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Overcoming the Challenges of Big Data Analytics Adoption for Small and Medium Sized Enterprises in the Manufacturing Industry

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OVERCOMING THE CHALLENGES OF BIG DATA ANALYTICS ADOPTION FOR SMALL AND MEDIUM SIZED ENTERPRISES IN THE MANUFACTURING INDUSTRY

A Project

Presented to the

Faculty of

California State University,

San Bernardino

In Partial Fulfillment

of the Requirements for the Degree

Master of Science

in

Information Systems and Technology

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by

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ABSTRACT

Advanced manufacturing technologies that enable big data analytics can boost productivity, increase efficiency, and enhance innovation. However, small and medium sized factories face unique challenges when implementing that technology. Plant managers of small and medium sized enterprises (SMEs) are often unsure of how to overcome those challenges in order to reap the benefits of big data analytics. This project examined the opportunities that have arisen due to the Fourth Industrial Revolution, also known as Industry 4.0; how small and medium sized manufacturers in the United States can move from traditional methods of manufacturing to advanced manufacturing, and how the additional data generated can enhance decision-making, specifically for plant managers. An investigation of the factors affecting big data analytics adoption in manufacturing SMEs was conducted, and case studies were examined in order to identify the unique challenges that exist and provide recommendations. The results of the investigation suggest that production managers should prioritize a specific area to focus on, use a big data lifecycle management framework, seek help to build and secure their operation systems, train and encourage employees, and collaborate with others in the industry.

DEDICATION

For Johnny and Lena.

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INTRODUCTION

"Passion provides purpose, but data drives decisions." -Andy Dunn

Factories worldwide are becoming more reliant on technology to keep their production lines running smoothly and efficiently. The days of traditional automation are nearing their end, and the dawn of fully connected, smart and flexible manufacturing is ahead (Rutgers, 2021). Devices and sensors connected to the internet are collecting and transmitting data and this digitization of manufacturing operations has the potential to give production managers new insights into their operations. Data that had never before been available can be gathered and analyzed to provide key metrics in real-time, support decision making, predict and therefore prevent machine breakdowns, monitor workforce safety, improve forecasting, increase productivity, lower costs, enhance agility and harmonize many critical operations (Delgado, 2016).

However, managers of small and medium sized factories are often slower when it comes to Industry 4.0 adoption because they are less prepared (Vrchota, 2019). Larger firms have more resources to facilitate adoption and implementation, and can bear higher risks and so tend to be early adopters of new innovations (Sun, 2016). Small and medium sized enterprises (SMEs) in the manufacturing industry face additional challenges and production managers must contend with competing priorities and limited resources. Regardless, the benefits of these innovations in data utilization are numerous.

This project will examine the opportunities in big data analytics that have arisen due to the Fourth Industrial Revolution, also known as Industry 4.0, how small and medium sized manufacturers in the United States can move from traditional methods of manufacturing to advanced manufacturing, and how the additional data generated can enhance better decision-making, specifically for plant managers.

Problem Statement

The benefits of big data analytics to manufacturers are abundant: it can boost productivity, increase efficiency, and enhance innovation. Small and medium sized enterprises in the manufacturing industry are just as eager to adopt new technologies as large enterprises but face challenges unique to their size, capital needs, and industry. However, plant managers of small and medium sized enterprises in the manufacturing industry are unsure of how to overcome those challenges in order to benefit from big data analytics.

Objective

The objective of this project is to explore the trends and challenges of advanced manufacturing in SMEs and to provide some recommendations to production managers of SMEs, including the steps involved in transitioning to advanced manufacturing and leveraging big data analytics to support decision making.

Research Questions

There are four research questions this study will attempt to answer:

1. What are the trends and unique challenges for the manufacturing industry regarding data collection and analysis?
2. How does advanced manufacturing affect small and medium sized manufacturer's ability to adopt and interpret big data analytics?
3. What factors specific to SMEs in the manufacturing industry have an impact on their adoption and utilization of big data analytics?
4. How can plant managers benefit from big data analytics?

Methodology

In order to understand how small and medium sized enterprises in the manufacturing industry can adopt and utilize big data analytics, the project will take a three-step research approach. First, an investigation of big data analytics issues specific to the manufacturing industry will be conducted. This will entail researching what the main uses of big data analytics are for manufacturers and what problems they commonly encounter in the industry. The investigation will also include issues specific to SMEs and search for patterns or recurring issues. Next, relevant case studies will be examined. This will provide real examples of what it takes for a small or medium sized factory to move from traditional manufacturing to smart manufacturing in order to utilize big data analytics, furnishing different perspectives and solutions. Finally, the cumulative research will be analyzed in order to draw conclusions and provide recommendations to plant managers of SMEs.

Research will mainly consist of documentary analysis, case studies and open-source surveys. The primary sources of literature will be peer-reviewed journals and articles found via the CSU library's OneSearch tool and Google Scholar. Furthermore, to ensure that the literature is high in quality, only articles from major journals and mainstream industry publications were used in the literature review. The OneSearch tool accesses content from all CSU schools' libraries, including over 150 databases (John M. Pfau Library, 2021). Google Scholar searches articles, theses, books, abstracts and court opinions, from academic publishers, professional societies, online repositories, universities and other web sites, from free and subscription sources. Since not all sources are open access, the results require more scrutiny. Secondary sources of data will be news articles and conference proceedings.

Organization of the Study

This project is organized as follows: Chapter 1 covers a review of literature on the research topic; Chapter 2 covers the background of the Industry 4.0 movement, big data and analytics, the manufacturing industry in the United States, SMEs in manufacturing and production management; Chapter 3 delves into the factors affecting big data analytics adoption; Chapter 4 discusses three relevant case studies; Chapter 5 contains the summary and recommendations.

CHAPTER ONE

LITERATURE REVIEW

Due to the nature of the topic relating to recent trends and the swift progression of new technology, research has been limited to literature published between 2016 through present, encompassing roughly five years. The literature pertaining to this project has been found using the following search terms: big data analytics, manufacturing and SME.

The initial results from OneSearch produced 2,028 results when filtered to only retrieve peer-reviewed materials and language set to English. The first 100 results, sorted by relevance to the parameters, were filtered again manually for relevance to the project's topic by reading the title and summary. This subsequently narrowed down the results to 26. Those were further filtered by reading the abstracts and skimming through the content in order to determine relevance. This resulted in nine relevant results.

The GoogleScholar search was also conducted with the same search terms and date range. The initial results produced over 17,000 results. The first 100 results were selected, sorted by relevance to the parameters and were manually filtered for relevance to the project's topic by reading the title and summary. Eight were found to be duplicates of the OneSearch results and thus removed. The remaining were further filtered by reading the abstracts to determine relevance. This resulted in ten relevant results although four required purchase to access the entire publication and one was found to be written in

Korean although the abstract was in English. That resulted in five final results from the Google Scholar search. The final results of both searches resulted in fourteen pieces of literature.

Research by Chonsawat & Sopadang (2020) used bibliometrics to identify five dimensions of readiness for SMEs in adopting Industry 4.0 technologies: Organizational Resilience, Infrastructure System, Manufacturing System, Data Transformation and Digital Technology. The authors developed a scoring system to indicate readiness and tested it in a small shoe factory in Thailand. Their research is relevant to the topic of this project; however it does not specifically focus on big data, nor does it provide specific recommendations directed toward production management.

Cochran et al. (2016) discussed how system design can assist in decision making. They proposed using a scientific approach to designing manufacturing systems in order to create opportunities for data capture and how system design helps determine the requirements for data analytics. The article did not discuss SMEs. Lazarova-Molnar et al. (2019) developed a framework for enabling collaborative data analytics of Industry 4.0 technologies. They proposed that SMEs can close the gap between their data analytics capabilities and those of large manufacturers by collaborating with other SMEs. The article focuses on only collaborative data analytics not big data analytics in general. Similar to the Cochran et al. (2016) research already discussed, Vickery et al. (2019) used axiomatic design to derive solutions for setting up data analytics systems. They did focus on SMEs. This article is very relevant to the topic of this project; however it differs because it focuses on a single methodology to determine data analytics requirements.

A paper by Moeuf et al. (2019) sought to identify Industry 4.0 risks, opportunities and critical success factors for SMEs by using statistical analysis. They found that the major risks of Industry 4.0 adoption in SMEs were lack of expertise and a short-term strategy mindset. They also found that there are opportunities during implementation for improving production processes and adapting new business models, and that a major factor for success is training. The study mainly focused on Industry 4.0 in general, not specifically big data analytics. Majeed et al. (2021) discussed additive manufacturing and sustainability. They produced a framework specific to that segment of the manufacturing industry for combining big data analytics, additive manufacturing and sustainable smart manufacturing. The article did not discuss SMEs.

Babiceanu & Seker (2016) reviewed the status of big data analytics for planning and control of manufacturing operations. They studied the development of predictive manufacturing cyber-physical systems by proposing a framework that included capabilities for attaching to the Internet of Things, and capabilities for complex event processing and Big Data algorithmic analytics. The article is one of the oldest in the selection and also did not specifically cover SMEs. Soroka et al. (2017) reported on a survey of manufacturing SMEs in the UK and their interest in using big data analytics specifically for customer insights in the context of redistributed manufacturing. The study was mainly exploratory and did not produce actionable recommendations. A paper by Ulrich et al. (2018) focuses on how SMEs approach data analytics issues and implementations. They came up with recommendations for selecting a data analytics system by type of SMEs according to four categories: niche provider, bureaucratic, innovative and diversified. This does not specifically address SMEs in the manufacturing industry, although it can be inferred that many small manufacturers are small because of their niche market or because of innovation (ex. new startups).

Bonnard et al. (2019) developed the architecture for a cloud computing platform to collect, store and process data in manufacturing SMEs. They developed the platform and then implemented and evaluated it in three Brazilian companies. The initial results were promising and benefits were apparent. However, the platform required more modification and further testing. This study is relevant as it showed that low-cost and simple to implement big data analytics solutions for SMEs are possible, although it only investigated the effects of their specific platform and did not produce actionable recommendations.

