Leveraging Artificial Intelligence to Enhance Productivity and Efficiency in the Manufacturing Sector – A Systematic Literature Review

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Abstract

Machine learning (ML) is a form of artificial intelligence (AI) algorithm adopted by manufacturing organisations to aid systems in learning and to improve based on past experiences without explicit programming. It is important to research the field of ML in manufacturing to uncover the range of benefits and how they affect manufacturing firms. This dissertation systematically reviews the existing literature concerning ML in the manufacturing sector. The methodology of this study searched for articles systematically using a specific search string across three databases, filtered the studies based on the inclusion and criteria, removed duplicate articles, removed articles with a title and abstract review, carried out a full-text analysis, and backward and forwards searched the articles. A total of 26 articles were narrowed down that qualified for data extraction.

The results of this study indicate that ML offers a wide range of benefits in the field of manufacturing. The identified benefits of ML include faster processing of data, greater accuracy in tasks compared to human effort, the ability to solve complex problems, and greater control and flexibility in manufacturing practices. Challenges identified amongst ML in the manufacturing field included employee skill, data quality, and information security. The conclusion can be drawn that ML plays a significant role in the manufacturing sector across an extensive range of applications.

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Attestation of Authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

Author's Signature: ____________________ Date: 29-November-2022

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Chapter 1: Introduction

1.1 Introduction of Topic

With the current state of technology, manufacturing is in the middle of the fourth industrial revolution. Industry 4.0, also known as digitalisation, is the rapid change in how organisations execute manufacturing practices (Vuković & Thalmann, 2022). Digitalisation drives industry 4.0. In the manufacturing sector, industry 4.0 embraces technological, economic, organisation and societal changes and relies on technology throughout the industrial value chain ranging from manufacturing warehouses to shop floor settings (Bécue et al., 2021). Critical foundations of industry 4.0 include automation, interconnectivity, real-time data analytics, and machine learning (ML) (Yuan et al., 2022). Such integration has proven industry 4.0 to be imperative in modern manufacturing, revolutionising the industry by increasing productivity, reducing waste output and decreasing the overall product lifecycle (Huang et al., 2021).

In particular, with the rise of artificial intelligence (AI) in the last decade, many organisations jumped on the trend of adopting AI technologies, such as ML to transform their manufacturing processes to achieve a competitive advantage and improvements, for example, increased quality control, innovation, cost reduction and design flexibility (Kinkel et al., 2022). Organisations of all shapes and sizes use ML, ranging from SMEs (Kaymakci et al., 2022) to large-scale organisations (Bettoni et al., 2022). Additionally, simulations are trained and run using ML (Huang et al., 2021) and provide information for manufacturing organisations to make informed decisions (Kamble et al., 2021). Furthermore, considering the favourable potential ML bring to manufacturing organisations, it is imperative to understand how organisations can leverage ML in the best way possible. Organisations can leverage ML to support the manufacturing process in various areas, such as the procurement of raw materials, process monitoring (Bécue et al., 2021), optimisation and troubleshooting processes (Wuest et al., 2016).

1.2 Practical and Statistical Applications of ML

There are various cases of ML and its applications. For example, Goh et al. (2020) discuss the application of 3D printing. ML and its algorithms in 3D printing impact the quality of printed items produced by the 3D printer, such as the strength, design, part and quality process optimisation, and quality control.

Likewise, Mayr et al. (2019) discuss the production of automotive transmission components. In the automotive supplier setting, there are many unpredictable variances and disturbances that can occur in the production process. Production data contains a range of process and quality parameters to meet regulatory and quality standards. ML forms, including unsupervised methods like cluster analysis and supervised methods in the form of decision trees, are used to detect failures effectively.

Schuh et al. (2019) explain the use of ML as a solution to anomalies in the production of hydraulic valves at a German-based engineering firm. For quality control purposes, they sample 1% of a batch. Complete batch testing takes form at the end of the manufacturing line. Such quality control methods can lead to increased indirect costs and increased delays between machined valves and measurement results. The solution to this issue is to utilise ML operations and process data from the machining process to predict the quality of bores in a valve.

Additionally, Schuh et al. (2019) provide a use case covering the deterioration of quality in cutting tools used to drill and ream the bores. Such tool wear leads to greater force and torque required to cut. The manufacturer measures the drive of the milling machine via motor current and torque. A solution was provided by utilising ML techniques to obtain latencies closer to zero in an industrial setting. Lower latency will result in better quality surveillance of cutting and ultimately enable earlier interventions with deviations in quality and save from a cost and resource perspective.

Furthermore, Bettoni et al. (2021) propose an AI maturity and adoption model, which suggests that the state of an organisation in its AI maturity stage can influence its adoption. Ultimately the success or failure of AI adoption in organisations is based on the model's five exclusive pillars, which surround an organisation's maturity stage. These models include digital and smart factories, data strategy, human resources, organisational culture, and organisational strategy (Bettoni et al., 2021). Organisations can apply the framework to ML and how it is leveraged towards enhancing productivity and efficiency in the manufacturing sector, based on the size of the organisation and its stage in AI adoption.

1.3 Motivation and Introduction of Research Questions

The field of research lacks the exploration of how manufacturing leverages ML. With the growth and acceleration of manufacturing in the industry 4.0 environment and the emergence of ML adoption amongst organisations, this research project aims to conduct a systematic literature review (SLR) that provides insight into the state of research in the field of leveraging ML, understanding the application cases, their impacts, benefits and challenges in the manufacturing sector".

- What are the strengths of ML in the manufacturing industry?
- What are the current and future application areas of ML algorithms in the manufacturing industry?

This dissertation consists of five chapters in total. Chapter 1 is the introduction to the thesis. Chapter 2 provides an overview of the main concepts and the literature on the topic. Chapter 3 presents the research methodology for the systematic data collection. Chapter 4 presents the findings from the systematic search. Chapter 5 presents the discussion of the findings, the practical and theoretical implications of the review, the limitations identified and future possibilities for research in this field. In doing so, this dissertation provides an overview of the literature on ML in the manufacturing sector. It puts forward avenues for future research to facilitate further exploration of this topic.

Chapter 2: Background Information

The fourth industrial revolution, also widely known as Industry 4.0, is the current state which captures the concept amongst the rapid advancements and changes in industries and their respective technologies and processes (Huang et al., 2021). The significance of industry 4.0 in the manufacturing sector demonstrates the digitisation of many processes and past activities performed manually or with complete human input (Jamwal et al., 2021). As industry 4.0 has grown towards maturity, key technologies contributing to its significance in the modern business environment include the internet of things (IoT), cyber-physical systems (CPS), blockchain technology and AI (Jamwal et al., 2021). Such technologies play an active part in industry 4.0.

This background information section provides an introductory discussion of industry 4.0, AI and ML. Such concepts serve as the foundation of this paper and are constantly referred to throughout this report.

2.1 Industry 4.0

Industry 4.0 is the digitisation of operations through adopting technology from the third industrial revolution, such as automation and computer technology and further develops these through the application of AI and ML (Dogru & Keskin, 2020). Similarly, Yuan et al. (2020) note that amongst the concept of industry 4.0, there is great emphasis placed on automated processes, ML, the interconnectivity of devices, software, real-time data analytics, and is driven by the digitalisation of data and processes being increasingly interconnected (Kaymakci et al., 2022).

The vision of industry 4.0 is to transition towards the creation of smart factories and create value through horizontal and vertical integration, create end-to-end solutions (Santos et al., 2021), enable computational self-awareness (Lepasepp & Hurst., 2021), and address common issues faced such as compatibility and operational issues to improve the agility and flexibility of organisational operations (Huang et al., 2021). The vision is further motivated by environmental perspectives, such as the environmental impact of specific business and operational decisions and the regulatory enforcement surrounding environmental perspectives upon business practices (Vuković & Thalmann., 2022).

Benefits emerging from industry 4.0 include computational self-awareness, automation, smart manufacturing, enhanced supervision (Lepasepp & Hurst., 2022), man-machine interaction and collaboration, real-time communication and intelligence decision-making (Jamwal et al., 2021).

2.2 Artificial Intelligence in Manufacturing

AI is defined as the ability of a system to correctly interpret external data and learn from it to achieve set goals and tasks (Kinkel et al., 2021). The feature of AI is that it combines several technologies, allowing software and machines in conjunction with one another to interpret, act and learn because of self-learning or augmented activities that humans can carry out (Jamwal et al., 2021).

With the rise of industry 4.0 in the last decade, AI has climbed to prominence and popularity across organisations and is viewed as a critical component of industry 4.0 (Vuković & Thalmann., 2022). In the past, AI had lacked the historical success to prove itself as a staple in the business world and was viewed as having limited capability (Lee et al., 2018). However, today AI is becoming an increasingly widespread technology that is present in manufacturing factory environments (Fahle et al., 2020).

There are multiple examples regarding the application of AI in the manufacturing sector. Organisations can apply AI to the manufacturing process for waste analytics, optimisation, price estimation and product scheduling (Abioye et al., 2021), real-time maintenance of manufacturing equipment (Sharp et al., 2018) and generative design in manufacturing for improved recommendations (Wang & Siau., 2019). The benefits of applying AI in the manufacturing sector include the ability of AI to enhance machine capability amongst production in a cost-effective manner (Jamwal et al., 2021). Furthermore, AI can improve operations, reduce maintenance costs, reduce the chance of equipment failure (Vuković & Thalmann., 2022), facilitate quality control checks, detect faults, predict maintenance and facilitate inventory monitoring (Bécue et al., 2021).

However, some challenges exist with the application of AI in manufacturing; such include compatibility issues, conflict amongst machinery and cybersecurity issues (Lee et al., 2018), lack of organisations maturity and skilled employees (Bettoni et al., 2021), lack of data quality and quantity (Bettoni et al., 2021 & Lee et al., 2018).

One branch of AI that stands out is the function of ML, which is suitable for intelligent systems, quality improvement and logistics and demand planning in manufacturing (Kaymakci et al., 2022).

