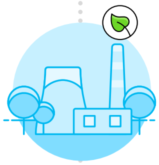
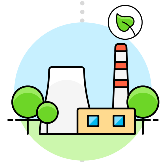


Digital Twin technology for better sustainable insights in manufacturing



Masterpiece for Modular Executive MBA Business & IT

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Foreword

After struggling in C-level meetings about certain topics during my career, I determined that the time was ripe for starting an MBA modular course to gain not only more background theory but also practical knowledge from fellow students. Five years ago, I started my modular MBA-BIT at Nyenrode Business University with the Business Process and Technology course. The core teacher for that module was Prof. dr. ir. Marijn Janssen. I enjoyed this module and learned so much from it and consequently decided to pursue my full MBA in Business & IT. This thesis represents a full-circle moment because Prof. dr. ir. Marijn Janssen was my intensive expert during this thesis period.

Through this thesis, I intend to help people to understand what digital twin technology is and how it can be used in manufacturing for more sustainable factories. In this thesis, the research methodology involved both the interview method and a quasi-experiment with the technical building of a digital twin application for a production line in a factory. With my technical background, an entire end-to-end solution was built with data from a factory production line with digital twin technology. This process also entailed a vast amount of time during the thesis writing period. Aside from conducting interviews, I needed to technically establish the solution and test it with the interviewees. The whole process was an intensive but rewarding.

In my current job, I work with customers who have an interest not only in the digital twin topic but also in the sustainability concept in different industries. This thesis has helped me to underline my knowledge about digital twins for various industries, especially manufacturing. I believe that the outcome of this thesis will be useful for my employer and customers, which can be the potential start of more sustainable digital twin implementations in manufacturing. The conclusion will also assist the market in having an effective start with the implementation of digital twin technology to monitor sustainability in every asset-driven industry.

I would like to thank several people who made my MBA journey possible. I am grateful to my first employer Winvision, where my journey began with the first module. I also want to express my gratitude to my family; I spent so many hours working in my study room for the modules, and this thesis was not always easy for them. Furthermore, I am thankful to my professors during the thesis writing process, especially Marijn and Ronald who offered valuable feedback on this thesis and guided me to achieve a successful result of this thesis.

Remco Ploeg
Zeist, 6 November 2022

Management summary

Sustainability is an important topic in the world, especially for the manufacturing sector. The manufacturing sector has one of the largest emissions outputs compared to other sectors, and emissions need to be rapidly reduced to save the Earth. The manufacturing sector also uses an enormous amount of gas to produce products. The current high gas prices due to the war between Russia and Ukraine have compelled factories to save gas and energy to lower operational costs and eventually reduce emissions.

Digital twin technology has been used since the 1970s, but it is not yet commonly utilized in the manufacturing sector, especially not in combination with sustainability. In this research, digital twin technology obtained different definitions from interviewees. Nonetheless, a digital twin is typically described as a virtual replica of one or more physical assets. In this virtual replica, data will move between the virtual and the physical asset(s) to have a copy of reality. This asset can be a single one, such as a (packaging) machine, or a whole set of assets, such as a (food) production line in a factory. Based on data from physical machines, data from ERP systems, or changes in processes, the digital twin will react and can even send back commands to the physical machines to, for example, accelerate the process. Most of the digital solutions in manufacturing are focused on one asset, the so-called point solutions, and those solutions are not working together to combine all the data in a digital twin for the factory. With one digital twin viewpoint, a factory can obtain an overview of the status of its operations and swiftly act on problems, conduct simulations to optimize the production process, or predict the particular machines that will fail with predictive maintenance applications. Despite the promises, there is a void in research regarding how factories can use digital twin technology to monitor sustainability insights and reduce emissions in their production lines and how to make this technology usable to factory employees.

The design science method was adopted in this research because the focus was on answering how questions by creating an artefact of a digital twin. It entailed developing a digital twin (the designed artifact) and testing three propositions through a quasi-experiment with several factories via experiment interviews (refer to Section 3.1). The following three propositions are derived from the void in the literature and were tested using a semi-experiment using the design artefact:

- Digital twins used for real-time control in manufacturing will reduce energy consumption.
- Including an extra "E" for energy in Overall Equipment Effectiveness (OEE) in a digital twin will generate sustainability insights.
- The 3D visualization of a sustainable digital twin contributes to the improved use of the technology.

The digital twin in this experiment was technically built by the researcher with sample machine data to test the above three propositions. The entire quasi-experiment was open sourced, thereby enabling other researchers to use the same technology to replicate the research results.

The manufacturing sector mainly uses the OEE framework for measuring the performance of its factories. This framework includes three measurements (i.e., availability, performance, and quality) that are connected to the products created in the production process. A sustainability measurement has yet to have a place in this framework. Jozef Glova proposed to extend the OEE framework with an extra "E" for energy in his research, however, this new measurement of the framework has not been tested in factories with digital twin technology.

In the quasi-experiment, the propositions were tested using the extended OEEE method for using the digital twin in a manufacturing setting. Every experiment interviewee who was involved in the quasi-experiment, recognized the clear advantage of using this new measurement (refer to Section 3.3). According to all of the interviewees the OEEE method was a valuable extension of the widely used OEE framework, and it provided direct insights into the expected and real energy usage per machine and of the entire production line. With these insights, the interviewees concluded that they would be able to steer their production better on data coming from several machines from the production line into one virtual replica of the production line in the digital twin and all based on sustainability data.

An addition to the digital twin dashboard that the interviewees welcomed was the forecasting of the energy consumption of the production line. By forecasting the energy usage, the factory can buy upfront cheaper energy to optimize its process another time with less emissions with the use of greener energy.