A paper by Garzoni et al. (2019) focuses on how digitization is changing business processes of manufacturing SMEs in a specific region in Italy. Their research is based on a European perspective, analyzing case studies of digitalization adoption in various sub-industries in manufacturing in South

Italy. They came up with a four-step approach for adopting digital technologies: digital awareness, digital inquiry, digital collaboration and digital transformation. They do not specifically focus on big data analytics although they briefly cover it in the fourth step of their approach. Their findings are relevant for a number of reasons but primarily due to the fact that big data analytics requires some level of digitization in the first place and their roadmap describes the process of getting to big data utilization.

Belhadi et al. (2020) discussed the interaction between big data analytics, Lean Six Sigma and green manufacturing and how those initiatives enhance environmental performance. The study only focused on big data analytics in the context of supporting those initiatives and did not discuss SMEs or how to implement big data analytics. Bag et al. (2021) explored what pressures influence the adoption of big data analytics-powered artificial intelligence. Their research was centered on South African manufacturers in the automotive industry. They found that pressures from governmental agencies, institutions and customers force suppliers to adopt digital technologies. The article did not discuss SMEs.

A study by Belhadi et al. (2019) developed a model that summarizes the main capabilities of big data analytics for manufacturing by performing a review of literature and case studies. Although the focus of the study was not on small and medium sized factories, their recommendations are relevant and useful to SMEs. The authors suggest that more research is needed on big data analytics capabilities for manufacturing processes using empirical studies and that research is needed in more specific contexts and industries such as SMEs or service providers.

In summary, the review revealed that there is an abundance of literature on the topics of big data analytics specific to the manufacturing industry, Industry 4.0 effects on SMEs, and data analytics for SMEs, all of which seem to be a popular research topic in recent years. However, as those topics are very broad, I did not find specific research that focused solely on big data analytics adoption and utilization specific to SMEs within the manufacturing industry and that produced advice or recommendations specifically geared toward factory management.

CHAPTER TWO

BACKGROUND

Industry 4.0 and The Digital Transformation

The world is in the midst of yet another industrial revolution and it is transforming how goods are produced. The first industrial revolution began in the latter half of the 18th century and centered around the use of iron and coal as well as advances in textile manufacturing (Britannica, 2021). This was when the first factories were built, although the revolution was mainly confined to Britain until the second industrial revolution spread to continental Europe, North America and Japan. The second occurred in the mid-19th century and involved the use of electricity, railways, communication by telegraph and the assembly line (Niiler, 2019). The third industrial revolution utilized computers and robotics to automate production in the late 20th century (iED Team, 2019). Now the fourth industrial revolution is utilizing smart technologies such as artificial intelligence for monitoring and inspection and Internet of Things devices to communicate with each other and collect data.

The term “Industry 4.0” and the concept behind it was first introduced in 2011 by a team of three German scientists in an article published by VDI Nachrichten (Kagermann, 2011). The three authors foresaw the imminent paradigm shift in manufacturing due to the adoption of “cyber-physical” systems. The article, originally published in German, explained that concept further as “the digital refinement of production systems and industrial products through everyday products with integrated storage and communication capabilities, wireless sensors, embedded actuators and intelligent software systems creates a bridge between the virtual world and the real world, right up to the mutual fine-grained synchronization between the digital model and physical reality" (Ref 9). However, this cyber-physical system concept is only one of many elements in the Industry 4.0 movement.

The Internet of Things, also referred to as IoT, is the addition of an internet connection to objects that traditionally did not have an internet connection (Priceonomics, 2019). This has enabled enormous opportunities in the modern factory, including the immediate collection and transmission of data related to machine failures, environmental conditions, quality assurance, power usage and so on. The use of IoT devices within specific industries such as manufacturing, healthcare, retail, utilities and logistics is referred to as the Industrial Internet of Things. For high volume, high speed production lines, the use of edge computing to process data and react faster is another trend. Cloud computing is making the adoption of smart factories more accessible by reducing or eliminating the need to invest in IT infrastructure. Another trend is the use of artificial intelligence, which can monitor machinery and other assets without much human interaction. All of these technologies are disrupting traditional manufacturing processes and creating immense pressure on organizations to remain competitive.

The digital transformation simply refers to the shift from old-fashioned, manual and labor-intensive processes such as paper reports to technology-driven processes, where the information is stored completely on digital devices or in the cloud and transmitted digitally over networks. This transformation has enabled another important element of Industry 4.0 known as big data analytics.

Big Data and Analytics

Smart technologies have become democratized and increasingly affordable. From mobile phones in nearly every pocket to wearable fitness trackers on millions of wrists (Statista, 2021), smart devices are everywhere and capture huge streams of data every second. The enormous amount of data being generated from such devices is referred to as “big data”. In fact, collections of data have become so large that typical data management systems can no longer store or process them. This has created new challenges for those wishing to extract meaningful information from these huge data sets. In the 1990s, analyst Doug Laney originally described big data as having three characteristics and coined the term the three V’s, for volume, velocity and variety (Grimes, 2016). Furthermore, big data consists of both structured and unstructured data. Structured data refers to data that resides in a fixed field within a file or record, is often stored in a relational database, and consists mainly of numbers (Smallcombe, 2020). Unstructured data is everything else. It is not structured via pre-defined data models or schema, may be textual or non-textual, human- or machine-generated and may also be stored within a non-relational database (Taylor, 2018). Some examples of unstructured data are emails, websites, media such as audio and image files, sensor data and social media data. The specific process of analyzing big data is called big data analytics, and it requires different skills and tools compared to traditional data analysis methods.

While smart device technology has become mainstream and readily available to the everyday person, it has already been put to use in the business world. Cheap and numerous devices are revealing data sets that were never available before. Complex statistical methods previously only utilized by data scientists and statisticians are now available to managers, analysts and other business professionals via interactive, easy-to-use software programs.

The analysis of big data streams can provide the extra edge needed to compete if the approach is well-structured. Utilizing the opportunities in big data analytics can enable managers to be more agile. For example, they can use automated dashboards linked to streams of real-time data instead of waiting for historical reports to be prepared and manually analyzed. Big data analytics also provides businesses with customer-specific recommendations on products and services. It can impart insight on feedback from social media, blog posts, and reviews which in turn gives management the opportunity to refine and redevelop existing services and products as well as crowdsource the research and development process for new products. Big data analytics enhances the management of inventory and production capacity, both of which are critical processes in the supply chain.

The United States Manufacturing Industry

In 2019 in the United States, the manufacturing industry added $2.35 trillion in value to the GDP (Appendix A). To put in context how large the American manufacturing industry is, this added value is larger than the entire economies of all but six other countries in the world (Appendix B).

The adoption of smart technology was and is inevitable for any company that needs to stay competitive. Those in the manufacturing industry are no exception. Just like many other industries, manufacturing is undergoing the digital transformation. The benefits associated with this digitalization generally outweigh the costs, but the drawbacks cannot be overlooked. The cost to completely overhaul a production line can be immense. Aside from the initial costs of implementation, a significant challenge is cybersecurity. More data being generated, in many different ways (sensors, networks, devices, etc.) means more connections that create more opportunities for persons with malicious intent to gain access to that data. Furthermore, employee resistance to change or insufficient skill sets can also be a hurdle.

Small and Medium Sized Manufacturers

Most manufacturers in the United States are considered small or medium sized, meaning less than 500 employees (United States Census Bureau, 2020). According to the most recent data from the US Census Bureau, only 6% of manufacturing firms do not meet the definition of an SME (See Appendix B). In fact, most manufacturing businesses are not large or medium sized - only 30% had 20 or more employees. Because small and medium sized manufacturers make up such a large proportion of firms and are the backbone of economic growth, their unique challenges deserve further investigation. Like larger organizations, SMEs typically have a hierarchical management structure (Moeuf, 2020).

A common challenge faced by SMEs is limited resources. They are not able to raise capital as quickly or easily as large firms. They also have fewer employees that can specialize such as a designated Chief Data Officer for example. They rely more on outside consultants for IT services. Machine downtimes can have a greater impact when there are fewer other production lines to make up for the loss in capacity. They are at a disadvantage when sourcing materials due to smaller purchases and economies of scale.

SMEs do have some advantages, however. They tend to be more agile and do not need to collaborate with numerous other business units or locations in order to make changes or alter strategy. They often have an entrepreneurial culture that fosters innovation. The founding owner is often still very involved in the day to day operations as opposed to a somewhat detached board of directors and shareholders in larger organizations. Leadership is more hands-on and there are fewer layers of management, resulting in a more “short” hierarchy (Moeuf, 2020).

Production Management

The reporting structure of an American manufacturing organization follows a hierarchical model, where the production manager reports to the executive management, the production supervisors report to the production manager, and the production workers report to the production supervisors. The production manager is responsible for overseeing the operations of the entire production facility. In smaller organizations, their responsibilities are broader as they may also be responsible for other departments such as supply chain, quality and engineering. Their highest priority is usually getting product out the door on time, but they may also be incentivized on quality and cost reduction. They generally require reporting and metrics on production capacity, throughput, inventory, labor costs, scrap/waste and quality. Production managers of smaller factories also feel pressure to take a DIY approach to projects. This entails learning while doing, having little or no prior experience and without the entire project being outsourced to paid experts. This approach can be risky but it is the reality for many small businesses short on resources.

In summary, running a production floor is a tough job with many competing priorities. There is constant pressure to output faster, cheaper and better, which is why utilizing big data analytics can be advantageous for them. Since companies in the United States cannot compete based on labor costs alone, it is especially important that they utilize advanced manufacturing and its components like big data analytics to improve efficiencies and processes. In order to understand how the production manager in an SME can benefit from big data analytics and why they should put forth the effort in upgrading their manufacturing technology, the specific factors influencing the adoption of big data analytics will be explored in the following section.