2.3 Machine Learning in Manufacturing

ML is a subset of AI that allows computers to recognise data correlations and make decisions on humans' behalf without predefined rules (Kaymakci et al., 2022) or explicit programming (Mayr et al., 2019). The significance of ML amongst industry 4.0 and the manufacturing sector is due to it being a dominant method in which AI is deployed in organisations (Vukovič & Thalmann., 2022). It is present in various forms: supervised, unsupervised, semi-supervised (Bécue et al., 2021) and reinforcement learning (Haricha et al., 2020).

ML has various applications in the manufacturing sector, such as determining correct cleaning schedules of manufacturing equipment and machines and predicting maintenance (Mayr et al., 2019). Further applications include automatic fault detection (Haricha et al., 2020), fraud detection, image recognition, inventory management, stock replenishment, and optimising logistical processes and warehouses (Sarker, 2021). The various use cases of ML in the manufacturing sector highlight its widespread use and application – making it a key feature amongst industry 4.0 and AI in the field of manufacturing.

Chapter 3: Methodology

This study elaborates on prior ML research in the manufacturing sector to understand how it can improve organisational outcomes. There are various existing types of literature reviews. Selecting a suitable type of literature review for this study was decided on the following constraints, including but not limited to the length of time to complete the study, level of detail, risk of bias that may arise and the overall comprehensiveness of the study (Grant & Booth, 2009). They additionally highlight the four most common types of reviews as a traditional or narrative literature review, rapid review, scoping review and SLR. An SLR is the most suitable choice for this study, as the projected time for completion was six months. However, Grant and Booth (2009) note that the potential timeframe for an SLR can range between 8 months to two years. In addition, the desired outcome for the study was to have a minimal level of bias and a comprehensive level of information covered by a SLR. In addition to the reasons listed above, a SLR can synthesise the existing field concerning the research topic, identify research gaps and propose avenues for future research based on those gaps (Templier & Paré, 2015). By conducting a SLR, the researcher will explore the different use cases of ML in the manufacturing industry and its associated benefits and challenges.

Templier and Paré (2015) state that the SLR's **first step** identifies the research problem. Here, the problem is synthesising the research field of the applications of ML in the manufacturing sector, its associated benefits and challenges, to develop an overview of the current state-of-the-art research and highlight any gaps that require further exploration. The material for this SLR came from multiple databases, including EBSCO/Business Source Complete, ScienceDirect and IEEE Xplore. The researcher selected the database for their focus on articles centred around business, manufacturing, technology and engineering disciplines.

Step two of the SLR process explains the requirement of searching for sources amongst the databases chosen by the researcher. Based on the initial readings and insights gathered from existing literature in the field, the following keywords were derived and used in a search string: "artificial intelligence" OR "machine learning" OR "industry 4.0" AND "manufacturing". The search using the above search string returned approximately 8322 articles across the three databases.

The **third step** comprised screening and evaluating the identified articles according to the developed inclusion and exclusion criteria.

The inclusion criteria applied to the results involved:

a) Years of publications to span a decade from 2012-2021. The period is appropriate. ML has developed rapidly in the last decade due to improved processing power, algorithms and big data (Breitenbach et al., 2021). The last ten years allowed me to gather insights from those fundamental developments in the field of ML.
b) Peer-reviewed journal articles and conference proceedings published in English

The exclusion criteria consisted of the following:

a) Articles outside the scope of research that were in the search results but did not address manufacturing
b) Articles focused on algorithms underpinning machine learning processes rather than applications to manufacturing

The researcher then filtered the initial search of 8322 articles according to the inclusion and exclusion criteria which removed 2326 articles and left a total of 5996 articles. A total of 905 duplicates were removed selectively by the researcher, leaving 5091 unique articles remaining.

The researcher then exported the 5091 unique articles to EndNote, whereby they carried out a search across the 5091 unique articles in their library. across the articles amongst the “title” OR “abstract” containing the phrase “machine learning”. The researcher was able to further narrow it down to a total of 1627 articles.

Next, the researcher conducted a title and abstract scan if required. A total of 1536 articles that did not align with the research topic were removed. A total of 91 papers were shortlisted and selected to progress toward a complete text analysis.

The **fourth stage** involved assessing the quality of the unique sources to determine if they aligned with the research questions and topic. According to Templier and Paré (2015), this step includes evaluating the quality and rigour of similar selected studies. It allows the researcher to eliminate the potential of any bias that may arise. The 91 studies were shortlisted to progress to a full-text analysis involving an assessment of the general quality of the paper. Data within the documents were analysed, along with the research design, motive, goals, findings and arguments, all concerning the research topic. The researcher removed 77 journal articles from the full-text analysis, leaving 14 papers. Among those 14 papers, they carried out a forward and backward search amongst the remaining literature to extend the search for literature aligning with the topic and research questions. The forward and backward search obtained an additional 12 papers among the fourteen sources. Conclusively, this left a total of 26 articles that were eligible for the extraction and synthesis of data.

Step five concerned the extraction of data from the papers gathered. The researcher extracted data from the 26 papers by reading through each one, highlighting them and coding key concepts and relevant information to help answer the research questions. The researcher utilised the academic coding software NVIVO to assist with the highlighting and coding of data.

Building on the progress from the fifth step, the **sixth phase** involved synthesising all the data generated from the data extraction in step five.

The data was synthesised using a thematic analysis, where amongst the data, excerpts from article text were highlighted and grouped into appropriate themes, subthemes and codes (Gupta & Sharma, 2022). Each theme identified assists in capturing and grouping important data gathered from the articles for the analysis of data (Margot & Kettler, 2019). By analysing the data, we can assess the information and draw upon it to create conclusions about the results of the data collected (Paré et al., 2016) and utilise it in the writing of the findings section.

Below, *Figure 1* presents a flowchart that outlines each step in the data collection process and how the search narrowed down to the final articles selected for data extraction and analysis. Following *Figure 1, Table A* presents an overview of the article title, author, year of publication, country and type of article. The table aims to provide an overview of the papers gathered through the SLR search process and their respective details.

Figure 1 – Flowchart depicting the article search and collection process

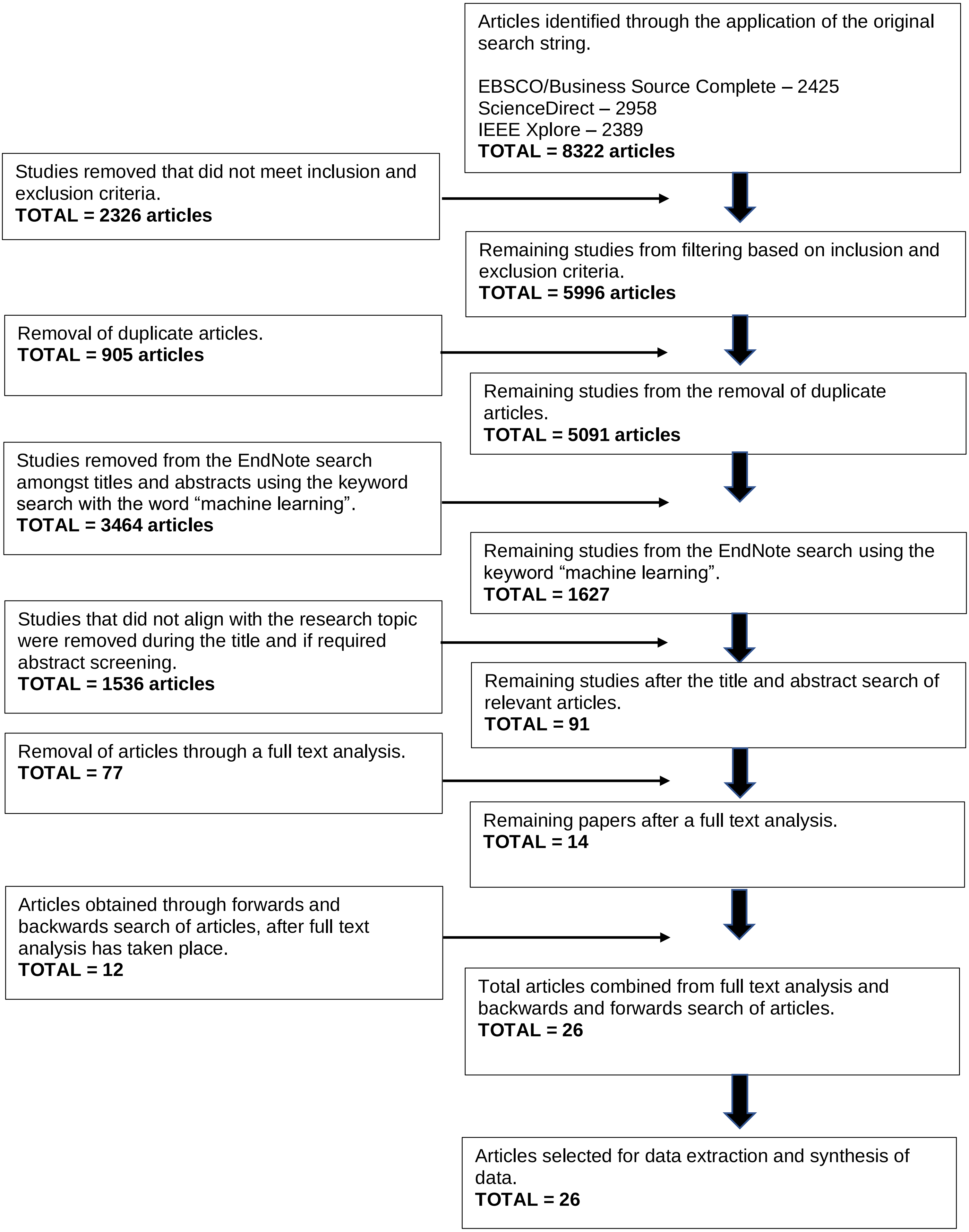

Table 1 – Summary *table of articles gathered and selected for the SLR*

#	Title	Author	Country/Region	Year Published	Article Type
1	A systematic review of machine learning in logistics and supply chain management: Current trends and future directions	Akbari, M., & Do, T. N.	Vietnam (Ho Chi Minh)	2021	Literature review
2	Machine learning: The new 'Big thing' for competitive advantage	Attaran, M., & Deb, P.	USA (California)	2018	Literature review
3	Predicting supply chain risks using machine learning: The trade-off between performance and interpretability	Baryannis, G., Dani, S., & Antoniou, G.	United Kingdom (England)	2019	Case study
4	Machine learning for industrial applications: A comprehensive literature review	Bertolini, M., Mezzogori, D., Neroni, M., & Zammori, F.	Italy	2021	Literature review
5	A systematic literature review of machine learning tools for supporting supply chain management in the manufacturing environment	Breitenbach, J., Haileselassie, S., Schuerger, C., Werner, J., & Buettner, R.	Germany	2021	Literature review
6	A supervised machine learning approach to data-driven simulation of resilient supplier selection in digital manufacturing	Cavalcante, I. M., Frazzon, E. M., Forcellini, F. A., & Ivanov, D.	Brazil, Germany	2019	Case study
7	Automated process monitoring in 3D printing using supervised machine learning	Delli, U., & Chang, S.	USA (Texas)	2018	Case study
8	AI in operations management: Applications, challenges and opportunities	Dogru, A. K., & Keskin, B. B.	USA (Mississippi & Alabama)	2020	Literature review

