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Artificial intelligence as an enabler of quick and effective production repurposing: an exploratory review and future research propositions

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ABSTRACT

The outbreak of Covid-19 created disruptions in manufacturing operations. One of the most serious negative impacts is the shortage of critical medical supplies. Manufacturing firms faced pressure from governments to use their manufacturing capacity to repurpose their production for meeting the critical demand for necessary products. For this purpose, recent advancements in technology and artificial intelligence (AI) could act as response solutions to conquer the threats linked with repurposing manufacturing (RM). The study's purpose is to investigate the significance of AI in RM through a systematic literature review (SLR). This study gathered around 453 articles from the SCOPUS database in the selected research field. Structural Topic Modelling (STM) was utilised to generate emerging research themes from the selected documents on AI in RM. In addition, to study the research trends in the field of AI in RM, a bibliometric analysis was undertaken using the R-package. The findings of the study showed that there is a vast scope for research in this area as the yearly global production of articles in this field is limited. However, it is an evolving field and many research collaborations were identified. The study proposes a comprehensive research framework and propositions for future research development.

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KEYWORDS

Repurposing manufacturing; artificial intelligence; flexible manufacturing; structural topic modelling; adaptable and reconfigurable manufacturing; text mining; bibliometric analysis

1. Introduction

The unpredictable spread of the coronavirus (Covid-19) pandemic has greatly affected the operations and businesses of global economies. Scholars and consulting firms have investigated the impact of the Covid-19 emergency on the manufacturing industry, mainly machinery, electronics, and automobiles got significantly affected. Also, the supply chain interruption was caused due to required quarantine measures and its negative impact on countries dependent on other countries which have their regional industry chain centres (Cai and Luo 2020). On February 27, 2020, it was reported by the Food and Drug Administration (FDA) that a Covid-19 emergency would affect the supply chain of medical goods with the potential disruptions to shortages or supply of crucial medical supplies in the US (FDA 2020). However, large-scale disruptions are also faced by supply chains and manufacturing operations because of political risks and natural disasters (Okorie et al. 2020). Therefore, tackling sudden disruptions or risks associated with manufacturing during or after pandemics is very crucial.

In this regard, the collaborations between companies in the form of evolution and ecosystem formation to develop

and produce innovations, for instance, ventilators can be seen for Covid-19 related repurposing (Liu, Beltagui, and Ye 2021a). These companies not only repurposed their manufacturing but created or employed innovations (Rapaccini et al. 2020), and also collaborated with other companies they might not work with previously for doing so (Chesbrough 2020). Due to the pandemic, firms' repurposing has been enabled by using specialised manufacturing capabilities to produce particular units with specific requirements within a period (Liu, Beltagui, and Ye 2021a). It has been reported that to tackle the worldwide scarcity of Covid-19 critical items, repurposing is a strategy that can use existing manufacturing capacity to save lives (López-Gómez et al. 2020; Pansare and Yadav 2022). Repurposing manufacturing refers to a 'methodology employed by manufacturers to swiftly shift to a new process of products' (Poduval et al. 2022). To provide critical public and medical materials and equipment amid the Covid-19 pandemic, several manufacturing companies have come forward (Jain et al. 2022) and successfully implemented repurposing in their existing plants (Poduval et al. 2022). Repurposing is a rapid response solution to address the global shortage of COVID-19 critical items (López-Gómez et al. 2020).

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Also, the need for regionalised, cost-effective, and rapid production has surfaced because of the critical time scale linked with the Covid-19 emergency (Shokrani et al. 2020). For this, mobilisation of a diverse workforce was made through existing networks among research facilities, medical institutions, and independent manufacturers. It involved the technology development to make use of a single ventilator for two patients and repurposing gear of scuba diving for personal protective equipment (PPE) (Shokrani et al. 2020; Pooler et al. 2020). The transition of a business model from a product-centric to a service-centric provides benefits to manufacturing firms to face disruptions and achieve stability (Kowalkowski et al. 2012). However, in terms of detrimental economic impact, the manufacturing sector is among the most severely affected sectors despite the availability of other options like collaborating or transitioning business models (Okorie et al. 2020).

Sell et al. (2021) reported that manufacturers are not completely prepared to confront novel threats and experts doubt that manufacturers could adequately deal with the catastrophic pandemic by scaling up a novel vaccine according to the timeline. Hence, several approaches were suggested for policymakers to adopt for expanding vaccine supplies during a pandemic such as stockpiling vaccines, reserving excess manufacturing capability, financing the assembling of new production capacity, and repurposing existing manufacturing services (Sell et al. 2021). In this regard, Okorie et al. (2020) observed that several manufacturing firms had adopted the repurposing approach during the pandemic by including several target products such as examination gloves, hand sanitisers, eye protection glasses, clinical care equipment, face shields, surgical masks, and medical PPE. Specifically, this transition of a manufacturing system to respond rapidly to sudden disruptions or changes in situations without excessive cost, effort, time, or reducing performance capability can be referred to as the flexibility of the system (Beach et al. 2000). Furthermore, when companies operate in turbulent conditions, achieving flexibility could be accomplished using digital technologies like 3D printing (Rong et al. 2020), robotics (Makris, 2021), Industry 4.0 (Hermann, Pentek, and Otto 2016), information and communication technologies (ICT) (Jackson, Efthymiou, and Borton 2016), artificial intelligence (Levin et al. 2020).

Digital technologies can assist companies to adjust production processes according to the high-demand products by using modelling tools to re-design manufacturing lines (PLU (Policy Links Unit) 2020). A study proved that manufacturing firms having a high level of digitisation exhibit higher adaptability and resilience in comparison to firms with lower digital adoption (Okorie et al. 2020). Also, resilient supply chains are less vulnerable to disruptions and can also handle any vulnerabilities that trigger problems (Ekanayake, Shen, and Kumaraswamy 2023). There have been several studies published so far that examine the connection between advanced technologies and certain performance enhancements that may be attained through their implementation (Chiarini, Belvedere, and Grando 2020). Industry 4.0's cutting-edge digital technologies are being considered and adopted

by manufacturing companies as a potential means of reducing the shock of pandemics by boosting the robustness and agility of the production function (Queiroz et al. 2022; Kumar et al. 2020). During the COVID-19 pandemic, Behl et al. (2022) showed the power of using AI and BD to build production resilience and gain a competitive edge. According to Kumar et al. (2020), digital manufacturing with AI capabilities may be the most effective way to manufacture items during the pandemic. By adopting AI and IoT to improve the predictability and availability of production systems, Wipro (2020) revealed that businesses are seeing a 7 percent increase in income. On the other hand, Myant, a textile computing company based in Canada, utilised AI in repurposing its manufacturing operations. Myant leveraged AI algorithms and machine learning to reconfigure their production lines and manufacture face masks and medical gowns during the pandemic. They used computer vision systems to monitor and optimise the production process, ensuring compliance with quality standards and efficient utilisation of materials (Myant 2020). Therefore, technologies and digitisation not only enable decentralised production but also improve the flexibility of the firms to quickly transition between product lines (Sell et al. 2021). Hence, it is necessary to shift from traditional repurposing by employing artificial intelligence-based technologies (Ho 2020). According to Lu (2019), artificial intelligence is 'a multidisciplinary technology, one with the capability of integrating cognition, machine learning, emotion recognition, human-computer interaction, data storage, and decision-making'. In the context of the Industry 4.0 paradigm, AI is being regarded as one of the key technologies to achieve the capabilities of self-optimisation, self-awareness and self-monitoring and to disruptively redefine the way manufacturing processes and business models are structured (Peres et al. 2020). Coupled with the ability to comprehend high dimensional data, AI provides the ability to transform large amounts of complex manufacturing data, which has become commonplace in today's factories, into actionable and insightful information (Arinez et al. 2020). The adoption of AI techniques has helped to enhance automation and provide better competitive advantages as compared to conventional approaches (Chien et al. 2020). AI is currently revolutionising industries such as manufacturing, retail, and telecommunications. The subfields of AI such as machine learning, natural language processing, robotics, computer vision, optimisation, automated planning and scheduling (Rao et al. 2022), have been applied to tackle complex problems and support decision-making for real-world problems. For instance, in the manufacturing industry, the advent of the fourth industrial revolution, commonly known as Industry 4.0 is geared towards automation, data-driven technologies and the application of advanced AI techniques (Yao et al. 2017). Around the world, the development of artificial intelligence has become a critical growth strategy to maintain security and enhance national competitiveness in countries (Rajkomar et al. 2018). Many industrial sectors are set to be revolutionised as a result of such advancements in techniques to deal with massive amounts of data, whereas it is also the dynamic force behind the creation of smart

factories, in which everything is done intelligently and automatically throughout each cycle of the production process (Kim et al. 2022). Various AI applications may help to prevent the negative impact of the Covid-19 pandemic by identifying the virus, diagnosing and repositioning, or repurposing the drugs (Khan et al. 2021; Lin et al. 2020).

Numerous studies indicate that manufacturing is a crucial aspect of pandemic management. This industrial issue encompasses the mass manufacture of medical devices and other items classified by the WHO as personal protective equipment (PPE) (Prather, Wang, and Schooley 2020; Kis et al. 2020). Other studies (Linton and Vakili 2020; Ivanov and Dolgui 2021) look at manufacturing from the standpoint of supply chain hazards and resilience. Manufacturing clearly has a crucial role to play in controlling the pandemic (Okorie et al. 2020). Regarding repurposing manufacturing during the sudden change in the production system, it may be convenient to understand whether AI can contribute to the rapid recovery of systems and the potential role that it may play in this. Therefore, this study was conducted to provide an understanding of previous literature conducted to examine the role of AI in repurposing manufacturing and its related themes. A systematic literature review is presented by gathering and thoroughly discussing the articles related to AI and repurposing manufacturing. To collect the relevant articles, the SCOPUS database was used by appropriate utilisation of related keywords to the selected field of research. In total, 437 article papers and 16 review papers were included to execute a systematic review after excluding other types of papers such as conference papers, reports, and non-English papers. The research was conducted to provide answers to the following questions:

- RQ1:* What are the different AI techniques used for solving repurposing problems in the manufacturing sector?
RQ2: What is the growth and development of the research in the field of AI and repurposing manufacturing?
RQ3: What could be the future research directions based on the existing literature for employing AI applications for manufacturing repurposing?

Furthermore, there is a dearth of literature that provides a systematic review of literature in the field of AI in RM. This may be the case because it is an emerging topic that may offer a huge potential to be worth exploring. The methodology of a systematic literature review is presented in section 2, which is used to generate articles from the SCOPUS database for the current study. The generated articles revealed that there were only seven review papers conducted in this field of study. Table 1 provides an overview of the review papers published between the period 2013–2023 in the selected field of study. It shows that only one study provided a bibliometric analysis, conducted by Ivanov et al. (2021). Their study, however, was limited to industry 4.0 in operations management and included 191 articles. The other reviewed papers presented in Table 1 are based on a narrative review in different research areas like flexible manufacturing systems, reconfigurable manufacturing systems, IT-based production, and scheduling problems. They provided

scope for this study to build its basis on repurposing manufacturing during the pandemic. Therefore, the current study will attempt to fill this major research gap by conducting a systematic literature review in the field of AI in RM.

The current study is organised in the following pattern. First, the study provides a systematic literature review and text mining technique, named structural topic modelling, which was adopted to produce the topics. To explore and examine the research developments, a bibliometric analysis was employed. The generated thematic topics were then analysed through a thorough review of the literature and the discussion of these topics was conducted along with providing future research propositions. Finally, discussion, implications, and conclusions are presented.

2. Systematic literature review

According to Xiao and Watson (2019), for academic research, the literature review is a crucial aspect that facilitates the advancement of knowledge based on existing prior research. Also, to develop an understanding of any field of research, it is crucial to know where the depth and breadth of the existing knowledge are, which can be done by the review of relevant literature (Ding, Ferras Hernandez, and Agell Jane 2023). In addition, a review of the literature should contribute to the literature along with addressing the subject matter by encompassing a dual approach of presenting a scholarly critique of theory and combining the available material (Kekäle et al. 2009; Okoli and Schabram 2010). Systematic literature review (SLR), according to Fink (2005) is described as ‘a systematic, explicit, comprehensive, and reproducible method for identifying, evaluating, and synthesizing the existing body of completed and recorded work produced by researchers, scholars, and practitioners’. Systematic literature review corresponds to extracting literature with well-defined research questions, and the process of searching, extracting and presenting data (Kitchenham et al. 2009).

The current study follows the approach of SLR to achieve a thorough understanding of the selected field concerning AI in repurposing manufacturing. Prior research was investigated and discussed thoroughly after employing a comprehensive and detailed methodological approach, which is crucial to performing any form of literature review (Okoli and Schabram 2010). The current study followed the SLR methodology as conducted by Agrawal et al. (2022). In this context, the methodological approach used in this study includes collecting relevant published articles related to the selected research area from the SCOPUS database, which is one of the largest databases with a significant and large number of peer-reviewed articles. The collection of articles for the systematic literature review was done by defining appropriate keywords and using those to search for study-related articles (Vinodh et al. 2020). On the other hand, various concepts like flexible manufacturing, adaptive manufacturing, reconfigurable manufacturing, etc. were used in the search terms as the concept is similar to repurposing manufacturing. For instance, according to Urtasun-Alonso et al. (2014), flexible manufacturing refers to ‘how organisations adapt their internal manufacturing-related processes and

Table 1. Overview of the previous review articles in the related field of study.

Authors	Article type	Year	Area	Type of review	Objectives
Tripathi et al. (2023)	Review	2023	Lean, green, and smart manufacturing	Systematic Literature review	Develop a framework to enhance the operational excellence and sustainability of shop floor organisation in an industry 4.0 environment
Touckia (2023)	Review	2023	Reconfigurable manufacturing system	Systematic Literature review	Integration of digital twin concepts into reconfigurable manufacturing system
Qin et al. (2022)	Review	2022	Machine learning in additive manufacturing	State-of-the-art review with bibliometric study	Aimed to analyse the applications of machine learning in additive manufacturing
Khorasani et al. (2022)	Review	2022	Industry 4.0 and additive manufacturing	A narrative review and research article	Examine the collaboration between Industry 4.0 and additive manufacturing (AM) while exploring the incorporation of data-driven manufacturing systems and product service systems as essential elements in the Industry 4.0 revolution.
Razak, Hendry, and Stevenson (2023)	Review	2021	Supply chain traceability and supply chain Resilience	State-of-the-art review	To examine the relationship between supply chain traceability and supply chain resilience through potential industry 4.0 solutions.
Morgan et al. (2021)	Review	2021	Reconfigurable manufacturing system	State-of-the-art review	To examine the application of industry 4.0 manufacturing machines to enable smart and reconfigurable manufacturing systems.
Ivanov et al. (2021)	Review	2021	Operations management	Bibliometric study	To identify the current state of knowledge regarding the application of industry 4.0 technologies in operation management.
Fatorachian and Kazemi (2021)	Review	2021	Supply chain performance	Systematic Literature review	To examine the impact of Industry 4.0 on supply chain performance and resilience.
Kunovjanek, Knofius, and Reiner (2022)	Review	2020	Additive manufacturing	Systematic Literature review	To identify the impact, benefits, and challenges of additive manufacturing on the supply chain.
Yadav and Jayswal (2018)	Review	2018	Flexible Manufacturing System	Narrative review	To review various modelling techniques used in the flexible manufacturing system.
Li, Li, and Gupta (2015)	Review	2015	Scheduling Problem	A narrative review and research article	To review the scheduling problem in a flowline manufacturing cell and proposed a hybrid harmony search mathematical model.
Renzi et al. (2014)	Review	2014	Reconfigurable manufacturing system	State-of-the-art review	Explore the role of optimisation in the design of cellular reconfigurable manufacturing systems by focusing on meta-heuristics and artificial intelligence methods.

products to the uncertainties they face'. Also, Peng and Mcfarlane (2004) refer to the concept of adaptive manufacturing as 'a manufacturing control system that is able to adapt its behaviour and/or its governing strategy in the face of changing environmental conditions'. Hence, after reviewing the literature and with experts' opinions, the authors added these definitions to the search string to identify relevant articles and conduct the systematic literature review. In this study, several researchers were involved in the selection and exclusion of articles to subjugate individual bias (Tranfield, Denyer, and Smart 2003). Table 2 shows the complimentary and equivalent concepts used for analysing the studies in the field of repurposing manufacturing.