CHAPTER THREE

FACTORS AFFECTING BIG DATA ANALYTICS ADOPTION IN MANUFACTURING SMES

Being competitive in manufacturing in a first-world country where wages are much higher than in China and other developing countries is critical for American manufacturers. Executives recognize that adoption of Industry 4.0 technologies is essential to competing with other manufacturers worldwide and they face great pressure to adapt. According to a 2020 survey by Deloitte Global of over 2,000 C-level executives, 7 in 10 respondents believe that long-term business success requires the integration of these technologies, although two-thirds of respondents said they had no formal plans yet to do so (Deloitte Insights, 2020). This suggests a disconnect between intention and readiness. Once intention has been established, what is holding them back?

Unclear Requirements

Plant managers are keenly aware of the pain points on their shop floors and along their supply chain. They likely have identified key performance indicators already, such as throughput, cycle time, capacity, defect rate, inventory turns, scrap and rework cost, changeover time or cost per equivalent unit. In SMEs, these indicators are usually reported on in a historical or intermittent fashion. In order for managers to make informed decisions, be proactive and make improvements, these metrics need to be generated in real-time. The problem is knowing which areas to focus on. Due to constrained resources, SMEs often find themselves needing to pick and choose which areas they need to attack as opposed to overhauling their entire system.

Complexity

Aside from the perception that the entire system needs to be overhauled, another obstacle to big data analytics adoption is the perception of complexity. The characteristics of big data are perceived as being difficult to understand and use (Sun, 2016). In smaller organizations, there are fewer specialists that have expertise in the newest technologies. This leads the managers to believe that pricey outside consultants are required to design and build a sophisticated analytics solution. Some companies may already have equipment with smart features and capabilities in place but are underutilized because they are seen as complicated or would require the factory to entirely transform their procedures. Alternatively, they may believe that their equipment must be completely replaced and are unaware of the modifications or add-on devices that can do what they need. For SMEs, this factor alone can stop a big data project in its tracks.

Unclear Benefits

Before the advent of Industry 4.0 technologies, analytics was typically performed in a historical fashion. This results in information that is often outdated before it can even be reviewed by managers due to pulling data from various disconnected sources and manually aggregating them. Big data analytics enables instant, up-to-the-minute metrics. Furthermore, big data analytics' ultimate goal is predictive - being able to foretell what is likely to happen so disruptions and waste can be avoided and different scenarios can be evaluated using more than just intuition. However, the realistic connection between big data analytics and these benefits is not always clear or easy to quantify. This causes hesitation in efforts to incorporate big data in their factories.

Cost

SMEs are particularly cost-sensitive for many reasons, such as difficulty in accessing the public capital market, shorter track record, greater information asymmetry, higher failure rate, fewer opportunities available to owners-managers for wealth diversification, and typically lower availability of collateral (Zubair, 2020). Their ability to invest and attain financing is also greatly affected by the economic environment. The current situation with the COVID-19 pandemic still underway has caused many SMEs to focus investment in essential areas such as e-commerce, personal protective equipment, social distancing barriers on the production floor, and so on, just to stay in business. This has left many organizations with fewer resources to improve their Industry 4.0 technologies. The pandemic has also raised concern about another financial crisis, especially since SMEs significantly cut back investment expenditures in the years following the onset of the 2008 financial crisis (Zubair, 2020). These factors are a huge concern for SMEs as they consider the costs of investing in the infrastructure necessary to implement big data analytics. Furthermore, in order to calculate the return on investment, both the cost and the value expected to be created need to be calculated. Those variables are difficult to quantify for reasons already covered in the two previous sections.

No Executive Support

In SMEs, the focus is often on the short-term (Moeuf, 2019); therefore, the case for investing in advanced manufacturing and analytics must be very strong in order to gain support from the top. Managing short-term and long-term goals is already a delicate balance, but that balance is particularly difficult for SMEs. If long-term investment activity is neglected, then the firm, even if initially successful, will gradually lose its competitive advantage, but if they focus too much on the long-run goals, the company might fail to produce the outcomes necessary to survive until the long-term benefits materialize (Olesiński, 2014). A survey by McKinsey Digital aimed at determining the most important factors in the success of analytics efforts found that for those firms lagging behind, a lack of strategy or tools isn't necessarily to blame (McKinsey Digital, 2016). Their findings indicate that not only is executive support important but the actual involvement of senior leadership in the analytics project was the most critical factor to success, even more important than its technical capabilities or tools. The results of their survey are summarized in a graph in Appendix E. These findings are extremely relevant for SMEs because a short-term mindset leading to lack of executive support and involvement in a long-term analytics project can make or break it.

Lacking IT Infrastructure

Once data is collected, it needs to be stored, processed and classified. Overall, big data analytics requires more IT resources than are usually in place. The greater volume of data requires much more storage, the velocity of data being collected requires more processing power and the variety of data, such as unstructured image files captured during quality inspection, requires a means of classification. Furthermore, IoT devices will need their own network or multiple networks, so the additional traffic does not interfere with the existing network connections. More networks mean more opportunities for security breaches. And more IT infrastructure means more support will be needed.

Security Concerns

Although any organization that uses technology must defend against cybersecurity threats, there are significant security concerns that are specific to big data. One of those concerns is distributed data. In order for the huge volume of data to be processed efficiently, the processing is often distributed over multiple systems. For example, Hadoop is a popular tool used to spread computation tasks to many different computers. However, it is an open-source software library that was not built with security in mind. In order to utilize it safely, additional security measures must be set up and configured. Another common big data solution that prioritizes performance over security is non-relational databases, such as NoSQL data stores (Mayaan, 2020). This means that traditional methods of securing a database are not adequate for the unstructured, non-relational data and security measures are more difficult to implement. Attacks on big data systems can also consist of information theft, DDoS attacks, ransomware or other malicious activities (Maayan, 2020). SMEs are attractive targets because they have information that cybercriminals want, and they typically lack the security infrastructure of larger businesses (SBA, n.d.). This is especially true for manufacturers that use smart technologies because they rely on this technology to keep their factories running. Adding advanced technologies to manufacturing networks requires equally sophisticated cybersecurity standards (Deloitte, 2021). This only adds to the cost and complexity, resulting in even more hesitation to proceed with a big data project.

The Human Factor and Workforce Training

The complex behavior of humans affects every organization and its endeavors. In fact, there is an entire field of academic study dedicated to understanding organizational behavior because of its significance. All of the past industrial revolutions have ushered in profound changes to the way people work and live, and Industry 4.0 is no exception. Changes can be scary and resistance to change must be addressed, especially when there is a perception that the changes may negatively affect people's livelihoods. Workers may fear that advanced manufacturing will take away their jobs or even that these technologies are a means of increasing surveillance of their work (Moeuf, 2019). Manufacturing jobs have indeed decreased in the US in the last decades due to both automation and outsourcing (Vardi, 2017). Even before the Industry 4.0 concept was introduced, factory automation has both eliminated jobs and made those jobs that remain more technical (Manufacturing.NET, 2003). Although automation already replaced a great deal of non-skilled work, smart technologies like artificial intelligence and machine learning will replace some skilled work now as well. This goes to show that there is validity to the fear. Even with retraining and upskilling the workforce, fearful and disengaged employees are not likely to be able to contribute to the inspired adoption of technologies—something which is essential for optimum implementation of company-wide solutions (Ecrion, 2021).

In summary, there are many obstacles that SMEs face in order to reap the benefits of big data analytics. First, priorities must be set so requirements can be defined. The perception of complexity and clarification of benefits needs to be addressed. Then the cost must be calculated and leadership support obtained. The IT infrastructure must be upgraded and security issues resolved. And finally, the human factor must be considered before embarking on the path to big data analytics. Once all of these issues have been thoroughly addressed, the organization can put its plans into action. In the following section, several case studies will be examined to investigate the effect of these factors in practice.

CHAPTER FOUR

CASE STUDIES

In order to answer the specific research questions of this project, actual real-life examples will be studied. One difficulty in answering those questions is that there is a shortage of case studies of big data analytics use in SMEs (Iqbal, 2018). Because the volume of research being done on these topics is increasing rapidly, this is a temporary problem for this field of research. However for the purposes of this project, three individual case studies will be utilized as opposed to a single in-depth case study.

A total of three case studies were chosen and all were from manufacturing companies. They were specifically selected because although each company faced at least one of the challenges discussed in Chapter 3, they found a way to overcome them in order to utilize big data analytics in a valuable way. Their approaches contribute to the development of the solutions to the research questions posed for this project.

Case 1: Vention Medical

Vention Medical was an American manufacturer of medical tubing, balloons and catheters. In March 2017, they were acquired by Nordson Medical. Prior to this acquisition, Vention Medical's annual revenue was $150 million with EBITDA of $48 million (MPO, 2017). Although Vention Medical as a whole did not meet the criteria for a SME, the following case study took place at just one of their 13 facilities as a proof-of-concept test (Verdigris Technologies, 2016). The management decided to target one specific area of significant expenditure: energy consumption. They were looking for a way to easily identify and quantify potential cost savings, achieve their goal of manufacturing more sustainably and track equipment malfunction to prevent downtime. Because their production process took place in cleanrooms, any disruptions to HVAC service or to the HEPA filtration system could jeopardize FDA-approved cleanroom conditions, contaminate materials and increase costs. Their existing equipment did not have a way to collect data in order to analyze their energy usage or monitor their HVAC system. They also faced other challenges: complexity and lack of IT infrastructure. For those reasons, they decided to contract with an outside company for the project. Verdigris Solutions was brought in to install hardware on their cleanrooms, lighting and HVAC equipment at their Sunnyvale, California location. The new hardware enabled the collection of real-time data that was fed into a comprehensive energy monitoring and notification system. This provided Vention's management with a dashboard of valuable information about energy trends and helped them uncover inefficiencies. The facility was able to realize cost savings on their electric bill and receive notifications about equipment downtime. Vention Medical saw potential for even greater savings by later implementing this technology in all its global facilities. This case study shows that Industry 4.0 technologies can be utilized on a smaller scale and for a specific purpose and does not necessarily involve overhauling an entire production line or significant and costly upgrades to equipment.

