EXPLORING THE USE OF AI IN MANUFACTURING COMPANIES

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Abstract: *Recent technological advances have created perfect conditions for the appearance of artificial intelligence (AI) and its application to real world problems for both the public and industry. The newest iteration of European manufacturing survey has enabled us to gather data on the usage of AI in manufacturing companies. Results are based on a subsample of 141 manufacturing companies located in Slovenia and are presented with the use of descriptive statistics. Results show that the use of AI depends on company size and the role of the company in the supply chain. Common barriers to the implementation of AI are also provided.*

Key words: *Artificial intelligence, manufacturing company, European manufacturing survey, Company size, Manufacturer role*

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This Publication has to be referred as: Kovic, K[lemen]; Ojstersek, R[obert]; Buchmeister, B[orut]; Javernik, A[ljaz] & Palcic, I[ztok] (2023). Exploring the Use of AI in Manufacturing Companies, Chapter 10 in DAAAM International Scientific Book 2023, pp.129-146, B. Katalinic (Ed.), Published by DAAAM International, ISBN 978-3-902734-39-6, ISSN 1726-9687, Vienna, Austria
DOI: 10.2507/daaam.scibook.2023.10

1. Introduction

Manufacturing is one of the main drivers of economic growth for both advanced and emerging economies. It offers opportunities to exploit the benefits of economies of scale, drives the technological advancement and learning, benefits from spillover effects to other sectors and create employment opportunities for workers with various skills. While the manufacturing productivity remains high in advanced economies, its share has declined due to the service sector, indicating that future manufacturing needs to constantly adapt to market changes and demands (Haraguchi et al., 2017; Naudé & Szirmai, 2012).

When talking about modern manufacturing, mainly advanced manufacturing technologies (AMT) and information-communication technologies (ICT) are considered. However, the last decade of technological advancement has been driven by advanced digital technologies which combine classic ICT technologies with the so-called "smart" or "intelligent" capabilities of industrial machines and finished products (Egger & Masood, 2020). These technological combinations enabled the creation of new concepts such as the Smart factory and the Digital factory. While the Smart factory (and its products, resources and processes) is characterized by cyber-physical systems (CPS) (Hermann et al., 2015), the digital factory is a model of a planned, future factory or a model of existing factory. The digital factory should be integrated with the smart factory and based on real time data and inferred information, enable better planning and control and improve future design and operations (Shariatzadeh et al., 2016). Both concepts rely on the Internet of Things which refers to the interconnected network where physical "things" are connected over the internet with the purpose of exchanging data with other connected "things" and control each other while requiring little to no human intervention (Sisinni et al., 2018; Takakuwa & Yoshida, 2021).

With more and more devices exchanging data, it is becoming more difficult to store, organise and analyse collected data for human analysts and managers. Some suggest that the amount of data already exceeded 8 zettabytes in 2015 but is expected to increase even further (Sagiroglu & Sinanc, 2013). This is where Artificial Intelligence (AI) can make an actual change. AI refers to a group of scientific disciplines and techniques that seek to mimic the mental abilities of humans. Although it may seem like a relatively young discipline, research and development in this field dates back to the Second World War, when Alan Turing and Warren McCulloch laid the foundations for so-called intelligent machines. The term AI, often used as AI, dates back to 1956, when it was coined by John McCarthy at a conference at Dartmouth (Haenlein & Kaplan, 2019). While the technology represented enormous potential and interest for both academia and investors as early as the 1960s, it progressed only slowly over the next few decades due to the inadequacy of computing power. In recent years, however, computing has undergone rapid and intense changes, which have led to an increase in the computational power of computers and, consequently, to the rapid development of AI. OpenAI was one of the first companies to offer a prototype of a chatbot called ChatGPT, which was made available to the public free of charge on 30 November 2022. In the first week, more than one million regular users were registered, and two months later the number of users exceeded 100 million (Hu, 2023).

The figures confirm that there is a very strong interest in AI among general public. Some in academia equate the rise of AI with the discovery and use of electricity (Hu & Goel, 2018). While there are numbers about the AI users from general public, this raises the following question: what is the usage of AI in the manufacturing sector? Are there differences between large and small enterprises? Does the role of the manufacturer impact the use of AI?

This chapter is organised as follows: first we present the general use of AI in manufacturing and fields of research interest. Second, the methodology of data collection and analysis of AI usage in manufacturing is presented. This is followed by the results of this analysis and lastly a discussion with conclusions is provided.

2. Artificial Intelligence in manufacturing

New digital technologies have increased the complexity of industrial environments and various governments have realised how important this new paradigm is and created strategies and initiatives to transform entire manufacturing sectors. One such initiative started in Germany under the term Industrie 4.0, also known as Industry 4.0 (Kagermann et al., 2013). Since Industry 4.0 strives toward highly customised and interconnected manufacturing systems, the necessary higher agility, productivity and even sustainability is only possible through advanced self-learning or intelligent systems which enable real-time corrections and optimization in manufacturing and other parts of the value chain (Kang et al., 2016).

AI presents a unique opportunity as an enabler for industrial systems to solve complex manufacturing problems and improve the performance of entire systems based on learning from collected data (Peres et al., 2020). AI can be applied to various tasks such as data security, planning and control, monitoring of processes, prediction and diagnostics and also for decision making purposes to achieve the desired goals. Authors also identify the four following advantages of using AI (Alenizi et al., 2023):

- Management of different company branches through smart systems.
- Error prediction and prevention through continuous analysis of different systems and processes.
- Scenario testing and simulation to improve the system performance.
- Pattern recognition and predictions for reduced short term costs and efficient use of human resources and assets.

While AI offers many benefits to users, current literature suggests that the majority of research in AI is limited to laboratory environments. Major barrier for this are the required changes in company structure and expenditures to integrate AI to the current company structure and systems (Arinez et al., 2020; Siaterlis et al., 2022). Current research trends show that AI is frequently paired with concepts such as Industry 4.0, Big Data, Industrial IoT and cyber physical production systems (CPPS). Other fields of interest include the supply chain optimization, additive manufacturing and AI as a decision support tool. Researchers are also mainly interested in energy optimization, predictive maintenance and quality control which is mainly done with deep learning techniques (Peres et al., 2020).

Researchers also state that the common design principles for AI in industrial settings are similar to those that Ghobakhloo outlines as the future of manufacturing: decentralisation, real-time capabilities and modularity (Ghobakhloo, 2018). There are also AI specific design principles which include interpretability (or explainability), robustness of AI and cybersecurity to preserve privacy. Due to the "black box" nature of AI and its decision making, it is still not independent and requires human collaboration to make a final decision. Miller defines interpretability as a degree to which a human operator can understand the cause of a decision made by AI (Miller, 2019). While interpretability helps understand why a decision was made, robustness and modularity enable that AI systems can gather data from multiple data sources from existing systems and is able to be tailored to additional functionalities as needed.