The four-stage review approach was employed in this study in which the first stage corresponds to a collection of data using appropriate keywords. In the second stage, the bibliometric study of the collected papers was carried out by using the R package and VOS viewer. In the third stage, research field analysis was done by using structural topic modelling (STM). To perform the STM approach, an R package was used and 12 emerging research themes in AI and repurposing manufacturing were generated. These themes were thoroughly discussed along with providing future propositions. The fourth stage comprises a comprehensive framework for future studies and based on the results discussion and conclusion were elaborated. The four-stage review

Table 2. Important related concepts.

Concept	Definition	Source
Repurposing manufacturing	'Methodology employed by manufacturers to swiftly shift to a new process of products'	Poduval et al. (2022)
Flexible manufacturing	'To reconfigure manufacturing resources to produce efficiently different products of acceptable quality'	Sethi and Sethi (1990)
Adaptive manufacturing	'The transferability of a process is its innate, host-independent ability to be adapted (where necessary), transmitted and assimilated, within a reasonable time and resource constraints'	Grant and Gregory (1997)
Reconfigurable manufacturing	'Designed at the outset for rapid change in structure, as well as in hardware and software components to quickly adjust production capacity and functionality within a part family in response to sudden changes in the market or in regulatory requirements'	Koren et al. (1999)
Agile manufacturing	'The capability of surviving and prospering in a competitive environment of continuous and unpredictable change by reacting quickly and effectively to changing markets, driven by customer-designed products and services'	Cho, Jung, and Kim (1996)

approach for the systematic literature review of this study is depicted in [Figure 1](#).

3. Bibliometric study

Bibliometric analysis is referred to as a scientific computer-assisted review methodology that helps researchers to recognise fundamental research or authors along with their association by encompassing all the published work in relation to a studied field of research (De Bellis 2009). The bibliometric analysis provides relational and abundant information on the selected field which makes researchers understand the overall landscape of the topic (Churruca et al. 2019). It offers a quantitative analysis of the written scientific research and publications (Ellegaard and Wallin 2015) and is used to identify the major keywords, researchers, affiliations, journals (Wahyuni, Vanany, and Ciptomulyono 2019), and research collaborations among institutions, countries, and researchers (Rejeb et al. 2020). It is often used to extract and manipulate data based on a citation or content analysis (Wallin 2005). It greatly benefits researchers due to its computerised data treatment which increased the number of publications in recent years within this field. Also, it is statistically reliable because it must incorporate a certain data volume to prove reliability (Ellegaard and Wallin 2015).

Therefore, the current study employed bibliometric analysis to examine the existing information related to AI in repurposing manufacturing. [Table 3](#) depicts the main information of the articles. The selected articles were published between the period 2013–2023 and the articles were collected from the SCOPUS database.

This section will provide an answer to the 2nd research question of the study i.e. the growth and development of the research in the field of AI and repurposing manufacturing. By analysing bibliometric data, we could be able to see the growth and development in the investigating area.

[Figure 2](#) shows the percentage of published articles based on the area of study in the field of AI in RM. As it is shown that the maximum percentage of articles fall under the

subject area of Engineering and Computer Science with 34.4% and 26.32% respectively, which are more than 50% of the total published articles. The research conducted in the area of AI in RM shows significant development in the engineering field. Also, other major subject areas are Business Management, Decision Science, and Mathematics.

[Figure 3](#) depicts the type of articles in the field of AI in RM. It is evident from the figure that of the selected articles used in this study, around 96.5% are research articles and only 3.5% are review papers published during the period 2013–2023. The scarcity of review papers shows a major research gap in this field of study which can provide a comprehensive knowledge background. Hence, this review paper will attempt to fill this research gap by providing a systematic literature review in the field of AI in RM.

The year-wise article statistics are presented in [Figure 4](#). It shows the growth trajectory of the conducted research in the field of AI in RM. As it is evident that the academic research interest in the current area dropped from the year 2013 to 2014 but gradually increased after 2015. However, the development of research in this field still needs to be expanded to show a significant surge in the application of AI in providing solutions to RM.

To understand the geographical distribution of the conducted research in the field of AI in RM, country-wise article statistics are presented ([Table 4](#)). [Table 4](#) depicts the top ten leading countries producing high-quality research work in the selected field between the years 2013–2023. The table is based on publications where the country appears as the main affiliation of the first author. Although several countries have been involved in knowledge production in the selected field of study, we considered only the top ten countries with the maximum published papers in AI in RM. China is at first rank with 226 published articles out of a total of 453 articles selected in this study and became the most influential country to produce research work based on AI in RM. Furthermore, India, the USA, and Iran also contributed significantly to the selected research field with 133, 80, and 51 published articles, respectively. Some of the highly developed European countries produced substantial research work

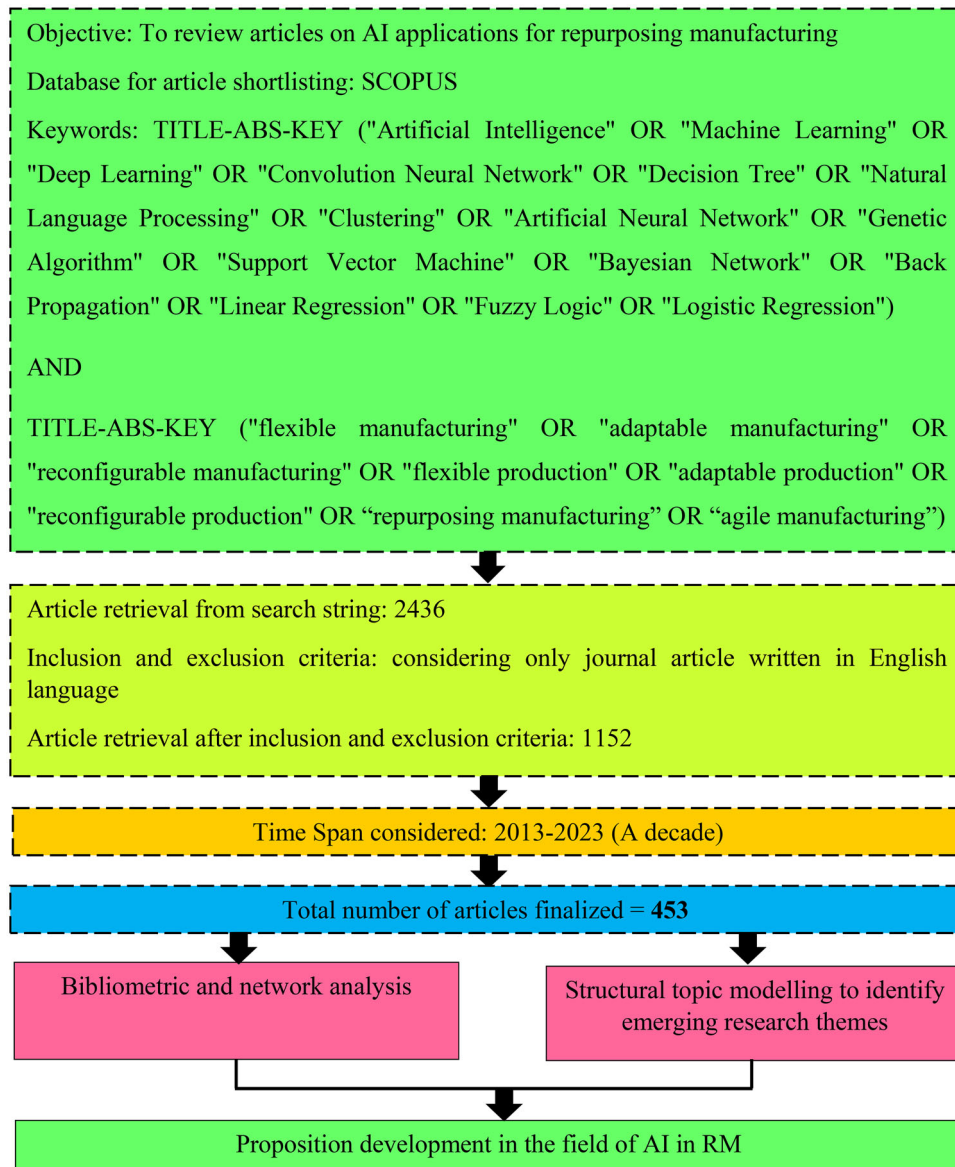


Figure 1. SLR process.

Table 3. Major information about collected articles.

Category	Findings
Primary information	
Timespan	2013:2023
Sources (Journals, Books, etc)	220
Documents	453
References	20990
Document types	
Article	437
Review	16
Authors	
Author Appearances	1585
Single-authored documents	24

in this field and are listed in the top ten leading countries such as France, Germany, UK, Italy, and Turkey. However, the highest knowledge production in the field of AI in RM came from three leading nations in this list which belong to Asia, and Malaysia is at ninth rank with a total of 25 published articles.

Table 5 presents the most prominent and important journals publishing articles in the fields of AI in RM. Although several journals have published scientific articles in the studied field, we presented here only the top ten journals that have published the maximum number of articles. It is crucial for future researchers to identify the role played by prominent journals in disseminating knowledge in their field of study so they can target those journals for future potential research and communicating innovations. As depicted in Table 5, the 'International Journal of Advanced Manufacturing Technology' and 'International Journal of Production Research' published the highest number of articles in the timespan of 2013–2023 in the chosen study field. Next on the list are the 'IEEE Access', 'Journal of Manufacturing Systems', and 'Computers and Industrial Engineering', with a considerable contribution of published articles to this research field. As it is apparent from the list of top ten journals presented in Table 5 that these journals are involved in computer-integrated technology and engineering

Documents by subject area

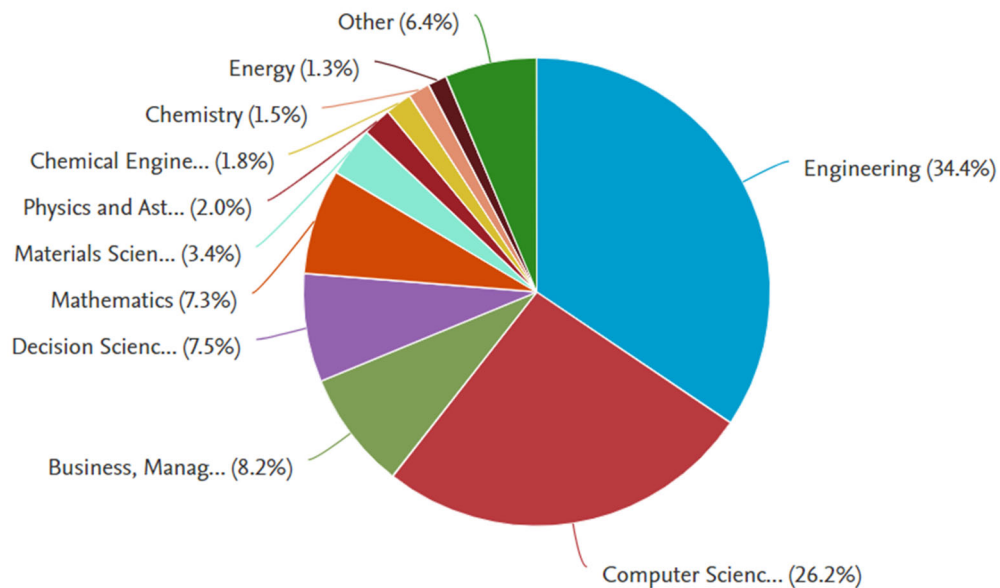


Figure 2. AI in RM articles based on the subject area.

Documents by type

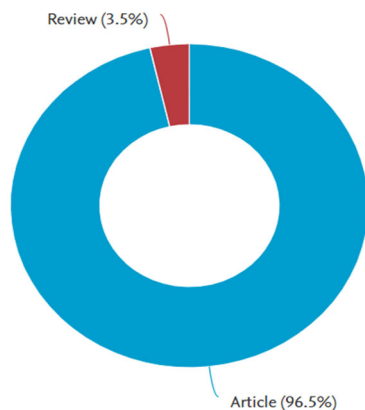


Figure 3. Documents by type of articles of AI in RM.

which is also demonstrated in Figure 2. So, it is recognised that research in the field of AI in RM is more intensive in the area of computers and engineering. Therefore, journals with other areas involving business, management, decision sciences, mathematics, etc., have a high scope of publishing potential research work in this field of study.

The ten most productive and influential organisations concerning the selected fields of research of AI in RM are listed in Table 6. However, the search of articles revealed that there are several organisations that uplifted the work of AI in RM, but we showed only the top ten universities that have produced the maximum number of scientific articles. Future researchers interested in the current research field can focus on these universities for further research. The institutions with the highest number of published articles in the SCOPUS database in the studied field of research are Islamic

Azad University, UAE and Southeast University, China with a total of 12 articles each. The following Chongqing University, China, King Saud University, Saudi Arabia, and Wuhan University of Science and Technology, China each produced eight scientific articles.

To identify and extract relevant articles from the SCOPUS database, well-defined and appropriate keywords were used. Based on those keywords, a total of 453 relevant articles were extracted. Then using those articles, we identified the total number of keywords used in those articles, and the occurrence of each keyword was identified. It is important to understand the occurrence and major keywords related to the selected field of research. Table 7 shows 20 such mostly occurred keywords when searching for articles in the field of AI in RM. It shows that the keywords 'genetic algorithms' and 'flexible manufacturing systems' occurred 152 and 134 times respectively while searching for the articles in the current field of the present study. It is followed by 'manufacture', 'scheduling', 'decision making', 'reconfigurable manufacturing system', 'computer aided manufacturing', 'artificial intelligence', etc. As this study is based on the applications of artificial intelligence, therefore various AI techniques occurred as top keywords in the search such as, 'optimisation', 'decision making', 'integer programming', 'algorithms', etc.

For the visual presentation of the most occurred and common keywords in the field of AI in RM, a word cloud was generated by using the Biblioshiny program of the R package. The word cloud is shown in Figure 5 which depicted the most occurred keywords related to the selected research field. The size of the word in the word cloud represents the occurrence of the word during the search process. The major keywords like 'manufacture', 'scheduling', 'computer aided manufacturing', and

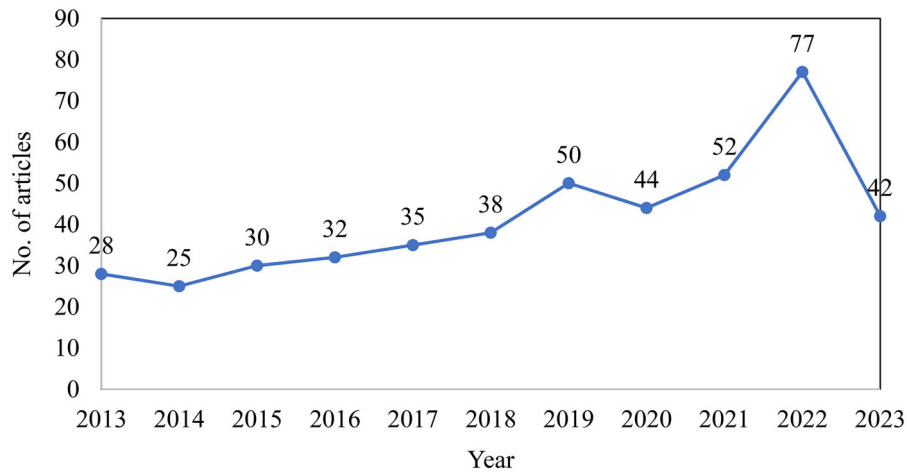


Figure 4. Year-wise published papers in AI in RM.

Table 4. Country-wise number of articles published in AI in RM.

Country	Occurrence
China	226
India	133
USA	80
Iran	51
France	49
UK	44
Germany	42
Italy	29
Malaysia	25
Turkey	23

Table 5. Prominent journals which published papers on the topic of AI in RM.

Journals	Articles
'International Journal of Advanced Manufacturing Technology'	45
'International Journal of Production Research'	31
'IEEE Access'	15
'Journal of Manufacturing Systems'	13
'Computers and Industrial Engineering'	9
'IEEE Robotics and Automation Letters'	7
'Journal of Intelligent Manufacturing'	7
'Robotics and Computer-Integrated Manufacturing'	7
'European Journal of Operational Research'	6
'Expert Systems with Applications'	6

'reconfigurable manufacturing system' appeared in the centre of the word cloud which is also present in the top keywords given in Table 7.