The case study helps answer all four of the research questions. The first question asked what the challenges are for collecting and analyzing data in the manufacturing industry. In Vention's case, they did have sophisticated manufacturing equipment but it still did not have a way to collect the data they needed to analyze their energy usage. They ended up resolving this issue by having hardware installed on their equipment and utilizing Verdigris' online dashboard. The second research question asked how advanced manufacturing affects an SMEs ability to adopt and interpret big data analytics. In Vention's case, the innovative technology of the comprehensive electricity monitoring and notification system for cleanroom manufacturing facilitated their data collection and analytics. Another research question asked what factors specific to SMEs have an impact on their adoption and utilization of big data analytics. Vention's Sunnyvale location did not have the in-house knowledge to implement a big data solution, just like many SMEs. The project was too complex and they did not have the IT infrastructure already in place. They resolved that issue by contracting with an outside vendor. Finally, the case study shows how plant managers can benefit from big data analytics. Vention was able to realize cost savings from the data they collected and analyzed. This is an easy win for production managers since they are responsible for keeping production costs in check. They also were able to prevent downtime and get closer to their goal of manufacturing sustainably.

Case 2: Dolle A/S

Dolle A/S is a Danish manufacturing company that produces staircases, loft ladders and railings (Dolle, 2020). They are headquartered in Nordjylland, Denmark and have production facilities in Denmark, Ukraine, Romania and China. Their annual revenues are approximately $10 million (DNB, 2020). They implemented a big data analytics project using IoT sensors on their machinery, tracking such activities as output pace and changeovers (Iftikhar, 2019). Although the sensors were programmed to produce alarms to notify staff when malfunctions occurred, Dolle A/S also put the raw data to use. Dolle A/S engaged researchers from a local university to use the data generated from their production processes to perform an exploratory analysis with the objective of determining the current and optimal output pace and changeover time. In addition to those objectives, the researchers were able to calculate an Overall Equipment Effectiveness (OEE) score. This score is a measurement of the time that the equipment is productive. Therefore, a score of 100% would indicate that the pace of production is optimal, without any unplanned stops and producing only good quality products. After analyzing the data using various methods, the results indicated that production performance could most be improved for Dolle by reducing machine downtime. This was extremely valuable information because it helped production management know which specific area would have the greatest impact so they could focus their efforts there. Not only were prescriptive analytics used but various machine learning algorithms such as logistic regression, neural networks, support vector machines, decision trees and k-nearest neighbors were applied on a historical data set to predict costly production line disruptions (Iftikhar, 2020).

Figure 1 shows an example of a data visualization created during the researcher's exploratory analysis. ScrewError and FaultyString both have weak to moderate effect on the number of unplanned MachineStops, however, the duration of these stops have a strong positive correlation with machine DownTime.

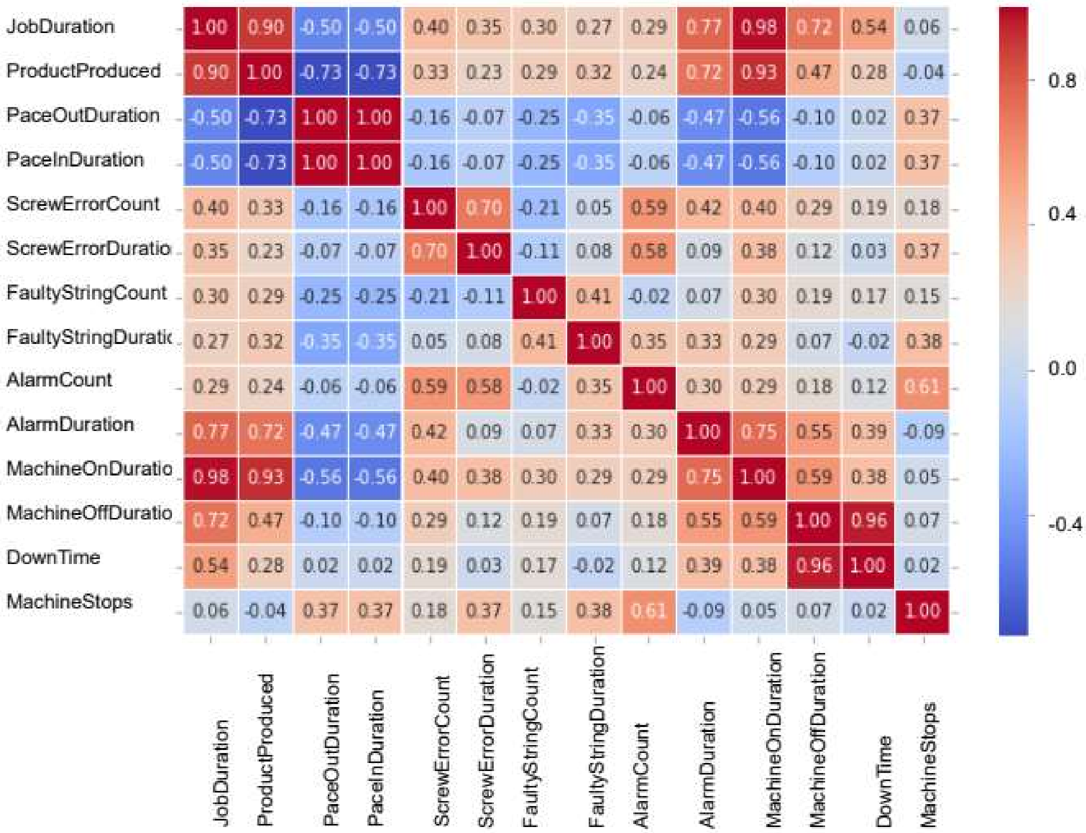

Figure 1. Sensor and alarm correlation heat map (Iftikhar, 2019)

Similar to the Vention case, Dolle also had sophisticated manufacturing equipment but it did not have the ability to capture the data they needed. Their solution involved the use of connected IoT sensors affixed to their equipment. Dolle did not have the in-house knowledge to develop an analytics system so they utilized outside resources. IoT sensors are an innovative technology which goes to show how advanced manufacturing can positively impact a manufacturers ability to use big data analytics. The data generated by the sensors were critical in helping Dolle's management improve their OEE score. The case study also shows how plant managers can benefit from big data analytics; keeping the equipment running smoothly and efficiently is one of their biggest priorities.

Case 3: Atlas Axillia

Atlas Axillia Company Private Limited is an SME located in Sri Lanka, whose main business is the manufacturing and distribution of school supplies such as pencils, pens, markers, refillable bottles and lunch boxes (Atlas, 2020). Their annual revenues are $5 million and there are 29 employees (Zoominfo, 2021). Some of their products are made by injection moulding. Injection moulding is a common process that involves the melting of materials such as polymers or metals and forcing them by injection into a cavity where they solidify into the desired shape. An in-house engineer documented the process of implementing a simple IoT framework allowing for the connectivity of several fully-automated but independent machines. The case study demonstrated the importance of Industry 4.0 and new opportunities within an application that is realized for an industrial injection molding machine with minimal expertise, knowledge and investment (Priyashan, 2020). Once the machines were connected, management was able to access real-time data about production counts, machine status, mould and environmental temperatures and other critical metrics. This enabled them to make better decisions as well as eliminate some redundant clerical tasks. Figure 2 shows the system inputs and outputs, and figure 3 shows the architecture of the IoT network.

Sensing Characteristic	Input Signal
Environment Temperature	MAX6675 K type temperature probe [45]
Mold Cavity Plate Temperature	MAX6675 K type temperature probe
Chilled water inlet temperature	MAX6675 K type temperature probe
Completion of Mold Close	From Injection molding machine control unit
Injection mold machine running condition	From Injection molding machine control unit

Action	Output
Production count	Node-RED Dashboard, InfluxDB, and HMI (Haiwell HMI C7S-W) [46]
Machine running status	Node-RED Dashboard and HMI (Haiwell HMI C7S-W)
Mold temperature	Node-RED Dashboard, InfluxDB, and HMI (Haiwell HMI C7S-W)
Environmental Temperature	Node-RED Dashboard, InfluxDB, and HMI (Haiwell HMI C7S-W)
Chilled water inlet temperature	Node-RED Dashboard and InfluxDB
Injection Machine Stop function	PLC (Haiwell T16S2T) [47]
Chiller set temperature variation	PLC (Haiwell T16S2T)
Chiller Start/ Stop function	PLC (Haiwell T16S2T)

Figure 2. System inputs and outputs (Priyashan, 2020)

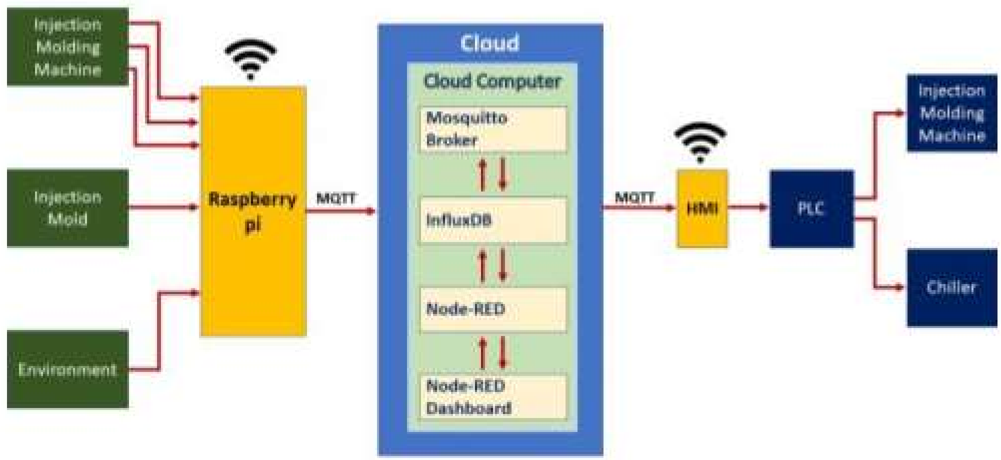

Figure 3. Architecture of the IoT network (Priyashan, 2020)

The case study follows the trend of the other two case studies that utilized additional hardware to capture the data they needed. As far as what specific factors affect SMEs in manufacturing, the case study demonstrates why utilizing big data analysis to help improve their processes is so critical for SMEs. SMEs that perform injection moulding typically have lower volume production runs and therefore have fewer opportunities for cost savings due to economies of scale. They must rely on other means of savings and improvements. The case study also shows how plant managers were able to benefit from big data analytics. The production managers at Atlas now have access to real-time data pertaining to their manufacturing operations which directly impacts their highest priorities: outputting faster, cheaper and better.