To summarise, the current major application areas in manufacturing are: process optimization, quality control, predictive maintenance and collaboration between humans and robots (Peres et al., 2020). In process optimization, the main focus is to make manufacturing processes more profitable and sustainable. Some applications of AI include prediction of energy consumption and optimization challenges (Qin et al., 2018), increase of production efficiency (Liang et al., 2019) and forecasting the demand (Chien et al., 2020). In quality control, early detection of defects during each step of the production is highly desirable. This includes automated visual inspection of parts (Ojer et al., 2020), multistage quality prediction (Peres et al., 2019) and online prediction of quality (Schmitt et al., 2020). Predictive maintenance is tasked with avoiding any unplanned or unexpected downtime while increasing machine uptime. Based on the maintenance effectiveness, costs, resources and previous data from multiple sources, the best maintenance strategy can be created (Yan et al., 2017). In the context of human-robot collaboration, AI enhances human-robot teamwork on the shop floor, boosting operator safety and efficiency (Bergamini et al., 2020) and also enables efficient workforce training and support (Ojer et al., 2020).

3. Methodology

Our research utilises data from the European Manufacturing Survey (EMS), a project facilitated by a network of European research institutes and universities. The EMS is designed to delve into the current trends and innovations occurring in the European manufacturing sector, focusing on various critical areas including technological advancements in value-added processes, the evolution of organisational concepts, global strategies for offshoring/outsourcing and backshoring of production and R&D activities, and the development of new business models that supplement product portfolios through the introduction of innovative services.

The EMS gathers in-depth data at the company level, offering insights into areas such as R&D investments, the launch of new products in the market, and the educational qualifications of employees. It also considers a range of control variables like company size, export activities, and the company's role in the value chain, as well as specifics regarding primary products and production processes. The survey helps in assessing performance indicators such as productivity, flexibility, quality, and returns, giving a rounded view of the company's operations (Dachs et al., 2019).

Conducted every three years, the EMS operates through a paper-based or electronic survey directed at companies. It contains a core questionnaire of six pages, which can extend to eight pages with the addition of nationally specific questions. It aims to engage a diverse range of manufacturing establishments that adhere to the NACE codes 10 to 33 in category C “Manufacturing,” and have a workforce of at least 20 employees. This approach ensures a representative cross-section of major manufacturing industries, including those involved in rubber and plastics, metal works, mechanical engineering, electrical engineering, and textiles, among others.

To allow for a comprehensive multinational analysis, all the national data undergo a harmonisation process. The individuals responsible for providing the data are usually in senior positions such as production manager, plant manager, or CEO, ensuring a well-informed response grounded in a broad understanding of industrial and business demands (Sartal et al., 2017).

In essence, the EMS seeks to provide a deep understanding of the use of manufacturing and informational technologies, new organisational approaches in manufacturing, and the incorporation of best management practices. It stands as a valuable tool in understanding and navigating the ever-evolving landscape of the manufacturing industry.

It should be noted that the analysis was conducted on the Slovenian subsample of this research and does not represent the state of AI in European Union.

3.1 Characteristics of research data

This research is based on the latest data from the Slovenian sample from the years 2022/23. In this latest round, 146 companies responded to the survey, which represented a response rate of over 15 %. The manufacturing companies in our study fall into the following NACE C groups:

13: Textile Manufacturing
14: Clothing Manufacturing
15: Manufacturing of Leather, Leather Products, and Related Items
22: Manufacturing of Rubber and Plastic Products
23: Manufacturing of Non-metallic Mineral Products
24: Metal Production
25: Manufacturing of Metal Products, Excluding Machinery and Equipment
26: Manufacturing of Computers, Electronic, and Optical Products
27: Electrical Equipment Manufacturing
28: Manufacturing of Other Machinery and Equipment
29: Manufacturing of Motor Vehicles, Trailers, and Semi-trailers
30: Manufacturing of Other Vehicles and Vessels
32: Other Miscellaneous Manufacturing Activities

For the purposes of this current research, we excluded the responses of companies in the textile and footwear sectors, leaving us with a database of 141 responses, predominantly from the metal-processing industry, electrical industry, and the synthetic materials industry.

Table 1 summarises the number of companies for each NACE classification, number of responses, response rate per each group and the share of responses.

NACE	Total nr. of companies	Nr. of responses	Response rate	Share of responses
22	125	22	17,6%	15,6%
23	47	9	19,1%	6,4%
24	33	7	21,2%	5,0%
25	376	45	12,0%	31,9%
26	46	11	23,9%	7,8%
27	55	6	10,9%	4,3%
28	135	25	18,5%	17,7%
29	42	11	26,2%	7,8%
30	12	0	0,0%	0,0%
32	32	5	15,6%	3,5%
Total	903	141	15,6%	100%

Tab. 1. Characteristics of EMS 2022 sample

Next, we looked at shares of companies per size. Most respondents were medium sized companies, followed by small companies. Large companies represent only 20% of our sample, small companies represent 31 % and the majority of companies in our sample are medium sized companies. Figure 1 summarises the structure of company sizes in our sample. If we compare the results for company sizes from the newest iteration of EMS, then we can see that there are some differences. First, the share of small sized companies is nearly the same as in the previous iteration, where small companies represented 32,3% share of all companies. The share of medium sized companies that are included in the newest research has increased from 42,5% to 49% - a 6,5% increase.

Lastly, the share of large companies has decreased. In 2018 large companies represented 25% of all companies but has decreased to 20% since then. This could be attributed to increased numbers of existing companies. Comparing to the last survey, the number of existing companies that are eligible to participate has increased from 778 to 903. The greatest increase in the number of existing companies is due to the companies that are in the following NACE group: Manufacturing of Metal Products, Excluding Machinery and Equipment. Since 2018 there was an almost 35% increase in companies that are classified into this category. This is followed by NACE group 22 - Manufacturing of Rubber and Plastic Products, which had only a 13% increase in eligible companies and NACE group 28 Manufacturing of Other Machinery and Equipment which had only a 5% increase in companies. This indicates favourable market conditions for these groups; however, this needs to be further researched.