9	Systematic review on machine learning (ML) methods for manufacturing processes – Identifying artificial intelligence (AI) methods for field application	Fahle, S., Prinz, C., & Kuhlenkötter, B.	Germany	2020	Literature review
10	Tool wear monitoring of a retrofitted CNC Milling machine using artificial neural networks	Hesser, D. F., & Markert, B.	Germany	2019	Case study
11	Machine learning applications for sustainable manufacturing: A bibliometric-based review for future research	Jamwal, A., Agrawal, R., Sharma, M., Kumar, A., Kumar, V., & Garza-Reyes, J. A.	United Kingdom (England), India	2021	Literature review
12	Imbalanced classification of manufacturing quality conditions using cost-sensitive decision tree ensembles	Kim, A., Oh, K., Jung, J., & Kim, B.	Republic of Korea	2017	Case study
13	Machine learning-based anomaly detection via integration of manufacturing, inspection and after-sales service data	Ko, T., Lee, J. H., Cho, H., Cho, S., Lee, W., & Lee, M.	Republic of Korea	2016	Case study
14	Data-driven smart manufacturing: Tool wear monitoring with audio signals and machine learning	Li, Z., Liu, R., & Wu, D.	USA (Florida, New York)	2019	Case study
15	Comparison of machine learning methods applied to the estimation of manufacturing cost of jet engine components	Loyer, J., Henriques, E., Fontul, M., & Wiseall, S.	Portugal, United Kingdom (England)	2016	Case study
16	Predicting shim gaps in aircraft assembly with machine learning and sparse sensing	Manohar, K., Hogan, T., Buttrick, J., Banerjee, A. G., Kutz, J. N., & Brunton, S. L.	USA (Seattle)	2018	Case study

17	A systematic review of the research trends of machine learning in supply chain management	Ni, D., Xiao, Z., & Lim, M. K.	China, United Kingdom (England)	2019	Literature review
18	A Bayesian framework to estimate part quality and associated uncertainties in multistage manufacturing	Papananias, M., McLeay, T. E., Mahfouf, M., & Kadirkamanathan, V.	United Kingdom (England)	2019	Case study
19	Identification and classification of materials using machine vision and machine learning in the context of industry 4.0	Penumuru, D. P., Muthuswamy, S., & Karumbu, P.	India	2019	Case study
20	Machine learning in manufacturing and industry 4.0 applications	Rai, R., Tiwari, M. K., Ivanov, D., & Dolgui, A.	USA (South Carolina), India, Germany, France	2021	Editorial
21	The interpretive model of manufacturing: A theoretical framework and research agenda for machine learning in manufacturing	Sharma, A., Zhang, Z., & Rai, R.	USA	2021	Literature review
22	A survey of the advancing use and development of machine learning in smart manufacturing	Sharp, M., Ak, R., & Hedberg, T.	USA	2018	Literature review
23	Performance analysis of IoT-based sensor, big data processing, and machine learning model for real-time monitoring system in automotive manufacturing	Syafrudin, M., Alfian, G., Fitriyani, N., & Rhee, J.	Republic of Korea	2018	Literature review
24	A review of machine learning for the optimisation of production processes	Weichert, D., Link, P., Stoll, A., Rüping, S., Ihlenfeldt, S., & Wrobel, S.	Germany	2019	Literature review

25	An approach to monitoring quality in manufacturing using supervised machine learning on product state data	Wuest, T., Irgens, C., & Thoben, K.	Germany, United Kingdom (Scotland)	2013	Literature review
26	Machine learning in manufacturing: Advantages, challenges, and applications	Wuest, T., Weimer, D., Irgens, C., & Thoben, K.	USA, Germany, United Kingdom (Scotland)	2016	Conceptual

This methodology demonstrated the SLR process used to obtain and analyse the information for data extraction. The following section is the findings which present information about the journal articles collected, such as; the time of publications, style of articles, the general themes amongst the broader field of literature reviews and publications by region.

Chapter 4: Findings

This chapter will present the findings from analysing the articles gathered through systematic research. A total of five themes have been identified, along with the relative sub-themes that emerged within those themes. The themes identified included ML and operations, quality management, supply chain management, cost and the future of ML. The findings of other themes will be discussed along with their underlying sub-themes concerning one another.

4.1 Overview

The overview of ML in manufacturing entails the style of articles and the time they were published, publication of articles by region, benefits of ML and the challenges in adopting ML in the manufacturing sector.

4.1.1 Article time published and style

Across the last decade spanning 2012 to 2021, the articles amongst the published findings experienced an increase in frequency as time advanced. The year with the most articles published was 2019. The years with no articles published included 2014, 2015 and 2022. Figure 2 below illustrates the articles' findings according to the year they were published.

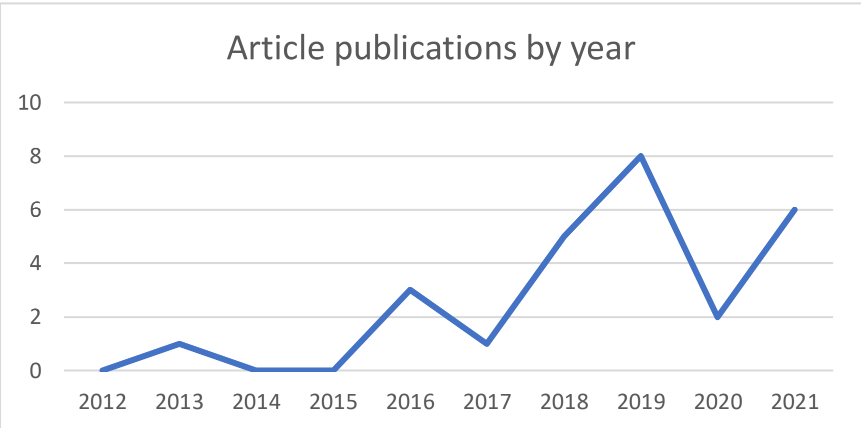

Figure 2: Article publications by year

Amongst the articles gathered, the results contained 13 literature reviews, 11 case studies, one editorial and one conceptual paper. Literature reviews showcase the literature surrounding the topic and further build on existing knowledge. Case studies demonstrate a real-life application of the research topic. Editorials provide objective viewpoints based on current knowledge, and conceptual papers summarise the topic in focus. Figure 2 below depicts the domination of literature review articles, with case studies following closely and the other articles amongst the findings gathered.

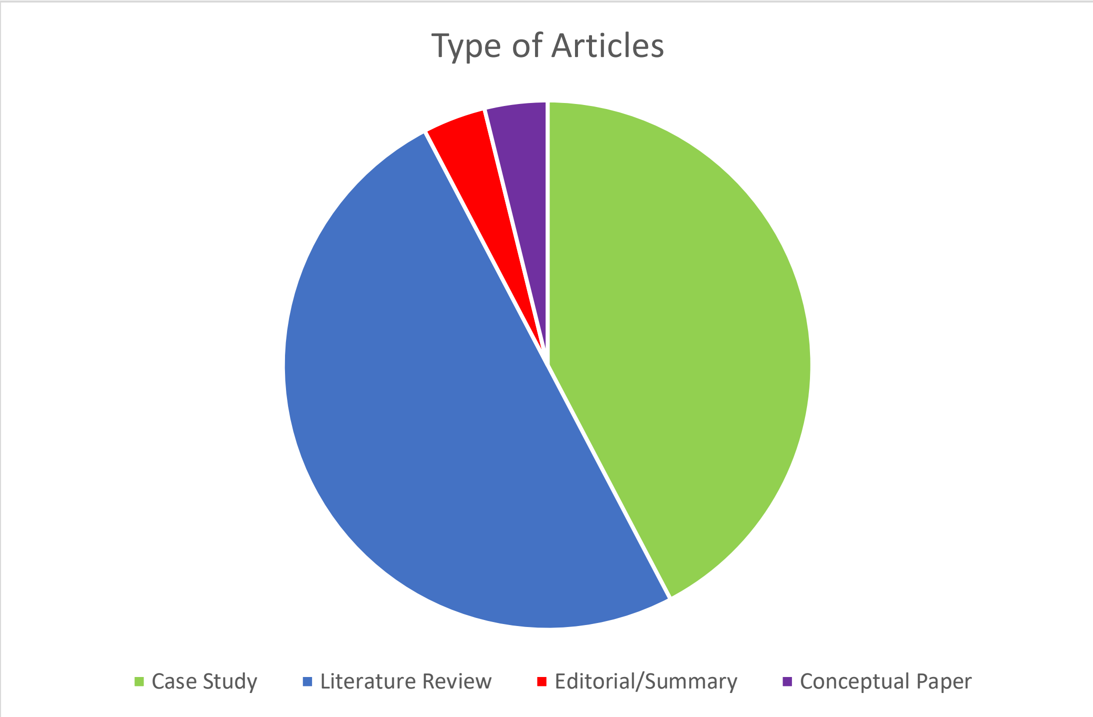

Figure 3: Pie chart showing the type of articles gathered

Table 2 below shows the type of articles published by the literature review scholars and gathered by the researcher in the systematic literature search. Additionally, Table 3 below showcases the various focuses of the literature review articles amongst the findings gathered by the researcher. The researcher was prompted to further analyse the research papers, given the increased number of publications and various forms of articles, to answer questions surrounding the current state of research concerning ML in manufacturing. Across literature review articles, there is some degree of overlap amongst the articles published, but each article has its own theme and focuses on its own respective aspect.