Although these three case studies entail very different types of big data analytics projects, they do show that it is possible to capture and process big data in meaningful and valuable ways. Each company found a way to incorporate big data analytics in their manufacturing facility or processes despite the challenges SMEs face. A summary of the cases and how they relate to the research questions are shown in Table 1.

Table 1. Summary of cases and how they relate to the research questions

	Question 1: **What are the trends and unique challenges for the manufacturing industry regarding data collection and analysis?**	**Question 2:** **How does advanced manufacturing affect small and medium sized manufacturer's ability to adopt and interpret big data analytics?**	**Question 3:** **What factors specific to SMEs in the manufacturing industry have an impact on their adoption and utilization of big data analytics?**	**Question 4:** **How can plant managers benefit from big data analytics?**
Case 1: Vention Medical	Vention Medical did not have a way to collect and analyze the data. They had hardware installed and used an online dashboard for analytics.	The innovative technology of the comprehensive electricity monitoring and notification system for cleanroom manufacturing facilitated the data collection and analytics for Vention Medical.	Vention Medical did not have in-house knowledge due to complexity and they did not have IT infrastructure in place. They had to contract with an outside vendor for the entire project.	Vention Medical achieved cost savings, prevented downtime, and achieved their goal of manufacturing more sustainably.
Case 2: Dolle A/S	Dolle A/S did not have a way to collect and analyze the data. They installed hardware and utilized researchers to develop an analytics system.	IoT sensors generated data that measured Overall Equipment Effectiveness, enabling management to identify areas for improvement. The sensors also captured data enabling both prescriptive and predictive analytics.	Dolle A/S did not have in-house knowledge due to complexity. They had to engage researchers for developing analytics.	Dolle A/S realized improvements to production efficiency and avoided costly disruptions.
Case 3: Atlas Axillia	Atlas Axillia did not have a way to collect and analyze the data. Their engineering department installed hardware and developed an analytics system.	IoT sensors generated data that was processed in the cloud and fed into a dashboard, allowing management to view and interpret key metrics.	Atlas Axillia had cost constraints. They developed a cost effective IoT network.	Atlas Axillia used real-time data about production counts, machine status, mould and environmental temperatures to make better decisions and reduce costs.

CHAPTER FIVE

SUMMARY AND RECCOMENDATIONS

Discussion

There is no doubt big data analytics can be a game-changer for production managers, and this project demonstrates why production managers should care about implementing it. The case studies showed notable benefits such as cost savings, increased performance and better decision making. Although the technology enabling advanced manufacturing is getting better and cheaper, there are still significant challenges faced by SMEs in the manufacturing industry as covered in Chapter 3. Smart technologies are becoming more democratized and IoT devices are becoming more affordable. These are encouraging trends from the SME perspective.

All three case studies utilized different means of implementing big data analytics in their factories. The Vention Medical case outsourced the project completely, the Dolle A/S case blended in-house expertise and help from researchers, and the Atlas Axilla case was handled completely in-house. This indicates that expertise and availability of resources is a significant factor for determining how much outside help is needed. Some organizations may be successful using a fully DIY approach while others may not. The difficulty is knowing what can be handled in-house and when to bring in the experts.

The project's objective to explore the trends and challenges of advanced manufacturing as it relates to big data analytics to benefit SME's has been achieved with the identification of eight specific factors that influence the adoption of big data analytics in American manufacturing SMEs. The combination of analyzing those factors, further research and the investigation of case studies has helped achieve the objective of providing some recommendations to production management. To address the issues of unclear requirements, unclear benefits and cost, the recommendation is to prioritize and focus on one specific goal. This also addresses the lack of executive support issue because each successful analytics project can be used to garner support for the next project. To address complexity, a robust data lifecycle management plan should be used. To address the lack of IT infrastructure and security concerns, seek help to build and secure the infrastructure. To address the human factor issue, training and encouragement by the production management is recommended. Finally, collaboration with others in the industry is recommended to address all of the factors collectively. Figure 4 provides a table showing the factors affecting big data analytics adoption in manufacturing SMEs in the columns and the recommendations provided by the literature sources used in this project in the rows. A discussion of the summary follows.

Recommendations:	Unclear Requirements	Complexity	Unclear Benefits	Cost	No Executive Support	Lacking IT Infrastructure	Security Concerns	Human Factor
Prioritize and Evaluate Readiness	✓		✓	✓	✓			
Use a Big Data Lifecycle Management Framework		✓						
Seek Help to Build and Secure the Infrastructure		✓				✓	✓	
Train and Encourage								✓
Collaborate	✓	✓	✓	✓	✓	✓	✓	✓

Figure 4. Summary of recommendations

Recommendations

Prioritize and Evaluate Readiness

When determining what the requirements are for data analytics, it is important to prioritize which areas to focus on especially for smaller businesses. Do not try to tackle too much at once. This approach is ideal for SMEs due to the smaller investment but also because smaller victories can be built upon and used as evidence of the value of big data analytics, encouraging the continuation of adoption of these technologies. Determine which metrics will be most valuable with real-time monitoring and alerts and how predictive analytics can improve them. Since the priorities of factory plant managers are mainly concerned with data generated on the shop floor or related to the supply chain for its components, it makes sense to first look at uses for big data analytics for in-house processes and inventory management (Nanivadekar, 2019).

Once requirements have been determined, the next step is to evaluate readiness. The University of Warwick in the UK designed a self-assessment tool to help companies determine their readiness (WMG 2021). Although this tool pertains to several business functions and is not specific to SMEs, it provides some valuable insights that apply to manufacturing and operations. This tool is an excellent starting point for plant managers to assess their current situation. Appendix D shows the inputs and results of the assessment for a test company.

Use a Big Data Lifecycle Management Framework

In order to use big data analytics to gain insights into the production process, data needs to be generated and collected. The flow of the data itself must be carefully planned. Consider utilizing the Big Data Lifecycle Management framework; it consists of multiple stages that will help address all of the factors in the data flow. While there is no rigorous universal systemic approach to the Big Data lifecycle, Dr. Mehmet Yildiz, a distinguished enterprise architect, defines the lifecycle as containing twelve phases: Foundations; Acquisition; Preparation; Input and Access; Processing; Output and Interpretation; Storage; Integration; Analytics and Visualization; Consumption; Retention, Backup and Archival; and Destruction (Yildiz, 2020).

The process begins with a foundation phase. This where the basis of the project is defined by reviewing the data requirements, scope of the solution, roles and responsibilities. The data infrastructure and data rules are also reviewed and validated. The second phase is data acquisition. This is where the sources of data will be identified. For manufacturers, there are many options: IoT sensors attached to the machinery as in the case studies; devices planted along conveyors or at various work centers; RFID tags attached to the product itself as it moves around the shop floor for tracking and timing; or even wearables affixed to the factory workers to monitor vital signs in dangerous environments. The next phase is data preparation. In order to utilize the raw data that was generated, it usually needs to be scrubbed to check for inconsistencies, redundancies, errors and duplicates. The fourth phase is data input and access. The input refers to the transmission of data to its repository or processing application. Access refers to the methods that will be used to access the data, such as relational databases, flat files or NoSQL (Yildiz, 2020). The next phase is data processing. Several processing tools commonly used in businesses are Apache Hadoop, Spark SQL and Hive. The data processing phase includes labeling the data and aggregating data from different sources. The sixth phase is data output and interpretation. At this point, the data should be in a usable format for business users. Only then can the data be interpreted and meaningful information be extracted.

The next phase is data storage. The storage infrastructure can consist of storage area networks (SAN), network-attached storage (NAS), or direct access storage (DAS) formats and can include underlying technologies such as database clusters, relational data storage, or extended data storage (Yildiz, 2020). The eighth and ninth phases overlap somewhat. Data integration, analytics and visualization involve integrating the big data with dashboards or data visualization applications such as Tableau. These applications create a visual representation of the data so it can be better understood and used to make decisions.

The tenth phase is data consumption. This is the stage where data is actually used to achieve a goal. This phase may also require architectural input for policies, rules, regulations, principles, and guidelines (Yildiz, 2020). This is to ensure the data is being accessed by only those that have been given access to it, as well as governs how the data is to be used. The final two phases involve the processes of retention, backup, archival and destruction. The data must be kept secure and protected with a robust backup and recovery process (DataWorks, n.d.). The data may also be sent to long-term storage such as a data center for archival. And since the amount of data generated and stored can grow very large, a data purge is periodically needed. To avoid excess storage costs or slow system performance, make sure to only capture data that is needed. This will also help prevent analysts from having to sort through and clean more data.

These steps can be adjusted as needed to fit the specific organizational needs and requirements of the big data solution being planned. By using these steps as a template to clearly define and document the flow of data throughout its entire lifecycle, managers can avoid headaches and help ensure their data strategy is robust and effective.