4. Network analysis

To examine the collaboration among authors, countries, and keywords, network analysis was conducted in this study. According to Chiesi (2015), network analysis is a 'set of techniques with a shared methodological perspective, which allow researchers to depict relations among actors and to analyze the social structures that emerge from the recurrence of these relations'. Several structures which comprise variables are referred to as networks in which variables are represented by nodes and edges represent the relationship among the nodes (Hevey 2018). The most widely used software packages for network analysis are Pajek, Gephi, VOSviewer, Histcite, however, we used VOSviewer software

Table 6. Most prominent institutions that have published papers in AI in RM.

Affiliations	Articles
Islamic Azad University	12
Southeast University	12
Chongqing University	8
King Saud University	8
Wuhan University of Science and Technology	8
Huazhong University of Science and Technology	7
Indian Institute of Technology (Ism)	6
Indian Institute of Technology Roorkee	6
Tsinghua University	5
Université De Lorraine	5

as it provides clear and understandable visual maps to show the collaborations. It is one of the most widely used software packages for bibliometric analysis, also used in cluster analysis, thematic analysis, and cartography (Shah et al. 2019). A wide range of bibliometric networks could be examined by using VOS viewer comprising journals, countries, authors, etc. (Van Eck and Waltman 2010).

4.1. Authors collaboration

To investigate the collaboration among authors in the field of AI in RM, we conducted network analysis using the VOS viewer software package of the R program. To conduct the analysis, a total of 336 articles were used which were collected from the SCOPUS database by using appropriate keywords. There were around 931 authors in the considered articles and authors who have a minimum of two articles were considered to form the clusters, hence the number of authors was reduced to 124. The analysis formed seven clusters which included 23 authors and other authors were removed because of low connectivity. Finally, the network analysis generated seven clusters which comprise 32 links and 36 total link strengths. Figure 6 depicts the clusters, with the red cluster being the biggest, with five authors, and the blue and green clusters each having four authors. With only two authors, the orange cluster is the smallest. The authors' cooperation network also reveals that Li X has the most connections with other writers, with a total of eight relationships and a total link strength of nine.

Table 7. Top keywords occurred in the selected documents.

Words	Occurrences	Words	Occurrences
Genetic algorithms	152	Integer programming	34
Flexible manufacturing systems	134	Industrial research	29
Manufacture	104	Learning systems	29
Scheduling	82	Multiobjective optimisation	28
Agile manufacturing systems	77	Optimisation	28
Decision making	60	Fuzzy logic	26
Reconfigurable manufacturing system	58	Job shop scheduling	26
Computer-aided manufacturing	55	Deep learning	25
Artificial intelligence	47	Flexible manufacturing	25
Production control	35	Heuristic methods	24



Figure 5. Word cloud of occurred keywords.

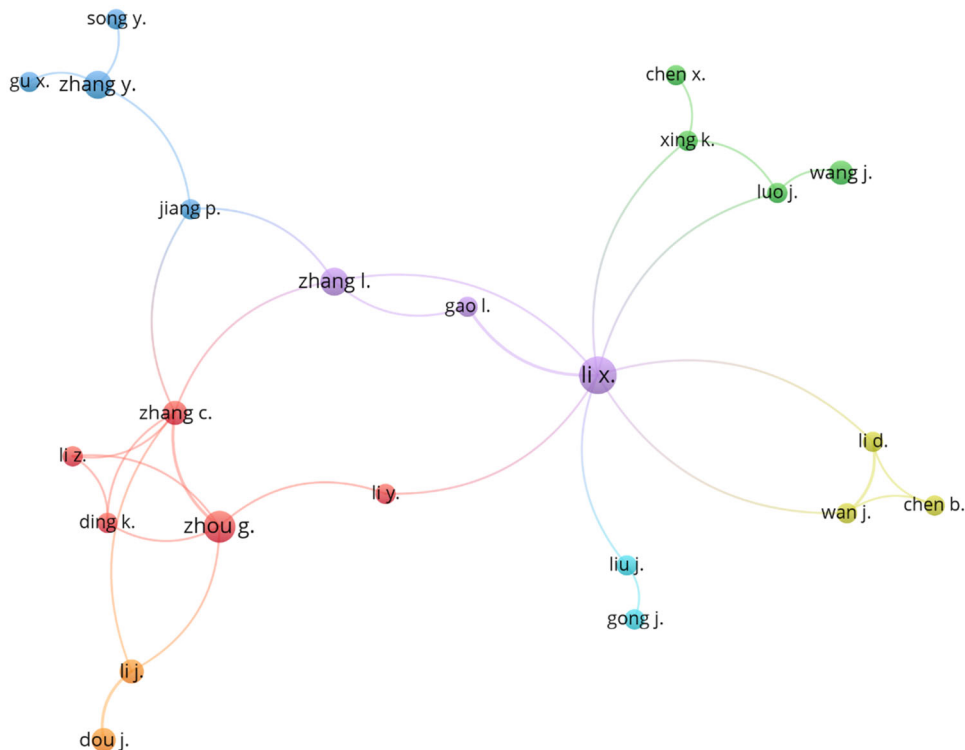


Figure 6. Author collaboration network in the field of AI in RM.

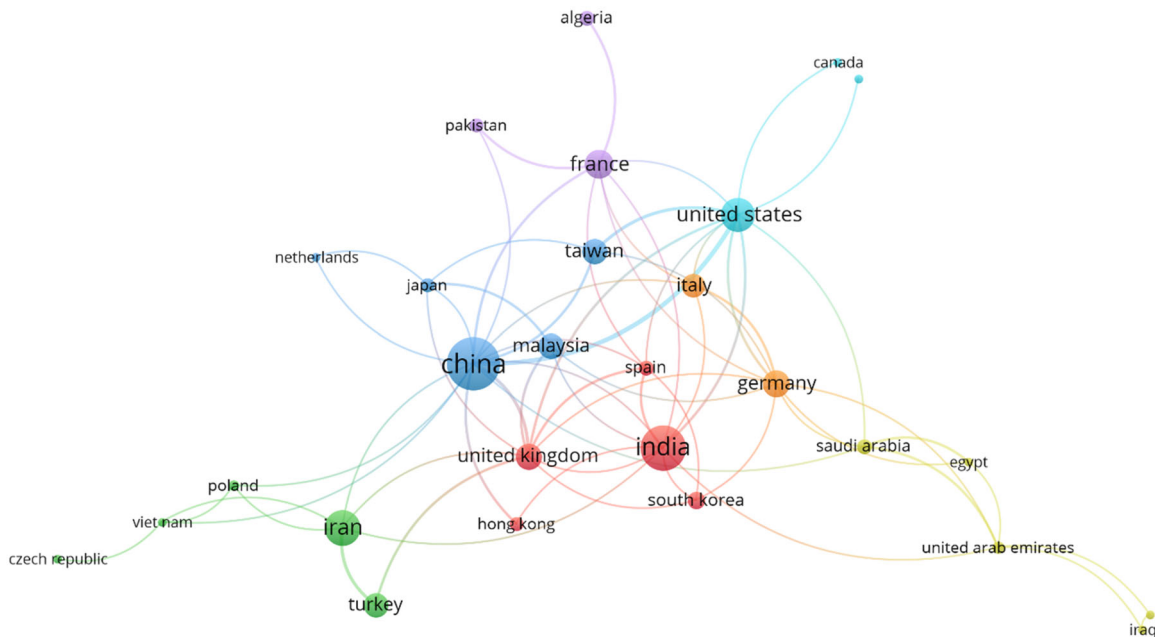


Figure 7. Country collaboration network in the field of AI in RM.

4.2. Country collaboration

To identify the collaboration between countries in publishing papers in the area of AI in RM, the generated 336 articles were used which consisted of around 60 countries. Only nations with at least two articles were included in the network analysis, bringing the total number of countries down to 37. After this, the clusters were generated and some countries were removed because of low connectivity, therefore seven clusters were formed comprising 28 countries. The network of seven clusters consists of 68 links and 95 total link strengths (Figure 7). The largest top three clusters are green, red, blue, and yellow comprising five countries each. The smallest cluster is the orange cluster with only two countries namely Germany and Egypt. The country collaboration network also shows that the country China has the maximum connection with other countries with a total of 15 links and the total link strength is 25.

5. Text analytics using structural topic modeling

Topic models are computer algorithms used to characterise the latent patterns of word occurrence with the word distribution in a collection of documents, and it provides a set of topics that comprise clusters of words that follow a specific pattern and co-occur in the selected documents (Jacobi et al., 2016). Topic modelling was used by researchers to interpret and organise a large volume of text data and it recently gained prominence (Kuhn, 2018) as it classifies the main themes which exist in a large and unstructured dataset (Blei, 2012). However, there exist very few qualitative papers that utilised topic modelling to categorise research papers (Nikolenko et al., 2017; Asmussen and Møller, 2019). STM is used to offer fast, replicable, and transparent analyses (Das et al., 2017). STM's findings show which topics occur throughout time, as well as their predominance and word

connection (Kuhn, 2018). This work used STM to analyse a huge dataset of AI-related publications published in RM. This text mining approach analysed the text based on word frequency and similarity from the documents and generated thematic topics using STM. The steps of the generative procedure of STM are adapted from Agrawal et al. (2022).

The text from the abstract, title, and keywords was used to generate the thematic topics from selected documents and used in the STM approach as input. Before the analysis, text cleaning was conducted by eliminating stop words and commonly used words. Then, equations, special characters, numbers, and non-English words were removed to make the text input compatible with the STM approach. Figure 8 illustrates the generated thematic topics which are obtained by using the selected 336 articles in the inbuilt STM library in R-package.

Table 8 shows the probabilistic distribution of the most commonly used keywords for the derived subject label. For example, as shown in Table 8, the terms 'product', 'model', 'optimum', 'flexible', 'assembly', 'line', and 'simulation' have the highest likelihood of generating subject label 1. Other subjects are created in the same way, based on the keywords in Table 8.

Table 8 presents Frex and Lift metrics. The lift metrics highlighted the most common words within a topic (Kuhn, 2018). Though, it is recommended to use Frex metrics which correspond to the restricted word frequency in a topic (Bischof and Airolidi 2012).

6. Emerging research themes of AI and repurposing manufacturing

This section provides a brief description of the generated thematic topics that were obtained by using the selected 336 articles in the inbuilt STM library in R-package. These thematic topics are discussed based on existing literature.

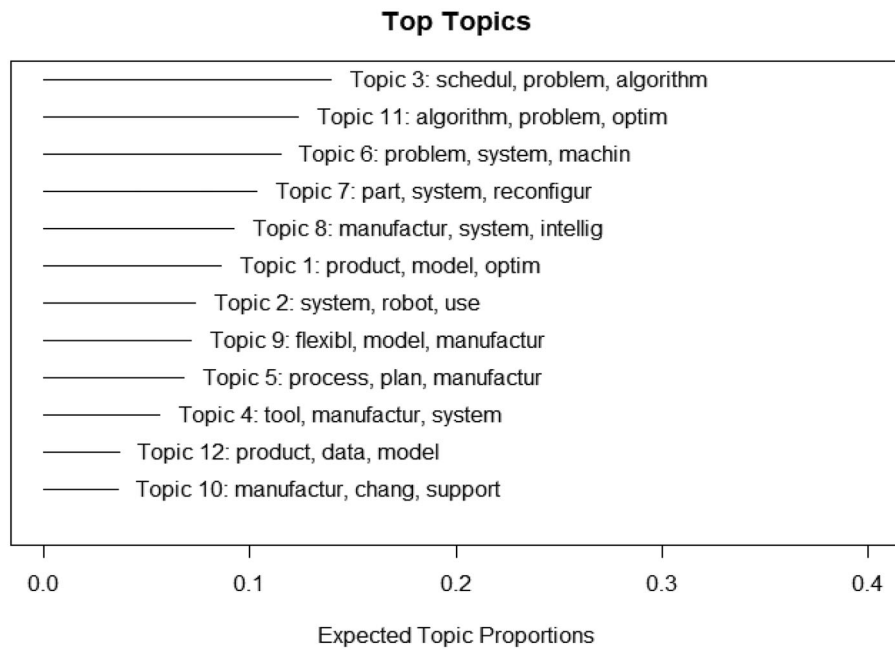


Figure 8. Generated topic labels from the STM approach.

Table 8. Top identified words under each topic.

S. No.	Topic label	Words with the highest probability	Frex	Lift
1.	Flexible assembly in manufacturing	product, model, optimum, flexible, assembly, agile, line, simul	assembly, buffer, line, product, simul, labour, balance	mixed-model, truck, encounter, indispensable, yet, buffer, labour
2.	Robotic systems in manufacturing	system, robot, use, control, machine, approach, method	robot, grind, rts, rule, error, control, human	ensemble, learning-bas, disadvantage, grind, heavily, insert, intervention
3.	Scheduling in flexible manufacturing	schedule, problem, algorithm, repurposing, flexible, time, manufacturer	schedule, makespan, job, shop, colony, ant	bidirect, chemic, energy-sav, conflict-free, deadlock-prone, disjunct, flowshop
4.	Smart machine tools for manufacturing	tool, manufacturer, system, machine, use, flexible, model	neural, wear, tool, cut, ANN, predict, reliable	ANN, forearm, iso, limb, piece, worn
5.	Process planning in manufacturing	process, plan, manufacturer, product, reconfiguration, configuration, approach	plan, configuration, multi-object, process, minimis, total, reconfiguration	cad, defect, greenhouse, region, single, unit, emit
6.	Systems operations flexibility	problem, system, machine, operation, flexible, propose, approach	rout, load, type, problem, literature, heurist, operation	metaheuristic, unbalance, unequal-area, constraint-chromosome, giffler, imbalance
7.	Reconfigurable manufacturing	part, system, reconfigure, manufacture, family, design, machine	family, reconfigure, format, part, rms, cell, similar	bypass, rearrange, scs, borrow, cater, coefficient, colour
8.	Intelligent technology in manufacturing	manufacture, system, intelligent, industries, technology, product, smart	digit, intelligent, smart, technology, inform, innovation, industry	holist, perceive, prognostic, resilient, SMEs, tag
9.	Flexible manufacturing system	flexible, model, manufacturer, use, FMS, method, measure	attribute, measure, criteria, company, rank, weight, custom	incomplete, credit, reproduction, satisfaction, supplier, unrestricted
10.	Manufacturing support system	manufacturer, change, support, differ, component, can, design	organise, active, mobile, loss, continual, people, worker	head, organise, people, frame, mention, unfortunate, now
11.	Optimisation algorithm in manufacturing	algorithm, problem, optimal, solution, genet, propose, search	particle, search, swarm, PSO, algorithm, solute, popular	retrieval, unequal, act, cuckoo, cyclic
12.	Data-based manufacturing model	product, data, model, order, manufacture, approach, use	inventories, stock, policies, planner, margin, supplier, management	imprecise, record, saturate, stock, contra, determinist, sell

The application of AI under each theme is discussed and evidence of different studies is provided to analyse the use of AI techniques in solving the problems associated with a particular area. To discuss these thematic topics, a thorough

review of the literature was conducted, and a research gap was identified and analysed. Finally, to fill the gap in the existing literature and advance the existing knowledge, future research propositions were offered. This section will

also provide the answers to the 3rd research question of the study i.e. the future propositions for the research by employing AI applications for repurposing manufacturing. The propositions offered were suggested by several authors involved in the study.

6.1. Flexible assembly in manufacturing

Sawik (1999, p. 1) defined a flexible assembly system as ‘a flexible assembly system (FAS) is a fully integrated production system consisting of computer numerically controlled assembly stations, connected by an automated material handling system, all under the control of a central computer. A FAS is capable of simultaneously assemble a variety of product types in small to medium-sized batches and at high rate comparable to that of conventional transfer lines designed for high volume/low variety manufacture’. In recent years concerning automation and manufacturing, the notions of reconfigurability and flexibility are heaping great relevance. A new standard for manufacturing systems has emerged with the integration of Industry 4.0 (Hermann, Pentek, and Otto 2016). In this regard, collaboration and interaction of humans and robots play a major role in the new manufacturing concepts (Tan et al. 2009). The integration of automation in high-volume manufacturing which is backed up by digital manufacturing tools created a more flexible or compliant production system, which can deal with unpredictable or unstable market demands (Jackson, Efthymiou, and Borton 2016).

Makris (2021) discussed the flexibility attributes of manufacturing systems that employ autonomous and highly interactive mobile robotic tools and used a multi-criteria decision-making method. Li and Huang (2021) developed a five-phase ‘Graduation intelligent Manufacturing System’ (GiMS) to enable resilience and flexibility in production intra-logistics and studied flexible assembly lines in an air-conditioner assembly workshop. Guo et al. (2021b) constructed a novel optimisation model combining flexible cellular manufacturing with digital twins to optimise air conditioner lines. Luo et al. (2022) studied automated flexible production lines in manufacturing enterprises and proposed a data-driven cloud simulation architecture. Kim and Lee (2021) stressed on flexible assembly system to minimise cycle time and for this, they analysed and proposed an efficient robot task sequence that involved assembly, 3D printers, material handling robots, post-processing, and inspection machines.