One of the major challenges of implementing digital twin technology is the "face" (i.e., How does one successfully show the digital twin to users who work with it?). Furthermore, all the interviews revealed the difficulty of explaining what a digital twin is to the interviewees and how to acquire value from it. In the quasi-experiment, a "face" of the digital twin was created, a 3D dashboard of the digital twin of a production line (refer to Section 3.3). With this view, the factory employee obtained an interactive overview of the production line and could directly steer on a problem in the whole production line, where the worker normally would need to go to the individual machine to check the status.

One of the key challenges in the quasi-experiment was data integration between the physical machines and digital twin technology. Challenges with data integration was also mentioned in the different interviews with vendors. In the manufacturing sector, a data standard for exchanging data between physical assets and the digital twin is currently unavailable. Highly expensive implementations of digital twin projects in the market consequently occur. Furthermore, this part of integration does not directly provide a business value, but it is a prerequisite for starting with a digital twin application in the factory. Several initiatives such as the digital twin Consortium strive to develop a general data model for the manufacturing sector. These efforts are undertaken together with vendors of digital twin applications and machine builders, which will hopefully result in one data standard, thus allowing factories to directly focus on adding business value within the digital twin, such as simulating their production line to optimize the emission output of their factories.

Digital twin technology helps in obtaining insights into emissions outputs on every level in the factory. Combining several sources of data (i.e., not only machine data but also ERP data) provides the factory with a true emission story which information cannot be tampered by humans, hence facilitating the reporting to the government. Aside from providing an understanding of emissions, these insights can represent the start of other digital twin applications in factories to help to save our planet.

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List of abbreviations

AI	Artificial Intelligence
CO2	Carbon Dioxide
CPS	Cyber-Physical Systems
DCS	Distributed Control System
DOI	Diffusion of Innovation
DT	Digital Twin
DTDL	Digital Twin Definition Language
ICT	Information and Communication Technology
IoT	Internet of Things
IIoT	Industrial Internet of Things
IS	Information Systems
MES	Manufacturing Execution Systems
ML	Machine Learning
SCADA	Supervisory Control and Data Acquisition
TOE	Technology, Organization and Environmental

Introduction

The manufacturing sector must transform in the short term to a more sustainable sector to achieve, together with other sectors and consumers, certain climate goals in the coming years. Especially lowering the CO2 emissions. Paul Polman, former CEO of Unilever, says that sustainability can drive more innovation: "Looking at the world through a sustainability lens not only helps us 'future proof' our supply chain, it also fuels innovation and drives brand growth" (Quality Gurus, n.d.).

Most factories lack innovation and expertise due to tight labor market, and they use old manufacturing systems. However, there is a large opportunity for innovative technology in this sector to support the climate goals. This chapter describes the context of this research in relation with the opportunity to use more innovative technology in manufacturing. Based on that, a management problem is described and combined with the research question.

1.1 Context of this research

Often called industrial production, manufacturing companies are producing on a large-scale using machinery. The scale of production continues to increase because of the significant demand in the new online economy and due to the COVID-19 pandemic (UNCTAD, 2021). Furthermore, these companies must build even more factories that are closer to their customers. However, those factories have been perceived negatively in the news in recent years—for example, Tata Steel in the Netherlands, which expels around seven percent of the country's CO2 emissions (Baardewijk, 2021)—and inhabitants of those countries have protested these unsustainable factories. So, there has been considerable pressure from countries, but also the EU, to rapidly decrease the emissions of the current manufacturing sector with the new EU industry strategy (European Commission, 2020).

To make the factories more efficient and greener, large investments are needed in new technology. However, it remains uncertain whether those investments will succeed in decreasing the factories' emissions, which causes confusion as to where to invest money as a manufacturer. In the past ten years, the sector has invested in the overall equipment effectiveness (OEE) framework, which is an industry-wide framework measuring the performance, quality and efficiency of a factory.

However, this framework does not consider sustainability elements, as it is completely focused on the efficiency of manufacturing products (de Ron & Rooda, 2006). As a result, factories have challenges to have sufficiently detailed insight regarding matters of sustainability. There is, of course, also demand for the sector to be greener and part of a more sustainable world.

1.2 Challenges in the research context

This section describes the business challenges surrounding the selected research context. Manufacturers must change their current factories to be more sustainable and efficient, but they do not have any detailed emission information about their production lines (see Chapter 4.1). Implementing these technologies near the production line poses challenges to acceptance and use by blue-collar workers. The challenges are labeled based on the TOE framework: technology, organization, and environment (Baker, 2012). This framework was chosen because it is specifically tested for the manufacturing sector (Gillani et al., 2020).

1.2.1 Technology

Technology is important within factories, but the required investments in technology are high and difficult to implement. With innovative technology factories can create new business models or be more sustainable with producing their products, but why are factories not doing that? Here follows a list of business challenges that manufacturing have with technology in their factories.

Testing is expensive

Making existing factories more sustainable is very expensive for manufacturers and does not always decrease operational costs (Mao & Wang, 2019). In the past years, a great deal of new technology has become available for factories to make themselves more efficient in the market. The challenge with that new technology is that the people in charge of the existing factories do not always know in advance whether it will help them make current machinery and production line setups more efficient or greener. Thus, gaining sustainability insight before investing in new technology for factories could help the manufacturing sector become more sustainable.