In the researcher's dataset, most journal articles collected were literature reviews. As stated in the findings, ML is in an early stage of development in the manufacturing environment. It raises the question; does the literature gathered use similar sources? To answer this, the researcher compared the datasets across the thirteen literature reviews compiled with their respective datasets to gain a deeper insight to draw conclusions based on their similarities and differences. In the findings section, tables 2 and 3 display the uniqueness amongst the papers' focuses that are spread out, yet have a small amount of overlap, but is not broad.

Additionally, based on the past growth of articles in the field of ML in the manufacturing industry, future applications can be expected to grow positively as time unfolds. Amongst the type of articles, the two dominant forms that emerged included literature reviews and case studies. On the contrary, articles in the form of case studies and editorials were limited.

#	Author	Article Title	Paper Focus
1	Akbari, M., & Do, T. N.	A systematic review of machine learning in logistics and supply chain management: Current trends and future directions	ML in logistics and supply chain management
2	Attaran, M., & Deb, P.	Machine learning: The new 'Big thing' for competitive advantage	ML for competitive advantage
3	Bertolini, M., Mezzogori, D., Neroni, M., & Zammori, F.	Machine learning for industrial applications: A comprehensive literature review	Industrial applications of ML
4	Breitenbach, J., Haileselassie, S., Schuerger, C., Werner, J., & Buettner, R.	A systematic literature review of machine learning tools for supporting supply chain management in the manufacturing environment	ML for supporting supply chain management
5	Dogru, A. K., & Keskin, B. B.	AI in operations management: Applications, challenges and opportunities	ML in operations management
6	Fahle, S., Prinz, C., & Kuhlenkötter, B.	Systematic review on machine learning (ML) methods for manufacturing processes – Identifying artificial intelligence (AI) methods for field application	ML for identifying AI methods for field application
7	Jamwal, A., Agrawal, R., Sharma, M., Kumar, A., Kumar, V., & Garza-Reyes, J. A.	Machine learning applications for sustainable manufacturing: A bibliometric-based review for future research	ML for sustainability
8	Ni, D., Xiao, Z., & Lim, M. K.	A systematic review of the research trends of machine learning in supply chain management	ML in logistics and supply chain management
9	Sharma, A., Zhang, Z., & Rai, R.	The interpretive model of manufacturing: A theoretical framework and research agenda for machine learning in manufacturing	ML theoretical framework

10	Sharp, M., Ak, R., & Hedberg, T.	A survey of the advancing use and development of machine learning in smart manufacturing	ML development
11	Syafrudin, M., Alfian, G., Fitriyani, N., & Rhee, J.	Performance analysis of IoT-based sensor, big data processing, and machine learning model for real-time monitoring system in automotive manufacturing	Sensor and big data processing and ML models for real-time monitoring
12	Weichert, D., Link, P., Stoll, A., Rüping, S., Ihlenfeldt, S., & Wrobel, S.	A review of machine learning for the optimization of production processes	ML in optimising production
13	Wuest, T., Irgens, C., & Thoben, K.	Machine learning in manufacturing: Advantages, challenges, and applications	ML advantages, challenges and applications

Table 2: Summary table of the articles used by literature review scholars

Author	Article Title	Paper Focus	Frequency	Mentioned in
Bengio, Y., Courville, A. and Vincent, P.	Representation Learning: a review and new perspectives	Representation learning	2	Articles 2 & 3
Harding, J., Shahbaz, M., & Kusiak, A.	Data mining in manufacturing: A review	Data mining	4	Articles 3, 6, 12 & 13
Köksal, G., Batmaz, İ., & Testik, M. C.	A review of data mining applications for quality improvement in manufacturing industry	Data mining and quality improvement	4	Articles 6, 9, 12 & 13
McAfee, A. and Brynjolfsson, E.	Big data: the management revolution	AI and big data	2	Articles 2 & 3
Ni, D., Xiao, Z. and Lim, M.K.	A systematic review of the research trends of machine learning in supply chain management	ML and logistics and supply chain management	2	Articles 1 & 4
Sharma, R., Kamble, S.S., Gunasekaran, A., Kumar, V. and Kumar, A.	A systematic literature review on machine learning applications for sustainable agriculture supply chain performance	ML and agriculture	2	Articles 1 & 7
Wuest, T., Weimer, D., Irgens, C. and Thoben, K.D.	Machine learning in manufacturing: advantages, challenges, and applications	ML	2	Article 1 and the researcher's paper
Zhong, Ray Y, Xun Xu, Eberhard Klotz, and Stephen T. Newman	Intelligent manufacturing in the context of industry 4.0	Industry 4.0	2	Articles 9 & 11

Table 3: Discussion table of the paper focus of literature review articles

4.1.2 Publications by region

The articles in the literature search revealed their country of origin. Most publications originated from developed nations, including the USA, Germany, the UK, France, Italy, Portugal, Korea and China. Developing nations were present, including India, Brazil, and Vietnam. Of the 26 articles, nine were from the USA, seven were from the UK, and eight were from Germany. France, Italy, and Portugal were present in one article each. China, Vietnam and Brazil were featured in one article, respectively. Twenty-seven per cent of total articles collaborated with other countries. Given the domination of literature reviews discussed and depicted in the figure above, across the 13 literature review articles, 10/13 articles were from a standalone country, while 2/13 articles were in collaboration with two countries from separate regions. Figure 4 below shows the publication by region with the breakdown of the style of articles.

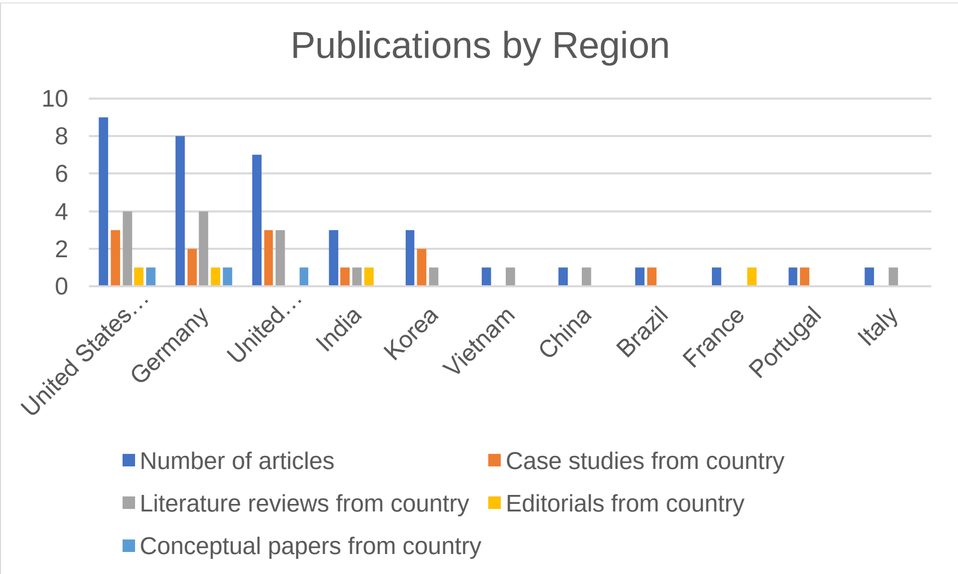

Figure 4: Publication of articles by region

With content from the literature reviews gathered, the authors reported on various topics. The main topics in focus of the literature included the application of ML in the logistics and supply chain field (Akbari & Do., 2021; Breitenbach et al., 2021; Ni et al., 2019), leveraging ML for a competitive advantage (Attran & Deb, 2019), applying ML to industrial settings and manufacturing environments (Bertolini et al., 2021; Fahle et al., 2020), ML benefits, challenges and opportunities (Dogru & Keskin, 2020), ML in sustainable practices (Jamwal et al., 2021) and ML in monitoring manufacturing and production quality (Syafrudin et al., 2019; Wuest et al., 2013).

A curious discovery was that developed nations provided the largest cluster of articles. The USA, Germany and the UK were predominant regions, followed by developing countries, namely; India, Vietnam, Brazil and China. The domination of developed nations in the literature reflects the prevalence of ML in the manufacturing sector and the popularity of ML adoption; developing countries report on ML, only with less frequency. Such frequency figures indicate that developed and developing nations exercise the application of ML with varying academic reporting and coverage levels. With technology and capabilities rising amongst developing nations, there is future potential for more coverage.

4.1.3 Benefits of ML

As far as ML is concerned, when integrated with manufacturing, it brings various benefits to the manufacturing organisation. The literature identifies multiple benefits of ML, such as greater accuracy, decision-making and faster processing of activities. Cavalcante et al. (2019) note that larger ML datasets have faster data processing times than traditional statistical methods. Similarly, Attaran and Deb (2018) claim that ML's critical benefits include faster processing of tasks and activities, producing reliable decisions, outcomes and results. They further argue that ML provides greater accuracy over humans in tasks such as programming, data capture, effort and time expenditure and offers more significant value creation in performing tasks with no need for human intervention. Improved efficiency of manufacturing systems and processes, resource utilisation and tool lifespan prediction benefits were identified by Jamwal et al. (2021). Both Jamwal et al. (2021) and Breitenbach et al. (2021) identify that ML, when applied correctly, can bring about greater control and flexibility in manufacturing practices and efficiently solve complex problems.