Proposition 1: *To provide an AI-enabled business model to enable flexibility in manufacturing systems to repurpose operations in the time of severe and unexpected disruptions.*

Proposition 2: *To identify general configurations of manufacturing systems and provide flexible solutions to produce high-demand products in parallel to other products.*

6.2. Robotic systems in manufacturing

The extent of automation and mechanisation in substituting humans for various functions partially reflects technological development (Jiang et al. 2014). Medina, Lorenz, and Hirche

(2015) asserted that in terms of minimising human efforts, human behaviour anticipation assistance has revealed exceptional performance, however, the prediction of human behaviour is a critical issue associated with prediction errors. So, a data-driven stochastic modelling approach was proposed where robot assistance is integrated to solve a complex optimal control problem (Medina, Lorenz, and Hirche 2015). In addition, to battling risks associated with the Covid-19 pandemic, humanoid robots, drones, autonomous vehicles, and other intelligent robots were used in various ways to diminish human contact and the spread of coronavirus (Zeng, Chen, and Lew 2020). Khan, Siddique, and Lee (2020) asserted the advancing role of robotics to limit the spread of the coronavirus in the healthcare sector and stressed the usage of medical robots in several medical procedures. Additionally, Malik, Masood, and Kousar (2021) presented an integrative model of collaborative robots to reconfigure ventilator production by exploring human-robot collaboration to increase the production of emergency products with modern production technologies.

Neythalath, Søndergaard, and Bærentzen (2021) asserted the cost-effective development of extremely diverse robotic control applications in a manufacturing concept and proposed a multi-layered knowledge encapsulation model. Currie et al. (2020) identified Covid-19 pandemic challenges and proposed the role of simulation modelling to create a decision support system in making informed decisions in the wake of the Covid-19 pandemic. To boost manufacturing efficiency Realyvásquez-Vargas et al. (2019) created a procedure to implement a human-robot collaboration system. Ji et al. (2021) focused on smart manufacturing and built an auto programming approach based on an automated robotic assembly to decrease cost and setup time for robots and minimal human assistance.

Proposition 3: *Future research must focus the human-robot integration in RM to ease operations and combat sudden disruptions.*

Proposition 4: *To develop a flexible robotics integrated manufacturing model to repurpose the manufacturing immediately during the disruption.*

6.3. Scheduling in flexible manufacturing

To solve problems related to scheduling over the years, various techniques were established (Baker and Trietsch 2013). The allocation of machines is determined by scheduling like performing jobs by machines (Paul, Sridharan, and Ramanan 2021). In the area of production scheduling, the most critical problems are flexible job-shop and flow-shop scheduling problems (Zan et al. 2020). In this regard, Zhang and Wong (2018) established enhanced ant colony optimisation metaheuristics in the job-shop environment to achieve integrated process planning and scheduling problem. Zhang et al. (2021) addressed a realistic state of a smart manufacturing system concerning complex multi-level product production scheduling using a hybrid multi-objective approach in the context of Industry 4.0. Yang and Xu (2021) proposed a novel ‘distributed assembly permutation

flow-shop scheduling problem with flexible assembly and batch delivery' (DAPFSP-FABD) which included seven algorithms to solve the planning problem of distributed manufacturing. Li and Xing (2021) studied deadlock-prone flexible assembly systems and their scheduling problem by proposing the heuristic beam search algorithm to reduce the make span. Zan et al. (2020) focused on multi-objective scheduling problems and offered a Pareto-based genetic algorithm solution in automated manufacturing systems.

Proposition 5: *To develop an AI-based model to solve multi-objective scheduling problems apart from flexible flow-shop and flexible job-shop, such as a deadlock-prone automated manufacturing system.*

Proposition 6: *To develop a multi-objective meta-heuristic model to overcome scheduling problems during an unpredictable disruption.*

6.4. Smart machine tools for manufacturing

The sudden disruptions or risks for instance Covid-19 pandemic have severely disturbed the manufacturing operations and supply chains (Tisdell 2020). Hence, manufacturers are pursuing effective solutions in the form of smart and reconfigurable machines to provide immediate solutions for demand upsurges or mitigating risks across the lifecycle of products (Morgan et al. 2021). Also, to adapt to the changing manufacturing environment like flexible production lines, personalised production, etc., industry 4.0 enabling technologies are required to incorporate into the current manufacturing environment (Jeon et al. 2020). Liu et al. (2017) with a focus on Agent-based design and Internet of Things (IoT), proposed an Intelligent Assembly System for Mechanical Products which is enabled by IoT technologies. Another study provided the solution for custom microsystem manufacturing to identify a dynamic transitional tool chain for 3D printed parts across the product life cycle and proposed a SMARTLAM reconfigurable manufacturing system (Scholz et al. 2016).

Chang, Lee, and Liu (2018) mentioned various AI techniques applications in their review article for smart machine tools, for instance, artificial neural networks, fuzzy modelling systems, cyber-physical systems based on industry 4.0, etc. Ghosh et al. (2021) asserted that digital twins can provide assistance to machine tools in the context of smart manufacturing by enabling autonomous troubleshooting and monitoring, and they proposed two computerised systems represented as Digital Twin Adaptation System (DTAS) and Digital Twin Construction System (DTCS) to adapt and construct the twin. Liu et al. (2020) emphasised bridging the gap between upper software applications and physical machine tools and provided a bi-directional data and control flows framework for this purpose, and an integrated model in smart factories was developed involving numerical control machine tool intelligent monitoring and data processing system.

Proposition 7: *To develop a mathematical model for solving the problems that arise from smart technologies because of the sudden increase in production during the pandemic.*

Proposition 8: *Future studies should develop a systematic literature review-based research to evaluate the application and effectiveness of several smart technologies included in manufacturing by providing real-time data during disruption.*

6.5. Process planning in manufacturing

Process planning concerns analysing the suitable assembly and manufacturing processes and the classification of the order in which the production is to be carried out, so it meets the specifications according to the product design documentation (Tarba et al. 2015). In process planning, the use of a computer automates the process of formulating a series of a product's manufacturing operations (Kumar 2017). AI techniques applications provide solutions for computer-aided process planning (CAPP) and manufacturing (Kumar 2017) and various algorithms have proven considerable advantages to solve complex process planning problems (Liu, Li, and Gao 2021b). In this regard, Jin and Zhang (2019) proposed a novel position-based mixed-integer linear programming (MILP) model for process planning concerning the reduction of total energy consumption and production time. Djurdjev et al. (2021) emphasised finding an optimal process plan for the operation sequencing problem and proposed a novel genetic crow search approach.

Rong, Ding, and Tang (2021) developed a data-driven operation and optimisation approach for adaptive high-order modification in CAPP for manufacturing hypoid gears and spiral bevels. Li, Chen, et al. (2021) asserted that the remanufacturing process planning affected the performance of remanufacturing and hence a hybrid method was developed with the integration of blockchain and case-based reasoning. Erden, Demir, and Canpolat (2021) solved problems related to scheduling, integrated process planning, and due date assignment and proposed a particle swarm optimisation approach. Chen (2021) stressed the need for a method that can enable complete automated process planning in the manufacturing process and explored an artificial neural network (ANN) based approach. Yuan et al. (2022) established a novel automated processing planning algorithm and incorporated an automated robot offline programming for multi-directional wire arc additive manufacturing.

Proposition 9: *To develop an AI algorithm for improving the efficiency and computational output of the manufacturing system during the pandemic.*

Proposition 10: *To provide a mathematical model enabling support in process planning and comparing other algorithms, optimisation models, and meta-heuristics.*

6.6. Systems operations flexibility

Operational flexibility is an ability to respond to uncertainty in a proactive or reactive notion and this ability has various dimensions which vary across environments based on its importance (Stevenson and Spring 2007). However, the detrimental impact of the Covid-19 pandemic brought severe consequences and many manufacturing industries are

fraught to manage and absorb its growing impact (Paul and Chowdhury 2020). Therefore, it is necessary to frame appropriate and effective operational policies to overcome losses in manufacturing and expand the consumption pattern to boost and recover the economy (Kumar et al. 2020). Operational flexibility is crucial for any manufacturing firm under such conditions of turbulence or disturbance. As, operations risks can be tackled by flexible process strategies through the adoption of a flexible manufacturing system (Gualandris and Kalchschmidt 2013).

Rajesh (2021) stressed upon flexibility and resilience of the manufacturing system during the Covid-19 pandemic and recognised five major flexible business strategies for accomplishing resilience. On the other hand, Schmidt et al. (2021) focused on vaccine manufacturing and supplying during the Covid-19 pandemic and proposed a digital twin model to optimise the operations of manufacturing and improve flexibility, robustness, and speed. Zhang et al. (2020) developed stochastic models to examine the operations of various types of flexible manufacturing cells and to optimise the performance indexes. Alolayyan and Ibrahim (2021) asserted system operational flexibility to recover from pressure and disruptions and proposed a mathematical model to examine the relationship between hospital performance and dimensions of operational flexibility.

Proposition 11: *To provide an AI-based model for operational flexibility of the manufacturing in the healthcare sector for producing PPE under immediate need or scarcity.*

Proposition 12: *To develop a mathematical model to achieve higher outcomes from the flexible operations of the manufacturing firms during disturbances or an outbreak of pandemics.*

6.7. Reconfigurable manufacturing

Due to global competition, high-frequency and unpredictable changes are faced by manufacturing companies. A new type of manufacturing system namely a reconfigurable manufacturing system (RMS) enables companies to stay competitive by adapting to rapid changes and achieving cost-effectiveness (ElMaraghy 2005). According to Koren et al. (1999), RMS is a system 'whose components are reconfigurable machines and reconfigurable controllers, as well as methodologies for their systematic design and rapid ramp-up, are the cornerstones of this new manufacturing paradigm'. RMS is an updated category of manufacturing systems that possess adjustable structures in both software and hardware structure. Its main objective is to improve the responsiveness of manufacturing systems to deal with unpredictable fluctuations in product demand (Koren, Gu, and Guo 2018).

A high automation RMS was exhibited by He et al. (2019), which had sequential stages classified into cells and each cell contained various machines and rail-positioned robots to explore line balancing algorithms aimed at obtaining optimal performance and minimising costs in a distributed production scheduling. Park et al. (2020) focused on a convergence architecture with a central robot for RMS and provided a

convergence framework that involved various technologies like Digital Twin (DT), cyber-physical production system (CPPS), and the P4R information model. On the other hand, Bortolini et al. (2021) asserted on dynamic management of RMS and proposed an optimisation linear programming model with the balanced incorporation of reconfigurable machine tools or intelligent machines.

Proposition 13: *To develop a model for RMS using an optimisation algorithm, heuristics, or meta-heuristics methods.*

Proposition 14: *To identify the challenges and barriers of using smart technologies and advanced algorithms in RMS.*

6.8. Intelligent technology in manufacturing

During the current emergency of the Covid-19 pandemic, medical experts and researchers worked very hard for searching new and effective technology to curb the impact of the Covid-19 pandemic (Khan et al. 2021). By enhancing resource efficiency and sustainability of the production processes, industry 4.0 can have an impact on the nature of manufacturing processes (Sony and Naik 2020). Recent studies provided evidence to show that AI is an effective and promising technology to get implemented in various sectors like healthcare, manufacturing, agriculture, etc. (Levin et al. 2020; Ishack and Lipner 2020). To combat risks associated with novel diseases like Covid-19, drug repurposing could be done by coupling it with AI technologies to detect the drugs and these technologies has the potential to reduce significant issues concerning drug repurposing (Khan et al. 2021). In this regard, Evans, Haven-Tang, and Jayal (2021) used machine learning and artificial intelligence to assess the standards for hand hygiene in hospitality, food manufacturing, and catering environment.

Peng et al. (2021) proposed the internet-enables resilient manufacturing for industries from a Covid-19 perspective. Improvement in the manufacturing of semiconductors in IoT by using intelligent technology was reported by Li, Chen, et al. (2021). They used statistical process control and a real-time feedback algorithm to optimise the manufacturing parameters. Pang et al. (2021) developed a new intelligent product quality control system by using BP neural network in the CPS valve manufacturing process. They concluded that the new system has good accuracy and practicability in controlling manufacturing processes. Vlachos (2021) applied socio-technical system theory to examine the adoption of a supply chain control tower (SCCT) in an effort to build an intelligent supply chain by a big manufacturing company. Fan and Zhang (2022) used cloud edge computing and deep neural network-based multi-fusion system in intelligent manufacturing. It was concluded that the used system can increase the work efficiency of up to 20% of different systems in the industry.

Proposition 15: *To develop a manufacturing framework using intelligent technologies to produce high-demand items to tackle sudden changes in demand.*

Proposition 16: *To develop a drug repurposing model using intelligent technologies and advanced algorithms for recovering vaccine/drug shortage.*

6.9. Flexible manufacturing systems

A flexible manufacturing system is defined as 'a system that combines with the existing technology of numerical control manufacturing, automated material handling, and computer hardware and software to create an integrated system for the automatic random processing of palletised parts across various workstations in the system' (Collins 1980). During the current situation of the Covid-19 pandemic, a flexible manufacturing system enabled many firms to rapidly transform their production processes and manufacture some urgently required tools like ventilators, hand sanitisers, medical gloves, etc. (Brem, Viardot, and Nylund 2021). The techniques of flexible manufacturing enable manufacturing facilities to shift more rapidly between scaling up production and products or relocating manufacturing capacity (Sell et al. 2021). Qi et al. (2021) stressed the scarcity of essential emergency supplies during the Covid-19 pandemic and gave importance to rapid response manufacturing by utilising AI, big data, IoT, etc.

According to Zimmerling and Chen (2021), the capability of advanced and flexible production technologies to offer enhanced adaptability of production capacity which is less vulnerable to disruptions like the Covid-19 pandemic proved that these technologies would transform the manufacturing operations. Javaid et al. (2020) discussed ten major industry 4.0 technologies and the firm's flexible technological capability to shift production rapidly for manufacturing specialised healthcare products to fight global medical emergencies. Ishack and Lipner (2020) addressed the problem of scarcity of ventilator valves, face shields, respirator masks, and PPE during the Covid-19 pandemic, and proposed a three-dimensional (3D) printing technology a robotic platform to shift production to critical products.

Proposition 17: *To develop a resilient and flexible manufacturing model using AI-based technologies like 3D printing, robotics, optimisation algorithms, etc to combat risks of the unpredictable outbreaks of viruses.*

Proposition 18: *To analyse and evaluate existing technologies by real-time applicability to manufacturing operations during uncertain situations.*

6.10. Manufacturing support systems

The advancements in technology have created opportunities for web technology and proposed approaches to establish a web-based support system for designing and manufacturing (Cheng et al., 2001). However, the development of a decision-support tool is essential for demand management in the healthcare sector during the pandemic (Govindan et al., 2020). Also, a manufacturing support system enabled by intelligent and advanced technology is required to tackle the rising demands for medical products like masks, gloves, face shields, sanitisers, etc. Deb and

Bhattacharyya (2005) developed a distinct decision support system based on a multifactor fuzzy inference system for manufacturing facilities. Stavropoulos et al. (2021) proposed a decision-support system framework for the manufacturing process of electric vehicles and applied a two-stage decision-support system. Paul and Chowdhury (2020) developed a production recovery model by using a mathematical modelling approach to recover the manufacturing system from essential items' demand during the Covid-19 pandemic.

Proposition 19: *To develop an AI-based mathematical model using various modelling and optimisation approaches to tackle the demand and supply during the pandemic.*

Proposition 20: *There is a dearth of literature in this area of manufacturing, therefore more support models can contribute to this field.*

6.11. Optimisation algorithm in manufacturing

The Covid-19 pandemic created an entire shutdown of manufacturing activities (Goodarzian et al. 2021), and many other processes were widely affected. However, it could be a driving force for the implementation of innovative technology throughout society with the long-term potential of many innovations (Zimmerling and Chen 2021). Many manufacturing firms shifted their focus to producing critical goods during the pandemic and used their resources in an effective way. In this regard, optimisation algorithms can play the role of a support tool for manufacturers to make effective decisions in increasing production efficiency. Therefore, to solve production and distribution problems during Covid-19, Goodarzian et al. (2021) proposed three hybrid meta-heuristic algorithms. Furthermore, Cao et al. (2021) conducted Laser powder bed fusion (LPBF) experiments and proposed a machine learning framework to generate optimal process parameters to obtain dimensional accuracy and surface roughness after optimisation.

