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The application and benefits of emerging digital technologies for Industry 4.0

By

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Declaration

I, **Nevek Govender**, declare that this thesis is an outcome of my investigation and research study. I declare that all sources used in this research have been acknowledged in the references list and cited appropriately within the content of the thesis.

This research was conducted at the Durban University of Technology as a requirement to obtain a degree of Master of Engineering in Industrial Engineering.

The research was supervised by Professor Oludolapo A. Olanrewaju and submitted by Nevek Govender.

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“When wireless is perfectly applied the whole earth will be converted into a huge brain, which in fact it is, all things being particles of a real and rhythmic whole. We shall be able to communicate with one another instantly, irrespective of distance.” - Nikola Tesla (1926)

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Abbreviations

4IR	Fourth Industrial Revolution
AI	Artificial Intelligence
BWM	Best Worst Method
CPS	Cyber-Physical Systems
DREAMY	REadiness Assessment MaturitY model
EAMS	Enterprise Asset Management Systems
GFMAM	Global Forum on Maintenance and Asset Management
IoT	Internet of Things
ISM	Interpretive Structural Modelling
MES	Manufacturing Execution Systems
ML	Machine Learning
MOM	Manufacturing Operations Management
RFID	Radio Frequency Identification
SMSRL	Smart Manufacturing Readiness Level
WMS	Warehouse Management Systems
WSNs	Wireless Sensor Networks

Table 1: Abbreviations

Abstract

Industry 4.0 technology advancement in recent years has enabled organizations to capitalize on new processes and tools towards making their businesses more profitable and efficient. 4IR Technologies such as Artificial Intelligence, Machine Learning, Condition Monitoring and Internet of Things have been at the forefront of the digital revolution and have transformed the way organizations do business.

However, these complex technologies come with many challenges such as startup costs, lack of knowledge experts as well as the limited technology foundation for both business owners, as well as their employees. Therefore, this study looks at the current knowledge of Industry 4.0 from individuals in the industry, which will provide information on the current trends as well as possible knowledge gaps. The research also explores the benefits of Industry 4.0 technologies by using machine learning technology to elaborate on how we can enhance organizations' efficiencies. The purpose of this study is to contribute towards the successful implementation of Industry 4.0 and provide encouragement for organizations to start their digital revolution.

The research follows both a qualitative and quantitative analysis process. The qualitative data is analyzed from a survey of individuals which enables us to dissect and better identify the current trends, and possible knowledge gaps whilst the quantitative data is analyzed using machine learning software to highlight the potential that can be attained if organizations decide to implement these types of technologies.

A content and grounded theory method was used to analyze the qualitative data, as the feedback from the interviewees was constantly reviewed and compared with each other whilst also comparing that to the initial hypothesis statements. It was seen that current trend is that individuals in the industry are excited and are aware of Industry 4.0, but there are still some challenges such as legacy machines, return of investment and knowledge gaps. For the quantitative data, a thematic analysis was used, in the form of machine learning software, to identify patterns in the results and interpret them in a way that can be understood better. From the analysis, it was seen that the machine learning software has a positive impact as the software was able to identify the highest points of failure as well as the type of failure which occurred for a machine. The timeline of failure was also deduced and therefore the organization would be able to put measures in place to restrict these failures from happening.

The research provides great benefit for future researchers as well as organizations on topics relating to Industry 4.0 towards connecting the power of the technologies to create a smooth transition within the workplace. The survey analysis offers a better understanding of the current trends in the industry, and the research in general provides a foundation towards the understanding of Industry 4.0, and provides valuable insight on the greater role that new digital technologies play towards creating a better future for organizations.

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1 Introduction

1.1 Introduction

In recent times, the focus on maintenance of assets in organisations has increased significantly. As companies grow, so do their assets. This places a lot of emphasis on the quality of a company’s maintenance management system (Lima et al., 2021a). The need for an enterprise asset management system has become more popular, as organisations try to focus on their main business operations. There are different types of enterprise asset management systems, each with their own unique characteristics. However, in today’s market, it is about the next generation technologies that these systems possess, which separate them from each other (El-Akruti et al., 2013). The recent introduction and use of technologies such as IoT (Internet of Things) and AI (Artificial Intelligence), has changed the way we think about how businesses should operate (Gbadamosi et al., 2021). The question is, how much of a difference do these new technologies make in the maintenance management realm? And if so, how do they actually make an impact? This, in summary, is the purpose of this study.

Understanding the technologies and current practises has been key during the literature review. Various questionnaires have been conducted to assess an understanding of the current knowledge on Industry 4.0. This helped to understand the problems that exist, and where there is a need or improvement that is required – this will provide the backing needed for the research questions stated. After understanding the background and technologies of all subjects (Enterprise Asset Management, IoT, AI, etc.), a questionnaire and data analysis regarding this topic has been provided to support the research.

This chapter introduces the essence of this study as well as the research intent. It provides the overall background to the study and elaborates on the key topics of Industry 4.0. The aim and objectives in line with the problem statement are provided which describe the need for the research as well as the research questions.

1.2 Research Background

1.2.1 Enterprise Asset Management

An enterprise asset management system can be defined as a system that plans, controls and executes asset-related activities to ensure the asset's performance is in line with an organisation strategy. The system is a key contributor towards the asset's lifecycle and efficiency (Amadi-Echendu et al., 2010).

As organisations develop their strategies, they start to experience significant shortfalls when it comes to asset reliability and performance. This is a result of failing to plan for new systems, technologies and asset maintenance plans (Miles et al., 1978). Maintenance is an integral part of an asset's lifecycle. Maintenance provides value to an organisation and has an impact on the capability and performance of assets (Ouertani et al., 2008). It affects all aspects of a business's efficiency, safety, environment, product cost, quality and customer service. As companies develop further, maintenance strategies are becoming a key function as part of their business (Attwater et al., 2014).

Currently there is a Global Forum on Maintenance and Asset Management (GFMAM). This forum consists of an Asset Management Landscape which incorporates a list of 39 asset management subjects and principles (Version, 2014). It also promotes a common global approach to asset management. It can be seen in the figure below:

Figure 1.1: 39 Subjects in GFMAM (The Asset Management Landscape Second Edition, 2014)

Nel and Jooste (2016) elaborate on the concept of “smart” asset management and how quality information is reflected in the 39 subjects of asset management. They further mention the importance of the quality and how it provides effective support to business decision making and processes. This provides the baseline of the present research, in order to investigate the impact of quality that new technologies have in some of these 39 subjects. There are many new features that an enterprise asset management system can possess, which assists organisations with their day-to-day activities. These systems can provide the following:

Asset Information Management

Organisations invest in an asset management system as they look to obtain better returns and profits for their business. Asset management has many key concepts which are technical and support the overall efficiency of the business (Lima et al., 2021b).

Asset Location

In the current world, organisations have become increasingly collaborative when it comes to the use of assets. Assets are often shared and distributed across different working areas, especially within the larger, asset intensive, organisations. Therefore, it is important that location information of the assets is provided to the people and systems within an organisation so that quick and informed decisions are made when it comes to business processes or real time actions that need to take place. Location based thinking is key towards both reactive and predictive maintenance (Kenley et al., 2014). Asset location tracking involves:

- Where is the asset presently?
- Where were they last (History/Timelog)?
- How many of them are present in a given location (Logistics)?

With this information, companies can then plan accordingly and take the necessary steps to supply the demand of customers (Ahmed et al., 2020). This helps tremendously in the health industry where the location of vital equipment is essential.

Asset Health

Asset health is one of the key aspects that contributes towards predictive maintenance. One of the challenges is to actively control, monitor and centralize all processes within an asset.

This is in addition to the Key Performance Indicators such as process efficiency and asset utilization and quality (Demoly and Kiritsis, 2012). As we understand how each asset is used and behaves, we can then start to enable more advanced maintenance tactics (Artificial Intelligence, Condition Monitoring, etc.).

Asset Information Technology

The use of technology has contributed greatly to the retrieval of asset information in recent times. With many complex systems and processes running, it becomes quite difficult to keep track of asset information (Dolgui and Proth, 2008). Technologies such as Radio Frequency Identification (RFID), sensors and drone technology provide great ways to get information as quick as possible.

RFID is said to become the primary technology for tracking of assets, managing of inventories, etc. There are many uses of the technology and therefore unique benefits for organisations (Dovere et al., 2015). An RFID system uses a tag which is a small memory chip which stores information of the asset, where a reader can retrieve information in an efficient way. It is said to replace barcodes altogether as they are capable of storing more data (Motamedi et al., 2013)

When it comes to maintenance and infrastructure inspection, drone technology has become increasingly popular. There is also an immediate safety benefit as it limits the need to inspect from height (e.g. from a high-rise building). It provides faster inspection times and reduces the need for specialist access and equipment training (Kabbabe Poleo et al., 2021). The benefit can also be seen in the agriculture/crop industry where health monitoring is critical. For many years, farmers spend a large amount of time visually inspecting crops and collecting ground samples. Drones have now increased efficiency within the industry using infrared photography which can then identify any abnormalities within an area, in collaboration with image analytics tools (Hafeez et al., 2022)

There are currently 2 main types of maintenance (Susto et al., 2015):

- <u>Corrective Maintenance (Run to Failure)</u>

This is the reactive maintenance that occurs when machines/equipment stops working. It is the simplest strategy since it is not planned. The production line is stopped when the parts are replaced "on the spot". This can also be referred to as sub-categories "Postponed" or "Instantaneous" Maintenance.

- <u>Preventive Maintenance</u>

This is a type of scheduled maintenance by means of a planned/calculated time-based schedule. It is a useful way to avoid failures.

Predetermined maintenance follows a factory schedule or pre-set interval to perform maintenance. Organisations rely heavily on their complex and costly physical assets. Any failure on the equipment or part of the equipment could result in damaging impacts further downstream. Depending on the type of organisation, the damages could be more than just a cost factor but also a social or environmental risk (Moerman et al., 2020)

Condition based maintenance can also be described as a sub-category of preventive maintenance. This is when maintenance work is done at a specific time when real-time analytics highlight an error or failure. This can be done by using vibration analysis, infrared, oil analysis, pressure analysis, etc.

1.2.2 <u>"Industry 4.0"</u>

"Industry 4.0" refers to the fourth industrial revolution which can be described as a new, and more digital level of control/management over an organisation's operations and business processes.

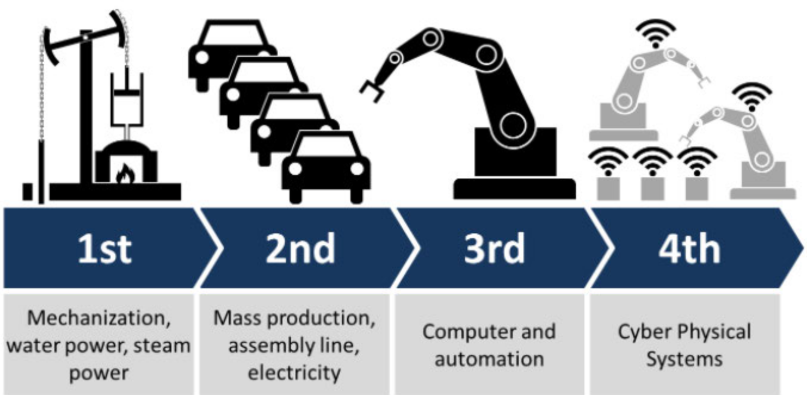


Figure 1.2 : The Fourth Industrial Revolution - (The Fourth Industrial Revolution Explained | Anchorcapital.co.za.)

"Industry 4.0" places a huge focus on connectivity between physical assets/machines and digital systems, hence the term "smart manufacturing". In order for this to be a success, many different and new technologies need to be utilized. The four main drivers of Industry 4.0 are Internet of Things(IoT), Industrial Internet of Things (IIoT), Cloud based manufacturing and smart manufacturing which help in transforming the manufacturing process into fully digitized and intelligent one (Erol et al., 2016). This then helps produce a better relationship and efficiency between all parties (Machines, systems, customers, etc.) (Rüßmann et al.,2015). The main goal is to be more agile within production processes by using digital technologies in order to increase overall efficiency throughout the business (Ghobakhloo, 2020)

Industry 4.0 can also be described as a popular trend towards automation and digitisation in the manufacturing industry or other environments. However, there are also core foundations that should be put in place before implementing Industry 4.0, such as end to end digital integrations across the organisation (Oesterreich and Teuteberg, 2016). These integrations can be rather costly, especially for smaller organisations since they have different priorities and challenges. There are many obstacles when it comes to implementing Industry 4.0 and therefore it is essential to find the best way to excite these organisations towards growing their business in a more digitized fashion (Koumas et al., 2021)

The Industry 4.0 concept is not limited to just manufacturing. It provides a complete end to end solution from suppliers to customers and all business processes in between. It is a specialization of the Internet of Things (IoT) within an industrial sector and therefore can provide the best "real-time" solutions for organisations (Alcácer and Cruz-Machado, 2019)

The idea of Industry 4.0 looks attractive at first, but there are many obstacles and challenges that come with the implementation of the concept, such as infrastructure, security and training to name a few (Sakib, 2022). The success of Industry 4.0 will be determined by how well all of these different operations work together as one. The benefits of a successful implementation can be defined as: greater output capacity, improved implementation speed of prototypes, better production flexibility, higher product quality (less production rejects), less machine downtimes (lower operational costs for organisations) and better customer satisfaction (Balamurugan et al., 2019)

Origins of Industry 4.0

The term "Industry 4.0" was first coined in Germany during the Hanover fair in the year 2011. Since then, it has become a key discussion within the manufacturing and academia (Rojko, 2017a). The key concept is to utilize new technologies within: IoT technology and the internet, technical and business processes in organisations and digitisation of companies.