In the current environment in which manufacturing firms operate, they all aim to be competitive in their market to be profitable, competitive and remain economically viable. ML can increase a manufacturing firm's competitiveness. ML, robots and interpretive technologies collaboratively serve as an ally alongside manufacturing firms to redeem and retain manufacturing competitiveness, particularly with ML's rise to prominence and its role in modern manufacturing practices (Sharma et al., 2020). There is a critical need to recognise the role ML plays. A firm's ability to leverage ML to increase their manufacturing competitiveness correctly will shift towards leading the forefront of their manufacturing practices. Overall, the benefits of ML in the manufacturing sector indicate that ML is the way forward over traditional methods involving human input. We now turn to explore the challenges faced in the field of ML in manufacturing.

4.1.4 Challenges in adopting ML

Despite the wide range of benefits ML brings to the manufacturing sector, various challenges stand in the way. Utilising ML requires employees that are skilled enough to be able to handle and understand the implications of ML in an organisational setting. Fahle et al. (2020) identify a critical challenge of ML; the shortage of workers within organisations that are trained and qualified to work alongside ML. Likewise, a skill deficit is identified by Akbari and Do (2021), where employees are not competent in operating techniques. Such deficits can limit the level of autonomy, whereby the level of staff skill can directly influence the level of autonomy in ML.

Moreover, data quality is a recurring issue discussed throughout the literature. Data with a lack of transparency in ML can create complexity, unfamiliarity and misunderstanding among ML techniques. Additionally, they make the decision-makers and practitioners in manufacturing settings doubt the results generated by ML (Akbari and Do., 2021). ML's growing complexity and capability have brought data quality under scrutiny. Issues exist regarding data quality used in training ML models, along with data containing missing values or frequently insufficient data for use (Bertolini et al., 2021). Similarly, Attaran and Deb (2018) argue that poor data quality and bias within data drag down the power of ML models, directly affecting how organisations utilise ML models and tools.

Furthermore, the security of information is a concern highlighted by Dogru and Keskin (2020). AI applications operate in a legal grey area with a lack of regulation. The challenge of custom products in the manufacturing sector is discussed by Papananias et al. (2019). Dogru and Keskin (2020) further build on this, explaining that the increased demand for customised products requires more information to collect, process and store personal information, both structured and unstructured. As a result of the increased personal information gathered, supply chains must invest a large amount of IT capital investment to hold confidence and ensure all data gathered is securely stored. Smaller firms are more likely to lack the infrastructure and capital requirements to utilise ML technology and will instead opt to engage with more prominent firms to provide such services. Syafrudin et al. (2018) contribute to the topic of security concerns. They identify security as an issue where the number of IoT devices being adopted and implemented adds further vulnerability to information security. Lastly, other concerns, such as the small size of datasets, errors, inconsistent values, and lack of accessible data, are raised by Ni et al. (2019).

4.2 ML and operations

Within the manufacturing industry, the operations field entails all functions that contribute to the operative practices of manufacturing. The field of operations is broad and can encompass various topics with the inclusion of ML, such as predictive and preventative maintenance, resource scheduling, production planning and control, performance management and evaluation, human-robot collaboration, process improvement, the requirement of skilled employees working with ML and investment decisions.

4.2.1 ML in predictive and preventative maintenance

Maintenance in manufacturing is an essential practice to ensure that manufacturing operations can be carried out in a reliable and consistent manner. Various forms of maintenance are present amongst manufacturing practices, for example, predictive and preventative maintenance. These two types of maintenance will be discussed, along with examples of applications in the manufacturing industry.

Predictive maintenance is an important area in the manufacturing sector. When manufacturing goods, machines must operate efficiently and reliably. With time, machines require maintenance. Machines can suffer downtime or breakages, which could come unexpectedly without maintenance. Predictive maintenance is the maintenance of machinery carried out by predicting when the optimal time is required for scheduled maintenance to be performed. It supports the running and lifespan of machinery by preventing unexpected machinery downtime, improving the availability of machinery and detecting faults and defects that occur when machines are in use (Rai et al., 2021). Likewise, ML techniques offer potential opportunities for predictive maintenance to achieve sustainable manufacturing (Jamwal et al., 2021). The application of ML to predictive maintenance is highlighted by Attran and Deb (2018). Hesser and Markert (2019) explored the exploration of retrofitting CNC machines with artificial neural networks (ANN). They revealed that the use of advanced analysis data from ML algorithms holds the potential for performing predictive maintenance on manufacturing machinery. Predictive maintenance is a prime example of the benefits derived from the digitalisation of manufacturing processes (Fahle et al., 2020). Hence, the topic of predictive maintenance demonstrates the role of ML and the value it provides.

Similarly, according to Sharp et al. (2018), preventative maintenance is dissected into three categories: cycle-based, current condition-based, and prediction condition-based. Cycle-based plans are designed to schedule maintenance based on a predefined number of hours or duty cycles (e.g., revolutions performed by a motor). Current condition-based plans perform maintenance when an assessment is carried out on the current state of machinery or reactively when a machine rises in the number of faults produced/experienced. Prediction condition based assesses all present and past states of the machinery along with its future projections of performance to predict when a fault is likely to occur, or the remaining lifespan of the machine left. Examples include previous predictions of tool life remaining in CNC machining and drilling, as highlighted by Papananias et al. (2019).

4.2.2 ML used in resource scheduling/production planning and control

Bertolini et al. (2021) define production planning and control as the activities required to manage and improve the operation of manufacturing processes. Resource scheduling is a subset of production planning and control. Furthermore, resource scheduling plays a vital role in the manufacturing process as it aims to reduce supply chain issues such as oversupply and shortage of products. Bertolini et al. (2021) discovered that utilising resource scheduling is most effective in volatile markets with high demand and short product lifecycles. Forms of ML algorithms utilised include support vector machines (SVM), k-nearest neighbour (KNN) and neural networks (NN).

In the task of factory scheduling amongst manufacturing operations, predicting lead time is imperative, as the performance of a manufacturing firm is dependent on the current operating capacity of the machinery in use. Applications of factory scheduling include just-in-time and just-in-sequence environments (Breitenbach et al., 2021). Ni et al. (2020) highlight that using ML algorithms will improve the overall accuracy of factory scheduling and balance constraints in manufacturing environments that use a build-to-supply production system.

4.2.3 ML used in performance management and evaluation

The value of ML in the manufacturing sector comes in the form of offering support through decision-making across various manufacturing applications in the field of performance management (Rai et al., 2021). ML models can evaluate data and provide feedback and overview, leading to improvements in cost, quality, lead time and flexibility of operations (Breitenbach et al., 2021). They present their findings on utilising ML to predict cycle time and improve supply chain operations' efficiency. They further claim that the models can be applied to predict the cycle time of various production lines, including complete production lines, line segments or single operations. Types of ML algorithms included Neural Networks and Decision Trees, which in a trial demonstrated predictions of 87.6% and 76.5%, respectively. Both were found for application in tasks including lean and cycle time prediction. Using predictive measures has applications in fields such as required time for manufacturing processes to complete a cycle, predicting future cycle times and examining the in-line performance. On the contrary, they argue that the ML algorithms listed above are not to be used to predict failures and downtime.

4.2.5 ML and human-robot collaboration

Robotics alone provides a wide range of applications in the ML field, including AI technologies and human-robot collaboration. In the field of human-robot collaboration, human safety is a priority (Fahle et al., 2020). ML, compared to human tasks and function, is at a present state that easily matches or exceeds human ability. Examples of this include image recognition and natural language processing. Abilities such as image recognition can automatically carry out tasks, such as identifying defects in the manufacturing process or failures in manufacturing equipment. With advancements in technology, interpretive technology is bound to evolve with cognitive function and ability.

4.2.6 ML and process improvement

Improving the existing process in manufacturing is something that ML can contribute towards creating improvements. A use case by Penumuru et al. (2020) explores the use of ML in identifying and classifying materials in manufacturing processes. They gathered a dataset and analysed it using a support vector machine (SVM) algorithm, whereby the results showed 100% accuracy and were cross-validated with ten different cases. The proposed methodology with SVM could be applied to conventional machine tools in factories with provisions for minor modifications to machinery. They further acknowledge that through integrating ML into machinery, the intelligence of machinery increases and becomes more industry 4.0 compliant through the integration of decision-making and cognitive perception skills.

Also, a second case study for manufacturing process improvement uses ML algorithms to predict the shims required to fill gaps in aircraft assembly, as discussed by Manohar et al. (2018). The size of the shims required to fill the gap was predicted using ML, which analysed historical data and streamlined the collection and processing of current data. Scans were taken and available in high-resolution data for greater accuracy. The PIXI_DUST ML algorithm could predict most gap values desired within tolerance, creating an accurately fitting shim.

4.2.7 Requirement of skilled employees working with ML

Having ML implemented in the manufacturing process requires the human skillset to understand the capabilities of the ML algorithm and leverage the ML algorithm/program for the organisation's benefit. Lack of doing so will create a black box effect, whereby the outcomes of the ML algorithms are not clearly understood. Skill deficits may exist around employees who are not competent and skilled in operating techniques, as outlined by Akbari and Do. (2021). Organisations with trained and competent staff should be comfortable to a degree with working with ML in operations, whereas organisations struggling to leverage the power and benefits of ML may want to reconsider their approach. With the above claims, Attaran and Deb (2018) argue that every organisation utilising ML requires staff that are qualified, trained, and dedicated to the utilisation of ML. It is a sizable investment that not all organisations are willing to commit to.