Implementation in factories is difficult

If factories implement new technology, then its implementation, operation, and acceptance is very difficult (Gillani et al., 2020). When implementing that new technology, the data infrastructure in factories can be a significant challenge. In addition, factory investments last decades and do not change much during that time, and older factories have very old information and communications technology (ICT) infrastructure that is incompatible with new upcoming technology. If factories are to apply and take advantage of new technology, such as artificial intelligence (AI) or digital twins (DTs), up-to-date data infrastructure is necessary. Furthermore, the lack of trust in and unknown advantages of new technology pose challenges to implementation (Gillani, Chatha, Sadiq Jajja, & Farooq, 2020). The blue-collar workers at the production line are normally low-skilled employees, which can present further challenges to implementing high-end technology.

Internet of Things is only a part of the solution

In the past years, the Internet of Things (IoT) has received a great deal of attention within manufacturing. There is even a specific term in manufacturing for the IoT: industrial Internet of Things (IIoT) (Boyes et al., 2018). In particular, machine builders are equipping their machines with IIoT sensors to collect data, but only for their own analyses. An example is predictive maintenance of a machine; normally, the machine builder would come to the factory every several months, but now, they can perform maintenance based on the sensor data from the machine. The challenge with this is that the factory does not always receive this machine data and, thus, completely relies on the machine builder. This causes challenges if the production line has several brands of machines with different sensor streams because it is almost impossible for the factory to get an overview of what is happening and how to be more efficient throughout the whole production line when there are different machine builders involved.

Digital twins as manufacturing technology

In the past years, the debate on digital twins as a new technological solution that could improve efficiency, quantity, and quality in production has intensified within the manufacturing sector (Kamble et al., 2022). The digital twin is receiving more attention to pave the road for better integration between the digital and physical worlds of a factory. Furthermore, it could present possibilities of having insight into the digital world before rolling out in the physical world. There are many definitions of what a digital twin can look like for factories, but it remains unclear how it can help with sustainability for the manufacturing sector and what kind of applications could be useful in and around the factories.

With the rise of Industry 4.0 (Liao et al., 2017), digital twin technology should help introduce more intelligent manufacturing technology, rapid design changes, and more flexible workforce training (Qi & Tao, 2018). The digital twin of a factory can go further than the factory itself. Since the factory is just a part of the supply chain of a product, a digital twin could improve the understanding of the sustainability of that supply chain (Kamble et al., 2022). This research will only focus on the sustainability goals of a digital twin of a production line in a factory and not the whole supply chain.

1.2.2 Organization

When a factory has new technology, it can be a challenge to embed that technology in the factory's organization. This section lists the challenges that a factory faces while implementing technology to its organization.

Overall Equipment Effectiveness for optimized factories has no sustainability focus

OEE is the leading framework used in the manufacturing sector to measure the status of a factory (de Ron & Rooda, 2006). This framework has a focus on performance, availability, and quality of delivering products in factories. The OEE framework does not have yet any focus on the sustainability goals of a factory, but the characteristics of the framework could help with that. For factories using the OEE framework, the outcome of the framework is based on one-day-old data; there is almost no use of real-time data, which makes it difficult for the OEE framework to make factories more sustainable. An example can be to shut down a certain machine in the process if that machine is not used for a certain time. That could result in less energy usage and, thus, less emissions.

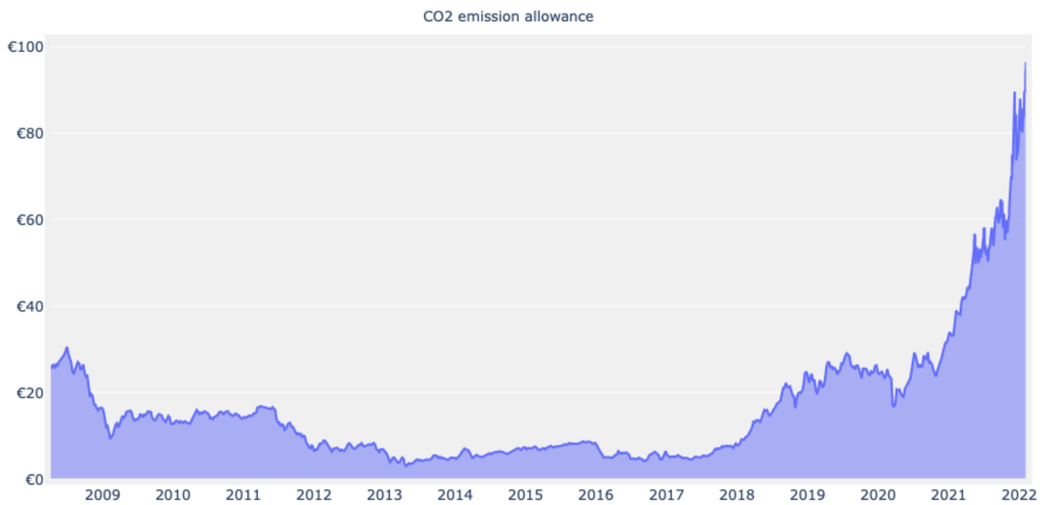
Data is scattered in the factory

Dedicated solutions to specific problems are what factories have invested in over the last years (Davies et al., 2006). They have bought technological solutions over the years with no clear vision on the factory or production line levels, which has resulted in the silos of technology and interoperability solutions not working together (Babu et al., 2021). This strategy makes it difficult for the factory to gain insight into each machine or a specific step in the factory process because the proper data is not collected. If the data from the machines in the production lines can be collected, maybe that could provide factories with sufficiently detailed sustainable insights.