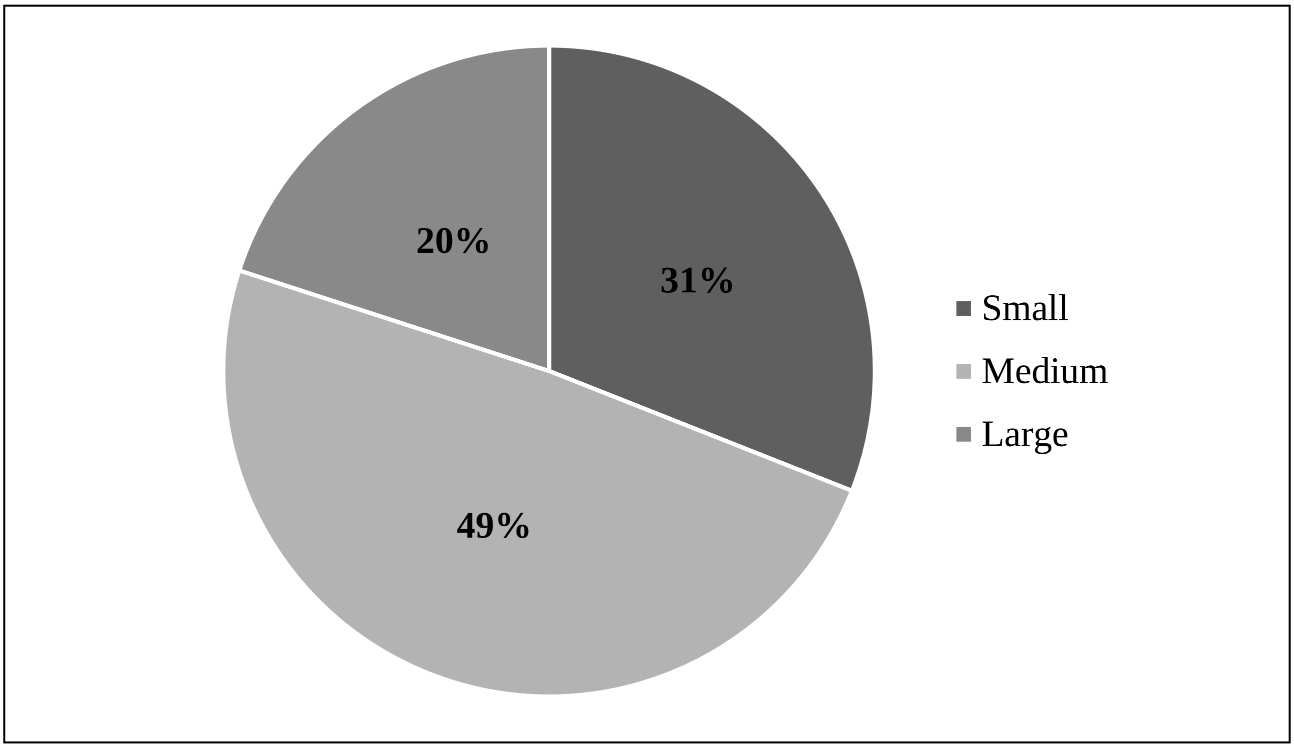

Fig. 1. Share of manufacturing companies based on size

We also analysed the share of manufacturers that have different roles. These roles are: OEM producers, suppliers, both, or contract manufacturers. Shares of companies based on their role are presented in Figure 2. Share of companies that have a role of producers and suppliers is virtually the same, while only 7,8% of companies act as both the producer and suppliers. Only a miniscule number of companies have a role of contract manufacturer.

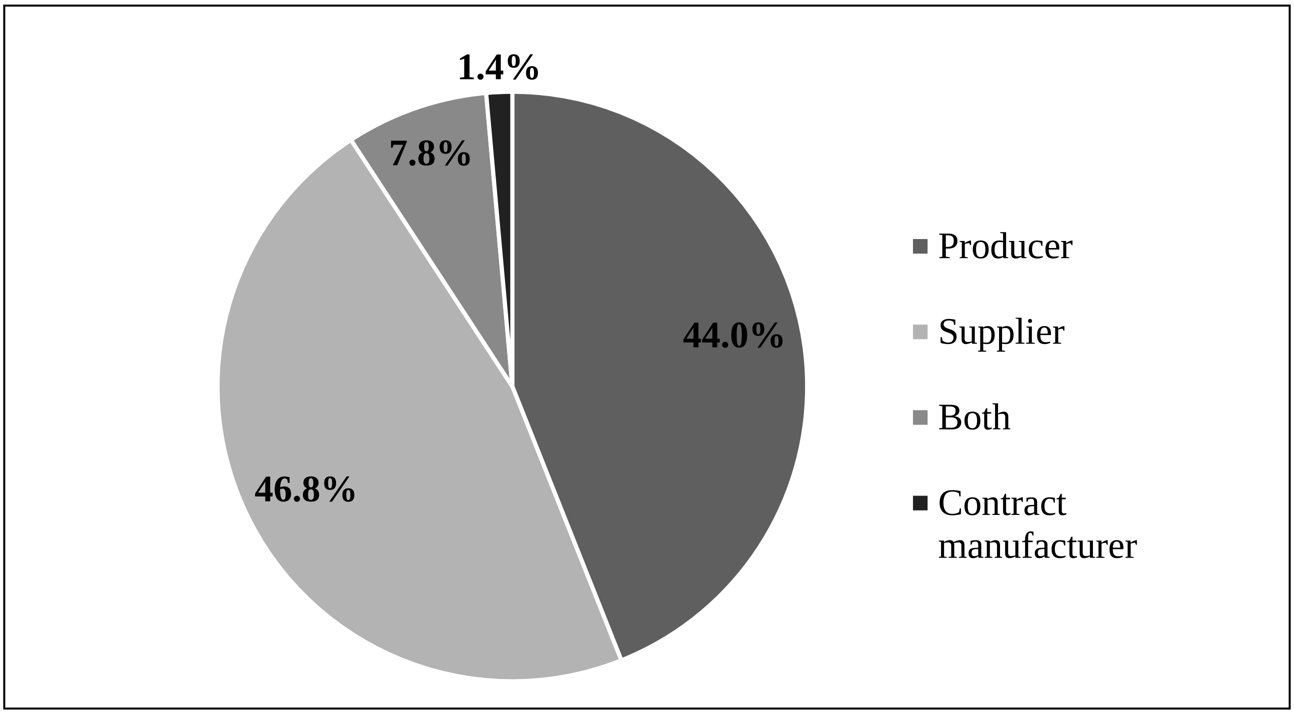

Fig. 2. Share of companies based on manufacturing role

3.2 AI related questions

The use of AI was explored through three questions. The first focused on data collection and processing. We asked whether companies have implemented systems for automatic data gathering and where they collect data (machines, warehouses, robots, production internal computers, or other sources). We were also interested in the purposes for which they collect data. These purposes were defined as:

- quality improvement,
- maintenance and repair planning,
- production capacity planning,
- productivity indicators preparation,
- performance indicators,
- and other, further defined reasons.

The second question pertained to the areas of application of specialised software and if that software also uses any elements of self-learning or more specifically: AI. We were mainly interested in the following areas in the manufacturing companies:

- production,
- process management,
- quality control,
- machinery and equipment maintenance,
- internal logistics management,
- energy management,
- and improvements or innovations in products or production processes.

