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Exploring the adoption of machine learning based manufacturing methods in the UK's aerospace manufacturing sector: a post Covid-19 perspective.

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Abstract. Machine learning (ML) is a branch of artificial intelligence which requires the application of data and algorithms to analyse information, identify patterns and learn from experiences. Despite various challenges, ML has proved to be a powerful tool contributing to various aspects of society, specifically in the manufacturing sector through operational optimisation, quality control, design, maintenance, and inventory management etc. Although ML is playing an increasingly important role in the aerospace sector, it faces adoption challenges specifically due to its high rate of maturity being asynchronous to the aerospace sector's rate of adaptability, specifically during times of technology disruption. This investigation applies a qualitative research design through two case studies and expert interviews to understand the various elements contributing to the dynamics of adoption of ML based manufacturing processes in the UK's aerospace manufacturing sector. The findings indicate a general recognition about the benefits of ML based manufacturing processes, however, there are business, organisational and technical challenges which need addressing to encourage adoption. The findings are envisaged to create a mutual appreciation of challenges faced between the aerospace manufacturing sector and the ML community to further future adoption practices.

Keywords: machine learning, aerospace, manufacturing, technology adoption

1. Introduction and background

Machine Learning (ML) plays a crucial role in the manufacturing sector [1]. ML is a subfield of Artificial Intelligence [2], having as a characteristic to learn from data and experience throughout the application of algorithms in different processes and functions [3]. ML is a disruptive technology focused on improving the decision-making process and obtaining an accurate prediction of events [4]. For example, with the use of algorithms and intelligent sensors connected to machines, failures can be detected before a machine breaks down [5]. The Aerospace Sector struggled to survive the impact of the pandemic, having shut down several manufacturing plants around the UK [6]. The Aerospace Sector is a vital element of the UK economy and the stability of the nation [7]; unfortunately, from the beginning of the pandemic, just in three months, the number of civil flights were reduced by over 70% compared to 2019 [6], affecting not only larger corporations, but also smaller corporations supplying parts. Therefore, thriving on the obtention of more efficient and sustainable manufacturing operations in the Aerospace Sector could help to recover the economic strength with the reduction of costs and the optimal use of resources. The application of ML technology in the manufacturing sector has resulted in effective solutions to face the most common manufacturing challenges such as scheduling, monitoring, quality, and failure prediction [4], and consequently the reduction of costs, the increase of product quality, and the optimization of processes [5]. Despite the advantages of ML, specifically in the aerospace manufacturing sector, there is a distinct lack of understanding about the adoption dynamics of ML based manufacturing process in the UK and elsewhere. As it is believed to be a sustainable option to support the Aerospace sector, with the optimization of operations and the reduction of manufacturing costs can enhance profitability and mitigate the financial impact caused by COVID-19.

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1.1 ML applications and the manufacturing sector

Mainly, there are three ML techniques: Supervised, unsupervised, and reinforcement learning [8-11]; IBM defines Deep learning as a subset of ML, highlighting the impact, evolution, and the results it has provided as part of the technology advance [12]. In manufacturing, supervised and unsupervised learning are commonly applied for predictive maintenance [13] and the prediction of disruptive issues in the supply chain and production process [14]. Additionally, several real-time scheduling problems have been solved using reinforcement learning [14].

In the manufacturing sector, the widely ML method is supervised learning, specifically applied regression methods, support vector regression [15], neural networks [16] and random forest [17]. The accurate application of these algorithms has resolved several challenges in manufacturing processes [18-21]. Contrary to supervised learning, unsupervised learning lacks input data [8]. For manufacturing, the clustering and anomaly detection techniques have been used widely to solve problems related to fault class prediction [13], product quality inspection [22], layout improvements [23], sales forecasting [24], equipment condition diagnosis [25], also for predictive scheduling and resource allocation [26]. Contrary to supervised learning, unsupervised learning lacks input data [8]. A reference model is created to find normal and abnormal processes in the system [13]. For manufacturing, the clustering and anomaly detection techniques have been used widely to solve problems related to fault class prediction [13], product quality inspection [26], layout improvements [27], sales forecasting [28], equipment condition diagnosis [29], also for predictive scheduling and resource allocation [30]. Reinforcement learning differs from other methods, as it learns through experiences and constant interaction with an environment [9]. Unfortunately, despite the positive results and benefits, the level of acceptance and adoption of reinforcement learning in manufacturing is still low due to its high complexity in implementation [9]. Deep learning, also known as neural networks, is an ML technique based on artificial neural networks specialized to imitate the human brain [31]. From manufacturing's perspective, it has brought positive results improving production processes [32], it has also been applied for bearings health analysis [33] to diagnose machinery fault [34], to predict product completion time [34], and to run an effective tool for decision support system [35].

