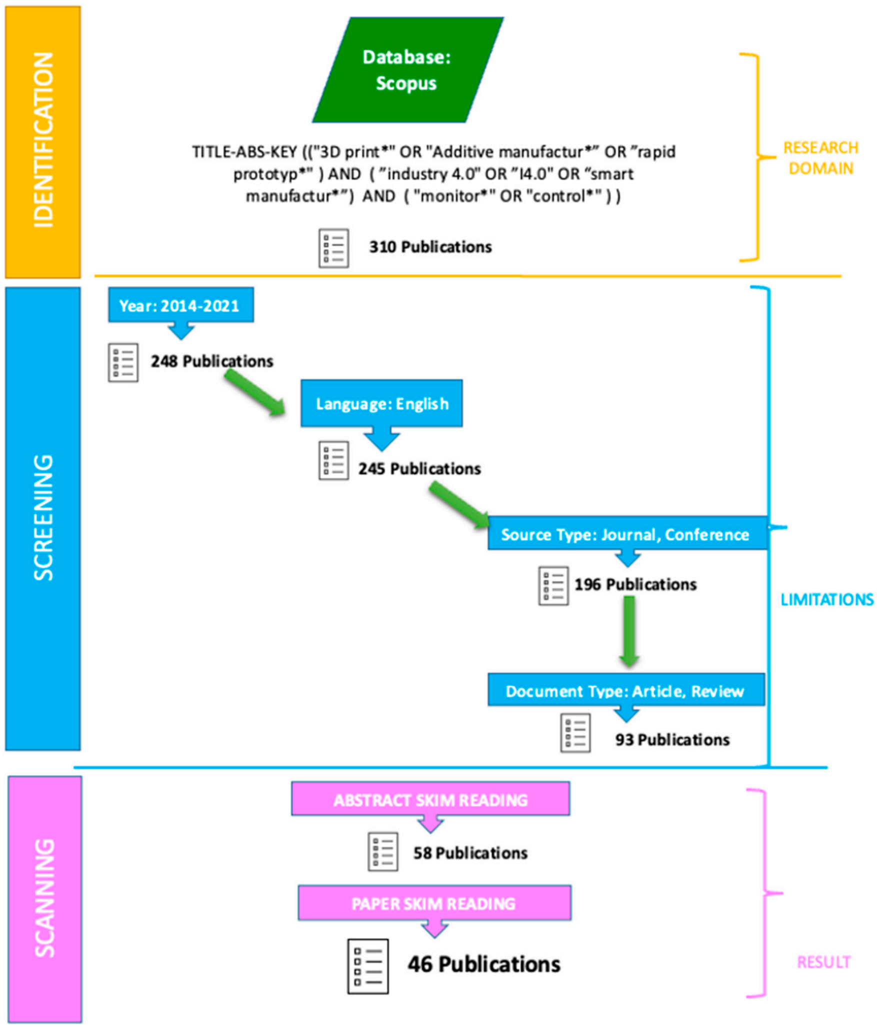


Figure 1. The process of data collection.

As depicted in Figure 2, the rate of research output has exhibited an exponential increase from 2014 to 2021. Consequently, the chosen time frame constraint was applied to cover this period, resulting in a reduction in the number of publications to 248. The subsequent application of a language constraint further narrowed down the selection, ultimately retaining 245 papers that were written in English.

To ensure a rigorous and high-quality survey, the third constraint involved limiting the sources to journal articles and conference proceedings, resulting in a reduction in the number of papers to 196. Furthermore, only article and review papers were considered as document types. As a result, 93 articles were obtained and evaluated in the next stage of the process.

During the skim reading process, the abstracts of the remaining listed papers were reviewed to further refine the selection and identify relevant papers. This step led to a further reduction in the number of relevant papers to 58. Subsequently, a detailed reading of these articles revealed that 46 of them were strongly aligned with the scope of this review paper.

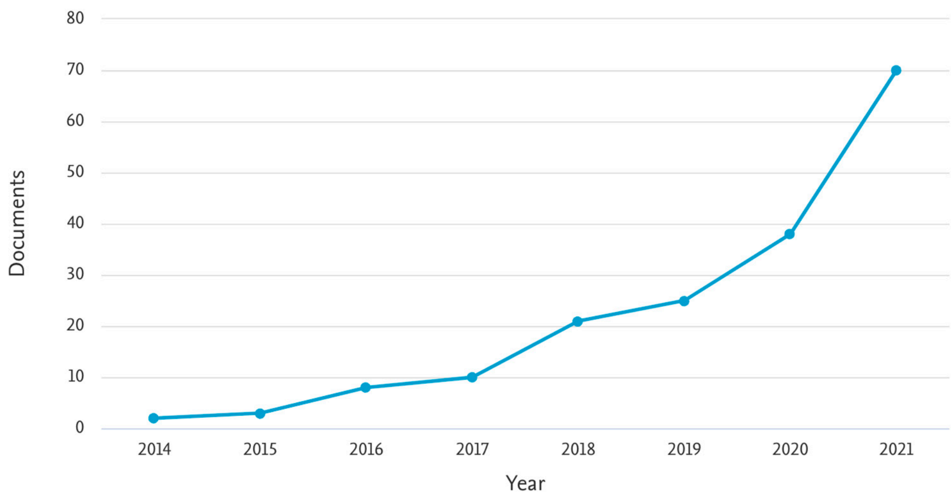


Figure 2. The number of publications (documents) per year between 2014 and 2021.

3. Literature Review

In this systematic literature review (SLR) study, monitoring and control phrases were considered at process, product and/or plant levels to analyze existing implementations according to sectors and operations.

Furthermore, additive manufacturing (AM) is considered both the primary application and the supportive technology that allows the achievement of the goals of monitoring and control. Hence, as shown in Figure 3, the results of the literature review are categorized into four sections according to the implementation types, application fields, cost-effective solutions, and sustainability studies. Additionally, implementation-based literature review results are divided into four subsections according to the common uses in the industry. The field of application-based literature is mainly focused on the chemical and healthcare industry, which widely uses AM in both monitoring and control aspects.