Feng et al. (2021) proposed a hybrid approach of particle swarm optimisation (PSO) and genetic algorithm (GA) to save printing time and wastage of materials and it is very helpful for manufacturers and designers. On the other hand, Tian, Ma, and Meng (2021) believed that classical PSO cannot assure to attain optimal solutions and they proposed the CMOPSO approach ('combined multi-objective particle swarm optimisation') to offer solutions for emissions and energy consumption concerning green manufacturing. For manufacturing workshops, Zhou et al. (2021) proposed a three-staged resource allocation optimisation method to enable rapid resource distribution decision-making. Aqil and Allali (2021) assessed a manufacturing optimisation problem namely the hybrid flow shop scheduling problem and proposed six algorithms based on the water wave optimisation algorithms and the migratory bird optimisation.

Proposition 21: *To solve RM and scheduling problems using optimisation algorithms during the pandemic and other disasters.*

Proposition 22: *To develop an RM model using artificial neural network (ANN), meta-heuristics methods, and other AI-based techniques for emergency production of critical items during the pandemic.*

6.12. Data-Driven manufacturing model

Manufacturing firms try to achieve the considerable potential to enhance their efficiency and productivity by implementing data-driven manufacturing (Gökalp et al. 2021). In recent years, the competencies of empirical methods have significantly extended because of the advancements in the field of machine learning and computational intelligence which are incorporated into the data-driven modelling field (Solomatine, See, and Abrahart 2009). Data-driven models develop the relationship in the system by employing an algorithm for manufacturing data such as ANN, linear regression, etc. (Kim 2017). Data-driven models are required to examine the manufacturing data which faced an unprecedented rise in terms of its generated volume because of the adoption of smart factories, cyber-physical systems, internet of things (IoT) in an industry (Sadati, Chinnam, and Nezhad 2018). According to Konchak et al. (2021), for the operational recovery from the Covid-19 crisis, a transparent and coordinated data-driven approach is essential which is based on a robust workshop testing capability.

Majeed et al. (2021) proposed a big data-driven framework for smart and sustainable additive manufacturing that can control energy consumption and product quality. Suvarna et al. (2021) asserted smart manufacturing and proposed the employment of data-driven modelling in cyber-physical production systems to transform manufacturing by making it more automated and intuitive. Wang et al. (2023) asserted sensor technologies and information technologies in data-augmented production systems and proposed a data-driven method integrated with an optimisation method to evaluate the impact of disruptions. Guo et al. (2021a) developed an industrial internet of things and digital twin-enabled graduation intelligent manufacturing system to support the reconfiguration of manufacturing during the Covid-19 pandemic.

Proposition 23: *A data-driven manufacturing model should be developed using fuzzy logic, a Bayesian network, and big data-enabled technology to consider the impacts of the pandemic.*

Proposition 24: *To provide and compare various data-analytical approaches for RM under ambiguity.*

7. Discussion and proposed research model

In the wake of the coronavirus (Covid-19) pandemic, the demand and usage of PPE have risen sharply e.g. face masks and medical gloves, etc. (Patrício Silva et al. 2020). The covid-19 situation along with social distancing, lockdowns, and quarantine measures across the globe had restricted the normal operations of the firms. In this regard, many firms used existing capacity by rapidly repurposing technologies

to meet the demand, and firms of different sectors repurposed their manufacturing and design to produce critical products immediately (Liu, Beltagui, and Ye 2021a). Similarly, it was argued that open innovation and repurposing manufacturing is the key at the time of disruption (Chesbrough 2020). According to López-Gómez et al. (2020), repurposing manufacturing is a rapid response solution by using existing manufacturing capacity to deal with the scarcity of critical items during the Covid-19 pandemic. However, the RM can be cost-intensive and could bring severe challenges in operations because of limited findings so far. Therefore, this study is conducted to provide a significant contribution to the field of AI in RM. The main aim of this study is to analyse the role of AI-based applications in solving the issues concerning RM under disruptions. Furthermore, bibliometric analysis was conducted to identify the growth in research in the selected study. The findings suggest that there is a surge in published articles in this field since 2015, however, the global output of research in this field still needs to be developed and provide more scope to fill this research gap. As far as, type or published papers are concerned, only approximately 3.5% are review papers and the rest are articles, hence, future researchers can work in this area to provide significant contributions through review papers. The keyword analysis provides researchers with an overview of relevant keywords associated with RM and can help to develop future studies. Also, network analysis shows major authors and countries and their collaboration stages globally. This provides an understanding of the collaboration scope between the authors and countries as well.

Moreover, the current study provided 12 generated thematic topics using STM such as Flexible assembly in manufacturing, Robotic systems in manufacturing, Scheduling in flexible manufacturing, Smart machine tools for manufacturing, Process planning in manufacturing, Systems operations flexibility, Reconfigurable manufacturing, Intelligent technology in manufacturing, Flexible manufacturing system, Manufacturing support system, Optimisation algorithm in manufacturing, Data-Driven manufacturing model. These thematic topics are discussed in section 6 and relevant studies were cited to prove a significant contribution of the role of advanced technology like big-data analytics, genetic algorithm, optimisation algorithm, particle swarm optimisation, etc. in enabling solutions for RM. Scaling up production and repurposing existing manufacturing to address the urgent shortage of critical supplies is essential during the Covid-19 pandemic or other life-risking disruptions (López-Gómez et al. 2020).

To manage Covid-19 related disruptions and surge in demand, many firms took the initiative of repurposing to meet the high demand for critical medical products and partly because of government pressure on manufacturing firms to tackle this shortfall (Mamo 2020; López-Gómez et al. 2020). Several technologies were employed to overcome the risks associated with Covid-19 such as 3D printing (Ishack and Lipner 2020), optimisation algorithms (Goodarzi et al. 2021), robotics (Khan, Siddique, and Lee 2020), intelligent manufacturing systems (Guo et al. 2021a). However, it is asserted that regarding the common innovation objective,

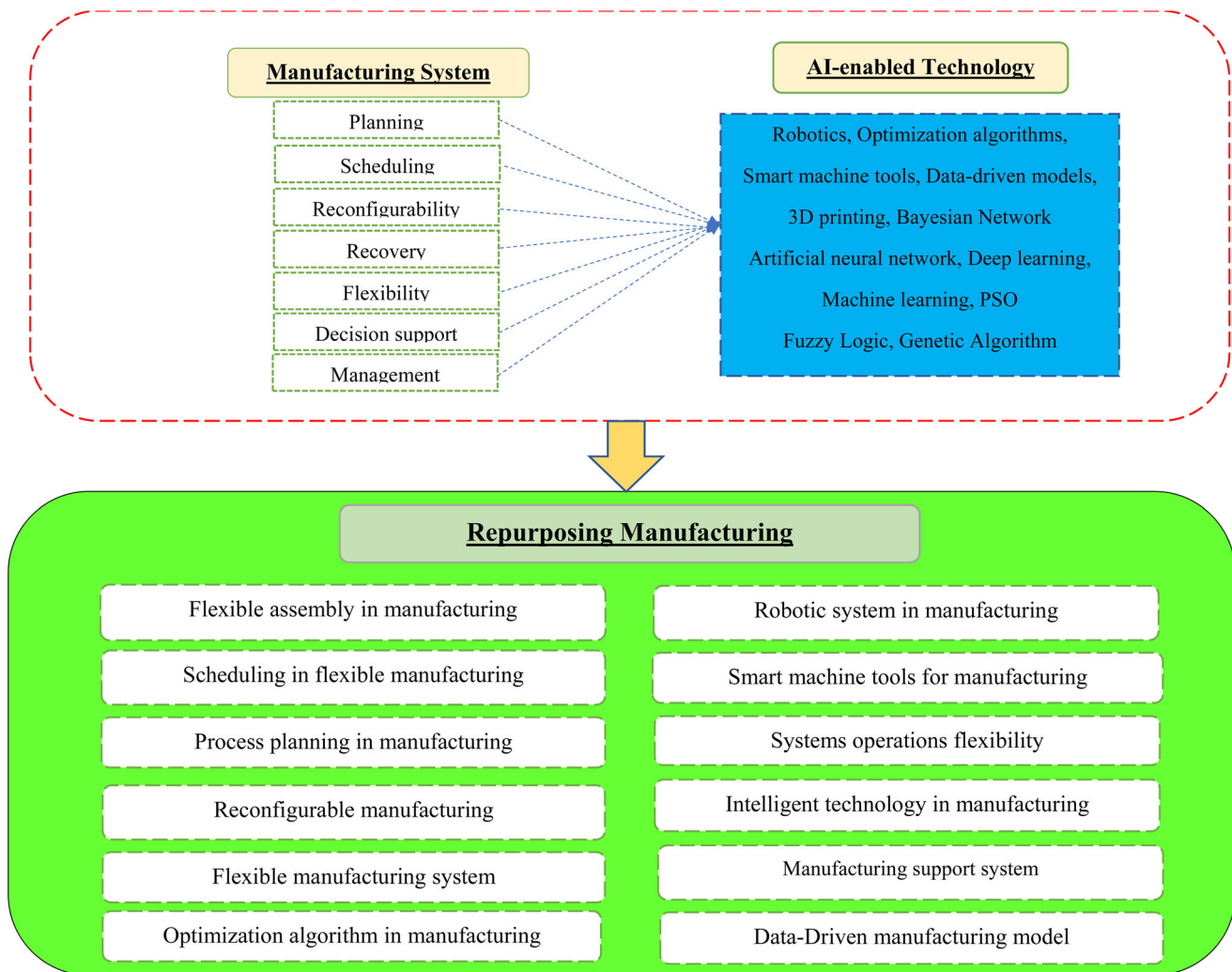


Figure 9. A proposed research framework for AI in RM.

companies must accelerate the process of innovation by working together and by repurposing existing technology instead of developing a new one (Liu, Beltagui, and Ye 2021a). In addition, under technological turbulence and disruptions in market conditions, manufacturing flexibility and design capability is crucial for innovation (Auernhammer 2020). In the present Industry 4.0 context, according to the findings of the study conducted by Pandey, Singh, and Gunasekaran (2021), supply chain managers should concentrate on disruption risk, cyber security risk, and safety risk. Since supply chain risk management is a developing subject of study in the context of Industry 4.0.

This section provided an answer to the 1st and 4th research question of the study i.e. the different techniques of AI and an AI-based model used in repurposing manufacturing which can help manufacturers to recover from the post-Covid-19 pandemic. The research framework (Figure 9) proposed in this study consists of 12 emerging research themes for RM and the incorporation of innovative technologies to combat risks associated with pandemics and severe disruptions. An attempt to group all generated emerging research themes along with manufacturing processes and advanced technologies based on the existing evidence of literature eventually led to proposing a comprehensive

conceptual framework. The comprehensive research framework disseminates the pros of AI-based emerging technologies in executing RM during the Covid-19 pandemic. Improving industrial technology competence is critical to overcoming the pandemic's disruptions. Companies should employ digitalisation, data analytics, information technology, and other tools to monitor production processes and manage related risks for this goal. Several technologies, such as AI, 3-D printing, Big data analytics, cloud computing, and the Internet of Things (IoT) are advocated in this respect by numerous studies addressed in section 6. The processes mentioned in the manufacturing system box in Figure 9 are adapted from Mehrabi, Ulsoy, and Koren (2000) and Meziare et al. (2000). Based on a thorough review of the literature on AI technologies and the generated thematic topics of this study using an STM approach, the research framework was proposed in Figure 9. This conceptual framework will serve as a roadmap for researchers, guiding them in developing their research plan. It will provide a clear structure for organising ideas and concepts related to the research topic. This structure enables them to think systematically and develop a coherent research plan which will enhance the rigour, relevance, and significance of the research, contributing to the advancement of knowledge in the current area of study. The

framework allows researchers to build upon each other's work, compare findings, and engage in meaningful discussions to advance knowledge in the field. This process helps researchers identify gaps or inconsistencies in current knowledge and research. It helps them identify the central research question and objectives, ensuring that the study remains focused and relevant.

Future studies may carry out a meta-analysis that solely focuses on the connections between the notions described in order to further support the framework. As a result, this thorough conceptual framework enables academics and practitioners to aggregate the linkages and make sense of them so that they may act on them in the context of an area or sector.

8. Implications

The current study aimed to provide a systematic literature review in the research field of AI in RM. The bibliometric study was performed to investigate the research developments and evaluate the existing studies in the selected field of study. The STM approach was employed to generate the emerging research themes associated with AI in RM and these themes were analysed and discussed thoroughly. The propositions for future studies were provided under each theme. This research was performed to fill the major research gap as there is a lack of SLR articles in the field of AI in RM. It provides the application of bibliometric techniques, structural topic modelling, and network analysis to integrate and discuss the most influential studies in the selected field of study.

As discussed above that there is a dearth of literature which provides a systematic review of literature in the field of AI in RM. Therefore, this study will provide evidence for future researchers to conduct empirical studies, case studies, and literature surveys in this field of research. The results of the present study provide possible directions for future research while other investigations discussed above provide further evidence. Knowing the increase of AI-related publications in RM in the Scopus database would be useful. This study may have given future researchers the opportunity to compare data from various academic databases without consideration to Scopus only and to gather more samples. The position of AI in the field of RM research as well as the breadth and productivity of academic databases research engines will be shown by comparing the findings from various academic databases. Future researchers will gain insight from this research and can develop their studies based on the propositions offered in this study. Also, the generated thematic topics in the area of AI in RM will help researchers to identify areas for their focused research.

The research findings of this study will provide significant help for managers to evaluate the application of recent intelligent technologies in repurposing their manufacturing operations. The review of the literature will provide practical applications, challenges, and benefits of AI-based applications and algorithms in recovering or repurposing the manufacturing system during the time of the pandemic. The study also provides practical applications of AI in other sub-areas of RM, see [section 6](#). This study will provide multiple optimal

solutions and opportunities for manufacturing firms and practitioners to achieve competitiveness and repurpose their manufacturing by employing recent technologies during an outbreak of a pandemic or other unexpected disruptions. In dealing with the challenges, various opportunities including flexible manufacturing, application of digital technologies, repurposing, scheduling, and reconfiguring have been identified. The manufacturing industry will ultimately bounce back as a reinforcing pillar of global economies, as this study suggests if it is provided with the correct instruments and initiatives. Future research should not be limited to examining the present Covid-19 difficulties; instead, it should focus on resilient manufacturing, which is capable of absorbing and minimising the impact of any large-scale disturbances.

9. Conclusion

In the year 2020, the outbreak of the novel coronavirus (Covid-19) disturbed the operations of the entire manufacturing system across the globe. The shortage of high-demand items such as face masks, hand sanitisers, toilet paper, and other PPE has put pressure on manufacturing firms to repurpose their operations to meet this surge in demand. In this regard, firms and companies are encountering social, governmental, and competitive pressures to incorporate a repurposing approach and collaborate with other firms to produce such items and overcome this disruption. For this purpose, AI-based intelligent technology has provided multiple optimal solutions to create resilient and repurposing manufacturing. These technologies enable firms to solve issues related to scheduling, flexibility, process planning, optimising production, reconfigurability, etc. The current study contributed to the field of research by providing a systematic literature review and by filling the major research gap in the field of AI in RM. The study focused on the review and thorough evaluation of the studies conducted in the selected field of study between the period 2013–2023. To produce a SLR in the chosen subject of research, bibliometric analysis and STM were used. The STM generated 12 emerging research themes which were reviewed and discussed in detail. This study will provide a better and deep insight into the field of repurposing existing manufacturing systems during the pandemic and the integration of AI in RM.