1.2.3 Environment

Factories must pay an allowance for their CO2 emissions per tonnage (EU, 2021). The price for that allowance has risen quickly over the past four years. Figure 1 illustrates this rise and the fact that it has more than doubled in the past two years. Of course, the factories are translating this higher price of emission allowance directly to their customers. However, factories that can lower their CO2 emissions achieve not only improved sustainability, but also lower prices for their products.

Figure 1: CO2 emission allowance per ton (ICE, 2022)



In addition, people living near factories that are responsible for high emissions are typically not happy about having those factories so close. One good example is Tata Steel in the Netherlands, where many residents have protested against the factory (Baardewijk, 2021). That is one of the reasons that manufacturers want to have greener and efficient machines in their production lines with less emissions. The challenge is identifying the machines or production lines that have a substantial impact on emission goals. Technology can potentially help to have insights or even reduce these (CO2) emissions in the production line.

In the last year, the higher—and increasingly uncertain—energy costs have motivated factories to be more energy efficient (ICE, 2022). This increasing gas pricing had also to do with the war between Russia and Ukraine that has affected that producing product prices were higher than before (Reynolds, 2022). If companies can produce their products with less energy due to technology, the emissions, but also the price of those products, will be lower for consumers.

1.3 Central research question

The previous section described the context and business problems facing factories regarding insight into their sustainability. Based on these challenges and upcoming technology, this research examines how digital twin technology can be used in factories to support the sustainability goals, especially regarding emissions monitoring. This is accomplished by asking the following research question:

How can digital twin technology be used in factories to improve sustainability insights?

Based on the research question and business challenges three sub-questions were identified within the theoretical literature and were investigated in the upcoming chapters. Together with the research question, a quasi-experiment was adopted (Cook, 2015). In section 3.3 the quasi-experiment is described. This experiment has tested three propositions described in Section 3.1. These sub-questions are listed in Table 1 and are related to the propositions number that are tested in this research (refer to Section 3.1).

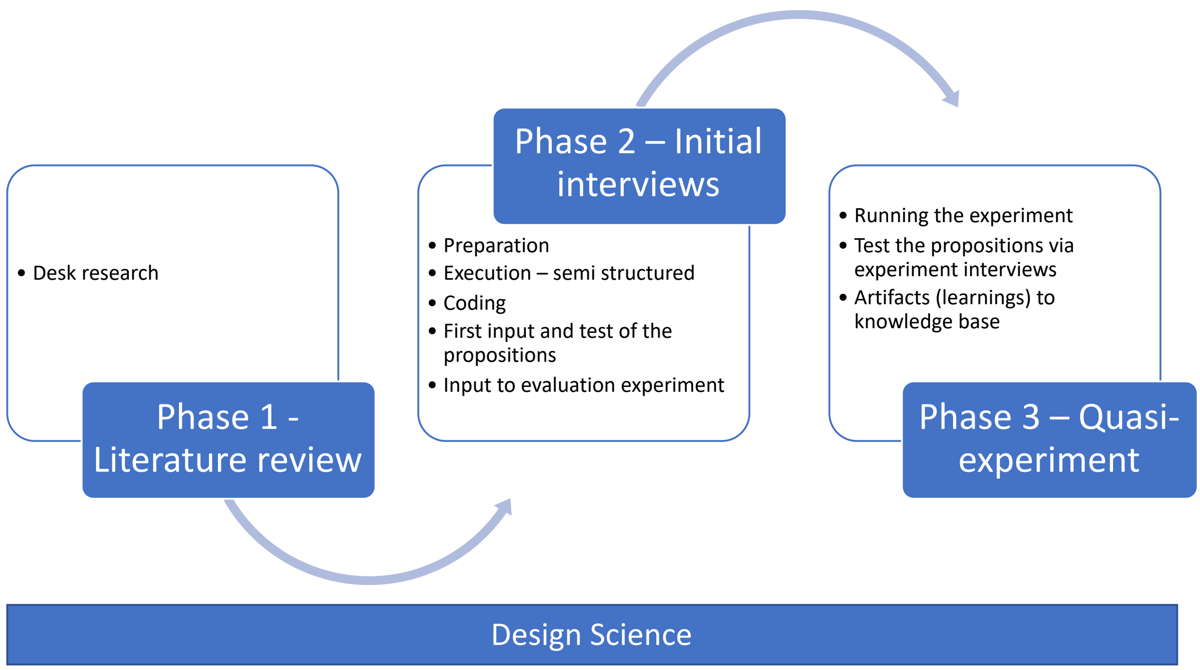
Table 1: Sub-questions in research question

Sub-question	Answered in	Tested in proposition number
What is the definition of a digital twin in manufacturing, and what are its characteristics?	This will be answered in the literature review in Chapter 2 and with the interviews in Chapter 4.1.	none
What are the frameworks to achieve sustainability insights and benefits from digital twin technology in manufacturing?	This will be answered in the literature review, tested in the interviews and quasi-experiment in Chapter 4.2	1 and 2
What elements are needed for a successful implementation of digital twin technology in manufacturing that result in higher sustainability?	This will be tested in the interviews in Chapter 4.1 and quasi-experiment in Chapter 4.2.	2 and 3

1.4 Research approach and methods

This research is experimental, hence empirical, based on theories that underline the relationship between digital twin technology, factories, and sustainability. The experimental testing approach makes the study also very practical and useful for factories. The research is based on the design science framework (Hevner et al., 2004). Based on the literature review in Chapter 2, propositions were created (refer to Section 3.1). These propositions were first partly questioned via initial interviews as input for the quasi-experiment. After the initial interviews a quasi-experiment was executed together with experiment interviews with the factory employees of the initial interviews. In a quasi-experiment the controlled group is chosen by the researcher. The digital twin technology is part of the information systems (IS) department of manufacturing companies, for which the design science framework is specifically designed. This framework structures experiments scientifically and presents the results from the experiment in a scientific knowledge base for sharing results. Figure 2 presents the three phases of the design science set up of this research.