By exploiting these technologies, Industry 4.0 aims to increase profits within the industrial sector by creating new concepts and possibilities where they may have been depleted in the past. It seeks to support the development of industrial initiatives for years to come. According to Rojko (2017b), Industry 4.0 factories could decrease production operating costs by 10-30% as well as logistic costs by 10-30%.

The development of Industry 4.0 is accelerated by emerging technologies on one hand, and by social and economic trends on the other. There are many trends which drive the need for this development: production and product development flexibility, demand for customized products, the demand for shortened development periods – faster innovation is required to stay competitive , efficient use of resources and digitalization and networking (Bogdanov, 2020)

Smart Factory technologies

Smart factories are the ideal collaboration of all systems and physical assets in an organisation. They create intelligent environments which create processes that are adaptable and flexible in their outcome (Radziwon et al., 2014).

Together with all Industry 4.0 technologies, it is vital that organisations also have the correct information systems in place to take advantage of the reliable data that is being retrieved. Systems such as Manufacturing Execution Systems (MES), Enterprise Asset Management Systems (EAMS) and Warehouse Management Systems (WMS) need to all be synchronized to see the maximum benefits of Industry 4.0 (Koumas et al., 2021). The integration of these systems can be referred to as Cyber-Physical Systems (CPS). It can be described as the enablement of physical and computational environments which allows for better management of connected systems (Pereira and Romero, 2017). The application of CPS in a manufacturing environment is called cyber physical production system (CPPS). This is where there is an existing setup of data processing, machine to machine communication and human-machine interaction (Wagner et al., 2017) .The first stage of CPS relates to the use of unique identification technology, such as RFID tags. The 2nd stage focuses more on the use of machine sensors and the 3rd stage is where multiple sensors are used which are able to store data and communicate with other networks (Weyer et al., 2015). The concept of predictive maintenance is possible when all have been applied in a structured way (Wagner et al., 2017)

Due to different organisations having customized production plans/setups, it poses a challenge to implement Industry 4.0 as there is no “one size fits all” solution (Asadollahi-Yazdi et al., 2020). Industry 4.0 technologies play a vital role in reaping the benefits of future digitalization and can transform current processes in order to create and deliver increased service value for customers (Rad et al., 2022a)

1.2.3 Internet of Things (IoT) Platforms

IoT can be seen as the extension of the internet into the physical asset world, which uses devices which possess sensor and identification technologies to collaborate with other systems. IoT envisions a future where digital and physical features can be linked as one to provide better communication (Miorandi et al., 2012). Production environments are becoming increasingly demanding and keeping up with rapid changes in technology can be a challenge. Therefore, organisations need to be more agile and start to look at technologies like IoT to enable a more seamless solution for their production plans. IoT provides autonomous coordination within a system which helps organisations become better at what they do by making them more adaptable and agile (Ben-Daya et al., 2019)

Adolfo, Juan, Pablo and Antonio (Marquez et al., 2020) mentioned the introduction of interesting features from IoT platforms as well as taking the platform characteristics into account when choosing an IoT platform. These characteristics provide great insight into business value and decision making when it comes to implementation of the technology and will greatly assist in the focus on the Enhanced/Health Monitoring Maintenance and Asset Optimization aspect.

Gubbi et al (2013) also provides great feedback on where IoT data is actioned for artificial intelligence tools. This information will be useful when analysing the different areas of functionality where IoT can be applied. The advancement in technology, specifically in communication such as Radio Frequency Identification (RFID) and Wireless Sensor Networks (WSNs), makes it easier for data to be transferred (Aldowah et al., 2019)

Security Challenges

One of the biggest challenges in implementing an IoT solution is security. As there is an increase in the use of IoT technologies, there have been more data attacks on the devices in use (O'Neill, 2014)

When various devices are connected to a system, almost everything will be connected to the internet. This opens a gap for global exposure and security vulnerabilities – which gives access to possible hackers to retrieve sensitive/private information (Abomhara and Koien, 2014). It is therefore the organisations responsibility to secure all information, including device data, for their customers/clients etc. (Caron et al., 2016). Due to the complicated systems as well as the great number of devices connected, it is also difficult to consider traditional security methods for an IoT system/solution (Sicari et al., 2015)

However, with good training for designers and developers, it is possible to integrate IoT solutions within a safe and secure environment, which will then make users more comfortable with using these solutions (Abomhara and Koien, 2014). Authentication is also a factor which can contribute to a secure system. It assists with security for both the system and its users. It makes sure that only authorised individuals gain access to the system, which protects the network and all resources/applications (Ning et al., 2012)

Network Challenges

Depending on the size of the IoT system, the network could have significant strain on the bandwidth (Newe, 2015). Since IoT solutions are relatively new, it also means that networks for these systems are non-traditional, which poses some difficulties for designers.

Data Challenges

IoT enables organisations to gather big data from equipment. However, retrieving a large amount of data continuously can be quite difficult to manage. Therefore, the development of new data processing models has become important for IoT. It is important for these models to make decisions based on analyzing the incoming data in rapid manner (Zheng, 2021)

1.2.4 Artificial Intelligence

Artificial Intelligence (AI) involves developing computer programs to complete tasks which would otherwise require human intelligence. AI algorithms can tackle learning, perception, problem-solving, language-understanding and/or logical reasoning (Lee et al., 2018)

AI enables machines to comprehend data to identify anomaly patterns, learn and adapt from previous experiences or data (Lee et al., 2020). Therefore, with AI, machines are able to predict the best results and thus make their own decisions in the support of better asset performance. The rise of mobile devices and mobile apps has also contributed to the advancement of AI. This benefits greatly from the rapid growth of data (Shi et al., 2022) . From the data that has been collected, AI methods like reinforcement learning helps by learning with the help of past experience and apply/reply with the suggestion/prediction and logic of the data (Aghav-Palwe and Gunjal, 2021). Therefore, the future behaviour of manufacturing systems can be predicted by using AI algorithms which will assist in the decision making of an organisation. By extracting meaningful information, we can then move towards a transformation towards sustainable practices (Moyne and Iskandar, 2017)

AI has therefore become extremely popular for maintenance systems. These systems have now evolved into a fail-safe approach for preserving equipment safety in terms of defect detection and remaining useful life (Paul et al., 2022). There are different types of technologies and methods that can be used for maintenance, and when all these technologies are applied, decisions are based on the collected data together with Artificial Intelligence - This can then be referred to as a smart factory (Schuh et al., 2014). By using AI techniques, the end goal is to achieve a more effective maintenance management system. This can be done by using general rule-based reasoning, or more complex optimization techniques using advanced algorithms (Kobbacy, 2012)

Besides security challenges, there are also other challenges like data quality when it comes to implementing Artificial Intelligence. Large and clean data sets are required to produce a successful AI model. Having inaccurate data can affect the results negatively further downstream (Lee et al., 2018)

However, as the process improves, it also has an effect on future of labour within a 'smart factory'. As the transition to Industry 4.0 occurs, it is likely that many jobs will become automated by means of AI and other technologies (Kergroach, 2017) . Routine jobs are at risk as the technological advancements could also lean towards a lower wage (Balliester and Elsheikhi, 2018)

1.2.5 Machine Learning

Machine Learning (ML) is a sub-category of Artificial Intelligence where computers/machines are programmed to learn patterns on their own without human intervention. Algorithms are created in order to find trends within data, and therefore make decisions based on the outcome. This has emerged as a powerful tool to develop intelligent predictive algorithms for many applications, including asset management systems (T. P. Carvalho et al., 2019)

The current trend in data processing and analysis is the use of these ML methods. Machine learning has evolved into a powerful tool that implements high quality intelligent algorithms for prediction. A feature of ML is the ability to process big data and therefore effectively find hidden correlations between them (Wuest et al., 2016a). These methods are called predictive analytics or exploratory data analytics, which helps to analyze the hidden information and patterns from the given data. This is important when learning to predict business decisions (Aghav-Palwe and Gunjal, 2021). The patterns are found from algorithms of the data. When we receive data, this is considered a mixture of categorised and non-categorised data points which can be referred to as semi-supervised learning. In the machine learning model for supervised learning, only the categorised data points are used. The model then attempts to use those points as input and output values constantly in an iterative process, to achieve the desired accuracy, as part of the training model (Theissler et al., 2021a). The quality of the data will contribute towards the accuracy of the model and thus the prolonged remaining useful life of the equipment (Angelopoulos et al., 2020). The ML categories can be briefly summarized as follows:

- **Supervised Learning:** This is a method where the output is known. The algorithm can then be trained by using these values along with inputs. This is considered as labelled models. Scientists usually have a set of rules to determine the output, however, the ML model will do the opposite by taking the outcomes and retracting the steps (Hornung et al., 2022) .The common rule is that 70% of the data set is used as a training data set and the remaining 30% is used as evaluation to adjust the parameters (Wuest et al., 2016b)

- **Unsupervised learning:** This is where the model finds patterns in an unknown data set in which no inputs are provided (No feedback). Here the idea is for the model to identify a pattern via clustering whereas in a supervised learning model it would find a pattern using known labels/outputs (Jain et al., 1999; Wuest et al., 2016b). The model would usually identify clusters or similarities within a dataset to determine the outcome (Hornung et al., 2022)
- **Reinforcement learning:** This model is based on the feedback of actions deriving from the training environment. It is similar to unsupervised learning where it would determine if the action resulted in a reward or not (Wuest et al., 2016b)
- **Deep learning:** This is a more complex model where there is no need for any human intervention. High amounts of data are handled in a complex algorithm which makes intelligent decisions (Sonntag et al., 2017)

However, it is quite difficult to understand which machine learning method needs to be used as different studies require different sets of data to be deemed successful (D. v Carvalho et al., 2019).

1.2.6 Predictive Maintenance

The implementation of Predictive Maintenance can help an organisation reduce various operational costs such as scheduled resource intensive activities (Syed et al., 2020). Predictive Maintenance reduces these costs by primarily using predictive data to accurately schedule future maintenance operations (Paul et al., 2022). Once the data is captured, it can then be used for defect identification, early fault detection, equipment health evaluation and equipment prediction. Besides operational costs, by having a predictive maintenance strategy, the organisation could also save on spare part costs. By keeping at least the predicted amount of spare parts on hand, there could be a reduced amount of inventory costs (Spiegel et al., 2018)

Technologies such as Machine Learning provide great advancements in the field of Predictive Maintenance - Lueth (2016) shows that there is a great demand for Predictive Maintenance with 79% of respondents seeing predictive and prescriptive maintenance of machines as the most important application of Industrial Analytics in the coming 3 years. This offers great room for growth as well as a need for investigation regarding this topic.

The article also mentions how Machine Learning is a crucial element for data-driven decision making. Stating that it is the “catalyst” that enables smart systems to extract value from the available data (Lueth, 2016). This technology will be important in the present study regarding the use of historic data and its effects. Industry 4.0 is revolutionizing decision-making processes within the manufacturing industry (Bona et al., 2021). Predictive Maintenance aims to reduce maintenance costs, implement zero-waste production and minimize production failures – all of which are important to almost every organisation (Pech et al., 2021). In order to have a successful predictive maintenance system, all “Industry 4.0 technologies” will need to work together systematically.

Historic data is a crucial part of predictive maintenance as it contributes to a more accurate prediction. This is also why big data analytics is so important (Waibel et al., 2018). Therefore, it is essential for the chosen modelling system to have sufficient capacity to store and access the necessary data, such as operational data, event history, etc. (Syed et al., 2020).

However, organisations are still very hesitant to modernize their infrastructure and systems due to several reasons:

- <u>Financial Restrictions</u>

  Large start-up costs such as sensor installation, integration preparation and modelling implementation pose a great challenge for organisations looking to implement predictive maintenance (X. Cheng et al., 2022).

- <u>Data Limits</u>

  At the start, organisations generally do not have sufficient data that is needed to start a viable predictive maintenance model (Maktoubian et al., 2021). Furthermore, sensors or any other condition monitoring equipment needs to be accurate as this can result in errors when it comes to the actual prediction model.

- Limitations of prediction models

  Since predictive maintenance works with many different elements, there is a lot of integration required. This requires an IT integration team to analyse the specific use case, which can be quite complex due to the knowledge required to build the infrastructure (Paleyes et al., 2021)

1.2.7 Condition Monitoring

Condition monitoring is a form of predictive maintenance where continuous monitoring of the performance of machine or condition of the specific part is monitored which will affect the quality of the product (Niijjaawan and Niijjaawan, 2010). "Condition monitoring is an evolution of predictive maintenance or proactive maintenance" (Jauregui Correa and Lozano Guzman, 2020). It monitors many parameters of conditions within the machinery to best suite the maintenance of the equipment. The data collected from monitoring points provides valuable information about the historic state of an asset and can be used for future efficiency.

There are various obstacles when trying to deploy a condition monitoring system (Shin et al., 2016), such as variation in operating conditions (Same equipment in different environments, etc.) and choosing the right design and system architecture.

but if implemented correctly, it can reduce many costs for an organisation. Early detection of failing equipment results in a shorter downtime for maintenance and therefore reduces great risks for an organisation (Awadallah and Morcos, 2003).