4.2.8 ML and Investment Decisions

The cost of manufacturing affects the feasibility, scale and profitability of the manufacturing being performed. Loyer et al. (2016) explain, whereby the cost of labour, cost of parts production, commercial discounts and period of manufacturing time can directly influence the cost of manufacturing. ML affects the cost of manufacturing by providing greater accuracy and efficiency of cost estimation according to variables such as production speed or capacity. When compared to human effort, calculating costs can be susceptible to human error and delays in calculations. Let us now consider the organisation's investment in ML algorithms for manufacturing processes.

An organisation choosing to invest in ML algorithms for their manufacturing processes is a decision that holds much weight and consideration. According to Sharma et al. (2021), for a firm to make investment decisions, such decisions need to be made considering the firm's business needs, capabilities and requirements. With the correct guidance and decision-making, the choice of ML algorithm will help drive such requirements.

The potential of cloud service technology to be part of a manufacturing organisation's business strategy is a discussion point acknowledged by Sharp et al. (2018), whereby they identify the potential benefits of migrating to cloud manufacturing, such as having access to data and resources in real-time and the ability to store enormous quantities of valuable data. Likewise, the adoption of cloud storage in manufacturing is highlighted by Rai et al. (2021), where organisations embrace it for data management and storage. Additional benefits include reducing costs and the drive for profitability through the reduced requirement of human effort in task management. We now turn to ML and sustainability in manufacturing.

4.3 ML and Quality Management

Quality management in manufacturing can broadly be defined as an area within a business that aims to achieve and maintain consistent standards. Quality management can be powered and supported by AI and ML. Technologies harnessed in quality management in conjunction with ML include augmented and virtual reality, robotics and additive manufacturing (Rai et al., 2021). Contrary to the presence and role of quality management discussed above, Ko et al. (2016) stress that the lack of quality control within organisational manufacturing practices can lead to poor quality and consequently, defective products, loss of consumer confidence and increased costs associated with handling returned items due to manufacturing defects experienced by the consumer.

Across the literature examined, there was a solid reoccurring focus of quality management in the manufacturing sector, being supported by ML. Quality management is reliant upon the correct resources to support the monitoring of quality across goods being produced. Additionally, monitoring quality involves detecting faults amongst production lines, real-time monitoring and predicting tool wear, and using RFID with ML models, all of which are discussed below.

4.3.1 ML used in fault detection and monitoring

Syafrudin et al. (2018) and Weichert et al. (2019) describe one of the quality management tasks, including fault detection. Fault detection in the manufacturing process aims to detect faults in manufacturing processes that may or may not be functioning in a usual manner. Regarding fault detection, Sharma et al. (2021) highlight that AI and ML have surpassed human ability in tasks such as natural language processing and image recognition.

Rai et al. (2021) argue that manufacturing fault detection must occur accurately and promptly. It provides organisations with a competitive advantage over their competitors by reducing the amount of downtime experienced. Utilising ML in fault detection is essential; it ensures that the level and quality of products produced by organisations are up to the required standards. Advanced technologies discussed by Rai et al. (2020) will further aid in fault detection, becoming increasingly more accurate and leading to further cognitive tasks in manufacturing led by ML (Sharma et al., 2021).

Monitoring quality in line is an effective way to detect errors in the manufacturing process and improve the quality of manufactured goods (Wuest et al., 2013). ML across the literature has been used as a tool to monitor the progress in manufacturing. Various forms of monitoring quality in manufacturing exist, such as real-time monitoring, which is explored by Syafrudin et al. (2018), automated process monitoring by Delli and Chang (2018) and similarly automatic visual inspection (Weichert et al., 2019).

Real-time monitoring, as proposed by Syafrudin et al. (2018), involves monitoring manufacturing processes through the internet of things (IoT) and big data. They proposed and developed a real-time monitoring system comprised of big data processing, IoT sensors and a hybrid ML prediction model to improve management's ability to monitor assembly line processes and locate and identify faults along the manufacturing line to reduce the number of preventable errors that could occur. The study showed that integrating IoT sensors and big data processing units is an effective way to analyse and process large quantities of sensor data more efficiently than existing traditional models.

Similarly, Delli and Chang (2018) discuss the concept of automated process monitoring in the form of a three-step process that integrates image processing and supervised ML for the real-time monitoring of 3D printing processes. Step 1 involved the identification of a checkpoint for 3D printing according to the geometry of the design. Step 2 took images of the part being produced in-process at each checkpoint. Furthermore, step 3 performed image processing and analysis. The outcome concluded that the method/concept could detect failure defects, including depletion of printer filament, printer filament, prints stopping halfway through progress and identifying structural defects amongst the item produced.

Wuest et al. (2013) note the large volume of complex and dimensional data gathered in performing quality management checks. In response, they developed a solution for handling big data by combining cluster analysis and a support vector machine (SVM) to address quality issues and improve the quality of the items produced throughout the manufacturing process. Kim et al. (2018) further support the claims of large and complex data gathered in the manufacturing process made by Wuest et al. (2013) and note that ML can be used to predict defects based on historical data gathered from the manufacturing process.

4.3.2 ML in the prediction of tool wear

Across the literature, a frequent occurrence was the use of ML to predict tool wear in manufacturing settings. Below, the application of ML to predict tool wear will be discussed in the CNC machining and milling environment.

Throughout the manufacturing process, tools are used to help manufacture products that are being produced. Such machines are subject to wear and tear, which can reduce the accuracy of the machining performed in the manufacturing process. One form of machining frequently presented throughout the literature was machine milling in computer numerical control (CNC) machines (Hesser & Markert., 2019; Li et al., 2019; Papananias et al., 2019; Weichert et al., 2019). Papananias et al. (2019) state that tool wear is an area that can be monitored through the use and application of ML and that machine milling, in conjunction with CNC machines, is an accurate machining method, including milling and drilling.

Predicting wear amongst CNC machinery is also highlighted by Hesser and Markert (2019). They retrofitted a CNC machine with an artificial neural network (ANN) to predict tool wear on a machining tool. Their approach was found to be successful and can be modified to form predictions for the remainder of the tool's lifespan by using an ANN based on supervised regression ML. Further success in accurate tool wear prediction was noted by Li et al. (2019). They utilised a novel-based signal audio approach to improve the accuracy of predicting tool wear amongst machines in milling operations. This was actioned through multiple cutting tests, where audio signals were collected and used to train and validate the predictive ML model. Results showed through one method that the audio signals extracted and related to the response of milling tool operations improved the prediction accuracy. With the use of CNC machinery in manufacturing, having the ability to produce customisable solutions, ML is a reliable tool to maintain and predict the required maintenance of the CNC machine.

4.3.3 Use of RFID with ML Models

Regarding the use of ML in manufacturing, tracking is done with radio frequency identification (RFID) technology, whereby goods can be tracked throughout the manufacturing process. The use of RFID technology and ML models in manufacturing brings considerable benefits, including detecting outliers, false positive readings, results and accurate asset tracking. Forms of ML utilised in conjunction with RFID technology include support vector machine (SVM), decision trees and logistics regression. Examples of decisions made with the help of RFID technology and ML contain the acceleration/slowing of manufacturing processes and tracking and locating defective products produced in line (Breitenbach et al., 2021).

4.4 ML and Supply Chain Management

Supply Chain Management (SCM) is a crucial area that is linked to the function of manufacturing. According to Bertolini et al. (2021), SCM involves planning, controlling and executing logistical flows. It ranges from acquiring raw materials to delivering end products in the most cost-effective way possible. SCM activities include inventory management and transportation, demand planning and sourcing. With the use of ML in SCM, there is plenty more exploration to be done. This section will discuss ML in the supply chain management area with a focus on ML used in SCM, ML used in sales and demand estimation, predicting SCM risks, transportation in SCM, ML used for supplier selection and ML in sustainability.

4.4.1 ML and sales, demand estimation in supply chain management

The sales and demand estimation in SCM is a vital function in which a great deal of planning is required for success. Sales and demand estimation in SCM is tricky at times due to accurate and good quality demand forecasting serving as a sales estimation for all potential estimations, which is complex to estimate. Utilising ML in demand forecasting is highlighted by Attran and Deb (2018). With ML algorithms in sales and demand estimation, the accuracy in predicting inventory level requirements and sales and demand forecasting can be improved. ML algorithms can further remove errors from datasets and provide non-linear models which suit demand/sales curves more accurately. Such algorithms are also not reliant upon accurate historical data, allowing ML algorithms to be promoted as an alternative for demand and planning in SCM (Ni et al., 2019). Akbari and Do (2021) explain the potential of ML in tasks such as tracking and enabling automation in the supply chain of the food and beverage supply chain industry, along with creating empowerment amongst vendors for the management of inventory replenishment systems. Overall, applying ML in sales and demand estimation in SCM creates a supply chain that is reliable, transparent and able to adapt to changing environments.

4.4.2 ML for predicting supply chain management risks

In terms of predicting supply chain management risk, a risk prediction framework for supply chain risk management (SCRM) is proposed by Baryannis et al. (2019), using data-driven AI techniques. It is reliant upon collaboration and interaction between AI and SCM experts. The framework emphasises linking the choice of metrics and algorithms to SCRM goals and the difficulties of working with imbalanced datasets. Effects may include the prioritisation of interpretability over predicting performance. The application of this framework in a real-life setting was with a case study of aerospace manufacturing supply chains affected by the risk of delayed deliveries. The case study results demonstrated that the author's framework could provide good performance across metrics, including predicting performance and interpretability using black-box and interpretable ML models (Baryannis et al., 2019). Another application area of ML in the field of risk prediction is identified by Breitenbach et al. (2021) for the decision-making surrounding manufacturing risks and in preventing potential risks that may arise in the manufacturing process. The integration and application of ML techniques allow for SCM risks to be detected and improve the performance and reliability of an organisation's supply chain.

4.4.3 ML transportation in supply chain management

Transportation in SCM is one key area in which goods and services are transported for delivery. Ni et al. (2019) note using ML applications to resolve issues with vehicle routing in SCM. In supply-chain delivery, the optimal routes desired often cannot be created by humans most efficiently compared to ML's skill and ability. Overall, ML algorithms and apps are skilled, hold the strong ability to analyse large datasets and provide fast, accurately forecasted results.