Seek Help to Build and Secure the Infrastructure

Building, securing and managing a factory's IT infrastructure is not a task to be taken lightly, especially with the extra burden of everything that goes into implementing advanced manufacturing technologies. For organizations with limited in-house IT resources, it may make sense to seek outside help for this phase in the project, as in the Vention Medical case study. Since technology is the foundation of advanced manufacturing, the supporting physical components, software and network must be carefully planned. When designing the IT infrastructure that will enable connectivity and data collection, cybersecurity must also be considered. Because it is nearly impossible to secure very large data sets, it is more practical to protect the data value and its key attributes (Benjelloun, 2015). Consider who needs access to the data and only grant access to the specific data the user needs. Also, be sure to build in the flexibility to scale up and add to the project scope later on. Another critical consideration is to have a separate network for the sensors and devices apart from the company's main network. By keeping all the IoT equipment on a separate network, any compromise will not grant an attacker a direct route to a user's primary devices where most of their data is stored (Cimpanu, 2019).

Train and Encourage

Encourage employees by asking for their thoughts and provide resources for them to learn (Innovu, 2019). Upskilling should be included in the project so employees do not feel left out or fearful of the changes. Upskilling entails learning new skills, but it also involves a cultural shift and change management (Cohen, 2019). Wise plant managers will use this endeavor as an opportunity to not only bring their factory into the 4th industrial revolution but will support their team members as well. By including them on this journey with guidance and mentorship, it will provide them the opportunity to gain experience and learn vital new skills.

Collaborate

Join a trade association to collaborate with other factories. By networking with others in the industry, production managers can gain valuable advice and acquire recommendations for vendors and consultants that have worked on similar projects. The National Association of Manufacturers is the largest manufacturing association in the United States, representing small and large manufacturers in every industrial sector and in all 50 states (Manufacturing Leadership Council, 2021). Within that association are various opportunities for sharing knowledge, such as The Manufacturing Leadership Council, which is composed of executives from all disciplines of manufacturing that share research, or the Power of Small, which enables small manufacturers to access forums, meetings and webinars . Collaborating within a larger network can help SMEs compensate somewhat for their smaller knowledge resources since organizations working together to address problems can achieve goals that seem to be out of reach when working alone (NI Business, n.d.).

Limitations of the Project

By searching only a limited number of databases and by using specific search terms in English, there is the possibility that some relevant studies and literature may have been missed. Furthermore, the recommendations are based on a theoretical perspective and have not yet been used in practice. The shortage of relevant case studies also limited the scope of the project.

Future Work

Future research should be done to incorporate the recommendations into real-life situations. The determination of what steps in the implementation process can be performed in-house versus what should be outsourced also requires more investigation.

Conclusion

Big data analytics for manufacturing involves much more than just installing a business intelligence software program. It requires careful planning and implementation of data collection systems. The appropriate solution depends highly on the type of manufacturing, the available resources and mindset of the management team. By being cognizant of the major factors influencing the success of advanced manufacturing implementation, production managers can avoid many pitfalls and get the most benefit out of big data analytics in their factories.

APPENDIX A

GDP VALUE ADDED BY MANUFACTURING INDUSTRY

Value Added by Industry

[Billions of dollars] Seasonally adjusted at annual rates

Bureau of Economic Analysis

Last Revised on: December 22, 2020

Line		2019 Q1	2019 Q2	2019 Q3	2019 Q4	2019 Average
1	**Gross domestic product**	21115.3	21329.9	21540.3	21747.4	21433.23
2	**Private industries**	18508.9	18703.8	18887.2	19075.1	18793.75
3	**Agriculture, forestry, fishing, and hunting**	170.3	172.8	178	180.4	175.38
4	Farms	131.9	133.7	138.6	140.1	136.08
5	Forestry, fishing, and related activities	38.4	39	39.4	40.3	39.28
6	**Mining**	316.9	319.2	301.2	300.6	309.48
7	Oil and gas extraction	198.1	199.5	186	188.8	193.10
8	Mining, except oil and gas	59.8	61.4	61.2	60.9	60.83
9	Support activities for mining	59.1	58.3	53.9	50.8	55.53
10	**Utilities**	329.2	332.7	338.6	340.6	335.28
11	**Construction**	880.1	887.4	897.7	905.5	892.68
12	**Manufacturing**	2323.9	2340.7	2348.7	2370.1	2345.85

APPENDIX B

2019 GDP IN US DOLLARS, TOP 10 COUNTRIES

All Countries and Economies

Country	Most Recent Year	Most Recent Value (Millions)
United States	2019	21,433,226.00
China	2019	14,342,903.01
Japan	2019	5,081,769.54
Germany	2019	3,861,123.56
India	2019	2,868,929.42
United Kingdom	2019	2,829,108.22
France	2019	2,715,518.27
Italy	2019	2,003,576.15
Brazil	2019	1,839,758.04
Canada	2019	1,736,425.63

APPENDIX C

US CENSUS BUREAU DATA

All Firms:

Number of Firms, Number of Establishments, Employment, and Annual Payroll by Enterprise Employment Size for States, NAICS Sectors: 2017

release date:03/06/2020

SOURCE: 2017 County Business Patterns. For information on confidentiality protection, sampling error, and nonsampling error, see https://www.census.gov/programs-surveys/susb/technical-documentation/methodology.html.

For definitions, see https://www.census.gov/programs-surveys/susb/about/glossary.html.

The Census Bureau has reviewed this data product for unauthorized disclosure of confidential information and has approved the disclosure avoidance practices applied (Approval ID: CBDRB-FY19-460).

FIPS STATE CODE	STATE DESCRIPTION	NAICS CODE	NAICS DESCRIPTION	ENTERPRISE EMPLOYMENT SIZE	NUMBER OF FIRMS	NUMBER OF ESTABLISHMENTS	EMPLOYMENT
01	Alabama	31-33	Manufacturing	01: Total	3,708	4,137	254,603
02	Alaska	31-33	Manufacturing	01: Total	455	534	12,348
04	Arizona	31-33	Manufacturing	01: Total	4,058	4,319	149,174
05	Arkansas	31-33	Manufacturing	01: Total	2,264	2,567	156,257
06	California	31-33	Manufacturing	01: Total	35,321	37,849	1,167,502
08	Colorado	31-33	Manufacturing	01: Total	4,871	5,108	123,930
09	Connecticut	31-33	Manufacturing	01: Total	3,796	3,979	155,755
10	Delaware	31-33	Manufacturing	01: Total	528	548	27,814
11	District of Columbia	31-33	Manufacturing	01: Total	115	116	1,095
12	Florida	31-33	Manufacturing	01: Total	12,557	13,390	312,032
13	Georgia	31-33	Manufacturing	01: Total	6,603	7,508	377,455
15	Hawaii	31-33	Manufacturing	01: Total	747	776	12,711
16	Idaho	31-33	Manufacturing	01: Total	1,783	1,873	59,993
17	Illinois	31-33	Manufacturing	01: Total	12,077	13,154	534,047
18	Indiana	31-33	Manufacturing	01: Total	7,062	8,045	512,254
19	Iowa	31-33	Manufacturing	01: Total	2,964	3,486	210,737
20	Kansas	31-33	Manufacturing	01: Total	2,507	2,760	159,506
21	Kentucky	31-33	Manufacturing	01: Total	3,234	3,691	245,475
22	Louisiana	31-33	Manufacturing	01: Total	2,854	3,173	116,856
23	Maine	31-33	Manufacturing	01: Total	1,620	1,683	49,789
24	Maryland	31-33	Manufacturing	01: Total	2,796	2,956	98,646
25	Massachusetts	31-33	Manufacturing	01: Total	6,119	6,418	223,386
26	Michigan	31-33	Manufacturing	01: Total	11,265	12,400	593,951
27	Minnesota	31-33	Manufacturing	01: Total	6,541	7,177	309,323
28	Mississippi	31-33	Manufacturing	01: Total	1,894	2,143	146,479
29	Missouri	31-33	Manufacturing	01: Total	5,250	5,770	264,899
30	Montana	31-33	Manufacturing	01: Total	1,291	1,330	18,996
31	Nebraska	31-33	Manufacturing	01: Total	1,565	1,758	96,270
32	Nevada	31-33	Manufacturing	01: Total	1,762	1,826	44,895
33	New Hampshire	31-33	Manufacturing	01: Total	1,705	1,787	70,366
34	New Jersey	31-33	Manufacturing	01: Total	6,988	7,328	222,454
35	New Mexico	31-33	Manufacturing	01: Total	1,281	1,325	25,357
36	New York	31-33	Manufacturing	01: Total	14,788	15,488	410,579
37	North Carolina	31-33	Manufacturing	01: Total	7,792	8,796	439,141
38	North Dakota	31-33	Manufacturing	01: Total	627	699	24,486
39	Ohio	31-33	Manufacturing	01: Total	12,371	13,902	666,886
40	Oklahoma	31-33	Manufacturing	01: Total	3,034	3,357	126,362
41	Oregon	31-33	Manufacturing	01: Total	5,195	5,547	174,693
42	Pennsylvania	31-33	Manufacturing	01: Total	12,262	13,502	542,823
44	Rhode Island	31-33	Manufacturing	01: Total	1,299	1,332	38,800
45	South Carolina	31-33	Manufacturing	01: Total	3,429	3,822	231,872
46	South Dakota	31-33	Manufacturing	01: Total	958	1,051	44,301
47	Tennessee	31-33	Manufacturing	01: Total	5,229	5,797	326,320
48	Texas	31-33	Manufacturing	01: Total	17,522	19,764	773,920
49	Utah	31-33	Manufacturing	01: Total	3,206	3,366	123,163
50	Vermont	31-33	Manufacturing	01: Total	979	1,030	28,569
51	Virginia	31-33	Manufacturing	01: Total	4,570	5,011	236,287
53	Washington	31-33	Manufacturing	01: Total	6,589	7,021	262,967
54	West Virginia	31-33	Manufacturing	01: Total	1,035	1,147	48,815
55	Wisconsin	31-33	Manufacturing	01: Total	7,722	8,817	457,963
56	Wyoming	31-33	Manufacturing	01: Total	547	573	9,483
				Grand Total	266,735	290,936	11,721,785

Firms with <500 Employees:

Number of Firms, Number of Establishments, Employment, and Annual Payroll by Enterprise Employment Size for States, NAICS Sectors: 2017

release date:03/06/2020

SOURCE: 2017 County Business Patterns. For information on confidentiality protection, sampling error, and nonsampling error, see https://www.census.gov/programs-surveys/susb/technical-documentation/methodology.html.