Condition Monitoring can also provide useful information about the system state for maintenance decision-making to improve the durability, reliability, and maintainability of industrial systems (Nguyen et al., 2019). This will then deliver a more efficient machine learning model. Condition Monitoring is mainly used within large organisations which have the correct infrastructure to obtain large amounts of data and where equipment failure is detrimental (Zabiński et al., 2019). It is therefore advised to perform condition monitoring techniques on high failure risk equipment. Condition monitoring can be seen as an advantageous strategy where instead of having fixed periods of maintenance, actual system data can be used to determine the correct timing of maintenance actions. Thus, the following advantages can be seen: lower number of failures, lower maintenance costs, less spare parts needed, higher lifecycle and higher asset utilization (Sobral and Guedes Soares, 2016)

With the acceleration of digitization within organisations, condition-based maintenance strategies are also becoming more popular. Now that sensor data for machinery is easily accessible, it provides great advancements towards intelligent/smart manufacturing. However, as the data sets become larger, this poses a challenge for the model as it is now more complex (Mei et al., 2022). Even though condition monitoring has become more attractive for deployment in recent years, some organisations are still hesitant due to several reasons such as:

- Asset quantity is too large – This means that high start-up costs are required for bigger organisations.
- Asset complexity – Many organisations have equipment that are custom and not similar. This makes the implementation more complex.
- Lack of knowledge - especially when it comes to the integration of technology.
- Uncertainty – Many companies lack experience in areas such as cyber security and IoT technology. This means additional costs will be needed for training/outsourcing.

1.2.8 Digital Twin

Digital Twin can be described as a virtual representation of a physical product where data is constantly transferred between the two layers. The "mirroring" of data allows for organisations to enable techniques such as simulation and modelling to evaluate and make key decisions on a product or system's best conditions (D. Jones et al., 2020)

Major advancements in Internet of Things, Artificial Intelligence and Machine Learning have provided further functionality for Digital Twin such as real-time monitoring and more accurate forecasting (Sharma et al., 2022). By using a Digital Twin, organisations are able to manipulate theoretical data and algorithms to test real life data. In this way, they can make effective decisions without any production losses (Sharma et al., 2022). As a result, Digital Twin is most effective in manufacturing and maintenance where asset lifecycle is a focused target (Kritzinger et al., 2018)

However, there can be some limitation when trying to implement Digital Twin in an organisation as organisations need to have a strong framework for analytics monitoring and forecasting capabilities, before they start to investigate the application of Digital Twin (Javaid et al., 2023). Another key challenge is also the integration and updating of legacy systems as well as machines, since an important contribution for a successful Digital Twin implementation is machine history (Attaran & Celik, 2023)

1.3 Problem Statement

The use of futuristic technology in organisations has been evolving over the past few years. Business processes are likely to change and therefore organisations need to be better prepared towards adapting next generation technologies as well as finding their way around the risks (Pawan Tamvada et al., 2022). For businesses to fully realise the benefits of Industry 4.0 technologies, such as IoT, there is a need to overcome its challenges (Dijkman et al., 2015)

The first sub-problem relates to the lack of current knowledge of Industry 4.0 from people in the industry as well as the unknown trends and knowledge gaps.

The second sub-problem is that the benefits of Industry 4.0 technology still have many unknowns, especially regarding the use of machine learning technology and how this can possibly be used to increase efficiencies of organisations.

Therefore, it is vital that organisations should firstly start upskilling their employees on these next generation technologies so that they are better prepared and equipped to deal with the advanced technological changes. By empowering the workforce and creating in-house subject matter experts, organisations will be better prepared to overcome challenges in future.

1.4 Aim and Objectives

Aim:

The aim of this academic research study is to determine the magnitude of the impact that new technologies are having within organisations as well as the benefits they provide. It is to investigate new ways in which these technologies can be used for different functionalities, and how they are able to provide better productivity within organisations.

Objectives:

- To provide a structured review of the use of Enterprise Asset Management Software, Internet of Things Platforms, Artificial Intelligence, Machine Learning, Predictive Maintenance, Condition Monitoring and Digital Twin.
- To provide great insight into the capability of new functionality that Enterprise Asset Management Software, Internet of Things Platforms, Artificial Intelligence, Machine Learning, Predictive Maintenance and Condition Monitoring can provide as well as identify current trends in the industry regarding these technologies.
- To outline/provide details of how much more efficient business/operational systems can be with IoT solutions.

1.5 Research Questions

There are many variables to consider when investigating the impact of these technologies, as presented in the above chapter. It is important to consider all aspects where these technologies are applied. Different variables have different problems. Therefore, it is important to understand the industry practises regarding these technologies.

More specifically, the following research questions need to be investigated:

Research Question 1: What are the current industry practises of IoT and AI? – This will be supported via the Literature Review

Research Question 2: What are the constraints/gaps found during these practises in the industry, and how can we overcome them? – This will be supported via questionnaires

Research Question 3: Currently, how effective are technologies like IoT and AI, and what is needed to reach the next phase? – This will be supported via data collection from existing sensors/condition monitoring data within the industry

1.6 Research Method

1.6.1 Research Purpose

The purpose of a research is typically derived from the research questions. This study touches on the relationships between some of the variables in order to understand the problem better. The questionnaires/surveys will assist in this regard. Due to the research questions being open-ended and more to explore the background of the topic, this thesis mainly follows an exploratory purpose (Akhtar, 2016). This is also due to the planned use of published books/articles that already exist to describe the background of the problem as well as to compliment my research.

However, the research also elaborates on relationships between variables towards understanding Research Question 3, by means of numerical results. Therefore, it will also partly follow an explanatory purpose.

The published articles, along with the findings of this study, will provide great support for the research. The background and constraint identification will be the first step of the research in order to create a solid framework.

1.7 Significance of the study

This study provides guidance to organisations who are currently in the process of digital transformation, or organisations who are deciding on investing in Industry 4.0 technologies and are looking into the potential that it can bring to their business.

Technology is forever changing, and many organisations are not equipped to handle the changes that it brings. Many organisations, especially smaller businesses, do not have the foundation and knowledge to integrate Industry 4.0 to empower their businesses. Therefore, this study showcases a questionnaire from participants to get a more relevant understanding of what is the current knowledge in the industry. This will assist businesses to get a better look into what is happening the current market. This study also demonstrates the use of machine learning technology, which can also provide businesses with ideas on how to use Industry 4.0 in their business to increase efficiency.

1.8 Hypothesis

The following are propositions that is based on existing knowledge and shows an alternative (a) and null (o) hypotheses:

1(a): The understanding of Industry 4.0 Technologies in the industry is at a basic level.

1(o): The understanding of Industry 4.0 Technologies in the industry is at an advanced level.

2(a): The current implementation of Industry 4.0 Technologies within organisations is still at an early stage.

2(o): The current implementation of Industry 4.0 Technologies within organisations is well executed.

3(a): Industry 4.0 technologies has positive/maximum effect on organisations business processes and efficiencies.

3(o): Industry 4.0 technologies have negative/minimal effect on organisations business processes and efficiencies.

1.9 Thesis Structure

The research outline provides a summary of the remaining chapters in this research.

The following chapter, Chapter 2, is the Literature Review which emphasizes on what other researchers and scholars have done to assist in achieving the objectives of the study.

Chapter 3 shows the methodology - The method which the study uses and how it plans on completing the research in order to satisfy the research questions. The grounded theory and content methods were used for the qualitative study while the convergent parallel mixed-methods design with a thematic analysis was used for the quantitative study.

Chapter 4 is the Results and Analysis which includes all supporting data from surveys, questionnaires, etc. It also includes the Data Review where an in depth analysis and review of the data collected takes place, in order to compliment the research questions

Chapter 5 is the conclusion of the research which summarizes the research as well as all references that assisted in the research. Future recommendations are also proposed, which couldn’t be accomplished in this study.

1.10 Conclusion

An introduction to Industry 4.0 technologies as well as the objectives, scope of the research and method were presented in this chapter. The chapter provided great insight on the definition of Industry 4.0 technologies and highlighted the capabilities that they possess. The aim and objectives were also presented to elaborate the direction of this research. The hypothesis was also presented as it provides the key alternate and null statements which provokes the thought of the reader and provides a base for the route that the study will take to elaborate on those statements. The next chapter will provide a literature review of Industry 4.0.

2 Literature Review

2.1 Literature Review Introduction

Chapter 1 provided the background to the study as well as key research questions, problems, etc. This chapter therefore provides us with a review of existing studies carried out by other authors to assist with the concepts that will provide guidance to achieving the research aim and objectives of this study. The review is divided into the Integration of IoT with Machine Learning, Asset Management in Predictive Maintenance, Digital Twin in maintenance, Readiness/Barriers of Industry 4.0 and Methods of implementation for Industry 4.0

2.2 Integration of IoT with Machine Learning

Machine Learning techniques have been effective towards getting the maximum out of IoT solutions. Ayvaz and Alpay (2021) developed a predictive maintenance system which used real time data that was generated by sensors in production lines to detect potential failures before they occur. They were able to successfully identify indicators of potential failures by using machine learning algorithms. Cheng et al. (2020) used a similar approach where machine learning algorithms were used for predictive maintenance. The authors were able to improve the efficiency of facility maintenance management by using an information layer as well as an application layer within the machine learning model. This allowed them to constantly update the data to ensure that the model received up to date information so that they can efficiently predict the future condition of facility components. Theissler et al. (2021b) investigated the challenges of predictive maintenance and machine learning in the automotive industry. It was found that there has been an increase in the number of publications regarding the machine learning topic and therefore there is a need for surveys to keep up to date about the topic. The authors categorized papers to deduce research directions and found that publicly available data assists research activities and also combining multiple data sources increases the accuracy of the research.

2.3 Asset Management in Predictive Maintenance

The use of an efficient asset management system has various benefits when it comes to predictive maintenance. Aremu et al. (2018) showcased a standard of practise in relation to asset data with the use of machine learning and artificial intelligence technology. The authors were able to provide a method which ensures that the data collected from the asset management system, is reliable and precise to achieve the best possible results for a predictive maintenance design. It was seen that by using poorly trained ML models, the value of the asset's life cycle could be jeopardized. Meng et al. (2022) looked at the relationship between failure modes and predictive benefits of Lithium-ion batteries. This proved to be a great way to quantify the benefits of the overall system. By using a cost-benefit analysis, they were able to make key decisions regarding the system, which is also an analysis that organisations can use to determine the return of investment of a system to identify if it is viable or not for their business. Márquez et al. (2015) used a model for criticality analysis and provided great insight towards the efficient handling of complex data in an asset management system. The authors mention that this is a key step towards asset management strategy design.

2.4 Digital Twin in Maintenance

Digital Twin is most often used in maintenance. Van Dinter et al (2022) used an active learning tool as part of a systematic review to analyse several studies on predictive maintenance which use Digital Twins and explores what are the current challenges on implementing Digital Twin. The authors found that complex models and assets as well as a variety of data were key topics to address. Harries et al. (2023) used an experimental statistical model by using data to calculate the remaining lifespan of machines in a factory. In addition, the authors used machine failure history to predict the degradation paths of the machines in their virtual factory. However, due to limited historical data as well as a lack of models, the results were speculative, yet still presented viable insights into the effectiveness of Digital Twins.

2.5 Readiness/Barriers of Industry 4.0 Technologies

As mentioned in the previous sections, there are many challenges when it comes to implementing Industry 4.0. Due to a lack of studies providing data about the transformation towards Industry 4.0, Tortora et al. (2021) conducted a questionnaire to determine the knowledge and readiness of the implementation of Industry 4.0. The questionnaire results proved that there is still limited knowledge about Industry 4.0 and that organisations are not prepared enough. De Carolis (2017) used a case study approach towards the validation for practical implementation. The author evaluated current maturity models such as DREAMY (Digital REadiness Assessment MaturitY model), SMSRL (Smart manufacturing readiness level), and MOM (Manufacturing Operations Management) as a way of analysing the barriers of change for Industry 4.0 technologies. This was useful as it provided valid techniques that can be used towards making an implementation of Industry 4.0 technologies a success. Relating to MOM, Mantravadi et al. (2023) used an interview approach to collect information from different industries on their interests in MOM and Industry 4.0, with a focus on supply chain. This proved to be a success as the authors were able to gather a wide range of data which was less biased. A keynote from the case study was the difficulty of extracting data from legacy machines. The study showed that even global manufacturers are still in the first phase of the Industry 4.0 journey. Khan and Turowski (2016) also used a similar case study approach by means of conducting questionnaires with experts in the field. This proved to be a success as they identified many challenges in the industry regarding data security, implementation costs as well as training of the existing personnel. When it comes to understanding real-life and complex issues, the case study approach improves social science methods and practises than that that of previous literature according to Hollweck (2016). This makes sense as the technologies are constantly improving and thus, it is needed to update case studies to individuals in the current time, which supports this research regarding the questionnaire approach.