The papers resulting from the SLR were categorized using NVivo® 12 software (Denver, CO, USA). Additionally, the software generated the word cloud shown in Figure 4, which is based on the hundred most frequently encountered words.

The word cloud analysis reveals that the previous literature has extensively focused on "process monitoring and control" within the manufacturing industry. Furthermore, the term "data" appears frequently, indicating that the findings from the literature review are expected to primarily revolve around methods that utilize process and machine data.

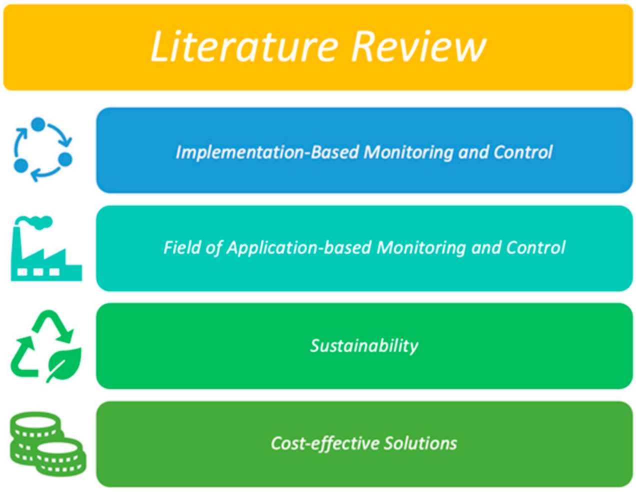


Figure 3. Overview of the literature review section.

Figure 4. The word cloud of selected articles.

3.1. Implementation-Based Monitoring and Control

The results from the literature review show that monitoring and control systems in AM have a wide range of applications in the industry; this section examines them under four subcategories.

Process Monitoring and Control—With the help of digital technologies such as I4.0, using the data gathered from the process/machine to optimize and develop the process will be the key technological development of the coming years. This part summarizes the literature related to process-specific monitoring and control systems which receive significant research efforts in both industry and academia to address the challenges associated with collecting data and their manipulation.

McCann et al. [10] reviewed the state-of-the-art on-line monitoring and control methods for the laser-based powder bed fusion AM methods. They explained using different kinds of sensors (e.g., acoustic, optical and thermal) in process monitoring, and concluded that integrating multiple sensors would increase monitoring performance. Additionally, they discussed advanced technologies and possibilities of using machine learning-based algorithms to keep the process under control. They pointed out the necessity of the monitoring and control systems and their effectiveness considering the cost and accuracy, and that research should focus on innovative sensing systems and their combined approaches.

Arrizubieta et al. [11] designed a smart nozzle for the laser metal deposition process. It measures the melt pool temperature to decide the required amount of laser power and keeps the powder flow constant along the surface. The nozzle also examines the geometrical accuracy of the deposited material by an optical sensor to help minimize post-processing and overall cycle time. Oehlmann et al. [12] used a nozzle equipped with a force sensor and thermistor to analyze and forecast the force into the nozzle in the fused filament fabrication method of AM. They trained an artificial neural network (ANN) by theoretical data as well as the real-time force and temperature data collected from the process. Although processing speed and printed part quality were optimized well, the need for more comprehensive models was emphasized by the researchers. Furthermore, Kadam et al. [13] installed a low-cost RGB camera on a Fused Deposition Modeling (FDM) machine and predicted defects by processing captured image data of each printed layer. They compared the accuracy and computational speed of different combinations of various pre-trained models and classification algorithms to identify the layer quality as good or bad. For on-line fault monitoring, the authors showed that Alexnet and Support Vector Machine algorithm combination showed the best performance.

The quality of the parts produced by AM is a challenge in the manufacturing industry due to many parameters and uncertainties. Kim et al. [14] followed a model-based engineering approach to decide key process parameters and optimize their values in a dynamically changing environment. They demonstrated their smart manufacturing system on a laser-based AM process. A regression model was first used to predict the performance metrics according to the changes around the process parameters, and then a multi-objective optimization was formulated with desired outputs. The proposed systematic approach would have challenges with uncertainty quantification and optimization stages when physics-based computer simulations replace or support the empirical models.

Digital twin technology can be explained as replicating the monitoring and control of the real system in a virtual environment. Gunasegaram et al. [15] explained the difficulties in comprehensive modeling to support the digital twinning of AM and discussed how they can be resolved. For the technical barriers caused by the complexities of AM process such as its multiscale-multiphysics nature, the authors pointed out that there is a strong need for high-fidelity computational models to explain the missing information in the experimental data. From non-technical aspects, standardization of the AM processes and lack of collaboration between different institutions is another challenge highlighted by the authors. In another study, Gunasegaram et al. [16] argued that the digital twinning of AM will achieve repeatability and cost-effective manufacturing. Zheng and Sivabalan [17] developed a digital twin with three pillars: (1) a Digital model visually represents the system and its working environment; (2) a graph-based model which applies constraints related to laws of nature, (3) a computational model that assesses process conditions to monitor and control the systems.

Following the developments in the digital twin of AM, Okwudire et al. [18] proposed a cloud-based control system for 3D printers. Instead of using the high-level G-code commands locally, the authors took advantage of the fast computational speed of cloud computing engines in Australia and South Carolina to directly generate low-level cloud-based motor control commands. While maintaining similar print quality, using a cloud-based controller resulted in printing time which is more than twice as fast as when the local controller was used.

Production Planning—Planning the production with the help of I4.0 technologies received considerable research attention to control machine usage as well as materials and logistics that support fabrication. SLR by Bueno et al. [19] showed the relationship between the five pillars of I4.0 technologies, IoT, CPS, BD, AI and AM, and production planning and control (PPC). They reported that IoT technologies are essential to develop and improve PPC processes by focusing on controlling both manufacturing operations and resources and helping plan capacity and manufacturing while allowing for optimization of planning to improve the sustainability of manufacturing.