Figure 2: Phases of research (Remco Ploeg, 2022)



1.4.1 Phase 1: Literature review

This research starts with desk research of the academic literature regarding the topics that are based on the research question. Apart from the academic literature, this study also examines reports from well-recognized business reviewers and vendors of digital twin technology in manufacturing. All the literature is coded in the software tool Maxqda so it can be analyzed for the interviews (*Maxqda*, 2022). More information about Maxqda can be found in Appendix C.

1.4.2 Phase 2: Initial interviews

The second phase of this research is the preparation and execution of initial interviews in the field. These initial interviews gathered information from different factories around Europe about if and how they work with digital twin technologies in combination with sustainability. Then, the challenges around sustainability and digital twins in the factory are discussed as an extra input for the propositions in the quasi-experiment. The plant- and innovation managers were interviewed because they are responsible for whole operations or innovations in the factory. Furthermore, domain experts of digital twin technologies in manufacturing were interviewed. The experts were needed because they have done implementations of digital twin in the manufacturing world. The experts were not sales focused and were experts in this topic. Based on the literature in the first phase of this research, the interview questions were prepared based on the code system of the literature in the data analysis tool Maxqda (see Appendix E). The interviewees received in advance an interview package to prepare themselves, thereby allowing for more efficient interviews (see Appendix A).

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1.4.3 Phase 3: Evaluation using a quasi-experiment

A quasi-experiment was chosen to test the propositions about the sustainability insights with the use of digital twins in a production line of a factory (refer to Section 3.4). The quasi-experiment was chosen, above a fully controlled experiment, because of the selected control group that was based on the initial interviews (Kampenes et al., 2009). Also, a fully controlled experiment was not possible due to an unfeasible timeline and resources that was available for this research. Because the quasi-experiment used simulated data from a production line, the implementation of the virtual replica of the production line with the digital twin technology was recorded (Ploeg, 2022c). This provided information to the knowledge base of the design science method (Hevner et al., 2004). The researcher created a digital twin solution of a food packaging production line to test the propositions (see Appendix F). This prototype was presented to the experiment interviewees online to receive feedback about the usefulness of digital twin technology with sustainability functions. The output and lessons of this experiment combined with the interviews flow back to the knowledge base of the design science method, but they are also used in the conclusion and recommendations of this research (see Chapter 6).

1.5 Literature review

There are research papers mentioning sustainability and digital twin technology in manufacturing, but most of them have never tested this new technology in the manufacturing sector. Therefore, business reports with a high reputation and specific EU reports are also used. Furthermore, information from respected experts on digital twin technology in the market is used because of their experience with implementing the technology in manufacturing. In the digital twin market, software suppliers and consortiums also have important information about possible use cases in the manufacturing market from a sustainability perspective.

In Table 2 the (non)-academic sources are listed that are used combined with the keywords to examine the literature in the different database sources.

Table 2: (non)-academic sources used for literature review

Description	Keywords (AND and OR search)	Database sources
Academic sources on digital twin technology and sustainability in manufacturing	digital twin, sustainability, manufacturing, use cases, virtual replica, twin model, and frameworks	EBSCO (EBSCO Information Services Service, 2022) Bielefeld Academic Search Engine, BASE (Bielefeld Academic Search Engine, 2022) ResearchGate (Researchgate, 2022)
Academic sources on the implementation of new technology in manufacturing	manufacturing, technology, digital twin, challenges, implementation, and frameworks	EBSCO (EBSCO Information Services Service, 2022) Bielefeld Academic Search Engine, BASE (Bielefeld Academic Search Engine, n.d.) ResearchGate (Researchgate, 2022)
Academic sources on a technology perspective in manufacturing	technology, vision, and manufacturing	EBSCO (EBSCO Information Services Service, 2022) Bielefeld Academic Search Engine, BASE (Bielefeld Academic Search Engine, n.d.) ResearchGate (Researchgate, 2022)
Non-academic reports from the EU about sustainability goals and EU-funded programs in manufacturing	sustainability goals, programs, manufacturing, implementation, and vision	Eurostat (*Eurostat*, 2022)
Non-academic reports from the digital twin consortium around manufacturing use cases	digital twin, manufacturing, digital twin model, vision, and standards	Digital twin Consortium (Digital Twin Consortium, 2019)

Within the Maqxda tool, all of the 36 journals were coded during the review process, resulting in a top-50 word code cloud that is displayed in Figure 3. These codes were valuable input for the interview questions that were held about the research question in Section 3.2. The full code analyses can be seen in Appendix E: Coding analyses literature.

Figure 3: Word cloud based on literature research from Maxqda (Author, 2022)

1.6 Scientific and business relevance

The scientific relevance of this research is that it combines the isolated theories about using digital twin technology to achieve better sustainability in manufacturing with a quasi-experiment with factory workers to test the usage of a potential sustainable digital twin. The artifacts flow back into the knowledge base of the design science framework as lessons for other researchers (Hevner et al., 2004).

The business relevance of this research is a result of its investigation of how digital twin technology can help to have insights in a more sustainable factory and if it can be embedded within the existing performance systems that manufacturing is using—namely, the OEE framework (de Ron & Rooda, 2006). Within this research also a quasi-experiment has been conducted featuring building a digital twin solution that gives insight into how factories are looking at real-time sustainability dashboards in production lines (refer to Section 3.3).