The third question pertained to the obstacles faced when implementing AI. Participants evaluated individual barriers on a scale from 1 to 5, with 1 meaning they do not perceive any barriers, and 5 indicating they perceive them to a very large extent. We inquired about their perceptions of the following barriers:

1. Lack of applicability to current products and processes.
2. Lack of clearly defined economic benefits.
3. Complexity of implementation, coordination, and learning.
4. Poor data quality, low reliability, and poor data integration.
5. Lack of trained personnel.
6. Lack of infrastructure, devices, software, and platforms.
7. Lack of management support.
8. Absence of a coherent digital strategy.
9. Lack of financial resources and abilities.
10. Concerns about data control, security, privacy, and the risk to the company's reputation.
11. Environmental impact concerns (data storage and computing).
12. Lack of support within the supply chain (suppliers or customers).

Through these questions, we sought to get a deeper understanding of the extent of AI utilisation in different facets of production and to understand the perceptible barriers in the path of broader AI adoption in the industry.

4. Results

AI in manufacturing companies was analysed with the use of descriptive statistics. Since data is the backbone of AI the first step was to get an insight into data sources for manufacturers and if they have established automatic data gathering systems. Out of 141 respondents, only 91, or 64,5% have implemented some form of automatic data gathering systems in their companies. The most common source of data for these 91 companies, are machines. Machines represent half, or 50,4% of all of the data sources for companies, followed by computers in the production system at 39%, robots at 23,4% and warehouse at 20,6%. However, when we analyse the use of automated data gathering systems, 78% of companies automatically gather data from machines, followed by computers at 60,4%. Robots and warehouses have the least automated data gathering systems at 35,2% and 31,9% respectively.

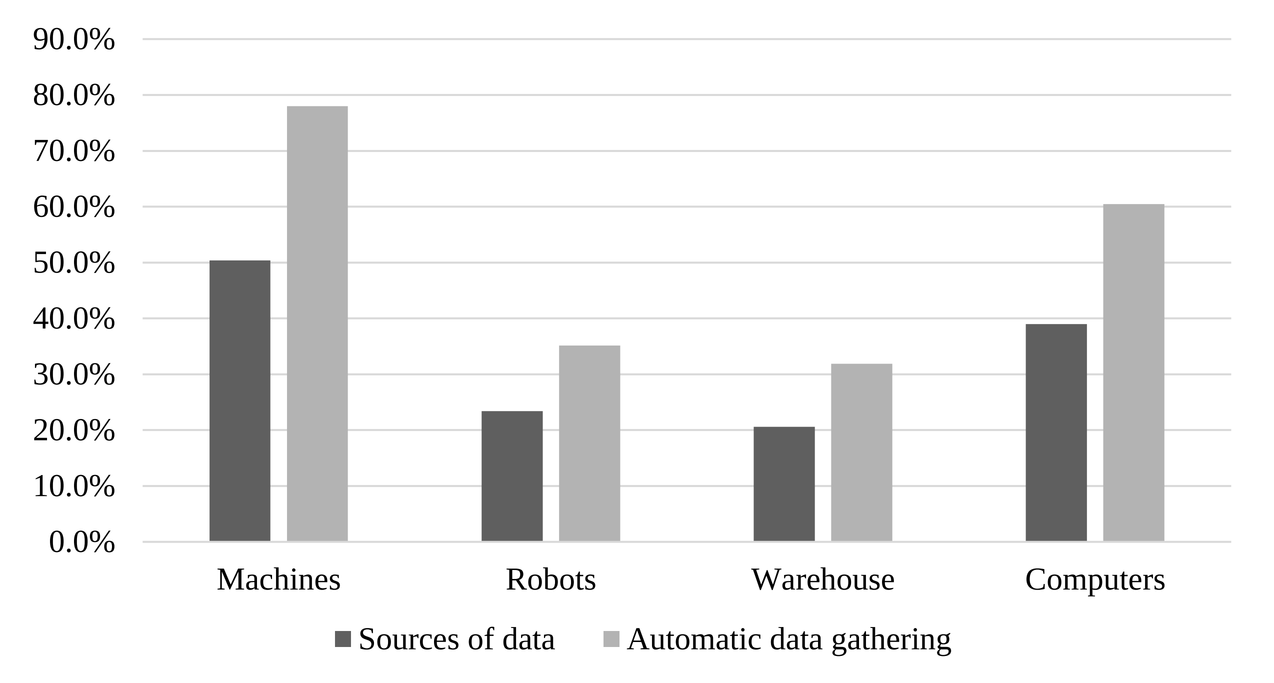

Fig. 3. Data sources and automation of data gathering

When we established which sources of data companies use the most, we analysed if companies process the collected data and for what purpose. In total, 106 or 75,2% of companies in our sample process data that they collect. Out of these companies that process collected data, 90,6% of them process data for preparation of key performance indicators (KPI's). Second purpose is the planning of production capacities at 78,3%, with quality improvement following closely behind at 69,6% and maintenance planning at 49,1%.

These results show that not all companies prepare KPI's and that more than half of companies in our sample do not plan their maintenance activities. Figure 4 presents the results of our analysis of data processing purposes.