Darwish et al. [20] studied production planning by developing new algorithms for task allocation and scheduling. They aimed to minimize the shortage of personal protective equipment and spare parts for venting machines during the global COVID-19 pandemic. Their proposed models increased the utilization of 3D printers on the shop floor while balancing the distribution of tasks among them. Elhoone et al. [21] established a cyber additive design and manufacturing system that consists of three stages. In the first stage, a database was created to identify the specifications of the 3D part design. In the second stage, AI was applied to decide a suitable AM method by using information such as the minimum wall thickness, post-processing method and printing resolution. The reported design accuracy of the ANN-based expert system was 90%. In the final stage, a cyber interface was employed to monitor and control the availability and capacity of the AM machines in the network. Their research showed that I4.0 technologies would be effective in distributing the tasks as well as in controlling and monitoring of the overall manufacturing system.

Customer-based manufacturing systems received particular attention in recent decades. Zawadzki and Zywicki [22] focused on smart product design and production control systems to maximize the efficiency of production systems and minimize the prototyping time, especially for achieving mass customization. They showed that automated and knowledge-based design systems are the enablers of mass customization. To boost the capacity of customer-based production, smart factory-based applications such as Factory-as-a-service (FaaS) by Kang et al. [23] have been developed. The multidirectional system serves for manufacturing, inspection, control and monitoring of the process as well as for visualization of the production environment, cloud-based work instructions and production planning. The developed model was used for two different scenarios to demonstrate the speed and effectiveness of the decision-making system.

Gupta et al. [24] analyzed the critical parameters that have an impact on the development of Cloud-based Enterprise Resource Planning (Cloud ERP) systems and their effects on improving a company's social, economic and sustainable performance. They concluded that the success of a Cloud ERP system in a company depends both on the size of the company and on the scope and type of cloud services. To support the cloud-based system planning and control, new communication methods are developed to enhance better communication between the systems and machines. In their study, Paszkiewicz et al. [25] surveyed the possible network methods to communicate between additive manufacturing machines and controllers. Additionally, Mazur et al. [26] developed a software-defined network to effectively allocate the resources in the system. The authors verified the planning and control-based system in their laboratory, and they emphasized that real-time algorithms should be developed for better resource allocation and hybrid models could be used in WAN communication environments. Xu et al. [27] proposed a novel approach to achieve on-time and on-demand manufacturing of medications by using the light from the screen of a mobile device as a photopolymerized light in a stereolithography-based AM machine. Their proposed system helps with managing connected devices and communication between them through a user-friendly solution.

Path Planning—In AM, robot arms can be used as building plates or print heads, or as quality control equipment to evaluate the manufactured parts. For this purpose, research on robotic control and tool path planning strategy is required to achieve better flexibility in product design and to produce high-quality components. Bordron et al. [28] equipped a robot with a laser sensor to collect measurement data from the additively manufactured parts and validate the surface quality and decide on the required post-processing operations. They developed an automatic path planning method that aims to achieve both the minimum digitalization time and high-quality point cloud. The motion flexibility of robots to access difficult-to-reach points in complex parts further improved productivity, resource efficiency and sustainability.

For robot-assisted metal AM, Zhu et al. [29] developed a novel approach by merging three disciplines, 3D CAD design based on AM, slicer strategy and path planning of the robot's head. They also created a virtual production environment to simulate the robot's path during the AM process. Wu et al. [30] developed a 3D profile maker for on-line analysis and control of the robotic cold spray coating process which was applied as a novel variant of AM. Firstly, the profile maker identifies dimensional errors by digitizing the surface using a 3D scanner. Then, the errors are compensated by updating the trajectory of the robot arm based on the deviations between the measured and desired surface. The proposed model shows positive outcomes from the perspective of adapting I4.0 technologies to improve current systems. For its application in smart factory settings, adaptation of I4.0 technologies was effectively demonstrated through a closed-loop, on-line system which monitors the workpiece quality, decides on the necessary actions while controlling the robot arms. The employed method and details of the studies covered in this section are summarized in Table 1.

Table 1. Employed method for the surveyed research studies.

	Method	**Research Goal**
Process Monitoring and Control	Review study	In situ sensing systems [10]
	Computational Fluid Dynamics (CFD)-based simulation	Smart nozzle design [11]
	Artificial neural network (ANN)	Smart nozzle design [12]
	Machine learning	Surface defect detection [13]
	Model-based approach	Process parameter adjustment [14]
Process Monitoring and Control	Overview and case study	Digital twin development [15,16]
	Cloud computation	Efficient control system design [18]
Production Planning	Systematic literature review (SLR) study	Smart production planning and control (PPC) systems [19]
	System architecture design	IoT-based scheduling systems [20]
	Artificial Neural Network (ANN)	Automated process design [21]
	Review	Smart manufacturing and design [22]
	Simulation-based system design	Personalized production [23]
	System modeling and development	Remote distributed rapid prototyping [26]
Path Planning	Automated data analysis	Inline control system [28]
	Review	General simulation environment [29]
Quality Control and Maintenance	Review	Optimization of quality inspections and control [31]
	Deep Learning	Distortion prediction [32]
	Artificial Intelligence	Error compensation [33]
	Image processing	Surface quality measurement [34]

Quality Control and Maintenance—By reviewing the current on-site monitoring and control methods that use sensing and machine learning technologies of I4.0, Di Cataldo et al. [31] analyzed the barriers and gaps in optimizing the quality control and inspection process of the metal powder bed-based AM operations. Firstly, they discussed the necessity of solving complex multivariable problems to study the effects of process parameters that can influence the part quality and find their optimal combinations that achieve faster processes with defect-free and high-quality parts. Secondly, for metal PBF, they explained possible manufacturing defects related to dimensional accuracy, surface quality, and microstructural and mechanical properties. After summarizing the available off-the-shelf sensors and equipment to control and monitor the manufacturing process, the study focused on the applications of AI in the PBF process. Finally, the research emphasized the lack of standards in AM and difficulties in managing big data acquired from the process.