This study also has some limitations, such as other aspects of the production system that can be included in future research to generate review articles. Also, this study is confined to journal articles, so future studies might include other papers to broaden the scope of the articles. In the review article based on AI in RM during a virus epidemic, it is also advised to look at the obstacles and barriers. This study only focused on the published papers under SCOPUS database, therefore, future studies can generate articles from other databases as well like WOS, DOAJ, Science direct, etc. Apart from this, publication years can be expanded as well.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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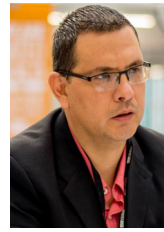
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References

Agrawal, R., V. A. Wankhede, A. Kumar, A. Upadhyay, and J. A. Garza-Reyes. 2022. "Nexus of Circular Economy and Sustainable Business Performance in the Era of Digitalization." *International Journal of*

- Productivity and Performance Management* 71 (3): 748–774. <https://doi.org/10.1108/IJPPM-12-2020-0676>
- Alolayyan, M. N., and A. S. Ibrahim. 2021. "Proposed Mathematical Model to Study and Analyze the Relationship between Operational Flexibility Dimensions and Hospital Performance." *Global Journal of Flexible Systems Management* 22 (4): 289–305. doi:10.1007/s40171-021-00275-9
- Aqil, S., and K. Allali. 2021. "Two Efficient Nature Inspired Meta-Heuristics Solving Blocking Hybrid Flow Shop Manufacturing Problem." *Engineering Applications of Artificial Intelligence* 100: 104196. doi:10.1016/j.engappai.2021.104196
- Arinez, J. F., Q. Chang, R. X. Gao, C. Xu, and J. Zhang. 2020. "Artificial Intelligence in Advanced Manufacturing: Current Status and Future Outlook." *Journal of Manufacturing Science and Engineering* 142 (11): 110804. doi:10.1115/1.4047855
- Asmussen, C. B., and C. Møller. 2019. "Smart Literature Review: A Practical Topic Modelling Approach to Exploratory Literature Review." *Journal of Big Data* 6 (1): 1–18. <https://doi.org/10.1186/s40537-019-0255-7>
- Auernhammer, J. 2020. "Design Research in Innovation Management: A Pragmatic and Human-Centered Approach." *R&D Management* 50 (3): 412–428. doi:10.1111/radm.12409
- Baker, K. R., and D. Trietsch. 2013. *Principles of Sequencing and Scheduling*. Hoboken, New Jersey: John Wiley & Sons.
- Beach, R., A. P. Muhlemann, D. H. Price, A. Paterson, and J. A. Sharp. 2000. "A Review of Manufacturing Flexibility." *European Journal of Operational Research* 122 (1): 41–57. doi:10.1016/S0377-2217(99)00062-4
- Behl, A., J. Gaur, V. Pereira, R. Yadav, and B. Laker. 2022. "Role of Big Data Analytics Capabilities to Improve Sustainable Competitive Advantage of MSME Service Firms during COVID-19—a Multi-Theoretical Approach." *Journal of Business Research* 148: 378–389. doi:10.1016/j.jbusres.2022.05.009
- Bischof, J., and E. M. Airoldi. 2012. "Summarizing Topical Content with Word Frequency and Exclusivity." In *Proceedings of the 29th International Conference on Machine Learning (ICML-12)* (pp. 201–208). Edinburgh, Scotland, UK.
- Blei, D. M. 2012. "Probabilistic Topic Models." *Communications of the ACM* 55 (4): 77–84. <https://doi.org/10.1145/2133806.2133826>
- Bortolini, M., E. Ferrari, F. G. Galizia, and A. Regattieri. 2021. "An Optimisation Model for the Dynamic Management of Cellular Reconfigurable Manufacturing Systems under Auxiliary Module Availability Constraints." *Journal of Manufacturing Systems* 58: 442–451. doi:10.1016/j.jmsy.2021.01.001
- Brem, A., E. Viardot, and P. A. Nylund. 2021. "Implications of the Coronavirus (COVID-19) Outbreak for Innovation: Which Technologies Will Improve Our Lives?" *Technological Forecasting and Social Change* 163: 120451. doi:10.1016/j.techfore.2020.120451
- Cai, M., and J. Luo. 2020. "Influence of COVID-19 on Manufacturing Industry and Corresponding Countermeasures from Supply Chain Perspective." *Journal of Shanghai Jiaotong University (Science)* 25 (4): 409–416. doi:10.1007/s12204-020-2206-z
- Cao, L., J. Li, J. Hu, H. Liu, Y. Wu, and Q. Zhou. 2021. "Optimization of Surface Roughness and Dimensional Accuracy in LPBF Additive Manufacturing." *Optics & Laser Technology* 142: 107246. doi:10.1016/j.optlastec.2021.107246
- Chang, C. W., H. W. Lee, and C. H. Liu. 2018. "A Review of Artificial Intelligence Algorithms Used for Smart Machine Tools." *Inventions* 3 (3): 41. doi:10.3390/inventions3030041
- Chen, N. 2021. "An Evolutionary Neural Network Approach to Machining Process Planning: A Proof of Concept." *Procedia Manufacturing* 53: 690–696. doi:10.1016/j.promfg.2021.06.083
- Cheng, K., P. Y. Pan, and D. K. Harrison. 2001. "Web-Based Design and Manufacturing Support Systems: implementation Perspectives." *International Journal of Computer Integrated Manufacturing* 14 (1): 14–27. <https://doi.org/10.1080/09511920150214875>
- Chesbrough, H. 2020. "To Recover Faster from Covid-19, Open up: Managerial Implications from an Open Innovation Perspective." *Industrial Marketing Management* 88: 410–413. doi:10.1016/j.indmar-man.2020.04.010
- Chiari, A., V. Belvedere, and A. Grando. 2020. "Industry 4.0 Strategies and Technological Developments. An Exploratory Research from Italian Manufacturing Companies." *Production Planning & Control* 31 (16): 1385–1398. doi:10.1080/09537287.2019.1710304
- Chien, C. F., S. Dauzère-Pères, W. T. Huh, Y. J. Jang, and J. R. Morrison. 2020. "Artificial Intelligence in Manufacturing and Logistics Systems: algorithms, Applications, and Case Studies." *International Journal of Production Research* 58 (9): 2730–2731. doi:10.1080/00207543.2020.1752488
- Chiesi, A. M. 2015. "Network Analysis, General." in *International Encyclopedia of the Social and Behavioral Sciences*, 2nd ed., 518–523. Oxford: Elsevier.
- Cho, H., M. Jung, and M. Kim. 1996. "Enabling Technologies of Agile Manufacturing and Its Related Activities in Korea." *Computers & Industrial Engineering* 30 (3): 323–334. doi:10.1016/0360-8352(96)00001-0
- Churrua, K., C. Pomare, L. A. Ellis, J. C. Long, and J. Braithwaite. 2019. "The Influence of Complexity: A Bibliometric Analysis of Complexity Science in Healthcare." *BMJ Open* 9 (3): e027308. doi:10.1136/bmjopen-2018-027308
- Collins, J. A. 1980. "Numerical Control and Flexible Manufacturing Systems. Factory Automation: Limited Papers." *INFORTECH* 8 (6): 125–147.
- Currie, C. S., J. W. Fowler, K. Kotiadis, T. Monks, B. S. Onggo, D. A. Robertson, and A. A. Tako. 2020. "How Simulation Modelling Can Help Reduce the Impact of COVID-19." *Journal of Simulation* 14 (2): 83–97. doi:10.1080/17477778.2020.1751570
- Das, S., K. Dixon, X. Sun, A. Dutta, and M. Zupancich. 2017. "Trends in Transportation Research: Exploring Content Analysis in Topics." *Transportation Research Record: Journal of the Transportation Research Board* 2614 (1): 27–38. <https://doi.org/10.3141/2614-04>
- De Bellis, N. 2009. *Bibliometrics and Citation Analysis: From the Science Citation Index to Cybermetrics*. Scarecrow press, USA.
- Deb, S. K., and B. Bhattacharyya. 2005. "Fuzzy Decision Support System for Manufacturing Facilities Layout Planning." *Decision Support Systems* 40 (2): 305–314. <https://doi.org/10.1016/j.dss.2003.12.007>
- Ding, B., X. Ferras Hernandez, and N. Agell Jane. 2023. "Combining Lean and Agile Manufacturing Competitive Advantages through Industry 4.0 Technologies: An Integrative Approach." *Production Planning & Control* 34 (5): 442–458. doi:10.1080/09537287.2021.1934587
- Djurdjevic, M., R. Cep, D. Lukic, A. Antic, B. Popovic, and M. Milosevic. 2021. "A Genetic Crow Search Algorithm for Optimization of Operation Sequencing in Process Planning." *Applied Sciences* 11 (5): 1981. doi:10.3390/app11051981
- Ekanayake, E. M. A. C., G. Q. Shen, and M. M. Kumaraswamy. 2023. "A Fuzzy Synthetic Evaluation of Capabilities for Improving Supply Chain Resilience of Industrialised Construction: A Hong Kong Case Study." *Production Planning & Control* 34 (7): 623–640. doi:10.1080/09537287.2021.1946330
- Ellegaard, O., and J. A. Wallin. 2015. "The Bibliometric Analysis of Scholarly Production: How Great is the Impact?" *Scientometrics* 105 (3): 1809–1831. doi:10.1007/s11192-015-1645-z
- ElMaraghy, H. A. 2005. "Flexible and Reconfigurable Manufacturing Systems Paradigms." *International Journal of Flexible Manufacturing Systems* 17 (4): 261–276. doi:10.1007/s10696-006-9028-7
- Erden, C., H. I. Demir, and O. Canpolat. 2021. "A Modified Integer and Categorical PSO Algorithm for Solving Integrated Process Planning, Dynamic Scheduling and Due Date Assignment Problem." *Scientia Iranica* 0 (0): 0–0. doi:10.24200/sci.2021.55250.4130
- Evans, E., C. Haven-Tang, and A. Jayal. 2021. Exploring food manufacturing, hospitality and catering industry perceptions of the application of intelligent technology to determine handwashing compliance. AML conference proceeding.
- Fan, L., and L. Zhang. 2022. "Multi-System Fusion Based on Deep Neural Network and Cloud Edge Computing and Its Application in Intelligent Manufacturing." *Neural Computing and Applications* 34 (5): 3411–3420. doi:10.1007/s00521-021-05735-y
- Fatorachian, H., and H. Kazemi. 2021. "Impact of Industry 4.0 on Supply Chain Performance." *Production Planning & Control* 32 (1): 63–81. doi:10.1080/09537287.2020.1712487

- FDA. 2020. *Coronavirus (COVID-19) supply chain update*. <https://www.fda.gov/news-events/press-announcements/coronavirus-covid-19-supply-chain-update>
- Feng, R., J. Jiang, Z. Sun, A. Thakur, and X. Wei. 2021. "A Hybrid of Genetic Algorithm and Particle Swarm Optimization for Reducing Material Waste in Extrusion-Based Additive Manufacturing." *Rapid Prototyping Journal* 27 (10): 1872–1885. doi:10.1108/RPJ-11-2020-0292
- Fink, A. 2005. *Conducting Research Literature Reviews: From the Internet to Paper*. 5th ed., 1–267. Los Angeles, USA: Sage Publications.
- Ghosh, A. K., A. S. Ullah, R. Teti, and A. Kubo. 2021. "Developing Sensor Signal-Based Digital Twins for Intelligent Machine Tools." *Journal of Industrial Information Integration* 24: 100242. doi:10.1016/j.jii.2021.100242
- Gökalp, M. O., E. Gökalp, K. Kayabay, A. Koçyiğit, and P. E. Eren. 2021. "Data-Driven Manufacturing: An Assessment Model for Data Science Maturity." *Journal of Manufacturing Systems* 60: 527–546. doi:10.1016/j.jmsy.2021.07.011
- Goodarzi, F., A. A. Taleizadeh, P. Ghasemi, and A. Abraham. 2021. "An Integrated Sustainable Medical Supply Chain Network during COVID-19." *Engineering Applications of Artificial Intelligence* 100: 104188. doi:10.1016/j.engappai.2021.104188
- Govindan, K., H. Mina, and B. Alavi. 2020. "A Decision Support System for Demand Management in Healthcare Supply Chains considering the Epidemic Outbreaks: A Case Study of Coronavirus Disease 2019 (COVID-19)." *Transportation Research. Part E, Logistics and Transportation Review* 138: 101967. <https://doi.org/10.1016/j.tre.2020.101967>
- Grant, E. B., and M. J. Gregory. 1997. "Adapting Manufacturing Processes for International Transfer." *International Journal of Operations & Production Management* 17 (10): 994–1005. doi:10.1108/01443579710176997
- Gualandris, J., and M. Kalchschmidt. 2013. "Product and Process Modularity: improving Flexibility and Reducing Supplier Failure Risk." *International Journal of Production Research* 51 (19): 5757–5770. doi:10.1080/00207543.2013.793430
- Guo, D., M. Li, S. Ling, R. Y. Zhong, Y. Rong, and G. Q. Huang. 2021a. "Synchronization-Oriented Reconfiguration of FPAI under Graduation Intelligent Manufacturing System in the COVID-19 Pandemic and beyond." *Journal of Manufacturing Systems* 60: 893–902. doi:10.1016/j.jmsy.2021.05.017
- Guo, H., M. Chen, K. Mohamed, T. Qu, S. Wang, and J. Li. 2021b. "A Digital Twin-Based Flexible Cellular Manufacturing for Optimization of Air Conditioner Line." *Journal of Manufacturing Systems* 58: 65–78. doi:10.1016/j.jmsy.2020.07.012
- He, C., Z. Guan, Y. Gong, C. Wang, and L. Yue. 2019. "Automated Flexible Transfer Line Design Problem: Sequential and Reconfigurable Stages with Parallel Machining Cells." *Journal of Manufacturing Systems* 52: 157–171. doi:10.1016/j.jmsy.2019.05.005
- Hermann, M., T. Pentek, and B. Otto. 2016. "Design Principles for Industrie 4.0 Scenarios." In *2016 49th Hawaii International Conference on System Sciences (HICSS)* (pp. 3928–3937). IEEE, Koloa, HI, USA. doi:10.1109/HICSS.2016.488
- Hevey, D. 2018. "Network Analysis: A Brief Overview and Tutorial." *Health Psychology and Behavioral Medicine* 6 (1): 301–328. doi:10.1080/21642850.2018.1521283
- Ho, D. 2020. "Addressing COVID-19 Drug Development with Artificial Intelligence." *Advanced Intelligent Systems (Weinheim an Der Bergstrasse, Germany)* 2 (5): 2000070. doi:10.1002/aisy.202000070
- Ishack, S., and S. R. Lipner. 2020. "Applications of 3D Printing Technology to Address COVID-19-Related Supply Shortages." *The American Journal of Medicine* 133 (7): 771–773. doi:10.1016/j.amjmed.2020.04.002
- Ivanov, D., and A. Dolgui. 2021. "A Digital Supply Chain Twin for Managing the Disruption Risks and Resilience in the Era of Industry 4.0." *Production Planning & Control* 32 (9): 775–788. doi:10.1080/09537287.2020.1768450
- Ivanov, D., C. S. Tang, A. Dolgui, D. Battini, and A. Das. 2021. "Researchers' Perspectives on Industry 4.0: multi-Disciplinary Analysis and Opportunities for Operations Management." *International Journal of Production Research* 59 (7): 2055–2078. doi:10.1080/00207543.2020.1798035
- Jackson, K., K. Efthymiou, and J. Borton. 2016. "Digital Manufacturing and Flexible Assembly Technologies for Reconfigurable Aerospace Production Systems." *Procedia CIRP* 52: 274–279. doi:10.1016/j.procir.2016.07.054
- Jacobi, C., W. van Atteveldt, and K. Welbers. 2016. "Quantitative Analysis of Large Amounts of Journalistic Texts Using Topic Modelling." *Digital Journalism* 4 (1): 89–106. <https://doi.org/10.1080/21670811.2015.1093271>
- Jain, S., B. Yadav Lamba, S. Kumar, and D. Singh. 2022. "Strategy for Repurposing of Disposed PPE Kits by Production of Biofuel: Pressing Priority Amidst COVID-19 Pandemic." *Biofuels* 13 (5): 545–549. doi:10.1080/17597269.2020.1797350
- Javaid, M., A. Haleem, R. Vaishya, S. Bahl, R. Suman, and A. Vaish. 2020. "Industry 4.0 Technologies and Their Applications in Fighting COVID-19 Pandemic." *Diabetes & Metabolic Syndrome* 14 (4): 419–422. doi:10.1016/j.dsx.2020.04.032
- Jeon, B., J. S. Yoon, J. Um, and S. H. Suh. 2020. "The Architecture Development of Industry 4.0 Compliant Smart Machine Tool System (SMTS)." *Journal of Intelligent Manufacturing* 31 (8): 1837–1859. doi:10.1007/s10845-020-01539-4
- Ji, Sanghoon, Sukhan Lee, Sujeong Yoo, Ilhong Suh, Inso Kwon, Frank C. Park, Sanghyoung Lee, and Hongseok Kim. 2021. "Learning-Based Automation of Robotic Assembly for Smart Manufacturing." *Proceedings of the IEEE* 109 (4): 423–440. doi:10.1109/JPROC.2021.3063154
- Jiang, H., S. Zhao, K. Yin, Y. Yuan, and Z. Bi. 2014. "An Analogical Induction Approach to Technology Standardization and Technology Development." *Systems Research and Behavioral Science* 31 (3): 366–382. doi:10.1002/sres.2272
- Jin, L., and C. Zhang. 2019. "Process Planning Optimization with Energy Consumption Reduction from a Novel Perspective: Mathematical Modeling and a Dynamic Programming-like Heuristic Algorithm." *IEEE Access*. 7: 7381–7396. doi:10.1109/ACCESS.2018.2889882
- Kekäle, T., P. de Weerd-Nederhof, S. Cervai, and M. Borelli. 2009. "The 'Dos and Don'ts' of Writing a Journal Article." *Journal of Workplace Learning* 21 (1): 71–80. doi:10.1108/13665620910924925
- Khan, Muzammil, Muhammad Taqi Mehran, Zeeshan Ul Haq, Zahid Ullah, Salman Raza Naqvi, Mehreen Ihsan, and Haider Abbass. 2021. "Applications of Artificial Intelligence in COVID-19 Pandemic: A Comprehensive Review." *Expert Systems with Applications* 185: 115695. doi:10.1016/j.eswa.2021.115695
- Khan, Z. H., A. Siddique, and C. W. Lee. 2020. "Robotics Utilization for Healthcare Digitization in Global COVID-19 Management." *International Journal of Environmental Research and Public Health* 17 (11): 3819. doi:10.3390/ijerph17113819
- Khorasani, Mahyar, Jennifer Loy, Amir Hossein Ghasemi, Elmira Sharabian, Martin Leary, Hamed Mirafzal, Peter Cochrane, Bernard Rolfe, and Ian Gibson. 2022. "A Review of Industry 4.0 and Additive Manufacturing Synergy." *Rapid Prototyping Journal* 28 (8): 1462–1475. doi:10.1108/RPJ-08-2021-0194
- Kim, H. J., and J. H. Lee. 2021. "Cyclic Robot Scheduling for 3D Printer-Based Flexible Assembly Systems." *Annals of Operations Research* 298 (1–2): 339–359. doi:10.1007/s10479-018-3098-2
- Kim, P. 2017. *Matlab Deep Learning With Machine Learning, Neural Networks and Artificial Intelligence*. (1st ed.), Berkeley, CA: Apress. doi:10.1007/978-1-4842-2845-6
- Kim, S. W., J. H. Kong, S. W. Lee, and S. Lee. 2022. "Recent Advances of Artificial Intelligence in Manufacturing Industrial Sectors: A Review." *International Journal of Precision Engineering and Manufacturing* 23 (1): 111–129. doi:10.1007/s12541-021-00600-3
- Kis, Z., C. Kontoravdi, A. Dey, R. Shattock, and N. Shah. 2020. "Rapid Development and Deployment of High-Volume Vaccines for Pandemic Response." *Journal of Advanced Manufacturing and Processing*. 2 (3): e10060. doi:10.1002/amp.2.10060
- Kitchenham, B., O. P. Brereton, D. Budgen, M. Turner, J. Bailey, and S. Linkman. 2009. "Systematic Literature Reviews in Software Engineering—a Systematic Literature Review." *Information and Software Technology* 51 (1): 7–15. doi:10.1016/j.infsof.2008.09.009
- Konchak, Chad W., Jacob Krive, Loretta Au, Daniel Chertok, Priya Dugad, Gus Granchalek, Ekaterina Livschiz, et al. 2021. "From Testing to Decision-