According to Hughes et al (2020), one of the biggest rewards for the implementation of industry 4.0 technologies is an increase in labour force. The authors referenced data from the Swiss World Economic Forum in 2018 which states that industry 4.0 will create 133 million new jobs in smart automation. However, this remains to be seen as we should also expect a large amount of job loss due to the vast amount digitization needed – roughly 75 million according to Hughes et al. (2020). Calzavara et al. (2019) looked at the risk of the ageing workforce due to the transformation implementations and found ways on how to make use of the more experienced workers together with these new technologies. This showed much promise for the future. Smith and Beretta (2021) used a paradox approach towards finding some of the challenges of digital transformation, which also focussed on employees in the workplace and the issues of alignment and integration. Jones et al. (2021) research finds that top management of organisations should also focus on their company culture to ease tensions of dramatic digital transformation. Digital transformation is not only tough on resources but also tough on integration between digital and service offerings. Chen et al. (2021) used a case study approach to investigate this integration and how a traditional manufacturer overcomes this adoption. They emphasized on three main characteristics, mainly being the creation of the need, the delivery of the service/product and the mechanisms used. Rajput & Singh (2019) also used a paradox approach and suggested that certain protocols and standards should be addressed globally for Industry 4.0. However, in contrast, this depends on the implementation as well as the maturity of the organisation, which then means that standards may differ based on numerous factors. It is important that organisations are ready for implementation of these technologies. Menz et al. (2021) looked into how digital transformation technologies influence strategies. The authors also mention how it contributes to the competitiveness between organisations as they battle towards becoming the best digitally advanced company. Müller et al. (2018) reveals that digitization and processes are transforming companies to become independent of their autonomous processes and allows them to develop systems that bring together the stakeholders and customers. Abdul-Hamid et al. (2020) also mentions that one of the challenges of implementing industry 4.0 technologies is unstable connectivity between organisation as well as employment disruptions. However, Herceg et al. (2020) also mentions that there are barriers when it comes to financial resources for the implementation which poses a difficult decision for organisations. Another key point towards the innovation of Industry 4.0 is an organisation's operations management. Fettermann et al. (2018) identified the contribution made by an organisations operations management by investigating success case studies. This showed that most organisations are currently using some form of IoT technology as well as mobile devices towards making their operations more digital. Rana and Rathore (2023) also looked into some of the barriers for organisations and found that insufficient technical knowledge was present where employees are not competent enough for the implementation of Industry 4.0 technologies and therefore there are issues with building the infrastructure to support these changes. Topics like Data Security is one of the key challenges faced. Organisational barriers were also looked at where in most industries there is some resistance to change due to fear of failure. There is also, in some cases, very limited financial support for big project like this as the ROI is not considered to be worth it at first. Moeuf et al. (2017) detected 23 different cases where Industry 4.0 was used and found that most of the technologies was focused towards monitoring of production processes and to improve flexibility within the organisation. However, many of the tools were not utilized to the full extent. It was found that the least expensive tools were being used in order to simulate processes. This could also be due to the lack of knowledge as well as cost of deployment for the more complex technologies. Li et al. (2017) used the case study approach towards retrieving knowledge in the predictive maintenance industry by means of the process of fault analysis and treatment in machine centres. They found that data mining is an integral part of predictive maintenance as it provides a level of precision amongst the complex data. They also place emphasis on the data model as well as the data collected which in turn provides a high level of accuracy. The authors also focused on the development of industry 4.0 with regards to different trends regarding innovation policy, paying attention to China and Taiwan. This study showed the difference between the two countries, but also noted the similarity between them when it comes to industry 4.0 , especially regarding the policy on tools used. Kiel et al. (2017) were able to find a few key barriers in the implementation of Industry 4.0 from their study. The main barriers were firstly, Competition where they highlight the efficiency of using Industry 4.0 technologies but also mention the threat they pose when it comes to the adaptation for smaller organisations due to a lack of knowledge, thus leaving a gap between them and the competitors. Data security and integration were also mentioned as the easier flow of data between systems poses a security threat if the correct cybersecurity processes are not put in place. Rasheed et al. (2020) used 79 different cases to develop a relationship between the enablers and barriers of the implementation of digital twins. The authors highlighted which enablers compliment the respective barriers. For example, communication technologies are said to assist towards data quality and security issues while the latest hardware helps performance issues. This shows us that there are mechanisms towards assisting the implementation of digital technologies for organisations to become more efficient and productive. Govindan and Arampatzis (2023) proposed a framework to assist the assessment of readiness for Industry 4.0. The authors used a Danish case study to determine the key barriers for implementation and found that one of the key barriers is leadership in the organisation. This relates to organisations decisions regarding return of investment.

2.6 Implementation of Industry 4.0

Analysis techniques are vital when it comes to understanding a company's current position before implementing new technologies. Wankhede and Vinodh (2021) used the Best Worst Method (BWM) where the challenges of organisations, based on the data, are prioritised. This makes it easier for an organisation to identify where there is room for improvement before fully investing into a project. In terms of literature analysis per technology, Zutin et al. (2022) used a distributed method for number of publications based on the different technologies. This identified the technologies which had the most publications and thus aided towards the data analysis in finding technologies where there was a gap in knowledge. The authors also analysed the number of publications related to Industry 4.0 by year. This showed a significant increase in the interest of the topic, especially between the years 2017 and 2019. Various articles also place focus on specific technologies. Furstenau et al. (2022) performed a thematic analysis on the Internet of Things (IoT) where key challenges and future opportunities were found. The type of data collected is also important as it depends on the specific organisation's operations. Various studies place focus on the type of industry that the study is based on. For example, Rad et al. (2022) looked at data within the supply chain industry and were then able to deduce benefits, challenges success factors for specific industry 4.0 technologies. The authors were then able to propose improvements for the industry, based on their data collection. Kumar et al. (2021) investigated the barriers in manufacturing organisations and used an Interpretive Structural Modelling (ISM) type of analysis which creates relationships among all barriers identified. The authors were then able to create a hierarchy for the barriers listed, such as "Resistance to change" and "Cyber security challenges". This gave them a clear insight into the knowledge that is currently in the industry. Karadayi-Usta (2020) also analysed the barriers of implementation by using an Interpretive Structural Modelling (ISM) technique. The main challenge they found was a lack of education. Therefore, it is suggested that more subject matter expects should be involved in the early stages of implementation as well as in the decision making process. When analysing industry 4.0 technologies, it is also important to understand the relationship between the main applications and the enabling technologies. This was performed by Liao et al. (2018) through a systematic review based on a descriptive analysis using keywords, publications, etc. The review was also interesting as it analysed the number of publications per country/region which gave us an insight into where there was a high interest in Industry 4.0, and which areas needs more information on the topic. This also raises some concern for those areas, especially for smaller organisations. Sommer (2015) highlighted that these smaller organisations might not have the necessary resources to progress with the digital transformation advancement, and thus will be left behind. In an attempt to assist subject matter experts with implementation, Qi et al. (2021) performed an overview of the key technologies as well as explaining their benefits and what they can be used for. Agostini and Filippini (2019) also mentions that the IT infrastructure that exists is a key condition for the success of digital transformation process.

Kamble et al. (2018) used a review approach towards reviewing the benefits of digital transformation when it comes to the environment and processes it is associated with. They proposed that Industry 4.0 technologies provide assistance towards making processes more sustainable and efficient. They also mentioned specific technologies, such as IoT, which can benefit energy efficiency. Ortt, Stolwijk and Punter (2020) also used a review approach when it comes to the implementation of Industry 4.0. They looked into the methods used by organisations, and initiatives that were utilized for the start of the implementation. This showed techniques that are currently used in the industry and also what is needed to bridge the gap to ensure a smoother transition._When it comes to data analysis, cloud computing and advanced data analytics is essential for an Industry 4.0 solution. Fernández-Caramés et al. (2018) used these technologies to create an advanced tracking solution in the ship industry. This is also relevant in the maintenance industry as dataset tracking is key for a strong maintenance execution system (MES) or machine learning models. Ejsmont et al. (2020) conducted a network analysis method which provided a great insight into the links between the different digital concepts such as real-time data, IoT and big data. This also emphasised on the positive effective that they have in organisations._Müller et al. (2018b) developed a research model to elaborate on the sustainability of Industry 4.0. The model showed various factors to consider, most notably – environment, people and competitiveness. These are elements which can either make an implementation a success, or a failure for an organisation._Barberá et al. (2012) used a graphical method called the Graphical Analysis for Maintenance Management (GAMM) which provided useful information the maintenance of systems and the reliability of equipment. However, a successful GAMM implementation requires a vast amount of experience as well as great knowledge about the subjected maintenance management system.

2.7 Conclusion

In this chapter, the readiness and barriers of the implementation of Industry 4.0 were discussed. There are various obstacles which needs to be overcome in order to successfully transition into the next phase of digital technology.

However, this chapter also discussed various methods used by different authors which provided great insight and assistance for organisations to better understand the link between business processes and the technology that enhances them. It also provided great support towards the research approach of this study.

The integration of the above-mentioned Industry 4.0 technologies changed the way we practise maintenance. The successful implementation of techniques, discussed by the authors above, highlights the potential of Industry 4.0 and how we are able to extend equipment lifecycles as well as reduce costs and increase manufacturing efficiencies.

The next chapter elaborates on the methodology used towards complimenting the research questions.

3 Methodology

3.1 Introduction

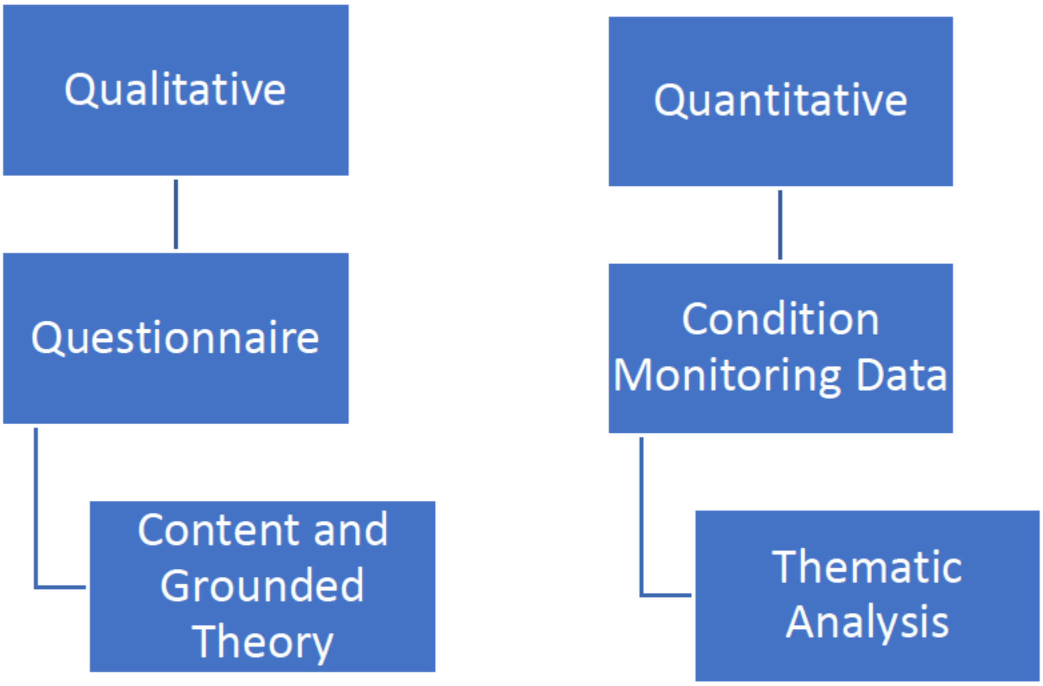
This section outlines the research methodology that was used in order to answer the research questions stated in this study. It explains the detailed steps taken when it comes to achieving the objectives of this study.

3.2 Research Approach

As mentioned above, this study has gathered data via a questionnaire. This means that the data relating to some of the research questions is non-numeric data (Zikmund, Babin, Carr and Griffin, 2012). However, this study used a theory testing approach by means of actual numerical data in order to elaborate on Research Question 3: Currently, how effective are technologies like IoT and AI, and what is needed to reach the next phase?

Therefore, this research is a combination of quantitative and qualitative data collection techniques and analysis tools (Dawadi et al., 2021). The method uses data collection and analysis processes sequentially (one after the other) but not as a combination together (Creswell and Creswell, 2018).

Thus, this research follows a mixed methods approach due to the requirement of the research questions which involves a sequential process. The following flow chart displays a summary of the methodology used:



The sections below provide detailed information regarding the methods used.

3.3 Data Collection (Qualitative)

3.3.1 Questionnaire

For the qualitative study, the research uses third party data collection via a questionnaire. The questionnaire consists of three different types. First, open ended questionnaire which is a type of questionnaire that gives an open opportunity to the respondent to provide an answer based on their own understanding of the topics (King, 1972). Secondly, a semantic differential questionnaire which uses a scale option where each end is marked with opposing statements, and lastly a multiple-choice questionnaire where options are given and the respondent chooses between the selected choices and does not provide his/her own answer.

3.3.2 Sampling Method

There were two types of sampling methods that were examined. The first was probability sampling where random sampling where all participants of the questionnaire have an equal chance of being chosen to be part of the research. It provides a vast amount of different types of feedback (Zikmund, 2002)

The second was non-probability sampling which focuses on smaller samples and is intended to examine real life problems. It is when a clear rationale is needed to include a specified audience (Saunders, Lewis and Thornhill, 2016).

For this research, non-probability sampling was used. More specifically, purposive sampling. Purposive sampling is defined as a strategy in which the participants are pre-selected deliberately to provide information that random participants cannot provide (Saunders, Lewis and Thornhill, 2016).