Francis and Bian [32] investigated the distortion issue that causes dimensional inaccuracy of additively manufactured parts. They developed a deep learning method to predict distortion using Big Data by correlating each location to more than 21,000 thermal images captured by a pyrometer within the total production duration (i.e., 66 min). The root mean square (RMS) error of predicting distortion of disk-shaped component (with 45 mm diameter and 5 mm thickness) was 24 µm for the training set. The authors pointed out that this value does not only meet the tolerance requirements, but it is also competitive with the outcome of machining processes. Moreover, the test set's RMS error was 56 µm, reassuring the promising performance of the proposed method. Omairi and Ismail [33] comprehensively reviewed the literature on AM technology, as well as the machine learning techniques to observe imperfections in AM and heuristic algorithm implementations for prediction models. Three AI-based error compensation methods were summarized, and each method showed success to compensate for imperfections such as thermal distortion and rate of shrinkage. The authors pointed out that the security issues of using cloud-based systems need to be solved. In a related study, Scimone et al. [35] developed a statistical model for monitoring the dimensional changes in complex shaped parts. Their model used point clouds to calculate the variations with the help of sensor technologies.

Okarma and Fastowicz [34] studied the surface quality of the 3D printed parts by using the image entropy method that does not require color information of the parts. Using a convolutional neural network (CNN) model, printed parts were identified under eight classes such as high quality, low quality and low quality with cracks. The training dataset contained a small number of images (78 images), and the quality control process was carried out offline. Thus, the study can be improved with a larger database and online measurement. In addition to the listed quality criteria of the built part such as surface roughness, porosity, and hardness, Klingaa et al. [36] created a predictive model for classifying surface oxidation. By using two different materials to produce parts using the laser powder bed fusion method and varying the gas flow of the process to control the surface oxidation level, they showed that the color change of the surface can indicate the level of oxidation. In addition, the authors emphasized that controlling and monitoring the real-time change in process parameters and their effect on the process and part quality is crucial to create digital twins.

Monitoring and control have a high potential to improve maintenance systems although very few studies exist in this area. Instrumenting an existing machine on the shop floor with, e.g., vibration sensors, enables process monitoring as well as reduced downtimes through predictive maintenance. Rusu et al. [37] developed a condition-based maintenance model for a 3D printer equipped with a vibrometer, thermal camera and sound level meter. They combined the collected vibration, temperature and acoustic data to build a Bayesian Networks Model and predicted the requirement for maintenance. The proposed model can be used in various applications to monitor equipment conditions and the effective scheduling of machine maintenance. In general, AM can address the financial and technological restrictions of manufacturers by providing cheap, fast, and effective solutions to speed up their shop floor operations. Sproch and Nevima [38] designed an innovative and cost-effective method to minimize the number of faulty parts manufactured in a medium-sized enterprise. Three-dimensional printers were used for the rapid fabrication of quality control parts that match and validate the holes' location, size, and countersinking dimensions. Table 2 summarizes the research trends and challenges identified in Section 3.1.

Table 2. Trends and identified challenges with reference to the relevant surveyed papers.

	Research Scope	Challenges
Process Monitoring and Control	▪ Sensors ▪ Smart Nozzle [11,12] ▪ Process improvement [13,14] ▪ Digital twins [15,16]	▪ Accuracy ▪ Cost ▪ Process complexity ▪ Process limitations ▪ Simulation capacity
Production Planning	▪ Systems assisted by AI/ML or algorithms [20,21] ▪ Smart factory [22,23] ▪ Cloud- or network-based manufacturing [24–26]	▪ Communication methods ▪ Algorithms capabilities ▪ System security
Path Planning	▪ Robots for quality control [28] ▪ General robotic AM planning software [29]	▪ Data storage ▪ Programming skills ▪ Large part printing
Quality Control and Maintenance	▪ Defect Detection [31,33] ▪ Dimensional Accuracy [32,35] ▪ Surface quality and porosity [34,36] ▪ Condition-based Maintenance [37]	▪ Sensor data acquisition ▪ Data storage and analysis ▪ Simulation capacity ▪ AI implementation ▪ Lack of standardization

3.2. Field of Application-Based Monitoring and Control

Although most of the previous research literature on using industry 4.0 technologies was focused on the manufacturing industry, chemistry and health are other fields in which there is a significant number of studies, as summarized in this section.

Chemical and Healthcare Applications—ML/AI technologies can provide new ways to monitor, control and improve healthcare and chemical applications. Elbadawi et al. [39] reviewed the potential ways to implement machine learning (ML) methods on the AM applications in drug development, e.g., design depending on specific dosage, drug release performance and quality control process. They argued that ML technologies will have a crucial impact on customized, patient-based medicine in the near future. Muniz Castro et al. [40] reviewed 114 articles and then created 968 formulations to guess the 3D printing process variables and in vitro dissolution characteristics of the drug delivery systems. Selected ML algorithms achieved 93% accuracy, they also successfully forecasted drug release information of the 3D printed medicines. The authors stated that 3D printing datasets, with the help of ML technologies, will have a crucial role in future discoveries. In the field of healthcare, Zhu et al. [41] argued that the assistance of AI is essential to enable in situ organ printing in the future. AI will help to understand, analyze and adapt to the condition of the manufacturing environment, and it will guide the entire process chain from design to production of patient-specific organs.

Awad et al. [42] reviewed the implementation of digital technologies such as sensors, robotics, 3D printing, and IoT technologies in healthcare. The main application areas are sensor data collected from the human body to support the diagnosis of diseases, and 3D printing technologies to produce personalized drugs and treatments. Using robots in the drug delivery process and the identification of diseases is another promising technology to minimize the required time to diagnose and treat diseases. However, the authors pointed out that the rapid change of technology and its applications in healthcare would require more attention to accuracy, safety, and standards. Tai et al. [43] proposed a comprehensive model involving AI and data science to demonstrate the potential future directions in laboratory developments. The AM system, which consists of multiple chemical steps, was equipped with embedded sensors and cyber systems to analyze the potential applications and the future directions of the term "closing the loop". The use of AI technologies was evaluated in optimizing the process quality according to the target product (i.e., inverse design) rather than using the initial parameters (i.e., forward design), and in redesigning the process with sustainable improvement opportunities.

O'Reilly et al. [44] studied AI-assisted manufacturing of drug delivery systems, particularly of orodispersible films (ODFs) to achieve personalized and just-in-time medicines sustainably. They explained that 3D printing technology can address the inherent sustainability-related issues of conventional manufacturing of ODFs by minimizing the need for post-processing and the amount of wasted materials. To resolve the manufacturing and quality control challenges of 3D printed medicines, they used ML technology to automate the analysis of near-infrared (NIR) spectra and classify the active elements with 100% accuracy, while using machine vision technology to identify physical defects. They showed that manufacturing of ODFs can become automated and more accurate using AI.