- Making: A Data-Driven Analytics COVID-19 Response." *Academic Pathology* 8: 23742895211010257. doi:10.1177/23742895211010257
- Koren, Y., X. Gu, and W. Guo. 2018. "Reconfigurable Manufacturing Systems: Principles, Design, and Future Trends." *Frontiers of Mechanical Engineering* 13 (2): 121–136. doi:10.1007/s11465-018-0483-0
- Koren, Y., U. Heisel, F. Jovane, T. Moriwaki, G. Pritschow, G. Ulsoy, and H. Van Brussel. 1999. "Reconfigurable Manufacturing Systems." *CIRP Annals* 48 (2): 527–540. doi:10.1016/S0007-8506(07)63232-6
- Kowalkowski, C., D. Kindström, T. B. Alejandro, S. Brege, and S. Biggemann. 2012. "Service Infusion as Agile Incrementalism in Action." *Journal of Business Research* 65 (6): 765–772. doi:10.1016/j.jbusres.2010.12.014
- Kumar, A., S. Luthra, S. K. Mangla, and Y. Kazançoğlu. 2020. "COVID-19 Impact on Sustainable Production and Operations Management." *Sustainable Operations and Computers* 1: 1–7. doi:10.1016/j.susoc.2020.06.001
- Kumar, S. L. 2017. "State of the Art-Intense Review on Artificial Intelligence Systems Application in Process Planning and Manufacturing." *Engineering Applications of Artificial Intelligence* 65: 294–329.
- Kunovjanek, M., N. Knofius, and G. Reiner. 2022. "Additive Manufacturing and Supply Chains—a Systematic Review." *Production Planning & Control* 33 (13): 1231–1251. doi:10.1080/09537287.2020.1857874
- Levin, Jeremy M., Tudor I. Oprea, Sagie Davidovich, Thomas Clozel, John P. Overington, Quentin Vanhaelen, Charles R. Cantor, Evelyne Bischof, and Alex Zhavoronkov. 2020. "Artificial Intelligence, Drug Repurposing and Peer Review." *Nature Biotechnology* 38 (10): 1127–1131. doi:10.1038/s41587-020-0686-x
- Li, B., R. S. Chen, and C. Y. Liu. 2021. "Using Intelligent Technology and Real-Time Feedback Algorithm to Improve Manufacturing Process in IoT Semiconductor Industry." *The Journal of Supercomputing* 77 (5): 4639–4658. doi:10.1007/s11227-020-03457-x
- Li, M., and G. Q. Huang. 2021. "Production-Intralogsistics Synchronization of Industry 4.0 Flexible Assembly Lines under Graduation Intelligent Manufacturing System." *International Journal of Production Economics* 241: 108272. doi:10.1016/j.ijpe.2021.108272
- Li, S., H. Zhang, W. Yan, and Z. Jiang. 2021. "A Hybrid Method of Blockchain and Case-Based Reasoning for Remanufacturing Process Planning." *Journal of Intelligent Manufacturing* 32 (5): 1389–1399. doi:10.1007/s10845-020-01618-6
- Li, X., and K. Xing. 2021. "Iterative Widen Heuristic Beam Search Algorithm for Scheduling Problem of Flexible Assembly Systems." *IEEE Transactions on Industrial Informatics* 17 (11): 7348–7358. <https://doi.org/10.1109/TII.2021.3049338>
- Li, Y., X. Li, and J. N. Gupta. 2015. "Solving the Multi-Objective Flowline Manufacturing Cell Scheduling Problem by Hybrid Harmony Search." *Expert Systems with Applications* 42 (3): 1409–1417. doi:10.1016/j.eswa.2014.09.007
- Lin, Jun., Weihao Huang, Muchen Wen, Dehong Li, Shuyi Ma, Jiawen Hua, Hang Hu, et al. 2020. "Containing the Spread of Coronavirus Disease 2019 (COVID-19): Meteorological Factors and Control Strategies." *The Science of the Total Environment* 744: 140935. doi:10.1016/j.scitotenv.2020.140935
- Linton, T., and B. Vakil. 2020. *Coronavirus is proving we need more resilient supply chains*. Harvard Business Review. <https://hbr.org/2020/03/coronavirus-is-proving-that-we-need-more-resilient-supply-chains>
- Liu, M., J. Ma, L. Lin, M. Ge, Q. Wang, and C. Liu. 2017. "Intelligent Assembly System for Mechanical Products and Key Technology Based on Internet of Things." *Journal of Intelligent Manufacturing* 28 (2): 271–299. doi:10.1007/s10845-014-0976-6
- Liu, Q., X. Li, and L. Gao. 2021b. "Mathematical Modeling and a Hybrid Evolutionary Algorithm for Process Planning." *Journal of Intelligent Manufacturing* 32 (3): 781–797. doi:10.1007/s10845-020-01703-w
- Liu, W., A. Beltagui, and S. Ye. 2021a. "Accelerated Innovation through Repurposing: exaptation of Design and Manufacturing in Response to COVID-19." *R&D Management* 51 (4): 410–426. doi:10.1111/radm.12460
- Liu, W., C. Kong, Q. Niu, J. Jiang, and X. Zhou. 2020. "A Method of NC Machine Tools Intelligent Monitoring System in Smart Factories." *Robotics and Computer-Integrated Manufacturing* 61: 101842. doi:10.1016/j.rcim.2019.101842
- López-Gómez, C., L. Corsini, D. Leal-Ayala, and S. Fokeer. 2020. *COVID-19 critical supplies: The manufacturing repurposing challenge*. UNIDO. <https://www.unido.org/news/covid-19-critical-supplies-manufacturing-repurposing-challenge>
- Lu, Y. 2019. "Artificial Intelligence: A Survey on Evolution, Models, Applications and Future Trends." *Journal of Management Analytics* 6 (1): 1–29. doi:10.1080/23270012.2019.1570365
- Luo, D., Z. Guan, C. He, Y. Gong, and L. Yue. 2022. "Data-Driven Cloud Simulation Architecture for Automated Flexible Production Lines: application in Real Smart Factories." *International Journal of Production Research* 60 (12): 3751–3773. doi:10.1080/00207543.2021.1931977
- Majeed, A., Y. Zhang, S. Ren, J. Lv, T. Peng, S. Waqar, and E. Yin. 2021. "A Big Data-Driven Framework for Sustainable and Smart Additive Manufacturing." *Robotics and Computer-Integrated Manufacturing* 67: 102026. doi:10.1016/j.rcim.2020.102026
- Makris, S. 2021. "On the Coordination of Multiple Cooperating Robots in Flexible Assembly Systems Using Mobile Robots." In *Cooperating Robots for Flexible Manufacturing*. Springer Series in Advanced Manufacturing. Springer, Cham. https://doi.org/10.1007/978-3-030-51591-1_3
- Malik, A. A., T. Masood, and R. Kousar. 2021. "Reconfiguring and Ramping-up Ventilator Production in the Face of COVID-19: Can Robots Help?" *Journal of Manufacturing Systems* 60: 864–875. doi:10.1016/j.jmsy.2020.09.008
- Mamo, L. T. 2020. *Insights From Africa's Covid-19 Response: Repurposing Manufacturing*. Tony Blair Institute for Global Change. <https://institute-global/advisory/insights-africas-covid-19-response-repurposing-manufacturing>
- Medina, J. R., T. Lorenz, and S. Hirche. 2015. "Synthesizing Anticipatory Haptic Assistance considering Human Behavior Uncertainty." *IEEE Transactions on Robotics* 31 (1): 180–190. doi:10.1109/TRO.2014.2387571
- Mehrabi, M. G., A. G. Ulsoy, and Y. Koren. 2000. "Reconfigurable Manufacturing Systems: Key to Future Manufacturing." *Journal of Intelligent Manufacturing* 11 (4): 403–419. doi:10.1023/A:1008930403506
- Meziane, F., S. Vadera, K. Kobbacy, and N. Proudlove. 2000. "Intelligent Systems in Manufacturing: current Developments and Future Prospects." *Integrated Manufacturing Systems* 11 (4): 218–238. doi:10.1108/09576060010326221
- Morgan, J., M. Halton, Y. Qiao, and J. G. Breslin. 2021. "Industry 4.0 Smart Reconfigurable Manufacturing Machines." *Journal of Manufacturing Systems* 59: 481–506. doi:10.1016/j.jmsy.2021.03.001
- Myant. 2020. *Myant to Produce 340,000 Masks Per Month to Help Protect Canadian Frontline Workers Combating COVID-19*. <https://myant.ca/myant-innovates-and-ramps-up-production-of-masks-to-help-protect-canadian-frontline-workers-combating-covid-19/>
- Neythalath, N., A. Søndergaard, and J. A. Bærentzen. 2021. "Adaptive Robotic Manufacturing Using Higher Order Knowledge Systems." *Automation in Construction* 127: 103702. doi:10.1016/j.autcon.2021.103702
- Nikolenko, S. I., S. Koltcov, and O. Koltsova. 2017. "Topic Modelling for Qualitative Studies." *Journal of Information Science* 43 (1): 88–102. <https://doi.org/10.1177/0165551515617393>
- Okoli, C., and K. Schabram. 2010. "A Guide to Conducting a Systematic Literature Review of Information Systems Research." *Sprouts: Working Papers on Information Systems* 10 (26): 1–51.
- Okorie, O., R. Subramoniam, F. Charnley, J. Patsavellas, D. Widdifield, and K. Salonitis. 2020. "Manufacturing in the Time of COVID-19: An Assessment of Barriers and Enablers." *IEEE Engineering Management Review* 48 (3): 167–175. doi:10.1109/EMR.2020.3012112
- Pandey, S., R. K. Singh, and A. Gunasekaran. 2021. "Supply Chain Risks in Industry 4.0 Environment: review and Analysis Framework." *Production Planning & Control*. doi:10.1080/09537287.2021.2005173
- Pang, J., N. Zhang, Q. Xiao, F. Qi, and X. Xue. 2021. "A New Intelligent and Data-Driven Product Quality Control System of Industrial Valve Manufacturing Process in CPS." *Computer Communications* 175: 25–34. doi:10.1016/j.comcom.2021.04.022
- Pansare, R., and G. Yadav. 2022. "Repurposing Production Operations during COVID-19 Pandemic by Integrating Industry 4.0 and Reconfigurable Manufacturing Practices: An Emerging Economy