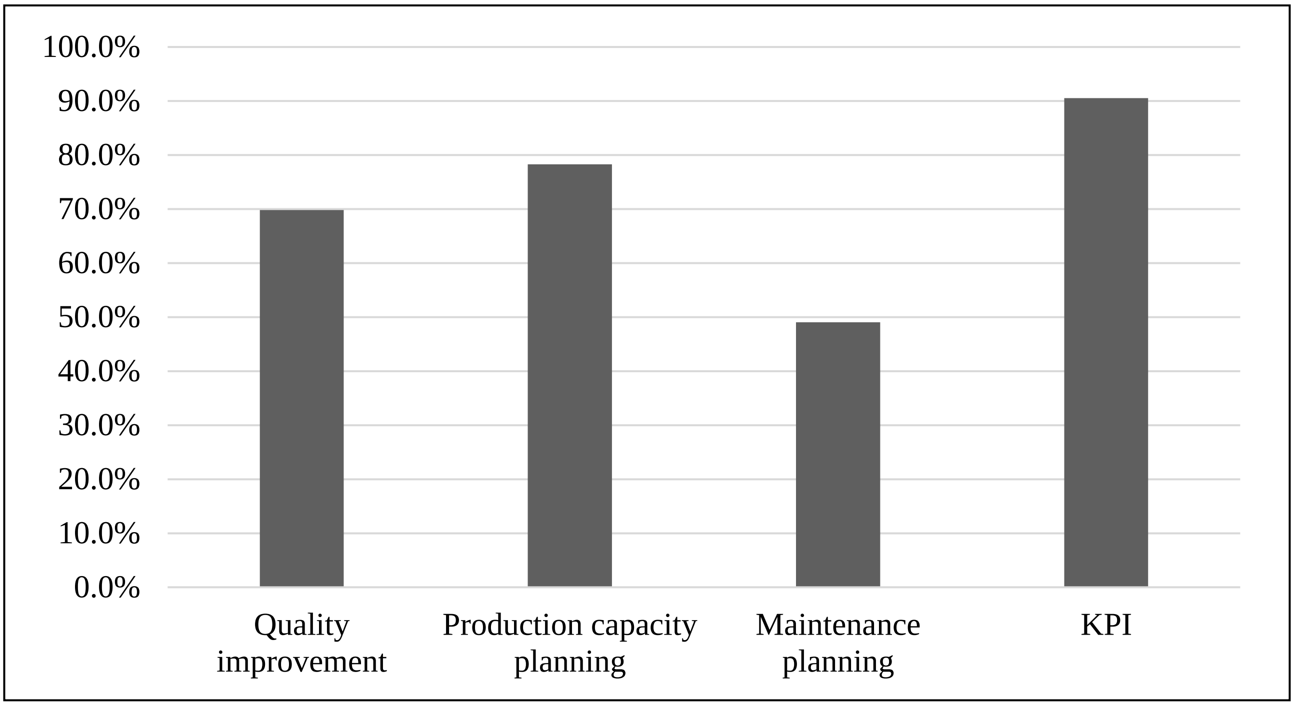

Fig. 4. Purpose of data processing

After we established which are the common sources of data and what are the purposes of data processing, we finally delved into the usage of specialized software and more importantly, if that software uses some kind of self-learning functionality or AI. Mainly we were interested in the following areas: management of production processes (Production), quality control with focus on defect detection (Quality), maintenance of machinery and equipment (Maintenance), Management of internal logistics (Logistics), Energy management (Energy) and Improvement or innovation of production processes (Innovation). First, the general use of specialised software and AI was explored and presented in Figure 5. In the latest survey dataset, we observed the incorporation of specialised software and AI functionalities in different operational areas of manufacturing companies. The data in Figure 5 highlights a predominant reliance on specialised software in the management of production processes with a 62% adoption rate; however, AI integration in this area is still at 9%. In the quality control, 43% of companies utilise specialised software, with 13% leveraging AI functionalities. Meanwhile, maintenance of machinery experiences a 38% adoption rate for specialised software, followed by management of internal logistics at 31% adoption rate. Only 9% of companies leverage AI functionalities for maintenance and 6% for internal logistics. The last two areas are Improvement or innovation of production processes and Energy management with 26% and 23% adoption rate respectively. Similarly, as before, only 9% of companies leverage AI functionalities in the area of improvement and innovation of production processes and only 6% of companies leverage AI in energy management.

Even though there are companies that use specialised software, there are only a few who actually use software with AI functionalities.

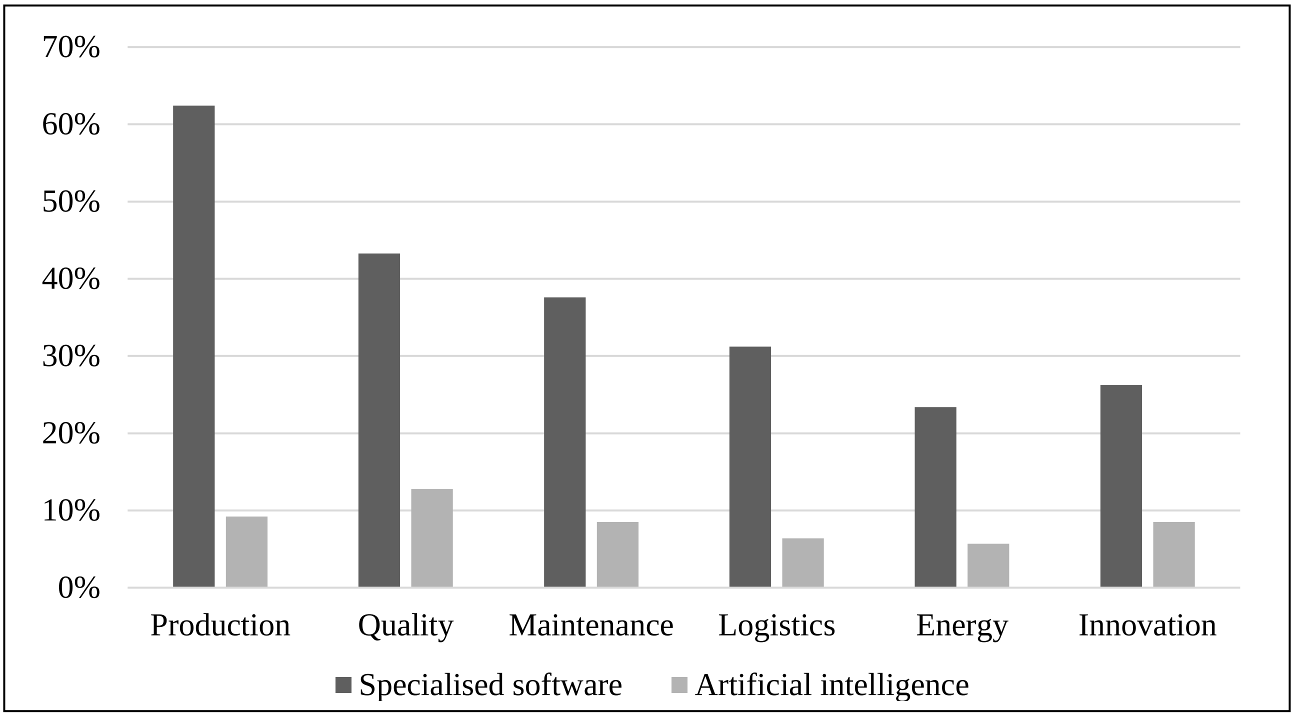

Fig. 5. General overview of specialised software and AI use

Then the research was divided based on company size and the manufacturer's role. As stated before, there are three company sizes: small, medium, and large. The four manufacturer roles are: OEM producer, supplier, supplier & producer, and contract manufacturer. First, AI use based on company size was examined. Initially it was expected that large companies would be dominating in the use of AI, however it turned out that out that our initial estimates were wrong. In our sample, out of all companies that use AI, small companies use AI the most. The production areas where the small companies are dominant users are management of production processes (Production), management of internal logistics (Logistics) and Improvement or innovation of production processes (Innovation). In these areas, small companies represent 46%, 44% and 42% of AI users respectively. Small companies also notably use AI for defect detection (Quality) at 39% and for maintenance of machinery and equipment at 33%. The least they use AI for energy management (Energy) with only 13 % of users being small companies. If we look at the medium sized companies, we can see that they use AI the most for energy management where they represent 50% of users and for maintenance of machinery and equipment where they represent 42% of AI users. In the areas of management of internal logistics and quality, medium sized companies represent 33% of users for each area. In the area of production management, they represent 31% of all users which is followed by only 25% of medium sized companies in the area of innovation. Lastly, we explore the use of AI in different areas for large companies. As it was stated before, it was unexpected that large companies generally represent the least share of AI users across the four areas of Production, Quality, Maintenance and Logistics. In these areas share of large companies that are

AI users is always lower than 30%. It is the lowest for management of internal logistics and for production management, with their shares reaching only 22% and 23% respectively. In the areas of energy management and innovation, their share increases to 38% and 33%, respectively. Figure 6 presents the results of AI users based on company size and different areas of manufacturing.