1.7 Structure of this thesis

Chapter 2 discusses the literature review in terms of the topics included in the research questions. Then, Chapter 3 presents the research model, method, experiment, and validations. After that, Chapter 4 presents the results and analysis of the research, as well as the output of the experiment. Chapter 5 provides a discussion about the results related to the literature review leading up to the conclusions. Finally, Chapter 6 presents the answer to the research question and sub questions, including further recommendations and limitations of this research.

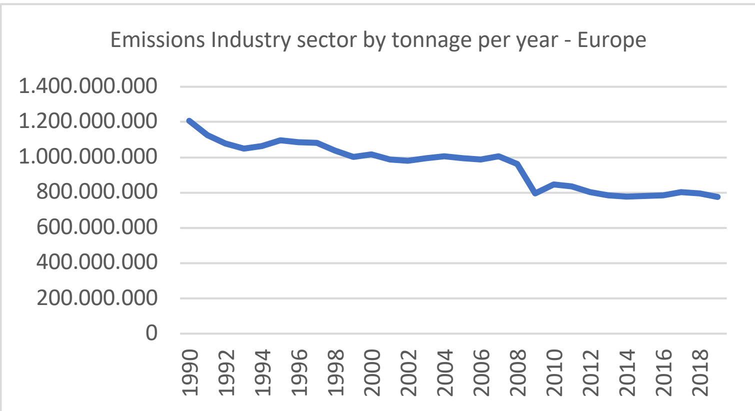
2. Literature review

This chapter starts with definitions of sustainability in manufacturing and digital twins, including their advantages and disadvantages in the manufacturing sector. This will allow for a better understanding of what theories are already used within the manufacturing sector and how that potential can be combined from sustainability and technology angles. After the definitions, the implementation of new technology in the manufacturing sector is investigated. The last paragraphs are about performance measurement frameworks that are common in manufacturing. This will improve the understanding of how sustainability and reducing factory emissions can contribute to the existing performance frameworks in manufacturing.

2.1 Introduction of sustainability in manufacturing

The Dutch manufacturing sector is expanding year after year, so failing to invest in solutions to solve this energy usage problem will impact the environment even more in the future (CBS, 2021). The manufacturing sector is lowering emissions by using more sustainable energy sources, such as wind and the solar energy. This method is lowering the CO2 emissions for the sector, resulting in a 35.78% decrease in Europe's emissions since 1990 (ICE, 2022). Figure 4 displays this downward trend.

Figure 4: Emissions of the manufacturing sector in Europe (ICE, 2022)



In the last years, there is no rapid decline anymore of the CO2 emissions per tonnage like in the nineties. This has been due to increases in the number of factories within Europe and growth of the demand for higher quantities of new products in the new online economy. According to the UN, the global population will keep growing to 10 billion by 2050, coming from 6.5 billion (UN, 2021). So, there will be a need for even more products and services in the consumer market that will result in even more emissions from the factories if they don't are able to lower their emissions more.

However, it is not only the environmental dimensions of sustainability that have an impact on manufacturing. According the Manufuture 2030 research that has been supported by the EU, manufacturing sector employees represent 22.1% of the total European workforce (Manufuture High-Level Group, 2018), meaning that the sector has substantial economic and social relevance throughout the EU.

2.2 Introduction to digital twin technology in manufacturing

The digital twin concept was first introduced by National Aeronautics and Space Administration (NASA) when it launched Apollo 13 in 1970 (Warke et al., 2021). NASA created two space vehicles: one that would fly to the moon and back, and the other that would stay on Earth and was called the twin. This twin was used by the engineers of NASA to simulate and monitor the condition of its counterpart in space. This helped NASA engineers test responses to emergencies that ended up happening during the mission, thereby saving the mission.

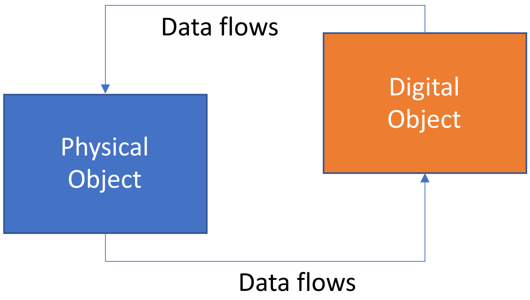
Since 1970, digital twin technology has been changed to a concept that is also used outside space programs. Between 1970 and 2000, the most digital twins were used as information monitoring models focused on research and development. Since 2000, the concept has become more accessible to more businesses, who use it for digital simulation—for example, in aerospace, the concept is used to predict the maintenance of airplanes. In 2014, the IoT became affordable for companies (Mims, 2013), and they could buy cheap devices to transfer data between physical and virtual spaces. With devices becoming increasingly available in the market, the data of those devices needed to be stored, which led to the big data environment. Since 2017, the concept has also supported decision making tools, for which technologies such as machine learning (ML) and artificial intelligence technology were used.

Garetti stated the definition of digital twin technology that is widely recognized within the manufacturing world as follows:

> The digital twin consists of a virtual representation of a production system that is able to run on different simulation disciplines that is characterized by the synchronization between the virtual and real system, thanks to sensed data and connected smart devices, mathematical models and real time data elaboration. The topical role within Industry 4.0 manufacturing systems is to exploit these features to forecast and optimize the behavior of the production system at each life cycle phase in real time. (Garetti et al., 2012, p. 361)

This digital twin definition is simplistically illustrated in Figure 5, in which data are synchronized between the physical and digital objects in real time (Qi & Tao, 2018). The data streams transpire in two ways, that is, the digital object can send for example commands or settings to the real physical object and vice versa.