3.3. Sustainability

In relation to the product life cycle, previous research shows that resource selection, logistics, production and recycling steps contribute significantly to the overall sustainability of a manufacturing process. Hence, monitoring, controlling and developing the existing systems using I4.0 technologies are required to support the sustainability goals.

D'Aniello et al. [45] designed a cyber-physical system to monitor and control the workplace with the help of a multi-agent system to address issues related to dynamic task arrival and machine downtime. Their system aimed to create a sustainable manufacturing environment by using a "Scattered Manufacturing Network (SMN)" to minimize waste, CO_2 emissions and production costs. Moreover, Dev et al. [46] developed a reverse logistics virtual model using six pillars of I4.0 technologies, and demonstrated it on the transportation network system of a refrigerator producer in India. By presuming that some parts of refrigerators are common, the proposed model helped develop the return system to improve the sustainability of the manufacturing system. The integration of the model with I4.0 technologies opened ways to investigate customer behavior as well. Even though the research is mostly at a theoretical level, it showed the necessity of a wide range of cyber-physical social networks.

Majeed et al. [47] proposed a BD-SSAM ("Big Data-driven sustainable and smart additive manufacturing") framework that merges smart manufacturing, AM, Big Data analytics and sustainability. The framework was applied to the manufacturing stage of the product life cycle to optimize process parameters based on Big Data-driven information for improved productivity, resource efficiency and product quality. The framework has several stages in which the entire manufacturing process data are gathered, stored and processed with the help of IoT technologies, and controlled and monitored through data mining and decision-making algorithms which can also help implement sustainable production performance. The authors performed a case study to demonstrate how BD-SSAM can help optimize the parameters of a powder-bed-based AM process for a new component introduced to a company. For the first time in the literature, they defined the SSAM system and made a step change to collect and create meaningful information from the big data sets.

AM could also be used to produce parts that improve the sustainability of existing manufacturing systems. Caruso and Filice [48] have designed and produced an innovative part via AM to increase resource efficiency in Aluminum alloy wire manufacturing. The role of the part is to provide an innovative deformation process by increasing the flexibility of the manufacturing process while controlling and adapting the mechanical strain of the wires. Furthermore, the new additively manufactured part helps minimize chip formation compared to traditional manufacturing methods.

The human–machine interface (HMI) is the main supporting technology of process monitoring and control as it enables gathering real-time machine/process data that can be further processed to optimize the parameters on-the-fly. Ardanza et al. [49] developed a multi-purpose HMI to collect and manipulate real-time data from the machine with IoT technology. In the meantime, to maximize sustainability they equipped existing machines with external sensors to avoid the negative effect of the rapid change in technology (i.e., buying new generation machines) and controlled their energy consumption. The authors tried this HMI in three settings: Additive manufacturing, motor control of a CNC machine and the digital twin of a collaborative robot. Results showed that the developed HMI system is suitable for monitoring and control as well as for improving the sustainability of the machinery.

3.4. Cost-Effective Solutions

Salem and Elksasy [50] developed a low-cost AM system (~$114) using off-the-shelf components to respond to AMs disadvantages such as low levels of monitoring and control, energy disruptions during the printing process and lack of remote control of AM machines. With its open-source software and hardware, the proposed system additionally aims to help manufacturers to cope with major disruptions (such as the global pandemic). Wang et al. [51] developed "Multi-modal best subset" model to increase cost-effectiveness in smart manufacturing systems by choosing the correct sensors and deciding on sensor locations. As a case study, they installed an infrared sensor, accelerometers and thermocouples on an FDM-type 3D printer, and then successfully found the most relevant sensory data to monitor a quality variable.

In relation to I4.0 technologies, Menolotto et al. [52] evaluated the state-of-the-art implementations of motion capture technology in various industries. They found that an optical camera is widely preferred in motion capture applications when compared to an inertial measurement unit. Although construction, robotics and automotive industries had significant use of motion capture technology for monitoring processes and goods, significant applications on health and safety applications were identified as well. The authors concluded that there is low-cost, easy-to-implement, off-the-shelf equipment that can be employed for specific use. Dobrilovic et al. [53] studied the design and implementation of innovative cyber-physical systems in cost-effective ways such as using open-source software, I4.0 technologies and low-cost off-the-shelf equipment. Their research has two stages: In the first stage, 600+ dust images were collected at the shop floor, and they were implemented in AI-assisted simulation to model the ventilation system on the shop floor. In the second stage, several low-cost Arduino-based sensors were used to monitor the shop floor to verify the simulation results. The authors stated that the implementation part is limited to ~174 packets per second data flow. However, this type of implementation can still be useful for, e.g., SMEs which have fewer data flow and financial restrictions.

The AM could help achieve the production of cost-effective monitoring and control equipment as well. For example, Borghetti et al. [54] used inkjet and aerosol jet printing methods not only to print electronics embedded in the parts but also to give them the functionality to serve as smart sensors in the industry. Thus, AM can be directly used to achieve low-cost, customer-based and flexible sensors specific to an industrial application and could help companies, e.g., SMEs, with financial inadequacies. As an example of the assistive use of AM, Mardonova and Choi [55] designed a low-cost underground mine monitoring system by using open-source hardware and software. Arduino microcontroller was used to process the environmental data acquired by temperature, gas, humidity and dust sensors and to merge and visualize the gathered data within the MIT App Inventor software. To save space and resources, the designed system was assembled inside the 3D-printed case which was then mounted on a mine truck. The resulting low-cost monitoring system (~$47) was validated in real underground conditions.

4. Results and Discussion

This systematic literature review (SLR) aims to identify the primary Industry 4.0 (I4.0) technologies applicable to monitoring and control in additive manufacturing (AM). It also seeks to explore the implementation areas and state-of-the-art applications of these technologies in the industry. Furthermore, the study examines the impact of monitoring and control systems on sustainability. Additionally, the SLR assists in evaluating the cost-effectiveness of the available implementations, particularly for small and medium-sized enterprises (SMEs) that face challenges in adopting I4.0 technologies.