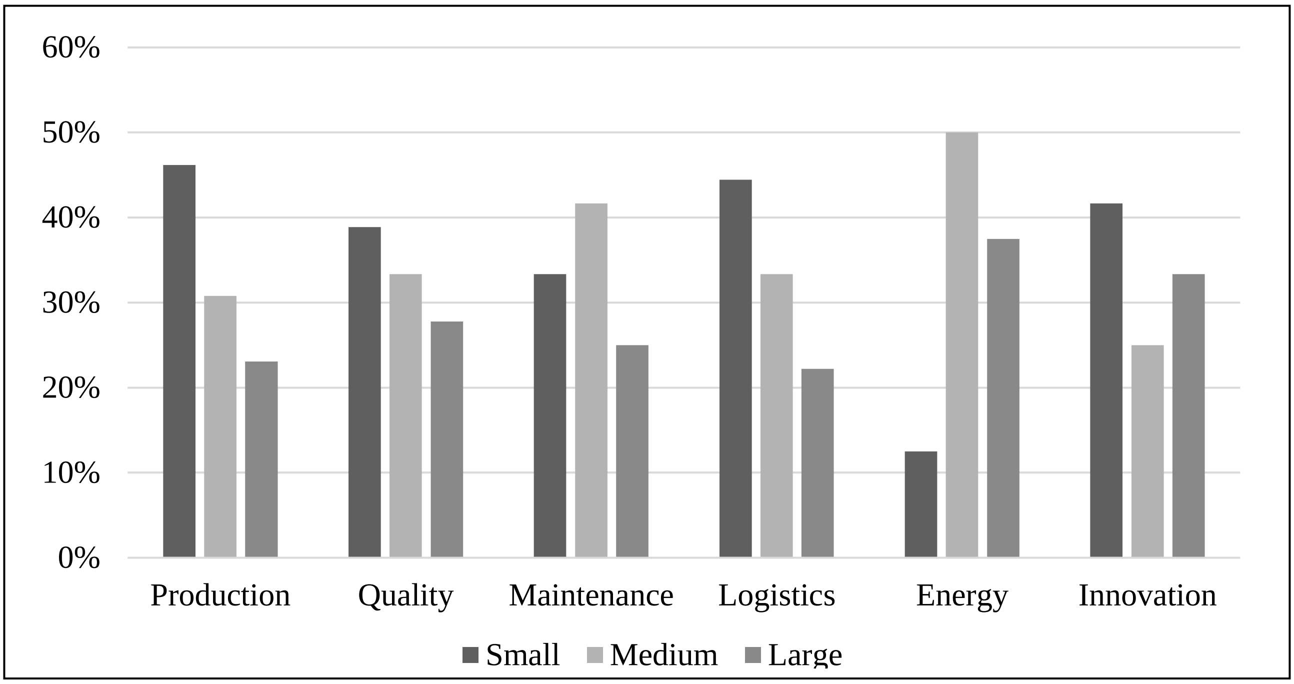

Fig. 6. AI usage based on company size

Next, we examined the use of AI based on the role of the manufacturer. First, we started by exploring all four roles; however, since the number of contract manufacturers was low it was discarded from further analysis and comparisons. The results of manufacturer role and the use of AI in different manufacturing areas are presented in Figure 7. At the first glance we can see that the companies that have a role of a supplier have a larger share of AI users in the four areas of Production, Quality, Maintenance and Logistics, than companies that have a role of OEM producers or both roles. Suppliers have the largest share of AI users in the area of internal logistics where they represent 78% of all users. The rest of the users in this area are OEM producers which represent the last 22% of users while manufacturers that are both OEM producers and suppliers do not use AI for internal logistics. Next, we look at the maintenance of machines and equipment where suppliers represent the second largest share of AI users. Here 67% of all users are suppliers and manufacturers that are producers or have both roles have the same share at 17%. In production area, suppliers represent 62% of users while producers have a 23% share and manufacturers in both roles have a 15% share of AI users. In the case of defect detection (Quality), the share of suppliers that use AI is decreased to 50%; however, the share of producers that use AI is increased to 39%, signalling the increased importance of quality for producers while manufacturers in both roles represent only 17% of users. Area of energy management includes only companies that are producers or suppliers while companies that have both roles do not use AI in energy management. Half of the AI users are suppliers, and the other half are producers which could indicate that this area is equally important for both roles of manufacturers. In the last area, Innovation, the producers represent the largest share of AI users. They represent 50% of users, followed closely by suppliers at 42% and the last 8% represent manufacturers in both roles.