4.4.4 ML used for supplier selection

Supplier selection in supply chain management is an important area that needs to be reliable and consistent. The primary function of ML applications in SCM is evaluating and selecting suppliers. Ni et al. (2019) note that ML algorithms can reveal potential correlations that may exist between supply chain complexity and the frequency of supply chain disruptions that may occur. Similarly, Cavalcante et al. (2019) discuss the selection of suppliers in the manufacturing sector using ML applications and data analytics to avoid any potential inconveniences, such as estimating the likelihood of disruptions and forecasting performance impacts. The likelihood of supplier disruptions was calculated using digital data amongst intelligent manufacturing systems and the impact on supply chain performance. The focus was directed on resilient supplier selection in the digital manufacturing sector. Tests were run using simulation tools and indicated that supervised machine learning (SML) could support resilient selection and decision-making processes, resulting in greater accuracy in predicting delivery from suppliers and improvements and decision-making. Selecting reliable suppliers can be successfully achieved with ML applications, detecting all potential risks and disruptions that may come with suppliers and their effects on manufacturing operations and the wider supply chain network.

4.4.5 ML and Sustainability

With the use of ML in manufacturing, sustainability remains an essential factor to ensure that the efforts and investments of ML can prolong the lifespan of activities and functions. ML techniques in sustainable manufacturing offer wider opportunities for sustainable development, including but not limited to predictive maintenance, supply chain management (Jamwal et al., 2021) and condition monitoring (Attran & Deb, 2018). Furthermore, a study by Jamwal et al. (2021) showed that adopting new ML approaches can bring improvements in the manufacturing industry, such as improved resource utilisation. Ni et al. (2019) note that a reduction in waste and emissions can be achieved thanks to accurate ML models across the supply chain network. In summary, sustainable manufacturing practices can be upheld with ML.

4.6 Future of ML

The prospect of ML growth and development in manufacturing holds various future potential scenarios which could occur. Each of these scenarios varies in its impact on the manufacturing sector. Future potentials to be discussed below include the transitional change in ML with cognitive robots, transition to industry 4.0, disruption of ML towards employment, and growth and digital development of ML.

4.6.1 Transitional change in ML with cognitive robots

Sharma et al. (2021) highlight the growing shift towards utilising cognitive robotics in combination with ML. Such a shift indicates that the robots used by organisations are becoming equipped with ML sensors and algorithms that can perform cognitive functions, including understanding the environment in which the robots operate, determining goals and planning actions to be performed. Furthermore, cognitive robots must consider the states of other entities in their environment, like humans. Alternatively, the prospects of man and machine in a shop floor environment are predicted to change with the introduction and growth of collaborative and cognitive robotics and 3D printing/additive manufacturing in the manufacturing industry (Sharma et al., 2021).

4.6.2 Transition to Industry 4.0

The fourth industrial revolution, aka Industry 4.0, is defined by Dogru and Keskin (2020) as the transition into the digital age, including the digitisation of manufacturing, adoption of computers and automated processes towards enhanced smart and autonomous systems powered by computers, algorithms, data and automated processes. Other drivers of industry 4.0 include autonomous robots, IoT, 3D printing/additive manufacturing, digital twins, augmented reality and blockchain technology.

4.6.3 Disruption of ML towards employment

Historically, robots have been excluded from human involvement in factory floor operations. The merge of ML, robots and humans indicates the evolution currently taking place and its effects on how ML, in conjunction with robots and humans, can work collaboratively in the manufacturing industry (Sharma et al., 2021). The authors, on the contrary, also identify that robotic and automated processes led by ML have been causing adverse results in the creation of well-paying jobs in the manufacturing industry, resulting in opposition from labour unions to such processes. Similarly, the growing concern of jobs requiring substantial training and education is under threat by ML technology (Attaran and Deb, 2018).

The evolution and advancements of automation technologies throughout history, such as AI and ML, have disrupted industries and employment for humans (Sharma et al., 2021). The authors unpack this element of disruption towards human employment and its impact on job losses. It is argued that cognitive automation will cause more significant employment disruption and loss of jobs for humans, who sit on the lower scale of income earning and level of education attained. Individuals who find themselves on the higher end of the scale will still be affected by the shift in the new requirements emerging for jobs tied to cognitive computing and the multidisciplinary approach of ML. Various driving forces behind ML are identified by Attaran and Deb (2018). These include the advent of big data, increased availability and utilisation of computing power, the growing understanding of technology, the value it provides firms and the growth and rise of economic forces. With the disruption ML brings towards the employment sector, the demands of roles in organisations will slightly shift, and organisations will need to adapt to such changes to minimise the interference ML creates in the job market.

4.6.4 Growth and digital development of ML

With the emergence of ML becoming a staple in the manufacturing industry, there are various future potentials and opportunities for continued growth and development, manufacturing operations improvement, and the need for greater variety among ML models used. Key areas of growth identified include the growth of ML and digital manufacturing.

ML is growing at an accelerated rate, along with all its associated technologies. Such advancements in technology will bring about greater accuracy in making predictions of customer behaviour and allow personalised changes to be made (Akbari & Do, 2021). Further building on the conversation about the accelerated growth of ML, Ni et al. (2020) calls for a greater need for variety among ML models. Based on the current algorithms utilised and explored in SCM, including neural networks and support vector machines, there is additional room for variety and more significant growth regarding the ML models utilised in SCM. For future organisations or departments to implement ML models in the manufacturing industry, models have the potential to be developed more robustly to avoid the black box effect of a bunch of unknown data being produced.

In turn, making the ML method harder to be accepted by the organisation, the better interpretability of ML algorithms will help organisations make more informed decisions when better convinced by the results of ML.
Shifting towards the field of smart manufacturing and its involvement with ML, Smart manufacturing can be strengthened by adopting and hybridising operation management techniques in conjunction with ML algorithms (Bertolini et al., 2021). The above claims are

similarly reported by Rai et al. (2021), where the current shift in manufacturing is assimilating and being transformed thanks to the adoption and utilisation of ML techniques.

Moreover, a study reported by Cavalcante et al. (2019) reported the results from an analysis carried out regarding integrating simulation and ML models, which can evaluate digital services performance in manufacturing. The approach is fully digital and holds value in areas such as validating new services at lower cost and in less time when placed in a digital manufacturing context. They also note that the emergence of data-driven cultures amongst manufacturing firms could potentially result in ad-hoc relationships between customers and suppliers. The model in focus uses data that is not reliant upon costly data acquisition system software and programmes. Such an approach is viewed as an essential piece in the prompt adoption of digital manufacturing. They further discuss that data strategies must be developed within manufacturing firms and executed through strategic decision-making to unlock ML benefits.

Chapter 5: Discussion

The systematic research findings revealed that ML is diverse and widespread across various areas of manufacturing, such as operations, quality management, supply chain management and cost. We can speculate that the diverse applications of ML can be attributed to the key strengths of ML discovered in the findings. This chapter will discuss the research publications, the strengths of ML applications and the future of ML applications, based on the areas of the research findings where ML is applied.

5.1 Research publications

The researcher gathered publications to provide insight into the application of ML in the manufacturing sector. This section will discuss the publications of articles by region and year, followed by the type of articles published in the existing research.

In the researcher's dataset, most journal articles collected were literature reviews. As stated in the findings, ML is in an early stage of development in the manufacturing environment. It raises the question; does the literature gathered use similar sources? To answer this, the researcher compared the datasets across the thirteen literature reviews compiled with their respective datasets to gain a deeper insight to draw conclusions based on their similarities and differences. In the findings section, tables 2 and 3 display the uniqueness amongst the paper focuses that are spread out, yet have a small amount of overlap, but is not broad.

5.2 Strengths of ML applications

The application of ML is widespread and diverse. It can be applied to many applications and provide benefits based on specific strengths. These benefits include the accuracy of ML applications when applied to disciplines like manufacturing (Ni et al., 2020), the function of decision-making surrounding manufacturing-related decisions (Breitenbach et al., 2021) and ML application's ability to process tasks faster (Cavalcante et al., 2019). Such benefits will be explored, along with discussing examples regarding how they tie into the roles of ML.

5.2.1 Accuracy

Regarding accuracy, it is relevant to ML and manufacturing as it is desired for manufacturing practices to operate smoothly and feasibly. The application of ML provides more accurate estimations compared to human effort. ML delivers accuracy by performing human tasks with delivering greater accuracy as it is an automated process, which is not subjective to human error. Examples of ML applied for accuracy-related benefits include use amongst predictive and preventative maintenance, factory scheduling, fault detection and monitoring, prediction of tool wear, sales and demand estimation and predicting supply chain management (SCM) risks.

When applying ML in maintenance settings for predictive and preventative maintenance, the estimations and decisions made by the ML algorithm are required to be accurate for effective routine maintenance. Accurately predicting the tool wear of manufacturing machinery is crucial for organisations to make appropriate decisions and respond to the wear of manufacturing tools. Organisations can predict tool wear through predictive and preventative maintenance, reducing the effects of potential machine breakages and reducing downtime and quality. The literature widely explores the use of CNC machine milling. For example, Hesser and Markert (2019) retrofitted a CNC milling machining with artificial neural network (ANN) ML technology which was proven successful in accurately predicting tool wear. Such provides the potential for facilitating predictive and preventative maintenance.

With respect to fault detection and monitoring, such ensures consistent manufacturing standards and reinforces the need for it to occur accurately and promptly. An accurate ML model is essential so manufacturing organisations can detect errors and faults in manufacturing processes. For example, Delli and Chang (2018) discuss a three-step automated process monitoring whereby using image processing and supervised ML, the failures amongst 3D printers could be detected along with the depletion of resources such as printer filament.

Another significant aspect of accuracy is the facilitation of factory scheduling, which allows organisations to manufacture products and goods at various output rates accurately. Scheduling depends on the machinery's operating output; this creates importance amongst ML in scheduling, as manufacturers need to schedule tasks accurately in the most efficient way possible to maximise production. Breitenbach et al. (2021) discuss factory scheduling in manufacturing environments, including just-in-time and just-in-sequence scheduling.