1.2 Advantages and challenges

Overall, within the manufacturing sector, ML has assisted in optimisation of production processes [4, 36], improved financial performance and resource management [1, 37, 17], streamlined quality control [38, 39], support decision making [1, 40] and management of supply chain [41, 42] etc. The aerospace manufacturing sector has also been the beneficiary of these advantages. Despite the positive impact ML based manufacturing processes, their adoption within the aerospace manufacturing sector has been challenging due to its high rate of maturity being asynchronous with the sector. It mainly appears to bring various challenges to the aerospace manufacturing sector, which could be classified as technical, organisational, and business related. In terms of technical challenges, fluctuating data quality due to non-standard practices and data management practices [38, 43-45], integration issues due to non-standardisation of systems, specifically at the data acquisition stage [4, 46, 47], security and data storage practices [1, 44, 48], and difference in algorithm approach in addressing the problems [4, 46], appear to be affecting the sector the most. Resistance to change and cultural issues [14, 49], workforce skills acquisition, training, and retention [45, 46, 50], investment obstacles [1, 51, 52], knowledge management [52, 53] and changing nature of the organisation's macro environment [4, 54] appear to be causing most organisational challenges. Business challenges mainly consisted of customers' trust and views on ML based manufacturing [25, 54], and consideration for green practices to decrease the carbon footprint because of increased computational strength [54]. Given the importance of the aerospace sector, this investigation aims to explore its adoption dynamics of ML based manufacturing processes in the UK. Therefore, it seeks to identify the most common applications of ML in the manufacturing sector, with the aim to apply them in the aerospace sector in the UK (RQ1), explore the benefits and challenges of the adoption of ML (RQ2, RQ3)

2. Methodology

A qualitative methodology was applied through a multi case study approach in two phases to explore the adoption dynamics of ML based manufacturing processes in the UK's aerospace manufacturing sector. The use of multi-case study can be used to identify patterns from a detailed analysis of more than one event or case

[55, 56]. This combined with practitioner perspectives, offers a wholistic view of the events, especially for exploratory studies in pursuit of new conceptions in situations where information is not reachable [56-59]. The first phase was based on two case studies in two organisations, with the application of semi-structured interviews. The second phase involved semi-structured interviews with ML experts, aiming to understand the perspectives and ideas of experts [56].

2.1 Data collection

The interviews conducted in phase one, were at two UK-based organisations (cases), both involved in the manufacturing and supply of large and small specialised aircraft equipment. In phase 2, the interviewees were primarily ML experts involved in the manufacturing industry. Two pilot interviews were conducted in each phase to revise and align the interview protocols in accordance with the research questions, to improve the quality of the data collection process [56]. A total of thirteen interviews were conducted, out of which six were pilots. All the interviews were conducted over Zoom due to Covid-19 restrictions. All the interviewees were informed about maintenance of their anonymity, purpose of the investigation and permission to record, and distribute the findings was sought. Ethical approval was sought from the authors' institution before collecting the data.

2.2 Data analysis

The interview transcripts were analysed using template analysis [60]. A priori template was created from existing literature in relation to the research questions, followed by the familiarisation of the interview transcripts through reading. The coding of the transcripts in relation to the research questions was performed by the first author, resulting in the initial template. The high order codes were allocated themes and all the transcripts were recoded using the initial template, resulting in the final template. After each coding stage, both the authors reflected upon the codes to minimise distortions caused by assumptions and preconceptions [60]. Interpretation and writing up of the codes followed post-acquisition of the final template.

3. Findings

3.1 Challenges

3.1.1 Resistance to change

Resistance to change may affect the adoption of ML technologies. E2 argued that resistance to change is a factor affecting all the projects implementing a new system or to change any processes, but particularly, there is a generational factor where the age of the workers and old practices in the organization directly influence the disposition to embrace change. Similarly, E1 found the 'fear factor' is linked to the resistance to change, employees anxious about new processes, systems, and threat to their employment.

"One of the major impacts of I feel that would be an impact to do the adoption of ML would be the fear factor: is the machine going to take over what I currently do? It will have the ability to do complex tasks? and I will be then resistant to change?" - E2

Alternatively, E3 exposes that the resistance to change mostly comes from a lack of knowledge; for that reason, E1 and EA2 agreed that re-training is fundamental in the success of an ML project. When people have the complete panorama and perspective from the implementation results, resistance to change can be minimized, and the organisation can benefit from peoples' disposition and support.