The first research question, which aims to identify the leading Industry 4.0 (I4.0) technologies in monitoring and control of additive manufacturing (AM) systems, was analyzed based on the prevalent technologies found in the related literature. Figure 5 demonstrates that sensors and artificial intelligence/machine learning (AI/ML) received the most attention and can be regarded as the driving technologies for monitoring and control applications. In addition to AI/ML, data-driven technologies such as cyber-physical systems, big data, and cloud computing are also widely implemented for monitoring and control purposes. However, the literature review reveals research and implementation gaps in digital twin and augmented reality/virtual reality (AR/VR) technologies, despite their high potential for monitoring and control applications.

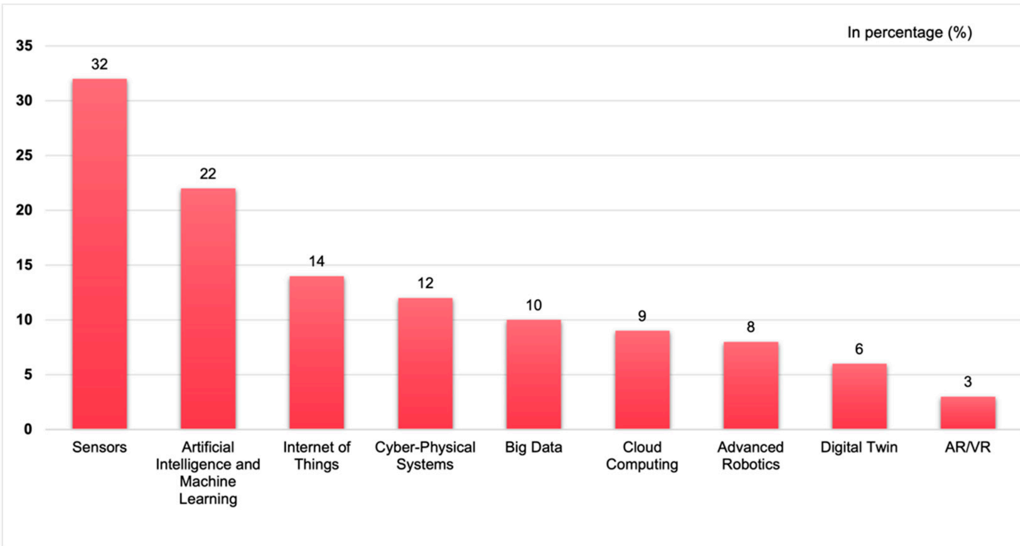


Figure 5. The most common I4.0 technologies utilized (shown in percentage) for monitoring and control implementations in AM systems.

To address the second research question, the literature review results were classified according to the implementation fields. As shown in Figure 6, nearly half of the literature review results pertain to implementation fields related to process control. This dominance in process control is expected as AM is a complex manufacturing process where parts are built in a single run under the influence of numerous interconnected parameters. The lack of standards in AM and the significant influence of manufacturing parameters on material, machine, and part design necessitate monitoring and control implementations. Moreover, the increasing material diversity and customer-based manufacturing systems have expanded the implementation scope of AM. Consequently, effective monitoring of process variables enables fine-tuning of printing conditions, thereby enhancing the efficiency of the manufacturing system and the quality of printed parts.

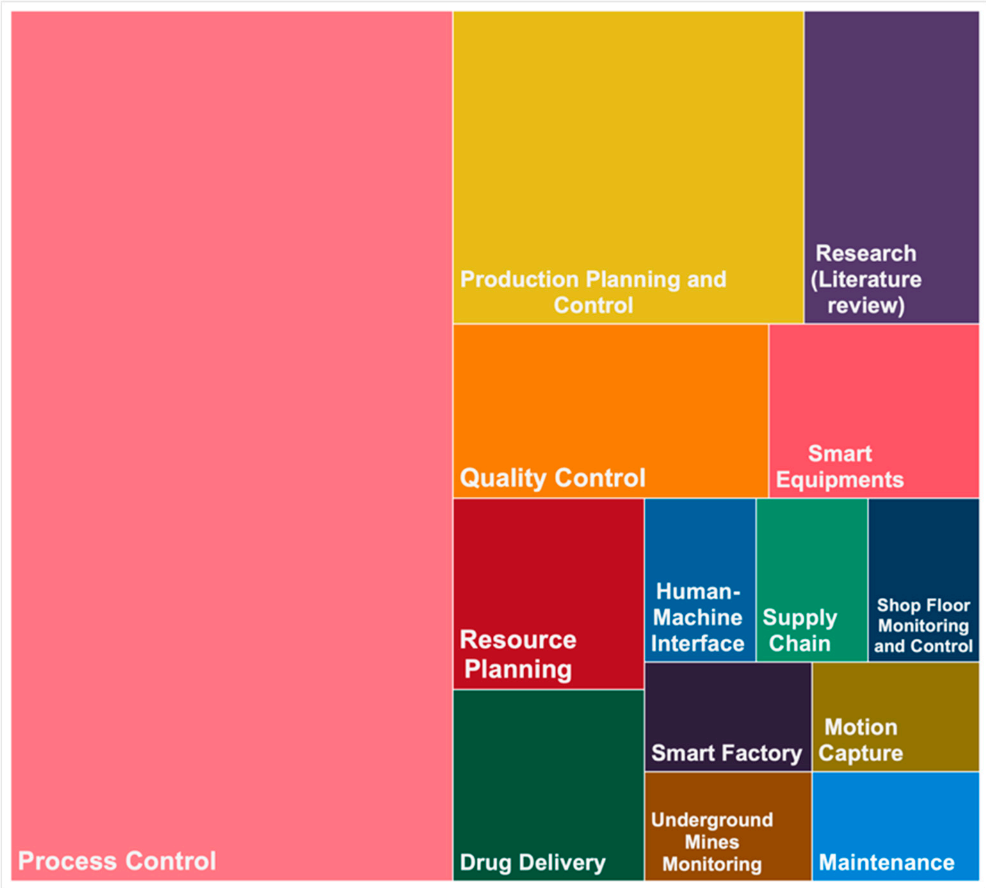


Figure 6. Implementation fields for monitoring and control research.