- Perspective." *Operations Management Research* 15 (3-4): 1270–1289. doi:10.1007/s12063-022-00310-7
- Park, K. T., J. Lee, H. J. Kim, and S. Do Noh. 2020. "Digital Twin-Based Cyber Physical Production System Architectural Framework for Personalized Production." *The International Journal of Advanced Manufacturing Technology* 106 (5-6): 1787–1810. doi:10.1007/s00170-019-04653-7
- Paul, M., R. Sridharan, and T. R. Ramanan. 2021. "Scheduling of an Assembly Job Shop: A Case Study Based on Hydraulic Manufacturing Industry." *Materials Today: Proceedings* 47: 4988–4992. doi:10.1016/j.matpr.2021.04.341
- Paul, S. K., and P. Chowdhury. 2020. "Strategies for Managing the Impacts of Disruptions during COVID-19: An Example of Toilet Paper." *Global Journal of Flexible Systems Management* 21 (3): 283–293. doi:10.1007/s40171-020-00248-4
- Peng, T., Q. He, Z. Zhang, B. Wang, and X. Xu. 2021. "Industrial Internet-Enabled Resilient Manufacturing Strategy in the Wake of COVID-19 Pandemic: A Conceptual Framework and Implementations in China." *Chinese Journal of Mechanical Engineering* 34 (1): 1–6. doi:10.1186/s10033-021-00573-4
- Peng, Y., and D. Mcfarlane. 2004. "Adaptive Agent-Based Manufacturing Control and Its Application to Flow Shop Routing Control." *Production Planning & Control* 15 (2): 145–155. doi:10.1080/09537280410001662529
- Peres, R. S., X. Jia, J. Lee, K. Sun, A. W. Colombo, and J. Barata. 2020. "Industrial Artificial Intelligence in Industry 4.0-Systematic Review, Challenges and Outlook." *IEEE Access*. 8: 220121–220139. doi:10.1109/ACCESS.2020.3042874
- PLU (Policy Links Unit). 2020. *The role of industrial digitalisation in post-Covid-19 manufacturing recovery, diversification and resilience*. <https://www.ciip.group.cam.ac.uk/reports-and-articles/role-industrial-digitalisation-post-covid-19-manuf/download/2020-10-08-DigitalBR.pdf>
- Poduval, Aadarsh, Maruti Sriram Ayyagari, Mohit Malinda, Vimal K.e.k, Anil Kumar, and Jayakrishna Kandasamy. 2022. "Barriers in Repurposing an Existing Manufacturing Plant: A Total Interpretive Structural Modeling (TISM) Approach." *Operations Management Research* 15 (3-4): 1315–1340. doi:10.1007/s12063-021-00209-9
- Pooler, M., J. Miller, H. Kuchler, and C. Bushy. 2020. The ventilator challenge will test ingenuity to the limit. *Financial Times*. <https://www.ft.com/content/28bc27d1-8561-4838-bd71-0d7884a15dfa>
- Prather, K. A., C. C. Wang, and R. T. Schooley. 2020. "Reducing Transmission of SARS-CoV2." *Science (New York, N.Y.)* 368 (6498): 1422–1424. eabc6197 doi:10.1126/science.abc6197
- Qi, Q., F. Tao, Y. Cheng, J. Cheng, and A. Y. C. Nee. 2021. "New IT Driven Rapid Manufacturing for Emergency Response." *Journal of Manufacturing Systems* 60: 928–935. doi:10.1016/j.jmsy.2021.02.016
- Qin, Jian, Fu Hu, Ying Liu, Paul Witherell, Charlie C. L. Wang, David W. Rosen, Timothy W. Simpson, Yan Lu, and Qian Tang. 2022. "Research and Application of Machine Learning for Additive Manufacturing." *Additive Manufacturing* 52: 102691. doi:10.1016/j.addma.2022.102691
- Queiroz, M. M., D. Ivanov, A. Dolgui, and S. Fosso Wamba. 2022. "Impacts of Epidemic Outbreaks on Supply Chains: mapping a Research Agenda amid the COVID-19 Pandemic through a Structured Literature Review." *Annals of Operations Research* 319 (1): 1159–1196. doi:10.1007/s10479-020-03685-7
- Rajesh, R. 2021. "Flexible Business Strategies to Enhance Resilience in Manufacturing Supply Chains: An Empirical Study." *Journal of Manufacturing Systems* 60: 903–919. doi:10.1016/j.jmsy.2020.10.010
- Rajkomar, Alvin, Eyal Oren, Kai Chen, Andrew M. Dai, Nissan Hajaj, Michaela Hardt, Peter J. Liu, et al. 2018. "Scalable and Accurate Deep Learning with Electronic Health Records." *NPJ Digital Medicine* 1 (1): 18. doi:10.1038/s41746-018-0029-1
- Rao, T. V. N., A. Gaddam, M. Kurni, and K. Saritha. 2022. "Reliance on Artificial Intelligence, Machine Learning and Deep Learning in the Era of Industry 4.0," in *Smart Healthcare System Design: Security and Privacy Aspects*, 281–299. doi:10.1002/9781119792253.ch12
- Rapaccini, M., N. Saccani, C. Kowalkowski, M. Paiola, and F. Adrodegari. 2020. "Navigating Disruptive Crises through Service-Led Growth: The Impact of COVID-19 on Italian Manufacturing Firms." *Industrial Marketing Management* 88: 225–237. doi:10.1016/j.indmarman.2020.05.017
- Razak, G. M., L. C. Hendry, and M. Stevenson. 2023. "Supply Chain Traceability: A Review of the Benefits and Its Relationship with Supply Chain Resilience." *Production Planning & Control* 34 (11): 1114–1134. doi:10.1080/09537287.2021.1983661
- Realyvásquez-Vargas, A., K. C. Arredondo-Soto, J. L. García-Alcaraz, B. Y. Márquez-Lobato, and J. Cruz-García. 2019. "Introduction and Configuration of a Collaborative Robot in an Assembly Task as a Means to Decrease Occupational Risks and Increase Efficiency in a Manufacturing Company." *Robotics and Computer-Integrated Manufacturing* 57: 315–328. doi:10.1016/j.rcim.2018.12.015
- Rejeb, M. A., S. Simske, K. Rejeb, H. Treiblmaier, and S. Zailani. 2020. "Internet of Things Research in Supply Chain Management and Logistics: A Bibliometric Analysis." *Internet of Things* 12: 100318. doi:10.1016/j.iot.2020.100318
- Renzi, C., F. Leali, M. Cavazzuti, and A. O. Andrisano. 2014. "A Review on Artificial Intelligence Applications to the Optimal Design of Dedicated and Reconfigurable Manufacturing Systems." *The International Journal of Advanced Manufacturing Technology* 72 (1-4): 403–418. doi:10.1007/s00170-014-5674-1
- Rong, K., H. Ding, and J. Tang. 2021. "Adaptive Data-Driven Modular Control Approach to Computer Aided Process Planning for Manufacturing Spiral Bevel and Hypoid Gears." *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture* 235 (3): 514–532. doi:10.1177/0954405420956767
- Rong, K., Y. Lin, J. Yu, and Y. Zhang. 2020. "Manufacturing Strategies for the Ecosystem-Based Manufacturing System in the Context of 3D Printing." *International Journal of Production Research* 58 (8): 2315–2334. doi:10.1080/00207543.2019.1627436
- Sadati, N., R. B. Chinnam, and M. Z. Nezhad. 2018. "Observational Data-Driven Modeling and Optimization of Manufacturing Processes." *Expert Systems with Applications* 93: 456–464. doi:10.1016/j.eswa.2017.10.028
- Sawik, T. 1999. "Flexible Assembly Systems—Hardware Components and Features," in *Production Planning and Scheduling in Flexible Assembly Systems*, 1–15. Berlin, Heidelberg: Springer.
- Schmidt, A., H. Helgers, F. L. Vetter, A. Juckers, and J. Strube. 2021. "Digital Twin of mRNA-Based SARS-COVID-19 Vaccine Manufacturing towards Autonomous Operation for Improvements in Speed, Scale, Robustness, Flexibility and Real-Time Release Testing." *Processes* 9 (5): 748. doi:10.3390/pr9050748
- Scholz, Steffen, Tobias Mueller, Matthias Plasch, Hannes Limbeck, Raphael Adamietz, Tobias Iseringhausen, Daniel Kimmig, Markus Dickerhof, and Christian Woegerer. 2016. "A Modular Flexible Scalable and Reconfigurable System for Manufacturing of Microsystems Based on Additive Manufacturing and e-Printing." *Robotics and Computer-Integrated Manufacturing* 40: 14–23. doi:10.1016/j.rcim.2015.12.006
- Sell, Tara Kirk, Daniel Gastfriend, Matthew Watson, Crystal Watson, Lauren Richardson, Anita Cicero, Tom Inglesby, and Nancy Connell. 2021. "Building the Global Vaccine Manufacturing Capacity Needed to Respond to Pandemics." *Vaccine* 39 (12): 1667–1669. doi:10.1016/j.vaccine.2021.02.017
- Sethi, A. K., and S. P. Sethi. 1990. "Flexibility in Manufacturing: A Survey." *International Journal of Flexible Manufacturing Systems* 2 (4): 289–328. doi:10.1007/BF00186471
- Shah, S. H. H., S. Lei, M. Ali, D. Doronin, and S. T. Hussain. 2019. "Presumption: bibliometric Analysis Using HistCite and VOSviewer." *Kybernetes* ahead-of-print (ahead-of-print): 1020–1045. doi:10.1108/K-12-2018-0696
- Shokrani, A., E. G. Loukaides, E. Elias, and A. J. Lunt. 2020. "Exploration of Alternative Supply Chains and Distributed Manufacturing in Response to COVID-19; a Case Study of Medical Face Shields." *Materials & Design* 192: 108749. doi:10.1016/j.matdes.2020.108749
- Patrício Silva, Ana L., Joana C. Prata, Tony R. Walker, Diana Campos, Armando C. Duarte, Amadeu M. V. M. Soares, Damià Barcelò, and Teresa Rocha-Santos. 2020. "Rethinking and Optimising Plastic Waste Management under COVID-19 Pandemic: Policy Solutions Based on Redesign and Reduction of Single-Use Plastics and Personal Protective Equipment." *The Science of the Total Environment* 742: 140565. doi:10.1016/j.scitotenv.2020.140565

- Solomatine, D., L. M. See, and R. J. Abraham. 2009. "Data-Driven Modelling: concepts, Approaches and Experiences." *Practical Hydroinformatics* 68: 17–30.
- Sony, M., and S. Naik. 2020. "Critical Factors for the Successful Implementation of Industry 4.0: A Review and Future Research Direction." *Production Planning & Control* 31 (10): 799–815. doi:10.1080/09537287.2019.1691278
- Stevenson, M., and M. Spring. 2007. "Flexibility from a Supply Chain Perspective: definition and Review." *International Journal of Operations & Production Management* 27 (7): 685–713. doi:10.1108/01443570710756956
- Stavropoulos, P., A. Papacharalampopoulos, C. Michail, V. Vassilopoulos, K. Alexopoulos, and P. Perlo. 2021. "A Two-Stage Decision Support System for Manufacturing Processes Integration in Microfactories for Electric Vehicles." *Procedia Manufacturing* 54: 106–111. doi:10.1016/j.promfg.2021.07.017
- Suvarna, M., K. S. Yap, W. Yang, J. Li, Y. T. Ng, and X. Wang. 2021. "Cyber-Physical Production Systems for Data-Driven, Decentralized, and Secure Manufacturing—a Perspective." *Engineering* 7 (9): 1212–1223. doi:10.1016/j.eng.2021.04.021
- Tan, J. T. C., F. Duan, Y. Zhang, K. Watanabe, R. Kato, and T. Arai. 2009. "Human-Robot Collaboration in Cellular Manufacturing: Design and Development," in *2009 IEEE/RSJ International Conference on Intelligent Robots and Systems*, 29–34. Louis, MO: IEEE. St.
- Tarba, I. C., S. Tonoiu, P. G. Tiriplica, and I. G. Ghionea. 2015. "Process Planning in Manufacturing Systems." *Applied Mechanics and Materials* 760: 745–750. doi:10.4028/www.scientific.net/AMM.760.745
- Tian, X., B. Ma, and C. Meng. 2021. "Research on CMOPSO Particle Swarm Optimization Algorithm for Green Manufacturing Energy System in Ecological Park," in *2021 IEEE 5th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC)* (Vol. 5, pp. 2155–2159). doi:10.1109/IAEAC50856.2021.9391053
- Tisdell, C. A. 2020. "Economic, Social and Political Issues Raised by the COVID-19 Pandemic." *Economic Analysis and Policy* 68: 17–28. doi:10.1016/j.eap.2020.08.002
- Touckia, J. K. 2023. "Integrating the Digital Twin Concept into the Evaluation of Reconfigurable Manufacturing Systems (RMS): Literature Review and Research Trend." *The International Journal, Advanced Manufacturing Technology* 126 (3–4): 875–889. doi:10.1007/s00170-023-10902-7
- Tranfield, D., D. Denyer, and P. Smart. 2003. "Towards a Methodology for developing evidenceinformed management Knowledge by Means of Systematic Review." *British Journal of Management* 14 (3): 207–222. doi:10.1111/1467-8551.00375
- Tripathi, V., S. Chattopadhyaya, A. K. Mukhopadhyay, S. Sharma, V. Kumar, C. Li, and S. Singh. 2023. "Lean, Green, and Smart Manufacturing: An Ingenious Framework for Enhancing the Sustainability of Operations Management on the Shop Floor in Industry 4.0." Proceedings of the Institution of Mechanical Engineers, Part E: Journal of Process Mechanical Engineering, 09544089231159834.
- Urtasun-Alonso, A., M. Larraza-Kintana, C. García-Olaverri, and E. Huerta-Arribas. 2014. "Manufacturing Flexibility and Advanced Human Resource Management Practices." *Production Planning & Control* 25 (4): 303–317. doi:10.1080/09537287.2012.690198
- Van Eck, N. J., and L. Waltman. 2010. "Software Survey: VOSviewer, a Computer Program for Bibliometric Mapping." *Scientometrics* 84 (2): 523–538. doi:10.1007/s11192-009-0146-3
- Vinodh, S., J. Antony, R. Agrawal, and J. A. Douglas. 2020. "Integration of Continuous Improvement Strategies with Industry 4.0: A Systematic Review and Agenda for Further Research." *The TQM Journal* 33 (2): 441–472. doi:10.1108/TQM-07-2020-0157
- Vlachos, I. 2021. "Implementation of an Intelligent Supply Chain Control Tower: A Socio-Technical Systems Case Study." *Production Planning & Control*. doi:10.1080/09537287.2021.2015805
- Wahyuni, H., I. Vanany, and U. Ciptomulyono. 2019. "Food Safety and Halal Food in the Supply Chain: Review and Bibliometric Analysis." *Journal of Industrial Engineering and Management* 12 (2): 373–391. doi:10.3926/jiem.2803
- Wallin, J. A. 2005. "Bibliometric Methods: pitfalls and Possibilities." *Basic & Clinical Pharmacology & Toxicology* 97 (5): 261–275. doi:10.1111/j.1742-7843.2005.pto_139.x
- Wang, J. Q., Y. L. Song, P. H. Cui, and Y. Li. 2023. "A Data-Driven Method for Performance Analysis and Improvement in Production Systems with Quality Inspection." *Journal of Intelligent Manufacturing* 34 (2): 455–469. doi:10.1007/s10845-021-01780-5
- Wipro. 2020. *Intelligent Manufacturing Post COVID-19: The Emergence of a New Era*. <https://www.wipro.com/process-and-industrial-manufacturing/intelligent-manufacturing-post-covid-19-the-emergence-of-a-new-era/>
- Xiao, Y., and M. Watson. 2019. "Guidance on Conducting a Systematic Literature Review." *Journal of Planning Education and Research* 39 (1): 93–112. doi:10.1177/0739456X17723971
- Yadav, A., and S. C. Jayswal. 2018. "Modelling of Flexible Manufacturing System: A Review." *International Journal of Production Research* 56 (7): 2464–2487. doi:10.1080/00207543.2017.1387302
- Yang, S., and Z. Xu. 2021. "The Distributed Assembly Permutation Flowshop Scheduling Problem with Flexible Assembly and Batch Delivery." *International Journal of Production Research* 59 (13): 4053–4071. <https://doi.org/10.1080/00207543.2020.1757174>
- Yao, X., J. Zhou, J. Zhang, and C. R. Boër. 2017. September. "From Intelligent Manufacturing to Smart Manufacturing for Industry 4.0 Driven by Next Generation Artificial Intelligence and Further on." In *2017 5th International Conference on Enterprise Systems (ES)* (pp. 311–318). IEEE. doi:10.1109/ES.2017.58
- Yuan, L., Z. Pan, J. Polden, D. Ding, S. van Duin, and H. Li. 2022. "Integration of a Multi-Directional Wire Arc Additive Manufacturing System with an Automated Process Planning Algorithm." *Journal of Industrial Information Integration* 26: 100265. doi:10.1016/j.jii.2021.100265
- Zan, X., Z. Wu, C. Guo, and Z. Yu. 2020. "A Pareto-Based Genetic Algorithm for Multi-Objective Scheduling of Automated Manufacturing Systems." *Advances in Mechanical Engineering* 12 (1): 168781401988529. doi:10.1177/1687814019885294
- Zeng, Z., P. J. Chen, and A. A. Lew. 2020. "From High-Touch to High-Tech: COVID-19 Drives Robotics Adoption." *Tourism Geographies* 22 (3): 724–734. doi:10.1080/14616688.2020.1762118
- Zhang, S., and T. N. Wong. 2018. "Integrated Process Planning and Scheduling: An Enhanced Ant Colony Optimization Heuristic with Parameter Tuning." *Journal of Intelligent Manufacturing* 29 (3): 585–601. doi:10.1007/s10845-014-1023-3
- Zhang, S., F. Tang, X. Li, J. Liu, and B. Zhang. 2021. "A Hybrid Multi-Objective Approach for Real-Time Flexible Production Scheduling and Rescheduling under Dynamic Environment in Industry 4.0 Context." *Computers & Operations Research* 132: 105267. doi:10.1016/j.cor.2021.105267
- Zhang, X., Y. Li, Y. Ran, and G. Zhang. 2020. "Stochastic Models for Performance Analysis of Multistate Flexible Manufacturing Cells." *Journal of Manufacturing Systems* 55: 94–108. doi:10.1016/j.jmsy.2020.02.013
- Zhou, B., J. Bao, J. Li, Y. Lu, T. Liu, and Q. Zhang. 2021. "A Novel Knowledge Graph-Based Optimization Approach for Resource Allocation in Discrete Manufacturing Workshops." *Robotics and Computer-Integrated Manufacturing* 71: 102160. doi:10.1016/j.rcim.2021.102160
- Zimmerling, A., and X. Chen. 2021. "Innovation and Possible Long-Term Impact Driven by COVID-19: Manufacturing, Personal Protective Equipment and Digital Technologies." *Technology in Society* 65: 101541. doi:10.1016/j.techsoc.2021.101541