3.1.2 Security

Security concerns are widely stated by the experts as a challenge to ML implementation. The UK Aerospace sector requires a high level of data security, with information being tightly controlled, however, it is an obstacle as E3 explains that a successful ML implementation would require having access to very detailed data. According to E1, data security is not only an issue for the UK Aerospace sector, but also all the industries and organizations. On the other hand, EA2 emphasizes the risk of extracting and storing data in the cloud, mainly because it is managed by a third company. Hence, E3 recommends being very cautious with the clauses specified in the contracts to prevent data leaks. While EA1, EA2, EA3, EB1, E1, and E3 believe this is a major issue, the E2 argues that the seriousness of the matter is overstated. From E3's point of view and experience as a Maintenance Manager, he pointed out that particularly, the maintenance data is not highly relevant, so security is not part of his concern or a barrier for the adoption of ML: "From a practical point of view, I mean who cares it's just maintenance data nobody's going to be able to use that information to do anything" – E2

3.1.3 Training

More than training concerns, experts agreed that training and re-training is beneficial for both: the company and the workforce. The participants stress that training must be given help people to understand the purpose of the ML implementation and the benefits it can bring to the company. E1 describes their experience where how post-training employees discover new knowledge to perform their work, increasing efficiency. Similarly, once ML is adopted, new opportunities and better salaries will be offered to those employees with the willingness of learning new skills.

"Because that will then train other people another people train other people and more people will get more exposure to it and it's the software and the solutions become more and more widespread that there'll be lots more opportunity for people to learn and to progress and so we need that progression I think all industries need that progression there will be people at the top of their game and they will command huge salaries but then there will be people at the bottom trying to gain that and have that experience to get to the top of that ladder" – E1

3.1.4 Protocols, legislations, and regulations

The UK Aerospace sector is highly controlled by regulations. EA1 claims that some operations are subjected to IATA or ITAR regulations, restricting to sharing information, especially in the cloud. Additionally, E1 believes there should be legislation and government guidance when organizations implement ML, comprising of all the industries, not just for the UK Aerospace sector. The perception of E1 is that, since ML is expanding its domain in developing machines towards human capacity, for instance, self-driving cars or robots; however, there should be legislation and protocols to avoid machines harming humans, and to define who will take responsibility if this happens. Another concern raised by E1 is to develop concrete regulations and protocols for the cyberspace to control nefarious activities and in this way, protect people against the illegitimate use of data and the internet.

"Depends on the product depends whether it's ITAR or not yeah that's what that's where we kind of got more uh major restrictions whether it's ITAR regulated yeah so some of the parts are obviously subject to ITAR regulation and that information is not open readily available to everybody, but that one restricts the use of certain technologies so you can you can't use, for example, this analytics cloud version because it's in the cloud and we don't have access, we are not allowed to share that information with other systems because you don't know what is going to end up" – EA1

3.1.5 Knowledge management

Knowledge management is another primordial factor which might drive a successful or unsuccessful implementation of ML. Tacit knowledge is experience-based learning, hence, EA3 explains the conflicts caused when people leave companies and there are no reinforcement practices to perform the role effectively. E1 and EA1 agreed that if the source of data collection is coming from people against change the information could be biased. Adversely, E2 mentions that if companies own an ERP system, the information will be ready to be merged with ML and other AI applications to execute algorithms and identify patterns: "I don't think that'll be a factor much, I think it'll be a case of get all of the data out of your SAP system or equivalent or perhaps from multiple different organizations and then use the AI to analyse that and have some clever algorithms in there to make decisions optimize strategies, so I don't think it will really require their knowledge so much" – E2

3.1.6 Cultural aspects

The adoption of new processes or technologies might vary according to the practiced culture, some experts claimed that cultural aspects are a barrier in the workspace. According to their experience, a cultural problem can arise and create conflict during the implementation of new technology. For instance, EA3 explained the different levels of disposition between two plants, one at the Northern Ireland and the other in England, where people with the same job role and same responsibilities used to take a different approach driven by the work culture and workers attitude.

"The two people in XXX do things completely different in the different ethos than people in XXX and XXX and they do the same job, you know, it's exactly the same job but they can take a different approach"-EA3

3.1.7 Lack of Trust

Lack of trust directly influences the adoption of new technologies as EA2 states, regulations do not trust in a software and the uncertainty of the coding inside the software. Similarly, EA1 expressed that the element of trust will be controlled once the company can contractually assure the data will be protected and this information will not be misused. On the other hand, E3 advised that trust can be built during the implementation process and since ML algorithms are not required from the beginning of the implementation process, the trust-building activities can be executed, first showing people how the system will behave and the advantages it will bring to the process.

"Regulations will make it difficult for the aerospace industry to apply ML, particularly because this software, this piece of software you don't really know what is, what they are doing inside, inside of the code, you don't have certainty. So, these companies that could sell this software and they need find a way to demonstrate that they can be trusted" – EA2

3.1.8 Other Challenges and interrelations

The experts mention various other challenges which might hinder the adoption of ML based processes in the UK's manufacturing sector. All the challenges are classified as first, and second level based on the number of mentions within the interviews. The consolidated list can be found in table 1.