Additionally, production planning and resource planning implementations represent the second-largest share of the literature results. These implementations focus on the intercommunication, monitoring, and control of AM systems within a broader smart factory environment rather than at the specific process level.

The third research question aimed to determine the distribution of industries focused on monitoring and control implementation. This question sought to identify potential industries where the development of monitoring and control systems could be considered. Figure 7 illustrates the results, indicating that the manufacturing industry, as the primary user of AM technology, accounts for 70% of the relevant studies. An important finding from the literature is the relatively significant presence of monitoring and control in healthcare fields. Within this domain, research is directed towards patient-centric, just-in-time, and on-demand drug production utilizing AM technology, along with the monitoring of patient data using I4.0 technologies.

Another research objective of the SLR was to examine the impact of monitoring and control implementations on sustainability. Consequently, the literature results were categorized according to whether the articles included information on sustainability. Figure 8 presents a comparison of the percentages of literature results categorized under "monitoring and control" and "sustainability".

According to Figure 8, only 24% of the studies considered sustainability in relation to monitoring and control practices. However, it is worth noting that monitoring energy consumption and CO_2 emissions, controlling resource usage, and planning logistics activities can contribute to improving the sustainability of both process-specific and overall production systems.

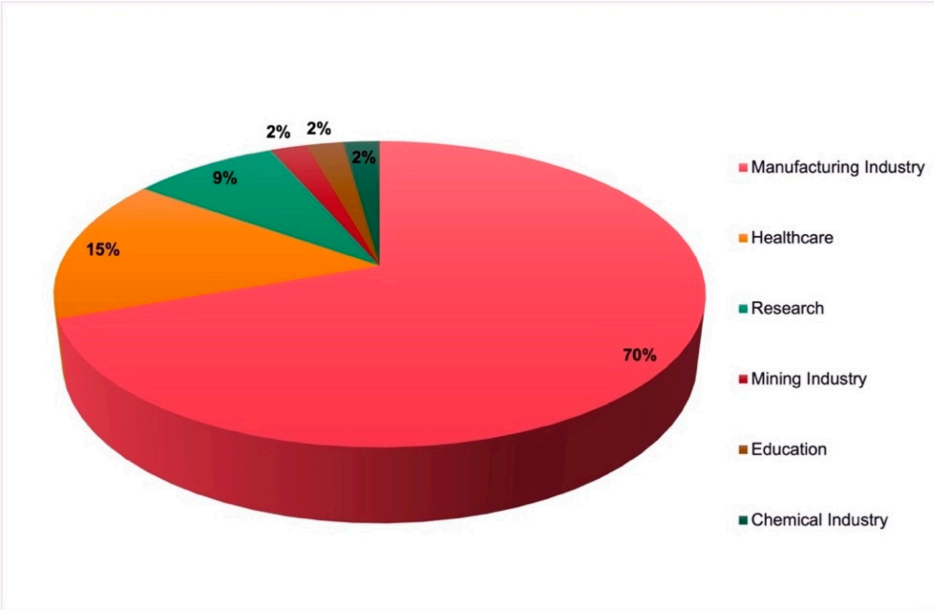


Figure 7. Distribution of monitoring and control applications by sector.

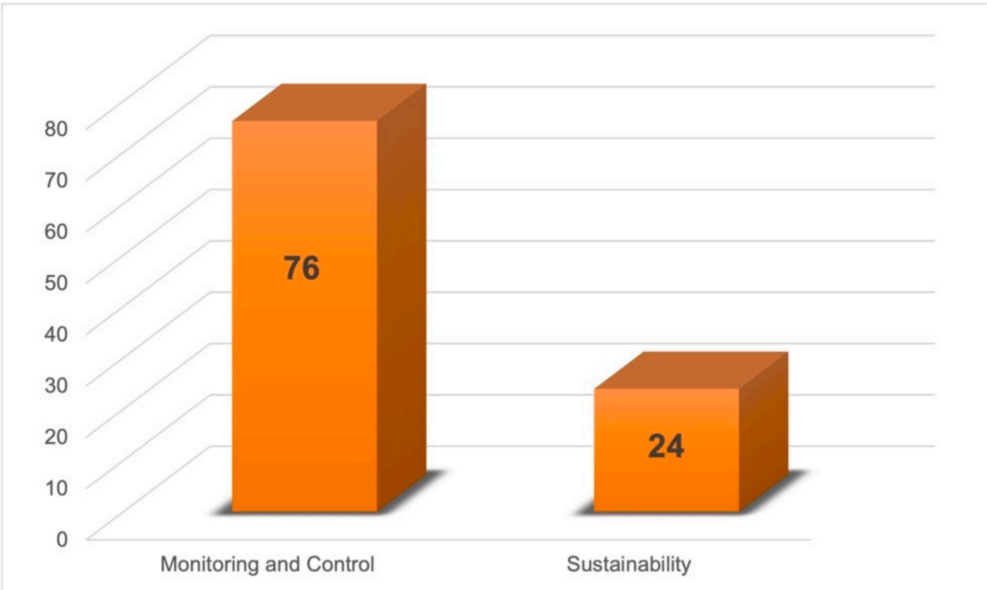
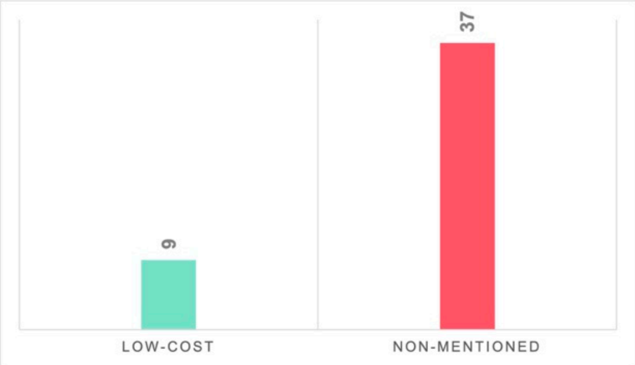


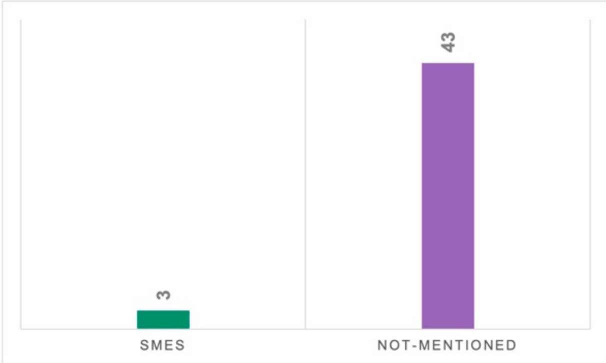
Figure 8. Comparison of the percentage of literature results based on "monitoring and control" and "sustainability".