This study samples and analyses responses from an audience that is familiar with the subject and have possibly worked with Industry 4.0 technologies before. Therefore, more concise, and informative results were expected. 13 participants took part in the questionnaire.

Section 4 analyses the samples collected using a content and grounded theory method, which is explained in the next section.

3.4 Data Collection (Quantitative)

3.4.1 Dataset

For the quantitative analysis of this study, a dataset was used which contains 10 000 data points for a specific motor. The data focuses on torque values in relation to points of failure Predicting Machine Failure Type | Kaggle, n.d.). The datasets are presented in the following figures:

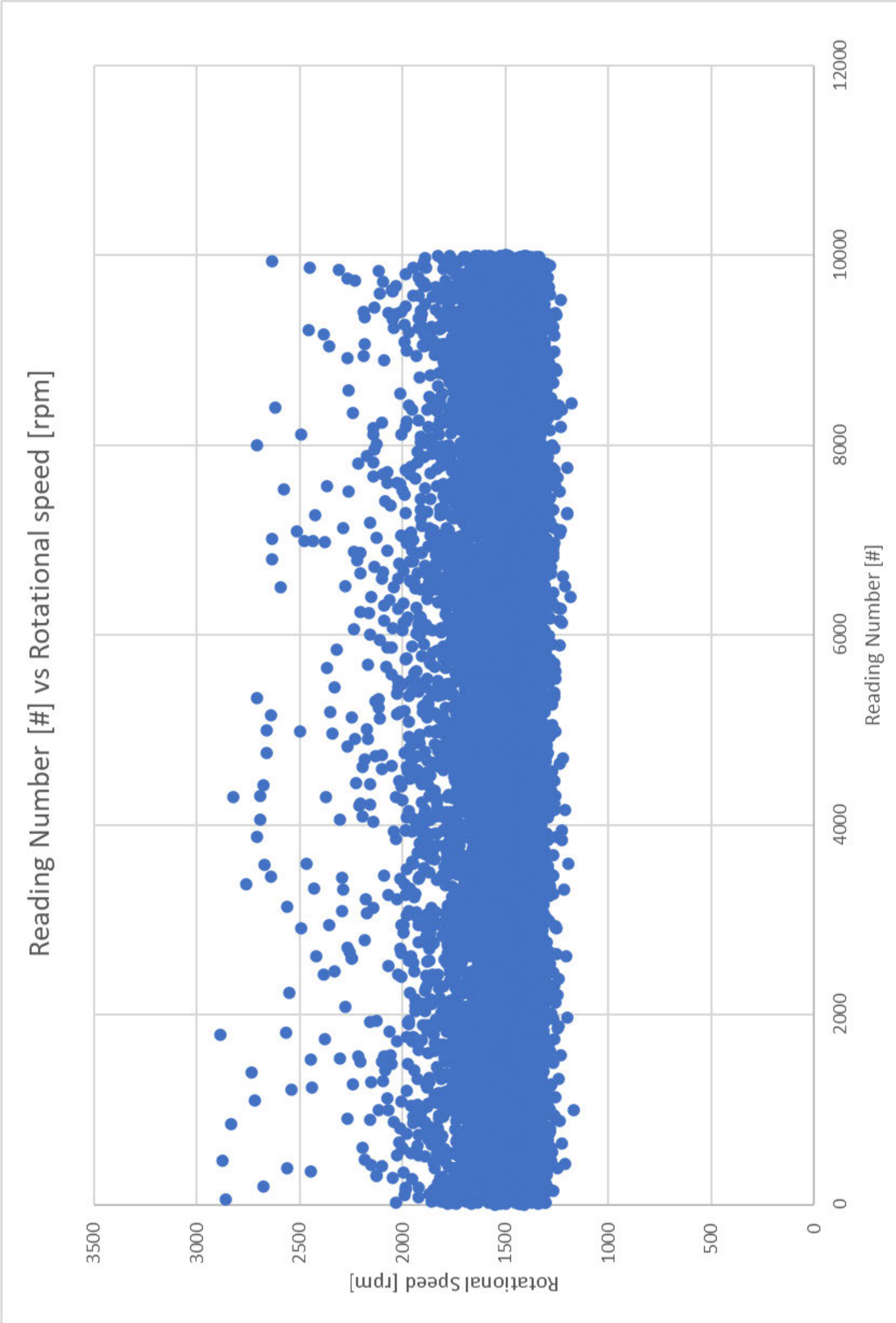


Figure 3.1: Reading Number vs Rotational Speed [rpm]

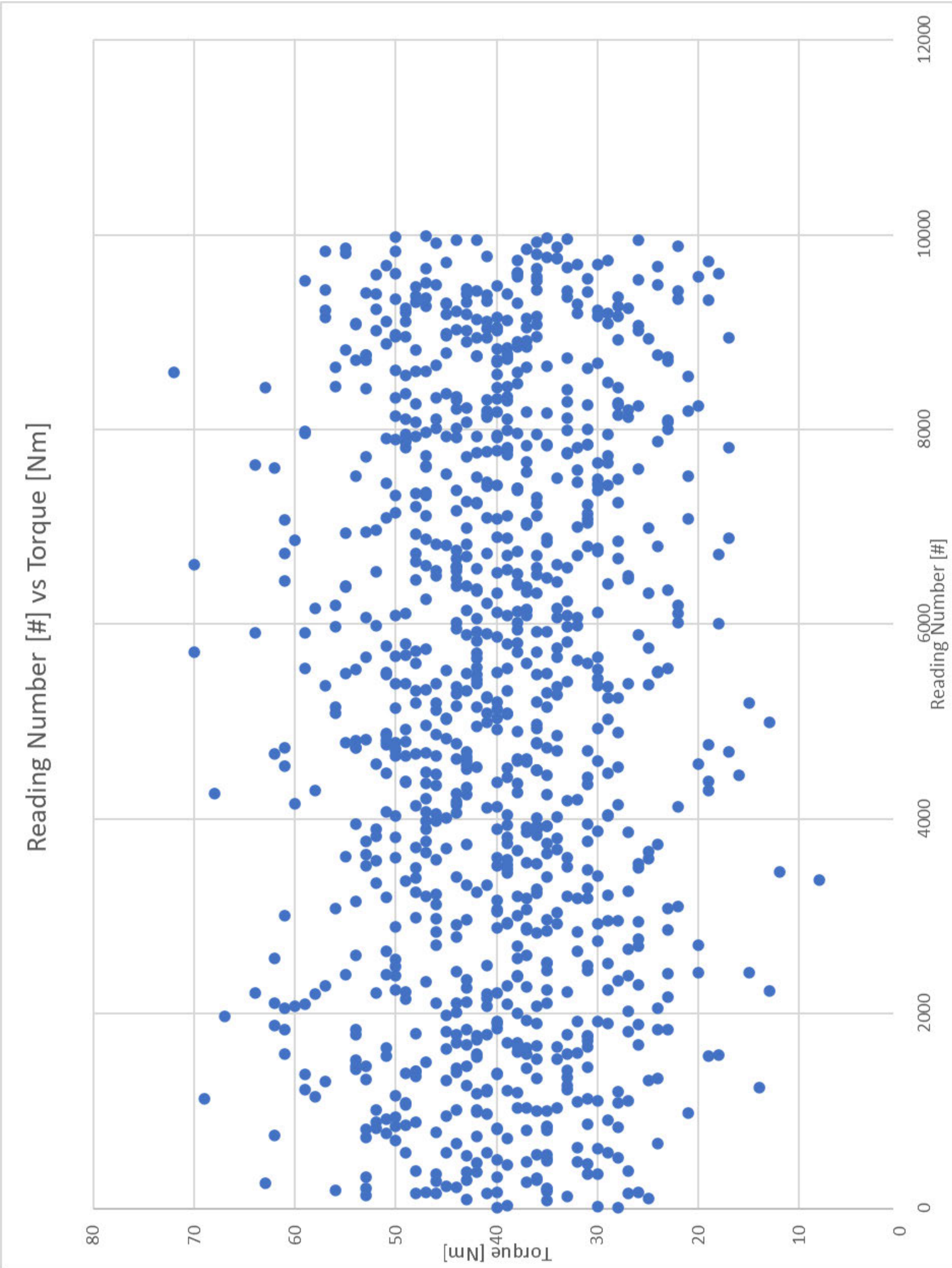


Figure 4Figure 3.2: Reading Number vs Torque [Nm]

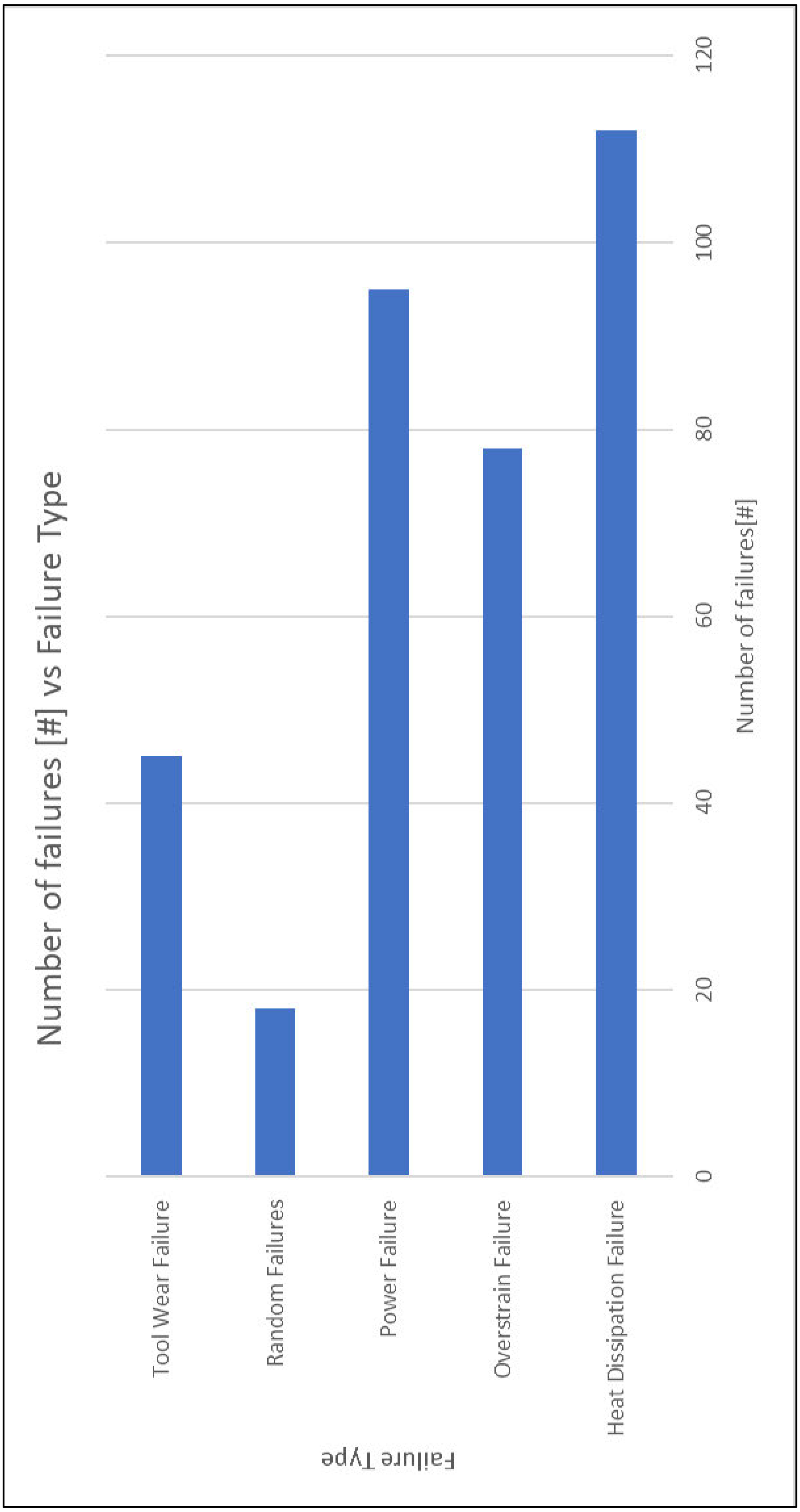


Figure 5Figure 3.3: Number of Failures vs Failure Type

3.4.2 Data Analysis Method

Interpretation and data analysis can be conducted using the following types of analysis:

- **Content Analysis**

  This refers to a continuous iterative process of reviewing your initial analysis compared to the outcomes that have been created. This helps to analyse concepts within the data to reach an outcome (Erlingsson and Brysiewicz, 2017)

- **Grounded Theory**

  This type of analysis looks to develop theory from the data obtained. A comparative analysis style is then used to determine relationships within the data. This is generally used within a qualitative study (Stough and Lee, 2021)

- **Thematic Analysis**

  This type of analysis identifies, analyses and interprets trends or patterns in the data (Khirfan et al., 2020). The data is closely examined to identify themes where patterns of meaning start to emerge. This type of analysis is generally used for quantitative studies.

The quantitative study focused on a Thematic Analysis to identify patterns in the results and interpret them in a way that assists the response to Research Question 3 – "Currently, how effective are technologies like IoT and AI.".