Figure 5: Digital twin concept and flows (Tao et al., 2018)



The prevalence of the digital twin concept within factories is also rising due to the growth of affordable digital technologies and possible integration between machines and the Internet (Corallo et al., 2021). Factories currently use digital twins to enable the analysis of physical and digital processes, assets or products, and people (Cimino et al., 2019). For instance, digital twins create a digital copy of a real product (e.g., machine) to analyze it.

A digital twin can have different hierarchies in the factory. In particular, it can be divided into three levels (Singh et al., 2021):

- Unit level: at this level, a digital twin can be a machine, material, or other small factors within the factory.
- System level: at this level, the combination of several units can result in, for example, a production line or a shop floor in a factory.
- System of systems level: this level involves the connection of more systems, combining, for example, factories or supply chains.

The different hierarchies present challenges in the definition of digital twins in factories. Most of the use cases of digital twin applications utilize the unit level, and the system or system of systems levels are less commonly used (Cimino et al., 2019).

2.2.1 Characteristics and conceptual framework of a digital twin

A digital twin has the following three characteristics (Warke et al., 2021):

- Synchronization with physical systems or processes
- Real-time data acquisition
- Behavior prediction

Synchronization with physical systems or processes

The first characteristic of a digital twin is the synchronization of physical systems or processes. When synchronizing physical data of machines, systems, or processes, a standardized data model agreement is needed (Jacoby & Usländer, 2020) to interact between the different levels of the digital twin and its software suppliers in the factory. This data model explains the standard agreement between parties to exchange data. One of the major suppliers of digital twin software, Microsoft, has created a standardized meta model called the digital twin Definition Language (DTDL) that is commonly used in many commercial services (Microsoft, 2021). Machine builders, process builders, and digital twin software builders must align their meta models so that they can easily send messages between the physical and digital counterparts. The DTDL can help with that. Figure 6 shows an example DTDL model that could be used in manufacturing to send temperature from the real machine to the digital counterpart and then to the digital twin suppliers in a standardized manner, thus improving the implementation of digital twin software.

Figure 6: Example DTDL model (Remco Ploeg, 2022)

```
{
    "@type": ["Telemetry", "Temperature"],
    "name": "temp",
    "schema": "double",
    "unit": "degreeCelsius"
}
```

The hierarchical view in the digital twin is very important to connect the different components, such as sensors, into one product or process (Singh et al., 2021). So, the digital twin can be seen as a series of interconnected DTDL messages that together form a product. In 2019, several large corporations from the technology and industry markets came together to create the digital twin Consortium (Digital Twin Consortium, 2019). This consortium tries to bridge the gap between the market and the technology suppliers to drive the implementation, interoperability, and development of digital twin solutions. One of the tasks within workgroups is making standardized and interconnection data models for digital twins specific to manufacturing. At the time of this research, no standardized model had yet been created.

Real-time data acquisition

There are several approaches to obtaining real-time data for a digital twin. One option is to receive the data directly from, for example, a machine and send it directly to the digital counterpart—called a direct connection. This can be a challenge when completely relying on the Internet or network. When the connection does not work, the factory does not have that machine data anymore. Another challenge with the direct connection approach, especially in manufacturing, is that a factory has hundreds of machines and, thus, hundreds of direct data connections. A factory must manage and secure all of those direct connections to the digital counterparts of the machines in the factory. One way to solve this challenge is to add a so-called edge computer to the factory (Qi et al., 2021). This is a small computer, placed near the machines, that transfers and processes the data of machines or Manufacturing Execution Systems (MES) systems in the factory. The advantage of this is that the data can be processed quickly in the factory, and decisions can be made locally. It can also buffer the data when there is no connection available to the digital counterpart (Qi et al., 2021). When the real-time data is collected in the synchronized meta model, simulations can be created for the factory.

Because the digital twin is connected to the physical device, it can also control and monitor the physical device remotely. This can help the manufacturers in, for example, the COVID-19 pandemic controls their site completely remotely, even during lockdowns (Adamenko et al., 2020).

Behavior prediction

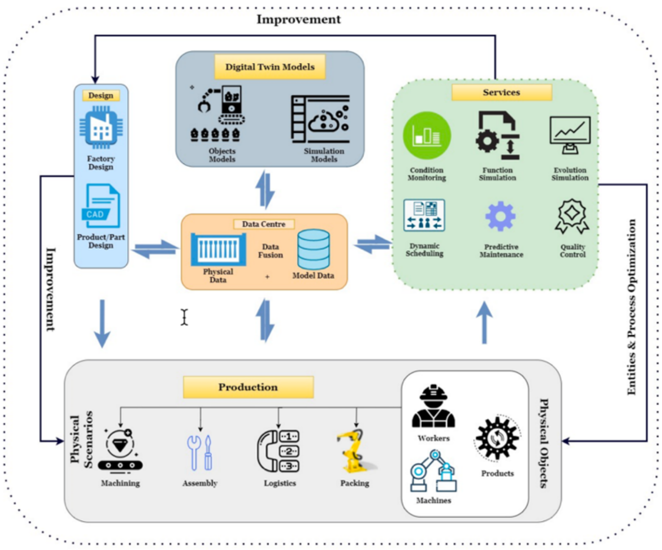
With the data stored in the digital twin, factories can predict the behavior of their machines, processes, or people. This means, for example, that factories can predict when a machine will break down or require maintenance, which can lead to more sustainable machines (Cimino et al., 2019). With behavior predication, workers on the production line can collect friendly advice from the digital twin regarding what to do as their next step in the process and what they can expect to do to make the operations more efficient.