Lastly, the literature review results were examined to assess the focus on small and medium-sized enterprises (SMEs) and analyze them from a financial standpoint. Both Figure 9 a,b illustrate a scarcity of studies addressing implementations in SMEs and exploring cost-effective solutions. This indicates a clear research gap in the development of cost-effective digital solutions tailored for SMEs.

The literature review results indicate that cost-effective solutions mentioned in the studies primarily utilized off-the-shelf equipment, such as sensors and low-cost microcontrollers. This is understandable given the financial constraints faced by SMEs, making it challenging for them to obtain loans and invest in expensive technological equipment.



(**a**)



(**b**)

Figure 9. (**a**) Distribution of cost-effective solutions by a total number of papers.; (**b**) Distribution of digital solutions provided to SMEs according to the total number of papers.

Out of the three articles specifically related to SMEs found in the review, two focused on cost-effective solutions, while the remaining one addressed sustainability in SMEs. This suggests a lack of research in the area of sustainability for 60% of companies worldwide.

According to the literature survey, cost-effective solutions in monitoring and control applications have been achieved through the utilization of inexpensive off-the-shelf microcontrollers, in combination with sensors and open-source software. Among the various microcontrollers designed for different purposes, the literature review suggests that the Arduino microcontroller is the most commonly used. However, alternative cost-effective controllers with potential include Raspberry Pi, BeagleBone, Asus Tinker Board and Launchpad. These systems, along with open-source software such as Arduino IDE and Python for programming microcontrollers, offer SMEs viable and cost-effective alternatives. It is crucial for SMEs to have easy access to ready-to-use code blocks from libraries or the user community, ensuring continuous support and development.

Furthermore, recent studies have demonstrated the growing attention towards cost-effective open-source software solutions developed for industry-based applications. For instance, Portalo et al. combined Arduino and Raspberry Pi to monitor and record temperature changes in photovoltaic generators, maximizing the performance of smart microgrids affected by high temperatures [56]. They used the open-source software Graphana to visualize temperature changes. Another study by Izquierdo-Monge et al. focused on smart microgrids, where a system was proposed to detect faults and send fault messages and maintenance notifications to related teams [57]. This system was built using MariaDB open-source software and the Node-RED programming tool. Additionally, a home assistant was employed as a human–machine interface, and Telegram software was used to send notifications to users.

Overall, the findings of the SLR study highlight the growing significance of data-driven monitoring and control studies. However, further research is needed to integrate these studies with complex simulation models of AM processes. Furthermore, areas such as chemical and healthcare applications, particularly in drug development and production, show promising potential for future advancements. Lastly, more research is required to explore sustainability and cost-effective solutions.

Future Research Recommendations

Based on the review results, several open research fields can be identified and summarized as follows:

⇒ There is a need for further research on the application of technologies such as digital twins, augmented reality/virtual reality and cyber-physical systems for monitoring and control purposes across various industries.

⇒ The properties of 3D printed parts are influenced by environmental conditions and parameter variations during the printing process. Therefore, comprehensive monitoring and control studies should be conducted in this field, focusing on tracking and analyzing the effects of materials, processes and their interactions on the final printed parts.

⇒ The use of Additive Manufacturing (AM) in medical domains and its adoption by small and medium enterprises (SMEs) require the development of economically viable monitoring and control systems. These systems should be specifically tailored to meet the unique needs of SMEs in the medical sector, while also addressing financial and technological barriers to their implementation.

⇒ Resource tracking and control are crucial aspects of sustainability studies. Therefore, more research is needed to develop cost-effective, user-friendly, and adaptable monitoring and control systems that can facilitate effective resource management while supporting sustainable practices.

These identified research areas highlight the need for further investigations and advancements in monitoring and control technologies to address specific industry requirements, improve process understanding, optimize resource utilization, and support sustainable development goals.

5. Conclusions

This literature review investigated current research on AM within the context of monitoring and control. For the first time in an SLR study, a wide range of applications, from process level to maintenance, were examined while considering various fields, ranging from manufacturing to healthcare.

The literature review conducted in this study had certain limitations imposed by the selection of keywords and specific constraints, including time, document type, language and source type. These limitations were applied to ensure a focused and relevant analysis of the research papers. The selected research papers were then analyzed based on the I4.0 technologies employed, the perspective of cost-effectiveness, and their impact on sustainability. These criteria allowed for a comprehensive evaluation of the literature and provided insights into the integration of I4.0 technologies, cost-effectiveness considerations, and sustainability implications in the field of study.

The evaluation of cost-effective digital monitoring and control systems has provided evidence of their potential to facilitate the digital transformation of SMEs and enhance their operational efficiency, functionality, and sustainability. While process monitoring and control in AM processes have led to significant improvements in the chemical and healthcare industries, there is a need for increased attention to biomanufacturing applications, which will be the focus of the authors' future work.

Author Contributions: Conceptualization, I.T. and Z.M.K.; methodology, I.T.; writing—original draft preparation, I.T.; writing—review and editing, I.T., Z.M.K. and P.B.; visualization, I.T.; supervision, Z.M.K. and P.B. All authors have read and agreed to the published version of the manuscript.

Funding: Idil Tartici is funded by the Ministry of National Education of the Republic of TÜRKİYE.

Data Availability Statement: Data related to the research results can be provided by the corresponding author by contacting email.

Conflicts of Interest: The authors declare no conflict of interest.

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