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FIPS STATE CODE	STATE DESCRIPTION	NAICS CODE	NAICS DESCRIPTION	ENTERPRISE EMPLOYMENT SIZE	NUMBER OF FIRMS	NUMBER OF ESTABLISHMENTS	EMPLOYMENT
01	Alabama	31-33	Manufacturing	08: <500	3,277	3,361	80,497
02	Alaska	31-33	Manufacturing	08: <500	430	447	4,127
04	Arizona	31-33	Manufacturing	08: <500	3,774	3,852	66,114
05	Arkansas	31-33	Manufacturing	08: <500	1,977	2,061	40,249
06	California	31-33	Manufacturing	08: <500	34,263	34,992	598,343
08	Colorado	31-33	Manufacturing	08: <500	4,612	4,693	61,516
09	Connecticut	31-33	Manufacturing	08: <500	3,593	3,664	74,746
10	Delaware	31-33	Manufacturing	08: <500	471	480	9,198
11	District of Columbia	31-33	Manufacturing	08: <500	106	106	903
12	Florida	31-33	Manufacturing	08: <500	12,097	12,299	167,041
13	Georgia	31-33	Manufacturing	08: <500	6,013	6,209	129,320
15	Hawaii	31-33	Manufacturing	08: <500	724	744	9,895
16	Idaho	31-33	Manufacturing	08: <500	1,681	1,711	28,012
17	Illinois	31-33	Manufacturing	08: <500	11,345	11,705	254,360
18	Indiana	31-33	Manufacturing	08: <500	6,415	6,667	174,314
19	Iowa	31-33	Manufacturing	08: <500	2,649	2,846	64,917
20	Kansas	31-33	Manufacturing	08: <500	2,242	2,355	57,501
21	Kentucky	31-33	Manufacturing	08: <500	2,811	2,956	74,318
22	Louisiana	31-33	Manufacturing	08: <500	2,629	2,755	51,158
23	Maine	31-33	Manufacturing	08: <500	1,531	1,560	24,927
24	Maryland	31-33	Manufacturing	08: <500	2,600	2,670	45,376
25	Massachusetts	31-33	Manufacturing	08: <500	5,763	5,863	116,014
26	Michigan	31-33	Manufacturing	08: <500	10,673	11,178	264,952
27	Minnesota	31-33	Manufacturing	08: <500	6,094	6,318	132,970
28	Mississippi	31-33	Manufacturing	08: <500	1,641	1,713	43,819
29	Missouri	31-33	Manufacturing	08: <500	4,866	5,058	103,369
30	Montana	31-33	Manufacturing	08: <500	1,244	1,263	13,388
31	Nebraska	31-33	Manufacturing	08: <500	1,402	1,467	29,927
32	Nevada	31-33	Manufacturing	08: <500	1,620	1,639	24,411
33	New Hampshire	31-33	Manufacturing	08: <500	1,573	1,604	30,460
34	New Jersey	31-33	Manufacturing	08: <500	6,621	6,767	133,928
35	New Mexico	31-33	Manufacturing	08: <500	1,211	1,226	15,084
36	New York	31-33	Manufacturing	08: <500	14,295	14,563	241,999
37	North Carolina	31-33	Manufacturing	08: <500	7,145	7,356	153,178
38	North Dakota	31-33	Manufacturing	08: <500	568	590	10,657
39	Ohio	31-33	Manufacturing	08: <500	11,529	12,089	285,256
40	Oklahoma	31-33	Manufacturing	08: <500	2,757	2,866	52,137
41	Oregon	31-33	Manufacturing	08: <500	4,905	5,031	84,635
42	Pennsylvania	31-33	Manufacturing	08: <500	11,509	11,988	260,938
44	Rhode Island	31-33	Manufacturing	08: <500	1,229	1,251	23,346
45	South Carolina	31-33	Manufacturing	08: <500	2,998	3,065	71,608
46	South Dakota	31-33	Manufacturing	08: <500	868	917	17,728
47	Tennessee	31-33	Manufacturing	08: <500	4,668	4,816	105,066
48	Texas	31-33	Manufacturing	08: <500	16,558	17,114	321,736
49	Utah	31-33	Manufacturing	08: <500	2,969	3,009	52,128
50	Vermont	31-33	Manufacturing	08: <500	927	961	16,062
51	Virginia	31-33	Manufacturing	08: <500	4,185	4,341	79,892
53	Washington	31-33	Manufacturing	08: <500	6,210	6,358	110,389
54	West Virginia	31-33	Manufacturing	08: <500	913	955	17,143
55	Wisconsin	31-33	Manufacturing	08: <500	7,171	7,627	205,883
56	Wyoming	31-33	Manufacturing	08: <500	506	527	4,837
				Grand Total	249,858	257,653	5,039,772
					94%		

Firms with <20 Employees:

Number of Firms, Number of Establishments, Employment, and Annual Payroll by Enterprise Employment Size for States, NAICS Sectors: 2017

release date:03/06/2020

SOURCE: 2017 County Business Patterns. For information on confidentiality protection, sampling error, and nonsampling error, see https://www.census.gov/programs-surveys/susb/technical-documentation/methodology.html.

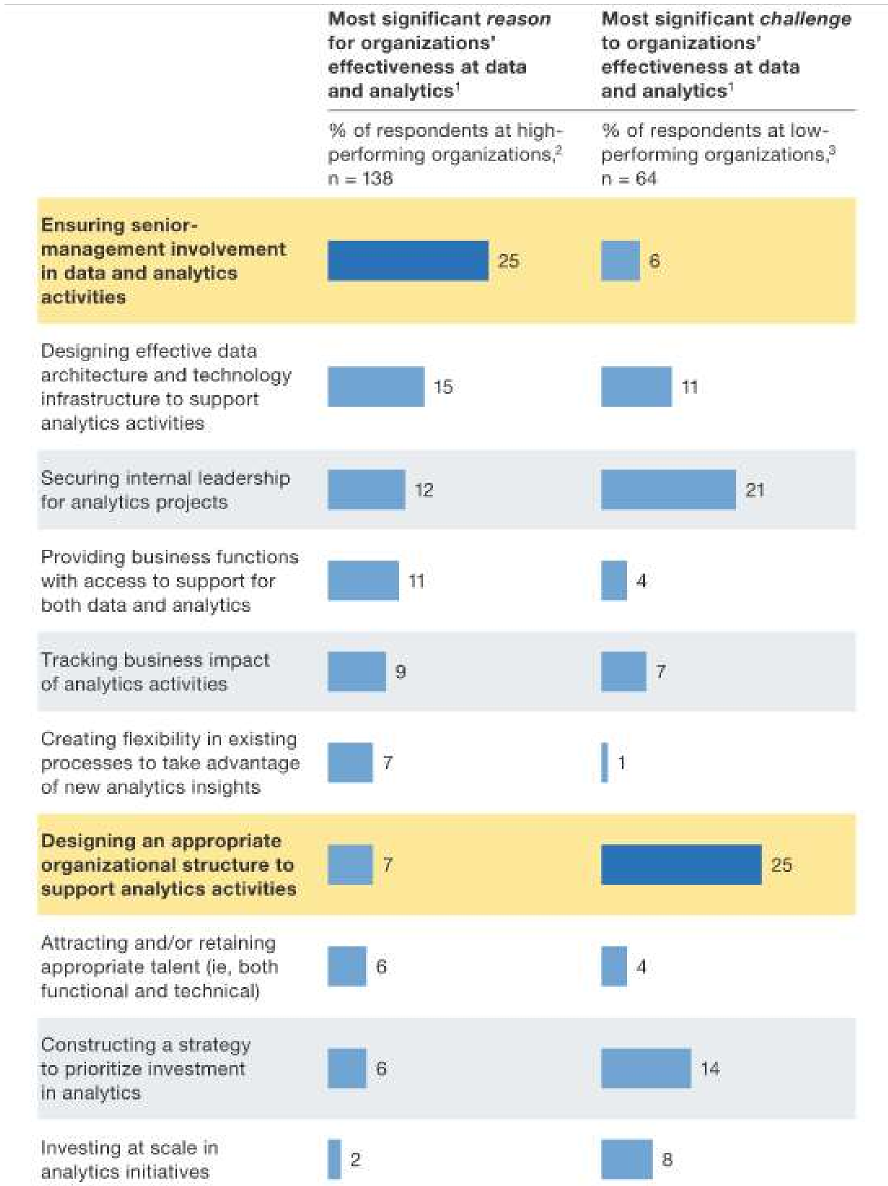
For definitions, see https://www.census.gov/programs-surveys/susb/about/glossary.html.

The Census Bureau has reviewed this data product for unauthorized disclosure of confidential information and has approved the disclosure avoidance practices applied (Approval ID: CBDRB-FY19-460).