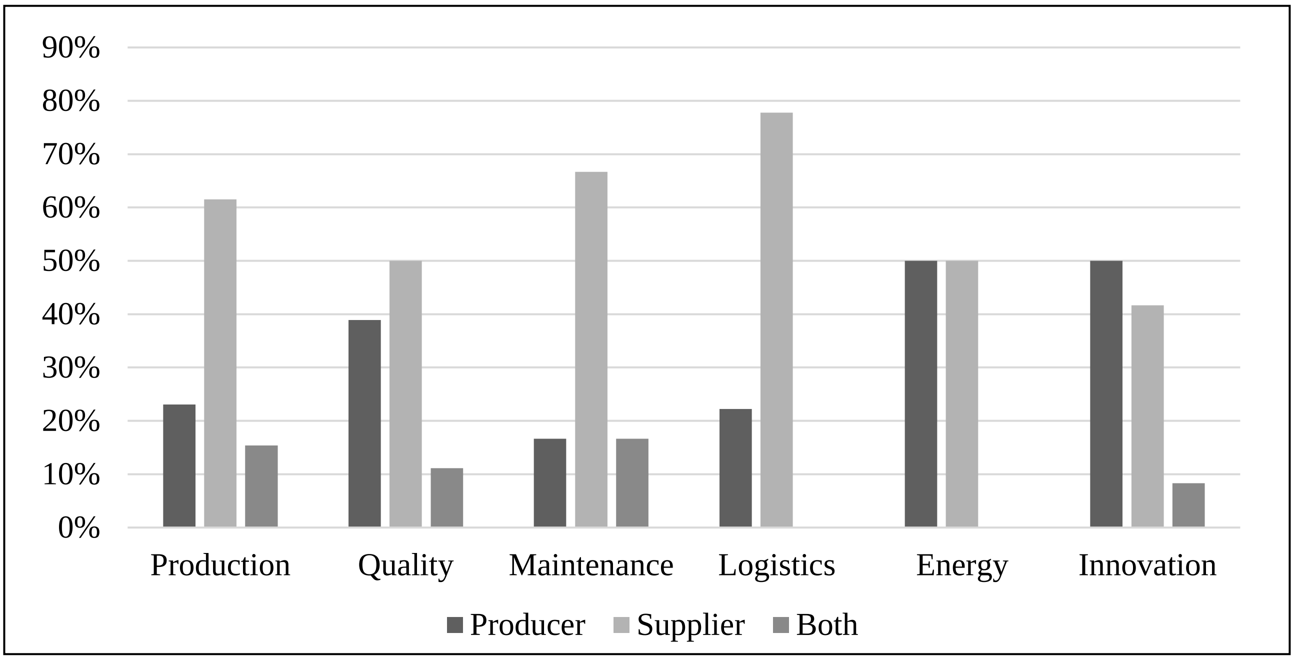

Fig. 7. AI usage based on the role of manufacturer

Since the previous results showed that AI adoption is low and there are differences between the adoption of AI based on the size of the company and the role of the manufacturer, we wanted to know if different barriers present different challenges for companies. We were interested to know which of the 12 barriers mentioned in chapter 3.2. present the biggest obstacles when it comes to implementing AI in manufacturing companies. Companies were asked to rank how they perceive these barriers on the scale from 1 to 5, where larger numbers indicate more challenging barriers. If they ranked a barrier as 1, it means that they do not perceive it as an obstacle. If they rank it as 2, then they have a low perception of the barrier. Number 3 represents a medium perception of the barrier, while 4 and 5 represent a high or very high perception of the barrier. First, a general baseline of perceived barriers was established based on the whole sample of participants. It shows a general perception for each of the barriers and is marked in black. Then the average values for each barrier were calculated based on the responses for each company size and the role of manufacturer. Again, contract manufacturers were excluded due to a small sample size.

First, a comparison of barrier perception based on company size was performed and the results are shown in Figure 8. It is immediately apparent that the lack of qualified employees presents the biggest obstacle for implementation of AI in manufacturing companies, and it only slightly differs based on the company size. While this barrier is generally ranked with an average value of 3.7, indicating a highly challenging barrier to overcome, larger companies rank it slightly lower at 3,5 than medium sized companies that rank it at 3,7 while small companies rank it higher, at 3,8. Next barrier towards AI implementation is complexity of integration with current processes. It is generally ranked slightly lower than lack of employees, with a value of 3,5, indicating that this is also perceived as a medium to high barrier. Medium and large companies rank this barrier at 3,6 and 3,5 respectively, which is slightly higher than the small companies which rank it at 3,4. With a value of 3,2, the third barrier presents the lack of necessary infrastructure. Medium sized companies have the most trouble with adequate infrastructure followed by small and large companies. The fourth and the final barrier, which is perceived as a medium to high barrier for AI implementation is the lack of economic benefits. It is generally ranked at 3,1 but medium sized companies rank it at 3,4 and large companies rank it at 3, while small companies rank it at 2,8 which is considered as a low to medium barrier. If we explore the barriers that are perceived as least challenging to overcome, we can see that there are four that are ranked as 2,5 or less, meaning that in general, companies perceive them as low to medium barriers. Security and support from the supply chain are barriers that are ranked as 2,5. In both cases, large companies perceive them as a less of a barrier than small and medium sized companies. The final two barriers are a lack of management support and ecological impact. It is encouraging to see that the lack of management support is perceived as a low barrier with a general value of 2,1. This implies that in general, management is open to the implementation of AI capabilities. This barrier is the lowest for large companies with the value of 1,6 and the highest for medium sized companies which rank it at 2,3.