3.5 Data Interpretation Design

As mentioned previously, this study follows a mixed method approach. Therefore, when it comes to the analysis, the following options could be used:

- **Explanatory Sequential Design**

  This is where quantitative data and analysis is completed first followed by qualitative data and analysis. This design is generally used when the qualitative findings will contextualize the quantitative findings (Subedi, 2016)

- **Exploratory Sequential Design**

  In comparison to the explanatory design, this design focuses on the qualitative data first before drawing better conclusions with the quantitative analysis (Subedi, 2016)

- **Convergent Parallel Mixed-Methods Design**

  This is where both the qualitative and quantitative methods are mixed to obtain a complete picture and better understanding of the topic. That being said, they are still both analysed independently using their respective approaches (Stewart, 2006)

For this study, the chosen design is the convergent parallel mixed-methods design. The study uses this design as it is a design where the qualitative data is analysed first before the quantitative data. The quantitative data will then hope to provide a confirmation for the qualitative analysis by means of a comparative study towards complimenting the findings from the questionnaire data. This fits perfectly with this study as the qualitative and quantitative data have been collected independently and therefore it makes it possible to analyse them in this way.

3.6 Research Structure

Research Question	**Type of data**	**Type of analysis**
1: What are the current industry practises of IoT and AI?	Literature Review	Qualitative - Content Analysis
2: What are the constraints/gaps found during these practises in the industry, and how can we overcome them?	Questionnaire	Qualitative - Questionnaire with non-probability sampling
3: Currently, how effective are technologies like IoT and AI, and what is needed to reach the next phase?	Questionnaire and Dataset	Quantitative - Thematic Analysis with exploratory sequential design

Table 2: Research Structure

3.7 Conclusion

This chapter presented the methodology used for this study. It elaborated on the use of a mixed method study, using both qualitative data by means of a questionnaire, as well as quantitative data by means of condition monitoring data using machine learning software. A thematic analysis was also mentioned since patterns of the data collected will be analysed in the next chapter to investigate the meaning behind them and how they could benefit future organisations.

4 Results and Analysis

4.1 Introduction

This chapter firstly presents the findings from the questionnaire (qualitative) as well as the analysis of the condition monitoring data (quantitative). The analysis of the questionnaire and condition monitoring data is discussed in correlation with the research questions.

4.2 Research Questionnaire (Qualitative)

The questionnaire used for this study was administered to company "X" Ltd. All names and personal details have been kept confidential. The results can be seen in Annexure D.

4.2.1 Questionnaire Analysis/Summary

4.2.1.1 Technology foundation

In summary, the questionnaire revealed that all respondents currently have a system which stores information that is related to their assets (Question 12):

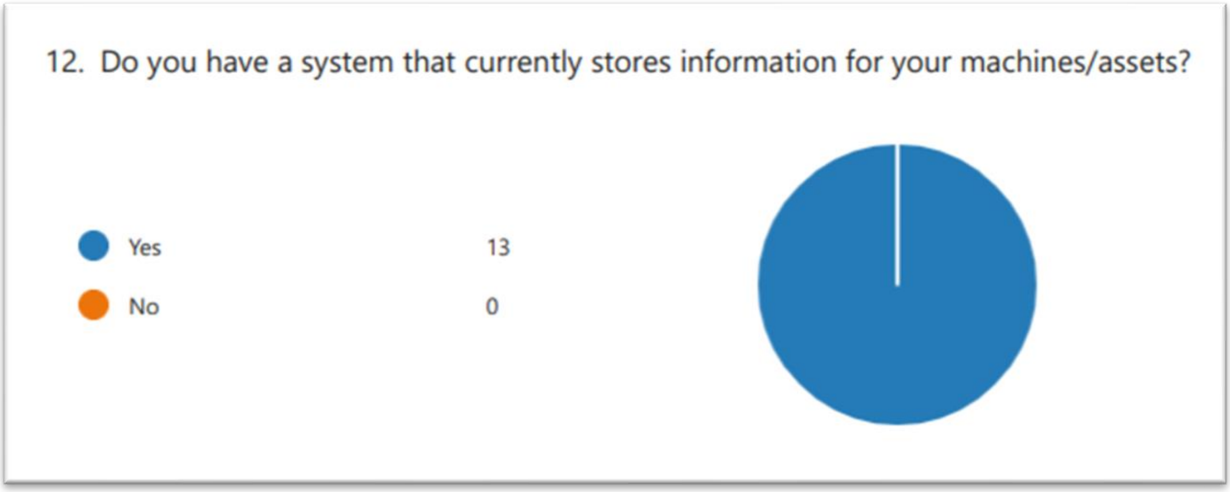


Figure 6: Technology Foundation Analysis

4.2.1.2 Challenges

However, after analysing further, most findings show that respondents' assets do not communicate with one another in an efficient way. In many cases, information that is viewed by employees is also not being analysed to improve current processes/systems. This is due to reasons such as machines being too old and not having the foundation for data collection points (Respondent 12).

There are also cases where data is being collected from the equipment, however for the majority of the findings, the data is not being utilized for predictive analytics or future improvements (Question 17):

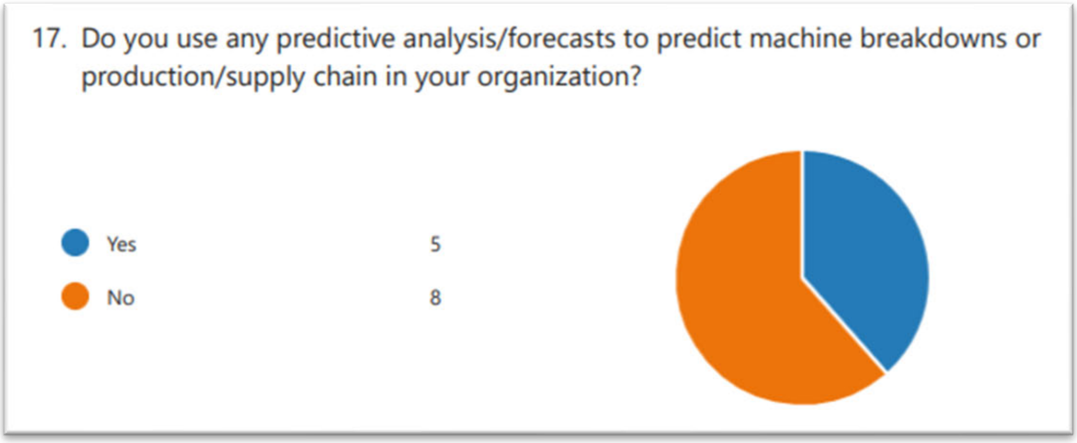


Figure 7: Challenges Analysis

Furthermore, some respondents also mention further challenges when trying to implement these technologies:

<u>Resources:</u>

> "I am not an expert, but it seems that the cost vs benefit calculation is still tough for these kinds of implementation as people do not really understand it yet. You need experts to be able to utilize and build on these technologies, and for that, the general population needs to be trained, adding more costs of implementation." – (Respondent 4)

<u>Data Security:</u>

> "…. security in all aspects is a major concern in many sectors of trade and industry" – (Respondent 3)

> "…. data security among our customers, connectivity (customers in remote regions with little infrastructure)" - Respondent 10

The above statements compliment the research done by Hughes et al (2020) as it shows a need for existing work force to not just have basic knowledge of the concept, but to also have experience in the field in order to make the implementation a success and to fully benefit from these technologies. The statements highlight the possibility to integrate and digitize the workplace, but also focus on the challenge in having the correct foundation and resources.

4.2.1.3 Lack of finances

The main challenge of implementing industry 4.0 technologies was seen to be the cost.

> "The technology is still maturing so finding the correct partner for your needs is difficult as there are many players, but creating internal capacity and capability is still difficult and costly" – (Respondent 7)

> "The biggest challenge when implementing industry 4.0 technologies is the costs."- (Respondent 9)

> "Management are reluctant to spend money on IOT/Industry 4.0 as the ROI are challenging and whether it will work and yield benefits on out Manufacturing Plants" – (Respondent 12)

4.2.1.4 Interest in implementation

Nonetheless, respondents still see the benefit in Industry 4.0 technologies. 75% of the feedback tells us that they have started, or currently starting the implementation of these technologies:

> "We have a Condition Monitoring leg in the business. We are focusing on digital elements of management within our software development. We aspire to AI and Machine Learning, but I am not sure that we are actively using it." – (Respondent 3)

> "Our company is using predictive maintenance on some equipment and is expanding in this field" – (Respondent 5)

> "The organization is starting to apply Industry 4.0 in some areas of the business as in maintenance. Few projects are actually on going. one of them is related to change the mentality of the employees to be more open about Industry 4.0" – (Respondent 9)

This tells us that there is excitement in the industry, and that organisations see the value and benefits in these technologies in terms of an increase in productivity and sales of the business, even though they face some constraints. Question 21 results also supports this feedback by indicating that around 80% of respondents are likely to implement industry 4.0 technologies in the future:

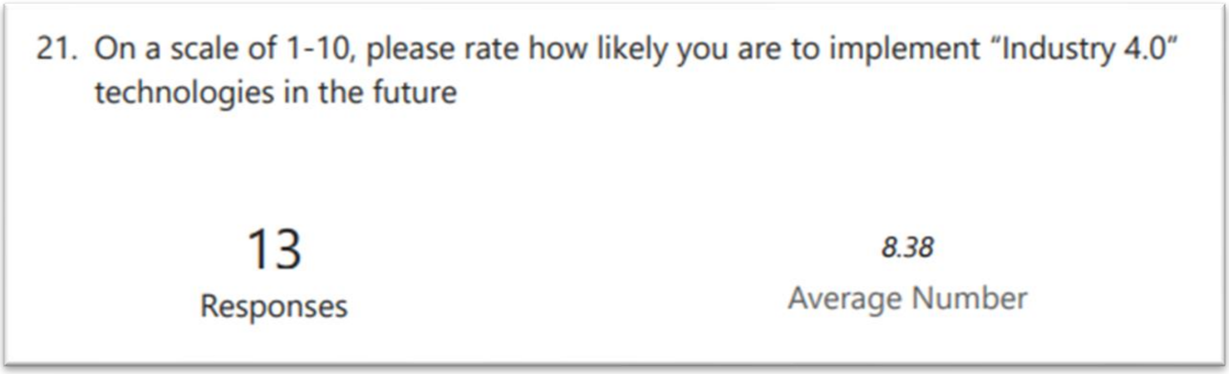


Figure 8: Interest in implementation

It is clear that the respondents expect to see various improvements with the implementation of these technologies. An increase in productivity and efficiency of the organisations were the main points:

> "To better improve productivity and efficiency. Which in turn leads to increased profitability and improved customer performance." – (Respondent 2)

> "The goal would be Improved Productivity and Improved Efficiency. Everyone wants to do the same kind of work with fewer expenses (people), and be more accurate (than people can be)." – (Respondent 3)

Costs and risk reduction coming from "data driven" decisions were also key points:

> "Improved asset utilization for clients - cost of maintenance reduction, risk reduction" – (Respondent 7)

> "Data driven decisions, move maintenance from predetermined to predictive, giving more realibility to our customers's production" – (Respondent 8)

> "Optimization of cost, processes and performance. Better decision making process driven by data and pattern which would be otherwise difficult to see" – (Respondent 10)

Therefore, relating to Research Question 1, it can be seen that current industries are in the process of applying these technologies are very much aware and interested in seeing the benefits in their organisation. However, the current practises do not seem to be in the advanced stages yet since many organisations are in the exploratory phase.

Regarding Research Question 2 – It can be seen that the main constraint is cost/funding for these technologies, as well as the knowledge maturity levels of internal stakeholders to develop and design these solutions.