FIPS STATE CODE	STATE DESCRIPTION	NAICS CODE	NAICS DESCRIPTION	ENTERPRISE EMPLOYMENT SIZE	NUMBER OF FIRMS	NUMBER OF ESTABLISHMENTS	EMPLOYMENT
01	Alabama	31-33	Manufacturing	05: <20	2,280	2,287	12,892
02	Alaska	31-33	Manufacturing	05: <20	381	384	1,641
04	Arizona	31-33	Manufacturing	05: <20	2,866	2,871	15,148
05	Arkansas	31-33	Manufacturing	05: <20	1,451	1,454	8,157
06	California	31-33	Manufacturing	05: <20	26,698	26,752	140,668
08	Colorado	31-33	Manufacturing	05: <20	3,750	3,757	18,337
09	Connecticut	31-33	Manufacturing	05: <20	2,611	2,611	14,664
10	Delaware	31-33	Manufacturing	05: <20	351	352	1,803
11	District of Columbia	31-33	Manufacturing	05: <20	94	94	423
12	Florida	31-33	Manufacturing	05: <20	10,024	10,040	44,980
13	Georgia	31-33	Manufacturing	05: <20	4,373	4,382	23,105
15	Hawaii	31-33	Manufacturing	05: <20	598	598	3,032
16	Idaho	31-33	Manufacturing	05: <20	1,322	1,328	6,539
17	Illinois	31-33	Manufacturing	05: <20	8,096	8,116	45,493
18	Indiana	31-33	Manufacturing	05: <20	4,306	4,310	26,458
19	Iowa	31-33	Manufacturing	05: <20	1,865	1,873	10,471
20	Kansas	31-33	Manufacturing	05: <20	1,565	1,572	9,225
21	Kentucky	31-33	Manufacturing	05: <20	1,920	1,923	11,462
22	Louisiana	31-33	Manufacturing	05: <20	1,962	1,964	11,223
23	Maine	31-33	Manufacturing	05: <20	1,213	1,216	5,883
24	Maryland	31-33	Manufacturing	05: <20	1,981	1,987	10,311
25	Massachusetts	31-33	Manufacturing	05: <20	4,206	4,213	23,965
26	Michigan	31-33	Manufacturing	05: <20	7,551	7,564	44,594
27	Minnesota	31-33	Manufacturing	05: <20	4,424	4,434	23,385
28	Mississippi	31-33	Manufacturing	05: <20	1,101	1,104	6,366
29	Missouri	31-33	Manufacturing	05: <20	3,587	3,594	20,015
30	Montana	31-33	Manufacturing	05: <20	1,061	1,066	5,003
31	Nebraska	31-33	Manufacturing	05: <20	1,029	1,032	5,552
32	Nevada	31-33	Manufacturing	05: <20	1,236	1,236	6,330
33	New Hampshire	31-33	Manufacturing	05: <20	1,150	1,151	6,473
34	New Jersey	31-33	Manufacturing	05: <20	4,869	4,878	26,323
35	New Mexico	31-33	Manufacturing	05: <20	1,004	1,005	5,068
36	New York	31-33	Manufacturing	05: <20	11,251	11,277	56,992
37	North Carolina	31-33	Manufacturing	05: <20	5,149	5,162	27,169
38	North Dakota	31-33	Manufacturing	05: <20	436	439	2,393
39	Ohio	31-33	Manufacturing	05: <20	7,929	7,963	47,936
40	Oklahoma	31-33	Manufacturing	05: <20	2,071	2,075	11,321
41	Oregon	31-33	Manufacturing	05: <20	3,826	3,842	19,634
42	Pennsylvania	31-33	Manufacturing	05: <20	8,110	8,136	47,791
44	Rhode Island	31-33	Manufacturing	05: <20	905	905	5,125
45	South Carolina	31-33	Manufacturing	05: <20	2,101	2,103	11,937
46	South Dakota	31-33	Manufacturing	05: <20	650	650	3,332
47	Tennessee	31-33	Manufacturing	05: <20	3,302	3,311	18,668
48	Texas	31-33	Manufacturing	05: <20	12,309	12,341	67,088
49	Utah	31-33	Manufacturing	05: <20	2,307	2,313	12,463
50	Vermont	31-33	Manufacturing	05: <20	725	728	3,318
51	Virginia	31-33	Manufacturing	05: <20	3,125	3,132	17,113
53	Washington	31-33	Manufacturing	05: <20	4,842	4,849	24,580
54	West Virginia	31-33	Manufacturing	05: <20	660	664	3,777
55	Wisconsin	31-33	Manufacturing	05: <20	4,716	4,736	28,006
56	Wyoming	31-33	Manufacturing	05: <20	429	431	1,775
				Grand Total	185,768	186,205	1,005,407
					70%		

APPENDIX D

MCKINSEY DIGITAL SURVEY RESULTS



[1] Respondents who answered "other" or "don't know" are not shown.
[2] Respondents who say their organizations have been effective at reaching the main objective of their data and analytics activities, and have more developed analytics capabilities than industry competitors. This question was asked only of respondents who said their organizations *have* met their analytics objectives effectively.
[3] Respondents who say their organizations have been ineffective at reaching the main objective of their data and analytics activities, and have less developed analytics capabilities than industry competitors. This question was asked only of respondents who said their organizations *have not* met their analytics objectives effectively.

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APPENDIX E

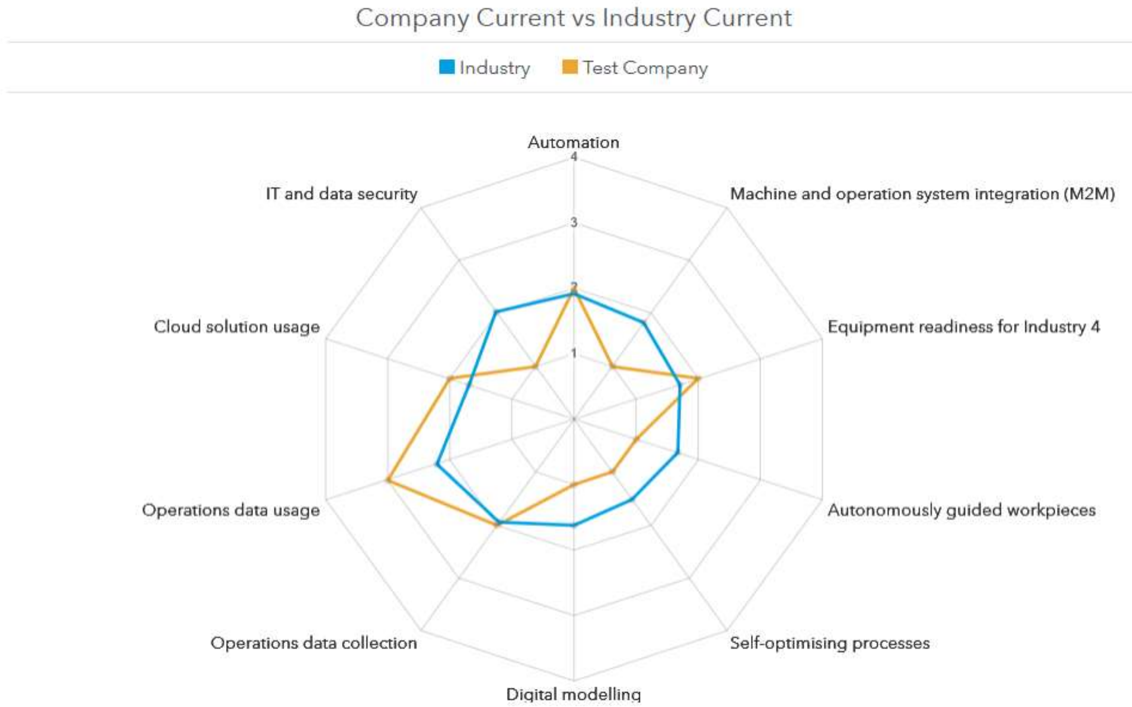
ASSESSMENT INPUTS AND RESULTS

Assessment Inputs:

Select your current company readiness for each of the sub-dimensions below.

Readiness level	Level 1 Beginner	Level 2 Intermediate	Level 3 Experienced	Level 4 Expert	Don't know	Not relevant
Automation	Few machines can be controlled through automation	Some machines and system infrastructures can be controlled through automation	Most machines and system infrastructures can be controlled through automation	Machines and systems can be controlled completely through automation	Don't know	Not relevant
Machine and operation system integration (M2M)	Machines and systems have no M2M capability	Machines and systems are to some extent interoperable	Machines and systems are partially integrated	Machines and systems are fully integrated	Don't know	Not relevant
Equipment readiness for Industry 4	Significant overhaul required to meet Industry 4 model	Some machines and systems can be upgraded	Machines already meet some of the requirements and can be upgraded where required	Machines and systems already meet all future requirements	Don't know	Not relevant
Autonomously guided workpieces	Autonomously guided workpieces are not in use	Autonomously guided workpieces are not in use, but there are pilots underway	Autonomously guided workpieces used in select-ed areas	Autonomously guided workpieces are widely adopted	Don't know	Not relevant
Self-optimising processes	Self-optimisation processes are not in use	Self-optimising processes are not in use, but there are pilots in more advanced areas of the business	Self-optimising processes are used in selected areas	Self-optimising processes are widely used	Don't know	Not relevant
Digital modelling	No digital modelling	Some processes use digital modelling	Most processes use digital modelling	Complete digital modelling used for all relevant processes	Don't know	Not relevant
Operations data collection	Data is collected manually when required, e.g. sampling for quality control	Required data is collected digitally in certain areas	Comprehensive digital data collection in multiple areas	Comprehensive automated digital data collection across the entire process	Don't know	Not relevant
Operations data usage	Data is only used for quality and regulatory purposes	Some data is used to control processes	Some data is used to control and optimise processes, e.g. predictive maintenance	All data is used not only to optimise processes, but also for decision making	Don't know	Not relevant
Cloud solution usage	Cloud solutions not in use	Initial solutions planned for cloud-based software, data storage and data analysis	Pilot solutions implemented in some areas of the business	Multiple solutions implemented across the business	Don't know	Not relevant
IT and data security	IT security solutions are planned	IT security solutions have been partially implemented	Comprehensive IT security solutions have been implemented with plans developed to close any gaps	IT security solutions have been implemented for all relevant areas and are reviewed frequently to ensure compliance	Don't know	Not relevant

Assessment Results:



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