3.2 Benefits and uses

3.2.1 Value

While EA2 expresses the difficulty to identify the value ML can bring to the UK Aerospace sector, E3 believes that one of the most important added value the UK Aerospace sector could gain is competitive advantage. The business experts accorded that the UK Aerospace sector relies on dated practices, and the implementation of ML can improve the processes that will be reflected in the reduction of inventory and the profit increase. EB1 focused on the value sector could gain if they start to monitor the machinery using ML to predict machinery failures to avoid breakdowns and production delays. E2 argued the lack of importance organizations place to the maintenance area, since the principal element on the shop floor is focused on the production goals. However, when malfunctions occur, it affects the whole supply chain process, with disruptions in the production process and deliveries. This results in increased costs from the repair and the delays related fines. With ML and historical data, machine breakdown is preventable. E2 also assured that ML could identify the machinery health in real-time with the using IoT, identifying the malfunctions' root cause. This could reduce costs and optimize processes in general.

"In that kind of thing so think monitoring machines and that will give us more data that then we are probably run-in conjunction with other data sets our ERP system, for example, and do some kind of multivariate analysis and that will give a lot of really strong, hopefully, strong correlations that will allow us to put the resources in the biggest issues" – EA1

Table 1. Consolidated template of challenges to machine learning adoption

Template (Challenges) First level; Second level		
	Literature Review	Interviews
Technical Challenges		

Data	X	X
Integration	X	
Security	X	X
Data storage	X	
Algorithm approach	X	
Coding errors		X
Project time		X
Organisational Challenges		
Resistance to change	X	X
Workforce acquisition and retention	X	X
Investment	X	
Knowledge management	X	X
Dynamic environment	X	
Protocols, regulations, legislations		X
Cultural aspects		X
Lack of trust		X
Old practices		X
Company size		X
Fear factor		X
Lack of resources		X
Lack of engagement		X
Unethical behaviour		X
Country classification		X
Political factors		X
Generational factors (age)		X
Proof of concept		X
Lack of real cases		X
Business challenges		
Customer expectations	X	X
Green practices	X	X

3.2.2 Upskilling

Some experts agreed that with the implementation of ML and the automatization of processes, redundancies will become common. However, organizations must consider training people that could oversee maintaining the solutions, the machinery, and supervising the adequate performance of ML processes. According to EA1, companies will require people with data science knowledge and, this will drive a new generation of engineers with good salaries and to provide more opportunities for others.

"There will be some unfortunate losses that will but there will be some games I think they will even out, eventually we certainly need some sort of ML is coming, people just need to adopt it and we need to retain the right skills of the people to train machines in the first place" – E1

4. Discussion and conclusion

ML has made significant progress in the last decade and keeps evolving. The innovations it has helped create in health, education, banking, and manufacturing, to mention some, has transformed work. From the perspective of the manufacturing sector, the use of ML can lead to process improvement in all the areas of an organisation. This study focused on the four main areas of the manufacturing process: Production planning and control, Quality management, Supply Chain Management and Plant Maintenance. This study, focused on the UK's aerospace manufacturing sector, with the aim of easing the impact caused by the coronavirus outbreak with the proposal of adopting ML to optimize processes and increase revenue. Thereby the investigation was centered to identify the challenges to ML adoption, advantages and uses. The primary challenges identified by this study are cultural factors, resistance to change, fear due to lack of knowledge and possible redundancies, legislation, protocols, and trust. Additionally, the investigation has highlighted the interrelations between the challenges and how they manifest in an organisation.

In the context of benefits and uses, experts marked the value the company could gain with the implementation of ML. Competitive advantage was mentioned by the experts and the importance to outperform the competitors; for instance, with the use of ML, the UK Aerospace sector could lead to efficient processes with the improvement of the supply chain, the reduction of scrap, quality control, allocation of resources, among others. Similarly, instead of considering training as a challenge, the experts explained that training is beneficial for the employees allowing them to upskill and obtain better internal positions, which will be a solution to the redundancy fears. Similarly, organisations are encouraged to offer incentives and structured training programs. Business experts agreed that ML can be beneficial for the UK Aerospace sector, but security concerns must be fulfilled as part of the protocols in organisations. The future of ML is positive, undoubtedly, as it appears to be a solution which many organisations will utilize.

This study recommends identifying the forces obstructing ML implementation to ease their impact, focusing on the resistance to change as one of the main forces on this process. Since this study was developed to identify the business and organizational challenges that companies could face during the implementation of ML, the technical challenges are mostly around data quality, compatibility of systems, algorithm approach, project time and data storage etc. It is important for future research to follow this direction to measure the importance of the impact that the implementation can cause and develop a strategic plan, contributing to literature in this field. Also, since the number of organisations implementing ML based manufacturing process in the aerospace industry is relatively low, further research needs to be conducted to observe consistency in findings, thereby allowing standardized frameworks for ML implementation.

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