The figure below presents a summary of the conclusions via a thematic analysis of initial findings vs themes. This helps to tie together the common themes from the data in relation to the associated research questions (Khirfan et al., 2020)

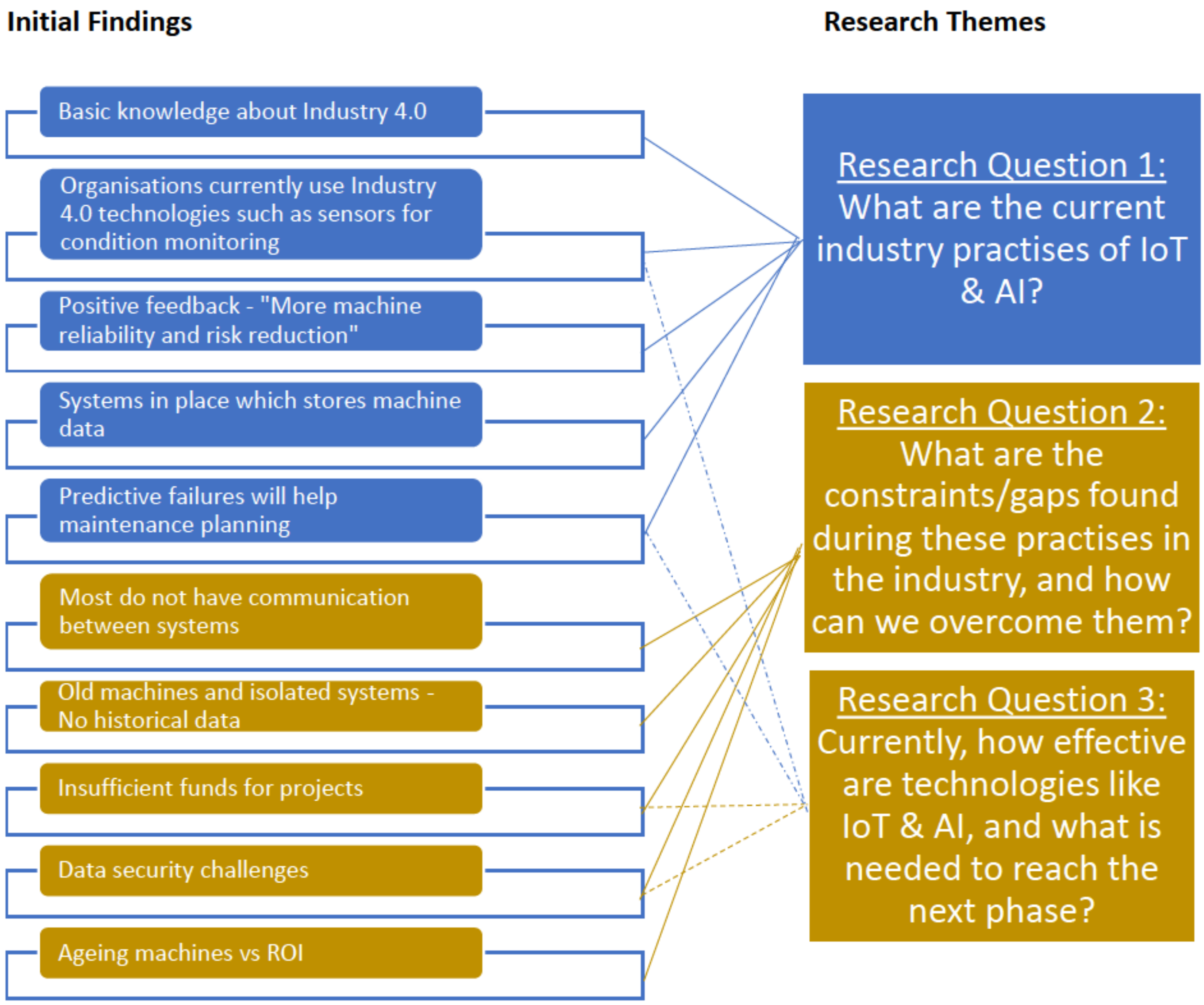


Figure 4.1: Initial Findings vs Themes

4.3 Research Analysis Results (Quantitative)

The following section includes condition monitoring data from an organisation. The intent is to use AI/ML technologies as best as possible to understand how they can help a business/operational system, which relates to the objectives of this study stated in section 1.3:

- To provide great insight into the capability of new functionality that the mentioned technologies can provide

- To outline/provide details of how much more efficient business/operational systems can be with IoT/AI solutions

4.3.1 Condition Monitoring Data Results and Analysis

Failures can be rather costly for organisations. Therefore, by being able to analyse when a failure will happen, we can save a great amount of income and also limit any risk for the company. As stated above in the methodology, the research observes the following six main principles of a Thematic Analysis (Braun & Clarke, 2006):

1. **Familiarise the data**

   As mentioned previously, the dataset was collected from an external source (*Predicting Machine Failure Type | Kaggle*, n.d.). In order to familiarise myself with the data, the headers and number of data points were fully analysed before a deep evaluation was done. However, at this stage, it was difficult to find patterns as the dataset was fairly large.

2. **Code the data**

   In order to code the data, this study made use of Computer Aided Qualitative Data Analysis Software (CAQDAS). The software used was Jupyer (*Project Jupyter | Home*, n.d.). We needed to analyse the data to ensure we focus on the key aspects. Therefore, we needed to sort the data in a logical way (Use of libraries - (Machine Learning for Equipment Failure Prediction and Predictive Maintenance (PM) | by Shad Griffin | The Startup | Medium, n.d.). This assisted with cleaning the data in order to make patterns more apparent. Figure of data after using machine learning software:

Reading	Rotational speed [rpm]	Torque [Nm]	Failure Type
1	1551	42.8	No Failure
2	1408	46.3	No Failure
3	1498	49.4	No Failure
4	1433	39.5	No Failure
5	1408	40.0	No Failure

Figure 4.2: Cleaning of Data

This also gave us a more clear indication of the rotational speed and torque in relation to the failure types.

3. **Identify patterns/themes**

The data was grouped together and analysed. Relationships between the data was now easily identifiable and therefore patterns started to emerge.

Figure of data after using machine learning software:

```
In [64]: df['Failure Type'].value_counts()

Out[64]: No Failure                  9652
         Heat Dissipation Failure     112
         Power Failure                 95
         Overstrain Failure            78
         Tool Wear Failure             45
         Random Failures               18
         Name: Failure Type, dtype: int64
```

Figure 4.3: Grouping of Data

This showed us the count of different types of failures in the machine. From here, the different types of failures could be analysed to determine which types are the most prominent in the machine. For example, this can then give the organisation a better idea on which area to improve on and where they could possibly invest more to reduce breakdowns.

4. **Review patterns/themes**

The patterns were then analysed in relation to what it means to the research topic and how do they contribute to the validity of the response to the research questions.

Figure of data after using machine learning software:

```
In [83]: plt.plot(df['Failure Type'])

Out[83]: [<matplotlib.lines.Line2D at 0x26ecae3c8b0>]
```

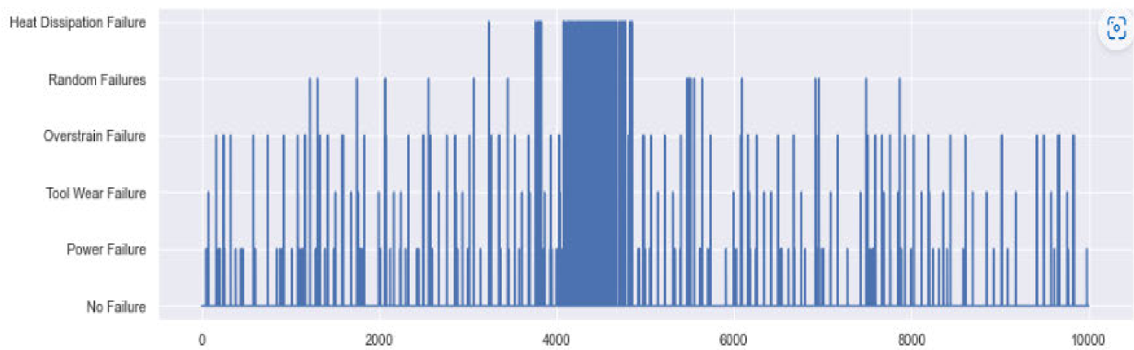


Figure 4.4: Visual Representation

By taking the highest key failure as an example, by means of a visual interpretation, we can see that Heat Dissipation starts to become more common after 4000 readings.

5. **Define patterns/themes**

   By defining the patterns, it can then be seen what the patterns mean towards this study and how does it satisfy the topic.

   In this case, it can then be investigated further to understand what the reason for the increase in heat dissipation is, and how we can overcome the issue– E.g analysing the torque values and other variables. For instance, this condition monitoring data can be used as an enabler towards predictive maintenance (Jauregui Correa & Lozano Guzman, 2020).

6. **Review**

   Here the data can be reviewed and interpreted in a way that correlates to the research questions. This is by means of comparison, etc.

As seen above, after making use of a digital technology we were able to firstly identify the types of failures in a more structured way. From here, we detected the failure which occurred the most and at which period it is mostly likely going to occur. For example, by using the machine learning data together with Digital Twin technology, we will be able to make adjustments to a model to create a simulation to identify what are the optimum conditions and possibly limit any failures. Using this information, one can work towards a strategy on eliminating the failure to reduce costs for the organisation and thus making it more efficient and profitable.

4.4 Conclusion

This chapter analysed two different datasets to investigate the application and benefits of emerging Industry 4.0 technologies. Firstly, the questionnaire results presented the current knowledge regarding Industry 4.0 of people in the industry. The current trends as well as the gaps were identified from the interviewees, which complemented the following research questions:

Research Question 1: What are the current industry practises of IoT and AI?

Research Question 2: What are the constraints/gaps found during these practises in the industry, and how can we overcome them?

Secondly, a condition monitoring dataset was analysed using machine learning software to further investigate what benefit the organisation could have by using this type of technology. This analysis complimented the following research question:

Research Question 3: Currently, how effective are technologies like IoT and AI, and what is needed to reach the next phase?

5 Conclusion

This research presented a literature framework of the Industry 4.0 concepts while also exploring current trends, implementation challenges, as well as investigating the capabilities of machine learning technology.

This research provided a summary of the current trends regarding Industry 4.0 from industry personnel as well as an overall view of the implementation of digital technologies and how they can be used to make organizations more efficient. It provided a review as well as great insight into the topic by analyzing work done by previous authors, focusing on the methods that they used. Secondly, the quantitative study presented a great example of how a business can be more efficient by using an Industry 4.0 technology, which satisfies the aim and objectives of this study.

The study also focused on methodologies presented by other authors to analyze the application of Industry 4.0 technologies whilst highlighting key successful methods as well as the main barriers of implementation. The section also looked at supportive case studies across different industries where Industry 4.0 proved to be a success.

The research then evaluates the current trends and industry practices of Industry 4.0 by using a qualitative research approach using feedback from a survey. The grounded theory and content analysis method proved successful as the research was able to identify the current trends as well as the knowledge gaps, based on the interviewee’s responses.

Lastly, a quantitative research approach was also explored by means of a condition monitoring dataset. The dataset was analyzed using a thematic analysis and consisted of machine operational data where machine learning software was used to breakdown the failure points of the machine so that the organization can better understand the failure patterns and make key decisions towards making their business more efficient in the future.

5.1 Summary

By using a grounded theory and content analysis method, the results from the questionnaire were reviewed to understand the current trends and gaps that are present based on the interviewees responses. It can be seen from the interviewees that there is awareness of Industry 4.0 technologies, however, there is still some work to be done regarding the implementation of the technologies. The results showed that many struggle with ageing machine data as well as the lack of capital to invest. Overall, the results showed positivity towards the application of these technologies and how they can benefit organisations and business processes.

By using machine learning software, this study was able to break down an organisations machine data by highlighting the highest number of failures. Furthermore, the type of failures were deduced as well as at which point the highest type of failure occured. By using this data, the organisation will be able to plan the necessary actions in order to minimize downtime and in turn reduce any costs associated with the failures.

By reviewing our hypotheses, we can also summarize the following:

1: The understanding of Industry 4.0 Technologies in the industry is at an intermediate level as many of the participants from the questionnaire knew about Industry 4.0 technologies, but there were also some of them who did not know much about them.

2: The current implementation of Industry 4.0 Technologies within organisations is still at an early stage. From the questionnaire results we can see that organisations have the necessary information to enable implementation of Industry 4.0 technologies and many of them have already started, however, they have not yet reached a stage where they are comfortable to sustain the technologies.

3: Industry 4.0 technologies has a positive effect on organisations business processes and efficiencies. We can see from the questionnaire that people in the industry are interested in Industry 4.0 and realise the benefits that they bring. From the condition monitoring data, we can see that by using machine learning tools we are able to highlight key information for organisations and thus creating a positive effect.

5.2 Recommendations

Since we are still in the early stages of Industry 4.0, many organisations find it difficult to get a great start for the design phase towards the implementation of these technologies. This study recommends the following for organisations who are looking to get a start:

- Technology Audit
  The first step would be to investigate the organisation's current technology capability and understand where they are positioned in terms of industry 4.0 standards. If the organisation has more modern technology available, then this implies that they are better prepared to adapt and digitize their operations (Hughes et al., 2020).

- Connectivity
  Machine to machine communication is a key point for industry 4.0, especially in an effort towards making more data-driven decisions. Therefore, having a system which can store big data in an efficient way is important. This was also seen as challenge based on the results from the questionnaire.

- Cost
  Industry 4.0 technology implementation can be costly and thus many organisations are hesitant to produce capital at first. Therefore, by creating a clear business model which showcases an increase in efficiency of the business as well as clear ROI projections, organisations will be more open to committing to industry 4.0 projects since they will be able to budget themselves accordingly.

5.3 Future Work

Firstly, I recommend future researchers to continuously conduct questionnaires with people who are working in the industry and who make use of these technologies. This will ensure that future research is always up to date, and which can be compared with previous research to analyse the improvements and advances made with industry 4.0 technologies, if any.

Secondly, conducting questionnaires within a different industry, other than maintenance, might also be a great idea to investigate how other markets are enabling these technologies and using them to their advantage. This will then possibly introduce new ways for other industries to use these technologies.

Lastly, future researchers could create a model which would predict when failures can occur for the dataset used in this study. From there, organisations can then predict failures before it happens and therefore eliminate unforeseen costs.