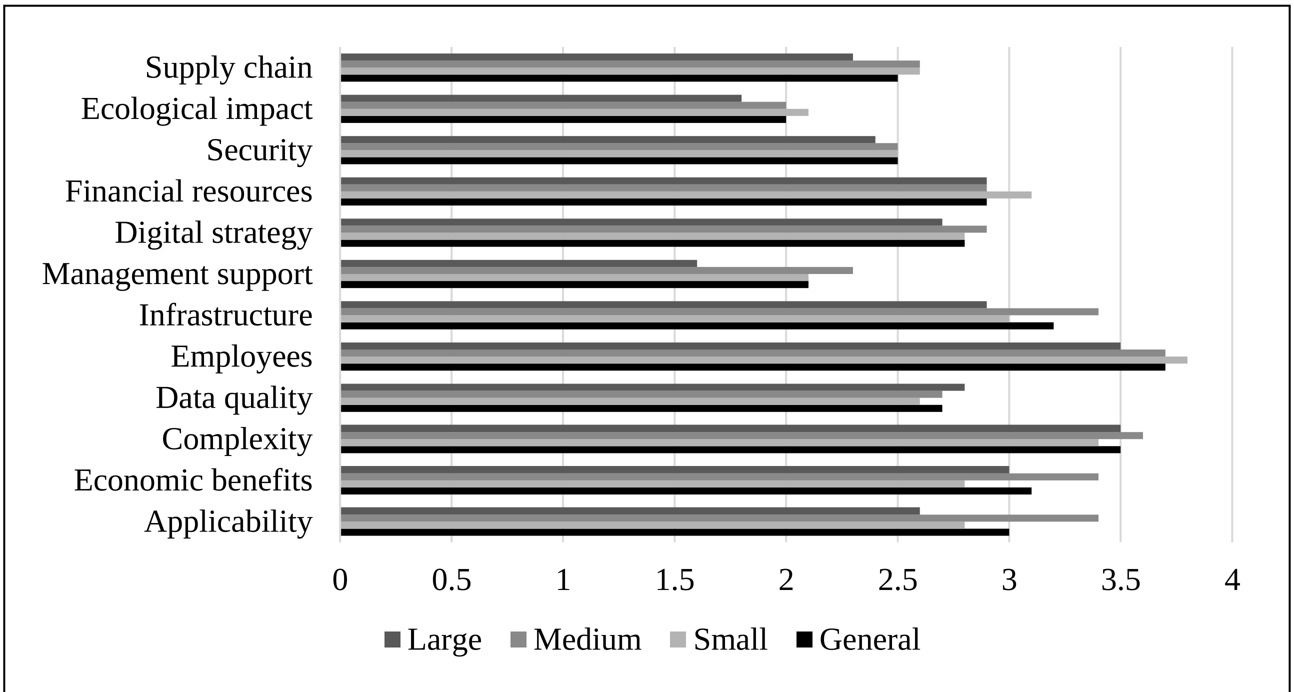

Fig. 8. Barriers to AI implementation based on company size

Next, we explored if there are any differences in the perception of barriers to AI implementation based on the role of the manufacturing company. The general levels stayed the same as in Figure 8, since they are based on the total number of companies in our sample. The results for perception of barriers by different roles of manufacturers are presented in figure 9. Similarly, as before, the lack of employees and complexity of integration with current processes present the biggest barriers to AI implementation, indicating a universal challenge for manufacturers. If we look at the values, then we can see that producers rank the lack of employees at 3,9, which is the highest perception of this barrier. Suppliers and manufacturers in both roles rank this barrier at 3,6. In the context of complexity, producers again have the highest perception of this barrier at 3,7 while manufacturers in both roles perceive rank this barrier at 3,6 and suppliers at 3,3.The third barrier, lack of infrastructure, is ranked the same for producers and suppliers at 3,3, while manufacturers that have both roles rank this barrier at only 2,2, meaning that they perceive it only as a low to medium barrier. If we summarise the perception of the biggest barriers based on the manufacturer role, then the first two barriers are the same, but the third barrier is different for each role. For producers, third biggest barrier presents applicability to current processes (with a rank of 3,3), suppliers perceive lack of infrastructure as the third biggest barrier (also rank 3,3) and the manufacturers in both roles perceive the lack of economic benefits (3,6) as the third biggest barrier. Looking at the barriers that are perceived as the least challenging barriers to overcome in AI implementation, we see that again, ecological impact presents the lowest barrier, followed by the lack of management support. While ecological impact is ranked by producers at 2,2, it is ranked by suppliers at 1,9 and manufacturers in both roles rank it at 2. Again, management support is perceived as a low barrier to AI implementation. The third least challenging barrier differs based on manufacturer role. For producers this barrier is the perceived lack of support in the supply chain (2,5), indicating that the producers expect little to no problems from other participants in the supply chain. Suppliers perceive security (2,5) as the third least challenging barrier to overcome when implementing AI. One explanation could be that due to their role or supplier, they already have sufficient security systems in place. And lastly, manufacturers that have both roles perceive the lack of infrastructure as the third least challenging, indicating that due to their role, they have sufficient infrastructure.

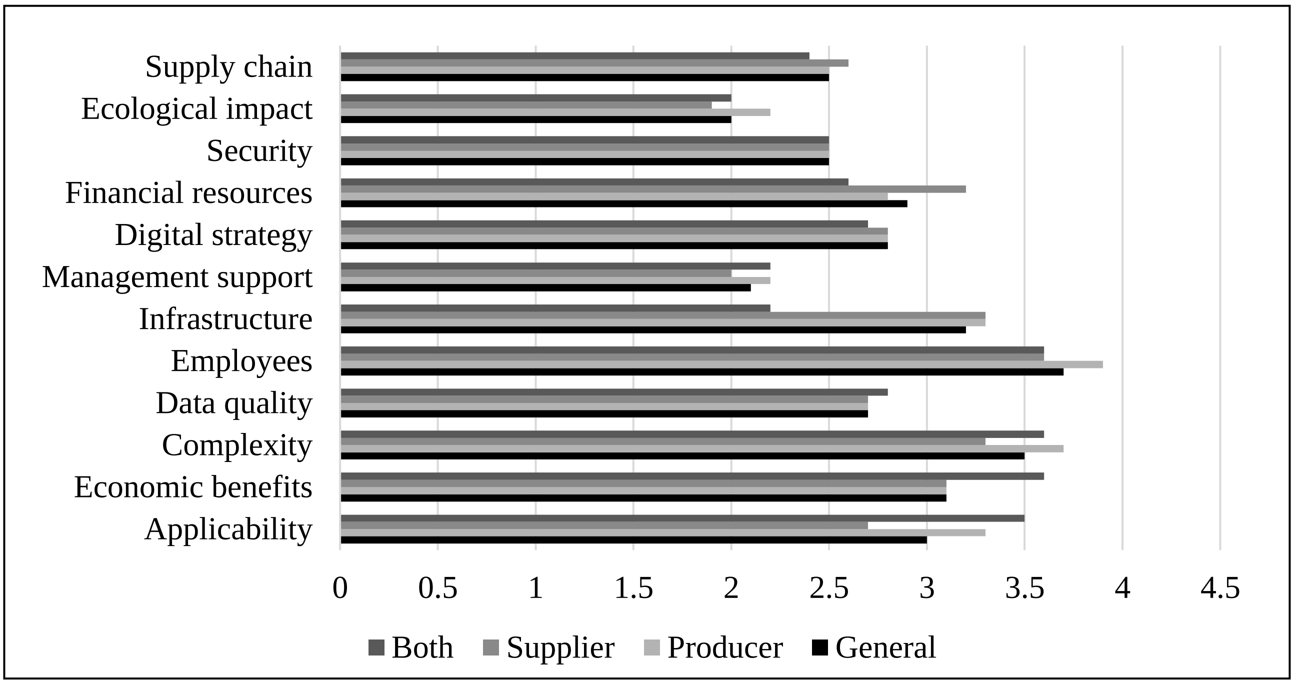

Fig. 9. Barriers to AI implementation based on manufacturer's role

5. Discussion and conclusions

In this chapter we have explored the current research trends and applications of AI in manufacturing companies. Four major areas of AI application are provided: process optimization, quality control, predictive maintenance and collaboration between humans and robots. In order to gain insights into actual use of AI and current areas of application in manufacturing companies, the data from the newest round of EMS 2022 was used.

As with all research, certain limitations and issues must be considered when it comes to reliability, significance and general applicability and use of obtained results. The first limitation is that the data was obtained from the Slovenian subsample of the research, which contains 141 responses in the newest iteration of the research. Although the sample size is sufficient, further research should encompass data from other countries thus creating a larger dataset with more statistically significant results. Another limitation of this study is the use of descriptive statistics which generally helps us with getting to know the data and distributions, but it does not tell us about statistical significance of interactions, correlations and comparisons. Future work will include the use of inferential statistics which will help us to make statistically important conclusions.

Currently, only company size, role of manufacturer and possible barriers were considered when exploring the use of AI. Further in-depth analysis will include more potentially explanatory variables (such as use of digital technologies, complexity of the products, type of production, etc.) and mainly what economic benefits does the use of AI bring for manufacturers.

During our research, we found that the use of AI is dependent on the size of the company and the role of manufacturing companies in the supply chain. However, in the case of company size it was discovered that smaller companies have the biggest share of AI users at different areas of manufacturing, followed by medium sized companies and larger companies are lagging behind. Considering the role of manufacturing companies, it was found that companies in the role of suppliers are leaders in the adoption of AI, while producers mainly use AI for energy management and innovation in production. A baseline for 12 of the perceived barriers to AI implementation was created for the total sample and the perception of barriers based on company size and role was analysed. While there were some marginal differences, it was found that lack of employees and complexity of implementation present the universal challenges for AI adoption. One of the barriers addressed the lack of managerial support. These results are encouraging, and management is generally in favour of AI implementation as indicated by low values for this barrier.

This research also includes practical and managerial implications. Results on the usage of AI adoption indicate the current state for different company sizes and roles of manufacturers which can help guide in the decision to implement AI in certain areas of manufacturing. One other benefit is the presentation of general state of barriers to AI implementation. This can help companies better understand what potential barriers await them and what they need to address to successfully implement AI in their environment.

6. Acknowledgements

The authors acknowledge the financial support from the Slovenian Research Agency (research core funding No. P2-0190).

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