Moreover, organisational sales are a way of measuring profitability. Organisations utilise demand estimation to forecast future demands and make decisions based on those forecasts. As discussed in section 4.4.1, sales and demand estimation is complex and requires an accurate ML solution. Akbari and Do (2021) support and elaborate on the potential applicability of ML technology to enable tracking and automation in SCM towards creating inventory replenishment systems. Integrating accurate ML technology will produce reliable sales and demand estimation, aiding organisations in precise and reliable future production planning.

5.2.2 Decision-making

We now turn to decision-making; organisations frequently use it when there is more than one viable option when action is required. Decision-making ties into the functions of ML when organisations utilise ML models to aid in making decisions. In the findings section 4.2.3, ML models add value in the manufacturing sector by providing the ability to evaluate data, provide feedback and provide an overview of the data collected. Examples of decision-making in the manufacturing industry involve decisions such as the selection of reliable suppliers for manufacturing goods (Cavalcante et al., 2019), cost-related choices (Loyer et al., 2016) and decisions surrounding investing in ML algorithms (Sharma et al., 2021).

Applying decision-making in SCM for the selection of suppliers is highlighted by Cavalcante et al. (2019). Manufacturing organisations that select suppliers need to ensure that the suppliers chosen are reliable, consistent, and meet the needs and expectations of partner manufacturing firms. ML offers improved decision-making through ML applications that analyse the data to avoid inconveniences that may occur. For example, unreliable suppliers who cannot deliver on time and, as a result, impact the ability to accurately forecast future manufacturing practices (Cavalcante et al., 2019).

The cost of manufacturing is essential to determine its feasibility and viability. Manufacturing operations are only viable if it is feasible to do so. Ensuring manufacturing operations are economically feasible will ensure they will be sustainable and have longevity; such can be encouraged through informed decision-making. For example, Loyer et al. (2016) identify financial variables subject to decision-making, including the cost of parts and labour, time spent manufacturing a product and production rate capabilities. When ML is adopted and utilised in decision-making, it produces better outcomes for manufacturing practices. Weichert et al. (2019) note that in scarcity of available resources in conjunction with manufacturers who struggle to remain competitive, ML is obligatory to reduce the unnecessary wastage of resources and, in turn, spare time and provide relief through freeing up resources and deciding where the resources should be allocated.

Likewise, informed and strategic decision-making needs to be at an organisation's forefront regarding investment-related decisions. Investing in the ML algorithm that best suits the organisation's requirements can improve its performance; with a lack of strategic decision-making surrounding ML investment, organisations can misallocate resources and budgets towards ML algorithms that are not best suited for their needs. Considerations surrounding ML algorithms are highlighted in section 4.5.2 by Sharma et al. (2021), whereby decision-making needs to encompass the manufacturing firm's business needs, capabilities and requirements to drive the correct selection of an ML algorithm.

5.2.3 Faster processing

Faster processing in manufacturing is significant as it is key to creating efficient manufacturing processes which deal with significantly large datasets where slow processing is simply not feasible. Faster processing is also one of the critical advantages ML brings when integrated with manufacturing tasks and operations. Thanks to ML, organisations can get faster processing in various manufacturing areas, such as performance management and evaluation, RFID tracking and supply chain management transportation.

Additionally, organisations can process tasks efficiently through the assistance of ML. It aids in faster processing in monitoring the performance of manufacturing firms. For example, Breitenbach et al. (2021) identified improvement in performance management amongst decision trees and neural networks that can accurately predict manufacturing cycle time. The benefits of faster processing amongst performance apply to other areas, including decision support. Further improvements through ML include the application of RFID technology, which aims to improve processing and tracking amongst manufacturing processes. Organisations with speedier processing of activities, and the ability to have processes tracked through radio frequency identification (RFID) technology, with the support of ML, will have greater transparency in their supply chain activities. For example, Breitenbach et al. (2021) note using various ML algorithms, such as logistics regression, support vector machine (SVM) and decision trees, to quickly identify defects through ML in conjunction with RFID technology.

Moreover, transportation amongst the manufacturing supply chain ideally requires efficient and reliable transportation. When planning routes for product delivery, variables such as traffic, picking and packing time, and route selection can affect the lead time across the supply chain. The integration of ML in the SCM transportation network supports after processing of vehicle delivery routing and the road to delivery throughout the manufacturing process. For example, Ni et al. (2019) explains the use of ML for faster processing in SCM transportation with ML applications to resolve issues in vehicle routing.
The strengths of ML applications are that they can provide timely forecasted results. Improved processing of predicted results will allow for more efficient supply chain lines.

5.3 Future of ML applications

Based on the existing knowledge base regarding ML's benefits in the manufacturing sector, what would the future effects and implications have amongst fields that ML influences? With cost being a more significant barrier to the organisational adoption of ML, it will still be a significant decision for organisations to make in the future.

Attaran and Deb (2018) note the sheer amount of data and its variety utilised amongst ML applications are increasing; this has resulted in organisations searching for fast, affordable and efficient hardware and software solutions so more data can be stored and used in ML models. If organisations can discover more affordable ML solutions, there would potentially be an increase in the adoption of ML amongst manufacturing organisations. Another future challenge is that organisations cannot keep up with the technology that ML offers. Papananias et al. (2019) elaborate on this, noting that market trends in modern manufacturing practices have ongoing changing requirements surrounding data.
Besides, the advancements in technology will accentuate the skills gap of organisations who lack knowledgeable employees trained in ML, as identified by Akbari and Do (2021), who note that organisations who lack employees trained in ML will not effectively understand how ML operates and in turn will lack the ability to leverage it for organisational gain. Such a deficit would undoubtedly slow the adoption of ML amongst organisations that have not yet done so.

Likewise, utilising ML across a wide range of applications in the manufacturing sector, if doing so is strengthened and proved over time to be reliable and effective, more organisations in similar industries will be willing to adopt ML with part of their processes based on the success of their peers.

Moreover, supply chain management risks come in various forms and can negatively impact a supply chain’s performance. Accuracy is an asset that allows for risk prediction to be carried out and mitigates risks that make cause adverse outcomes for organisations. The risk of delivery delay is outlined by Baryannis et al. (2019), who explored the impact of delayed delivery in aerospace manufacturing supply chains. Manufacturing organisations that operate on tight production schedules with little buffer room can benefit from ML technology. Examples include data-driven AI techniques that collaborate with SCM experts to predict risks that may arise without being detected or predicted within due time. Such could have harmful effects on the organisation's supply chain.

Chapter 6: Conclusion

The purpose of this literature review was to determine insights into the current state of the literature regarding ML in the manufacturing sector and address the applications and use cases of ML in manufacturing along with the associated benefits and challenges.

This study has identified that publications concerning ML in manufacturing are increasing globally as time advances, with publications occurring more frequently among developed nations. The research has shown that ML can produce reliable decisions and process tasks and activities faster and more accurately than human effort. One main finding was that ML is involved with manufacturing firms from an operational perspective, with the ability to schedule and predict maintenance when required, manage performance amongst machinery, improve existing processes, and collaborate with humans and robots.

Secondly, another significant finding was that ML has a place in quality management tasks such as fault detection, tool wear monitoring, and tracking in conjunction with RFID technology. Other findings included the application of ML amongst SCM tasks, such as predicting SCM risks and selecting suppliers.

Additionally, ML can influence decisions surrounding cost and its prospects of future growth in digital forms. It will cause future disruption in employment. The skill deficit surrounding employees and their ability to understand ML will further contribute towards ML being complex to understand and interpret.

A limitation identified is the missed articles from when the search for systematic literature began to the time of writing this publication. From the time the literature search started until the time of writing this publication, the researcher would have missed all the new publications in manufacturing and ML. Such publications could have provided further insight into the topic field in support of the paper's argument.

Moreover, another limitation identified was the exclusive use of three databases only. The researcher utilised three academic databases in this literature review: Business Source Complete /EBSCO, ScienceDirect and IEEE Xplore.

Moreover, the researcher encountered the challenge of scoping the research by formulating an exact search string suitable for commencing the systematic search for literature in the field of ML in the manufacturing sector.

The limitations discussed above impacted the research conducted. Future recommendations for research are discussed below, along with suggestions for addressing the limitations identified in this literature review.

Future research will have the ability to explore publications released since the writing of this literature review commenced. Researchers can explore a broader range of publications by utilising more academic databases and Business Source Complete/EBSCO, ScienceDirect and IEEE Xplore to capture research amongst ML in the manufacturing sector. Using more databases in conjunction with a search string will open up more potential articles to add to future research and writing.

Interestingly, the aviation industry was among the research literature, utilising ML for predicting and manufacturing suitable aircraft shim gaps (Manohar et al., 2018). Researchers could conduct more studies in the aviation industry to discover ML's developing role in manufacturing components. Another was using ANN ML algorithms to facilitate tool wear prediction in CNC machining. Researchers could conduct a future study comparing the various ML algorithms used to predict tool wear and their respective accuracy levels.

Moreover, additional future research could be conducted in another decade to compare the growth of ML in the manufacturing sector, focusing on comparing the publications and use cases amongst developed and developing nations. Such will help to gain a better perspective on the growth of ML in manufacturing amongst such countries and see what trends are evident based on the adoption of ML.

The research papers consisted of thirteen conceptual literature reviews and eleven case studies. The conceptual papers' common focus was ML amongst logistics and supply chains, ML application areas including ML in predicting tool wear and ML in monitoring manufacturing quality. Gaps amongst the case studies included estimation of lead time. There are a significant number of case studies that are close behind the number of conceptual papers. Furthermore, future applied research can be conducted in empirical form and a quantitative approach to gather primary data surrounding ML in manufacturing applications and gain additional knowledge to understand its effects on manufacturing practices over literature reviews and conceptual papers.

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