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Annexure

Annexure A: Ethics Checklist

Zertifikat Certificado
Certificat Certificate

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[REV : 20220217]

Annexure B: Coding for Quantitative Data

```
import numpy as np

import pandas as pd

In :

import os

for dirname, _, filenames in os.walk('/kaggle/input'):

    for filename in filenames:

        print(os.path.join(dirname, filename))

In :

import matplotlib.pyplot as plt

import seaborn as sns

In :

---------------------------------------------------------------------------

In :

df=pd.read_csv("predictive maintenance data  - Nevek MEng.csv")

In :

df.head()

Out:
```

	Reading	Rotational speed [rpm]	Torque [Nm]	Failure Type
0	1	1551	42.8	No Failure
1	2	1408	46.3	No Failure

	Reading	Rotational speed [rpm]	Torque [Nm]	Failure Type
2	3	1498	49.4	No Failure
3	4	1433	39.5	No Failure
4	5	1408	40.0	No Failure

In :

```
df.shape
```

Out :

(10000, 4)

In :

```
for i in df.isnull().sum().index:
    print(df.isnull().sum()[i])
```

0

0

0

0

In :

```
l=['Unnamed: 0']
for i in df.isnull().sum().index:
    #print (df.isnull().sum()[i], end=" ")
    if (df.isnull().sum()[i]>1000):
        l.append(i)
l
```

Out :

['Unnamed: 0']

In :

df.columns

Out :

Index(['Reading', 'Rotational speed [rpm]', 'Torque [Nm]', 'Failure Type'], dtype='object')

In :

df['Failure Type'].value_counts()

Out :

No Failure 9652

Heat Dissipation Failure 112

Power Failure 95

Overstrain Failure 78

Tool Wear Failure 45

Random Failures 18

Name: Failure Type, dtype: int64

In :

plt.plot(df['Failure Type'])

Out :

[<matplotlib.lines.Line2D at 0x251d7b9b280>]

Annexure C: Questionnaire

The questionnaire includes the following questions:

1) Location?
2) Profession /Occupation?
3) Sector of current profession?
4) Before reading the information sheet, did you know any technologies associated with Industry 4.0? (e.g Internet of Things, Artificial Intelligence, etc.)
5) Does your organization make use of any of these technologies?
6) Please elaborate on the question above
7) After reading the information sheet, do you think these technologies can be adopted in future within your organization?
8) How/Why not?
9) What benefits do you wish to see from these technologies, if they are implemented within your organization?
10) Do you have a system that currently stores information for your machines/assets?
11) Do your current machines/assets communicate with one another to ensure an efficient process flow?
12) Can an employee view information from machines/sensors in your organization to ensure seamless flows and prevent breakdowns?
13) Do you use data obtained from various machines and sensors to analyze your manufacturing/system processes?
14) Please elaborate on question above.
15) Do you use any predictive analysis/forecasts to predict machine breakdowns or production/supply chain in your organization?
16) What challenges do/will you encounter when implementing these industry 4.0 technologies? E.g Costs, data security, etc.
17) Please elaborate on question above
18) On a scale of 1-10, please rate your current knowledge on “Industry 4.0” technologies
19) On a scale of 1-10, please rate how likely you are to implement “Industry 4.0” technologies in the future

20) Any additional comments?

Annexure D: Questionnaire Results

Respondent	Location	Profession/ Occupation	Sector of current profession	Before reading the information sheet, did you know any technologies associated with Industry 4.0? (E.g Internet of Things, Artificial Intelligence, etc.)	Does your organization make use of any of these technologies?
1	Durban, KZN, South Africa	Project Engineer	Engineering - Physical Asset Management	Yes	Yes
2	Durban, KZN, South Africa	Supply Chain Manager	Manufacturing	Yes, AI	No
3	Cape Town- South Africa	Lecturer	Education	Yes. I have a general understanding of these concepts.	Yes.
4	Cape Town, Western Cape	Projects Manager	Consulting, Manufacturing	I have heard about it, but not knowledgable	Some yes.
5	Italy	Maintenance Engineer	Packaging	Yes	not yet in full
6	USA	Maintenance Specialist	Engineering	yes	yes
7	Italy	Digital Solutions Consultant	Food & Beverage	Yes	Yes

8	Cape Town	Industrial Engineer	Asset Management Information systems	Yes	Yes
9	Brazil	Automation Engineer/ Global Maintenance Expert	Food and Package	Yes	Yes
10	Modena - Italy	MRE	Food Industry	Few	Starting to apply these technologies
11	Italy	Reliability Engineer	Manufacturing	IoT, AI, ML	Yes
12	Midrand	Engineer	Professional Services (Consulting)	yes	Yes
13	Gauteng	Business Systems Manager	Manufacturing	Yes	Yes - very limited

Respondent	**Please elaborate on what technologies**	**After reading the information sheet, do you think these technologies can be adopted in future within your organization?**	**How/Why not?**	**What benefits do you wish to see from these technologies, if they are implemented within your organization?**
1	Currently in the process of enabling IoT & Condition Monitoring	Yes	Can be used for sensors on all of our machines	Will help us gather historical data and predict failures for machines
2	Industry does have this leave of technology advancement	Yes	Research, together with Trial and Error processes.	"To better improve productivity and efficiency. Which in turn leads to increased

3	profitability and improved customer performance."			If cutting-edge technologies are applied in methodical, planned ways to raise the caliber of education, I can then say that A.I Technology is the way forward. The use of technology speaks to the minds of the young who's cognitive abilities and learning are enhanced in fundamental ways.
4	With the Pandemic, many organisations, mine included, have gone online. My organisation has a workshop where power machines are used as well as tool making equipment. Different courses require different machinery. These machines correlate with Artificial Intelligence, whereby computer programs are used to complete tasks.	Yes	"In order to give pupils a more engaging experience, AI will play an increasingly important role. Students will be able to further tailor their educational experience, making it faster and simpler to locate the appropriate resources at the appropriate time.	The goal would be Improved Productivity and Improved Efficiency. Everyone wants to do the same kind of work with fewer expenses (people), and be more accurate (than people can be).
5	AI will be able to pinpoint the subjects and skills that students struggle with the most, as well as the best way to help them perform better."	If cutting-edge technologies are applied in methodical, planned ways to raise the caliber of education, I can then say that A.I Technology is		productivity increases and possibility to do different activity to give better services

		the way forward. The use of technology speaks to the minds of the young who's cognitive abilities and learning are enhanced in fundamental ways.		
6	We have a Condition Monitoring leg in the business. We are focusing on digital elements of management within our software development. We aspire to AI and Machine Learning, but I am not sure that we are are actively using it.	Yes	We offer Asset Management as a core service. Condition Monitoring, AI and Machine learning will have to be a core part of the development of our software offerings if want to remain market leaders. Things like providing Digital Twins for the machines we maintain, and actively being able to predict when machines will fail based on machine behaviour will have to be a core part of our business.	better maintenace services - doing the right work at the right time
7	We are stunding how to implement on our applications	Yes	AI can be introduced to do basic data collection	Better awareness, control and efficiency of our production environment.

8	our company is using predictive maintenance on some equipment and is expanding in this field	Yes	predictive maintenance is a growing field - we are striving to implement this technology and take the next steps towards AI	Improved asset utilization for clients - cost of maintenance reduction, risk reduction
9	We do extensive use of Big data, AI, IoT, Condition Monitoring, Advanced Robotics, RFIDs and cybersecurity solutions. We also explored VR applications.	Yes	We already implemented most of them.	Better awareness, control and efficiency of our production environment.
10	We have services focused on condition monitoring wit IoT and are exploring ML/AI	Yes	Try and build our software to ensure easy access to data and to allow ML/AI algorithms to send request to the system as part of predictive/proactive maintenance	The new technologies will help the organization to follow the actual industrial development and consequently will help also our Customers to be more efficient by using the new capacities that the new technologies will offer.
11	We do use some algorythms for data analysis using Machine Learning. Also the connectivity in place on the machines make possible the use of	Yes	The organization has a clear view of inovation and be part of the 4th revolution so our future projects will have even more embarqued electronics and automation to enable it.	Optimization of cost, processes and performance. Better decision making process driven by data and pattern which would be otherwise difficult to see

	data like Condition Monitoring, Key Measuring Points.			
12	The organization is starting to apply Industry 4.0 in some areas of the business as in maintenance. Few projects are actually on going. one of them is related to change the mentality of the employees to be more open about Industry 4.0	Yes	By changing the culture of the employees by helping them to have a bigger vision and information about Industry 4.0	If successful, will provide efficiency gains and risk reduction.
13	These technologies are used in combination with domain knowledge to capture opportunities related to optimization of	Yes	is essential to keep investing. It is a revolution which has just begun. We are dealing with new technologies that are opening up a world of opportunities and the more this will	"More Reliable Machines Optimize through put Predictability"

	processes and performance		spread the more benefits it will create as well as increased development pace	

Respondent	Do you have a system that currently stores information for your machines/assets?	Do your current machines/ assets communicate with one another to ensure an efficient process flow?	Can an employee view information from machines/sensors in your organization to ensure seamless flows and prevent breakdowns?	Do you use data obtained from various machines and sensors to analyze your manufacturing /system processes?	Please elaborate
1	Yes	No	Yes	No	We do not have the technology yet
2	Yes	No	No	No	"Due to number of machines and no advanced technology to automatically
3	Yes	No			There are systems in place at my orgnisation, however, better operating systems need to be allocated for better results. Condition monitoring, Artificial Intelligence and Machine Learning need to be implemented to enhance performance, better stable machinery and equipment, and generate accurate results.

4	Yes	No	No	No	The client that we service (I can not name the client due to IP restrictive policies) utilises condition monitoring to monitor some aspects of their packaging and processing equipment. Machines are actually being designed with these sensors and capabilities. Today, the majority of the machines make use of installed Kits. There is good integration between the systems capturing the data, and processing it, but the knowledge transfer has not evolved to an Industry 4.0 level, in my opinion.
5	Yes	No	Yes	Yes	This part is not yet implemented
6	Yes	Yes	Yes	No	we have many systems and processes that are linked and the information gathered is used to improve our designs

7	Yes	Yes	Yes	Yes	Our machines constantly log data that we use to continuously improve our production processes.
8	Yes	Yes	Yes	Yes	We have created a service that combines all the mentioned points to assist clients with generator uptime and readiness
9	Yes	Yes	Yes	Yes	All data is there but few individuals have access to this data; some models are being updated for better failure analysis.
10	Yes	No	Yes	Yes	Actually our installed base is not using fully the condition monitoring. Some assets have in some part of the equipment this functionality but the organization has admitted that for the new machines generation the data analyse should be based on assets communication, machine sensors information to ensure reliable data to prevent breakdowns and help to manufacturing system process.
11	Yes	Yes	No	No	Data from assets are collected and analysed to address specific points
12	Yes	No	Yes	Yes	We have isolated systems, but are starting to introduce asset health monitoring

					services for the market. Early stages.
13	Yes	No	No	No	Our machines are very old and does not have integrated data points and information flow.

Respondent	**Do you use any predictive analysis/forecasts to predict machine breakdowns or production/ supply chain in your organization?**	**What challenges do/will you encounter when implementing these industry 4.0 technologies? E.g Costs, data security, etc.**	**Please elaborate**	**On a scale of 1-10, please rate your current knowledge on "Industry 4.0" technologies**
1	No	AI technology is a factor. We have CM enable mental but no machine learning methods	-	10
2	No	Costs will be a major factor	"As the first cost implemented would be research.	6
3	No	"> Allocation of funding	The next cost factor would be trial and error."	6
4	No	> Security risks"	"My organisation is government funded, and being allocated resources has proven to be difficult.	3

5	No	I would say cost.	Along with most areas in the country, security in all aspects is a major concern in many sectors of trade and industry. "	6
6	Yes	fear of failing and not being effective and not reliable in short time	I am not an expert, but it seems that the cost vs benefit calculation is still tough for these kinds of implementation as people do not really understand it yet. You need experts to be able to utilize and build on these technologies, and for that, the general population needs to be trained, adding more costs of implementation.	7
7	Yes	start up costs, data security, people, customer acceptance	Time to increase reliability on data analysis and possible extra cost is one of the road blocker to speed up the implementation	9
8	No	Data quality and system scalability	initial costs for development can be high, knowledgeable people to review analyze the information, correct processes after evaluation to implement the changes, customers that prefer "the old way of doing things"	6
9	Yes	The technology is still maturing so finding the correct partner for your	"In an industrial context it is hard to keep all the sensors and the raw data sources in good conditions,	8

		needs is difficult as there are many players, but creating internal capacity and capability is still difficult and costly	and more in general we often run in dirty data issues.	
10	Yes	Costs, data security among our customers, connectivity (customers in remote regions with little infrastructure).	It is also hard to scale and expand systems once a big investment is done to implement them."	4
11	Yes	The biggest challenge when implementing industry 4.0 technologies is the costs.	Data security I think is ok, with the whole world focusing on it I think the real challenge lies in effective data utilization and data Engineering elements to ensure your algorithms are fed good data	7
12	No	Data security and time for development are key to be addressed	Costs, data security among our customers, connectivity (customers in remote regions with little infrastructure).	7
13	No	We have design challenges and issues with developing the business case	The implementation of Industry 4.0 technologies in new equipment generation has to be very well studied because it's not possible to apply all the new technologies available without affecting	6

			production and equipment costs. it is useless to have equipment capable of giving information about its current health if you cannot sell it because it's very expensive. A balance between technologies and costs should be applied to get a reliable asset.	

Respondent	**On a scale of 1-10, please rate how likely you are to implement "Industry 4.0" technologies in the future**	**Any additional comments?**
1	10	
2	7	
3	10	"This was an excellent task.
4	9	AI makes it possible for intelligent automation and optimisation to improve human performance. Today, systems can be created that carry out tasks well beyond the capabilities of the average person. This study will definitely aid how we operate and effectively change the world.
5	5	Great work
6	9	
7	9	
8	8	
9	10	
10	8	Good Luck
11	9	
12	10	
13	5	