Furthermore, the simulation functionality is embedded within behavior prediction (Corallo et al., 2021). This is an advantageous aspect of the digital twin for the manufacturing sector, as changes in factory production lines can be very expensive for manufacturers. With simulations, factories can test their changes in advance in a virtual world before making the necessary investments.

Factories can also simulate changes in certain processes to see if they can achieve more optimalization in the production line or simulate how they can save energy by changing the settings of a certain machine. Based on planning data from, for example, enterprise resource planning (ERP), the simulation can determine in the virtual world whether the machines can handle more orders before sending them to the real machines in the production line—so-called "what if" scenarios (Adamenko et al., 2020).

Based on these characteristics of a digital twin, a conceptual framework is presented in Figure 7 (Warke et al., 2021).

Figure 7: Conceptual framework of a digital twin (Warke et al., 2021)



This conceptual framework consists of the following elements, from bottom to top:

- Production: the physical machines, robots, and workers in the factory
- Design: the designs of the products or machines
- Data center: the place where the dynamic real-time data from the factory, such as machine data, is stored.
- Digital twin models: where the structure of the physical devices is stored
- Services: work that the factory can offer internally regarding maintenance, monitoring, and quality control

The model in Figure 7 also displays the interaction between the several elements. This shows how the digital twin interacts via the data center with the physical counterpart.

2.2.2 Architectural frameworks in smart manufacturing

If factories are to implement new technologies such as digital twins into their production lines and digital environment, they must apply certain architectural frameworks that are specific to manufacturing. Digital twin technology should have a place in these frameworks to be successfully implemented. There are several well-known smart manufacturing frameworks in the manufacturing industry that are used by factories. Table 3 lists the most common architectural frameworks related to the digital twin definition.

Table 3: Architectural frameworks in manufacturing.

Architecture framework	Is a digital twin part of the framework?	Digital twin unit level (refer to Section 2.2)	Commonly used
ISA-95	No	None	Yes
CPS 5C	Yes	Unit level	Yes
CPS 8C	Yes	System level	No
Digital twin Framework	Yes	System level	No

The most well-known architectural framework for smart manufacturing is the ISA-95 model, which was proposed by the International Society of Automation (ISA). The ISA-95 architecture consists of four levels, where the IT and automation systems of manufacturers are divided based on their functionality (Jiang, 2018).

Within this model, there is no direct place for the digital twin concept. ISA-95 argues that the digital twin concept could live in all of its levels and does not need any special place in the architecture (Ting, 2019). The ISA-95 model also focuses more on a vertical integration (down to up) and less on a horizontal integration of automation systems in manufacturing. It does not involve any outside facets of the value or production chain of a factory, such as customers or partners. However, a digital twin has that horizontal approach and needs information from customers and partners. Furthermore, the ISA-95 model does not have any specific requirements regarding sustainability improvements.

A newer smart manufacturing architecture is the cyber-physical system (CPS) proposed by the German government to support Industry 4.0 (Warke et al., 2021). The CPS architecture is focused on five levels (5C).

In this architecture, a digital twin model is described in level three, the cyber level. Their twin model is primarily focused on components and machines in the factory and not on the production line or higher levels. In the literature on the CPS, there is no clarification that the twin model can be used on other levels, such as the whole factory or with customers and partners. The CPS 5C architecture is like the ISA-95—vertically, instead of horizontally, focused.

Jiang proposed the CPS 8C architecture, which is based on the original CPS 5C architecture (Jiang, 2018). This architecture adds a horizontal level—that is, the customer, content, and coalition—to the model. This model adds a cross vertical integration in the architecture, one of the characteristics of a digital twin. Based on the horizontal focus of this model, the factory can respond quickly to new demand in the market and adjust their manufacturing processes just in time.

Another architectural framework specifically focused on the digital twin and based on the CPS 5C architecture is called the digital twin framework (Warke et al., 2021). The extension of the existing CPS 5C framework is the top layer, called the virtual layer. In this virtual layer, the architecture helps the decision making, optimalization, and predictions of virtual processes or tasks in manufacturing. An important addition to the architecture is the feedback loop from the virtual layer—the digital twin—to the physical layer—the real device). This provides the ability to give feedback to the real devices and machines based on the real-time data.

2.2.3 Applications of a digital twin in a factory

During the research, many applications were found for digital twins in manufacturing. In this section, the most coded applications in the researched literature in the Maxqda tool are described in alphabetical order (*Maxqda*, 2022).

A decision making application is helping the factory make better judgments based on the data in the digital twin. In this process, the digital twin receives data from the physical machines. With this data, the factory can make decisions about the flow of products based on the expected demand. Decision making can result in improved efficiency or quality of products in the factory, which could result in better sustainability scores for the factory (Holmes et al., 2021). Decision making is also used in combination with simulations. Simulations are a significant advantage of digital twins, but also one of the most difficult ones to achieve (Warke et al., 2021). With simulations, factories can test in advance if a new process or product will run efficiently in the production line, resulting in less misplaced investments.

Maintenance or predictive maintenance is an important application of the digital twin. Based on the data from machines, the digital twin can predict when a machine needs maintenance before it breaks down, thus improving the factory's OEE score (Kamble et al., 2022). Predictive maintenance can also help the factory to be more sustainable, when the right maintenance is done on a machine, the machine in the end will work longer and maybe even more efficient what can result in a lower energy usage per machine.

The application that is frequently used as a first step in digital twin implementation is the monitoring of machines (He & Bai, 2021). With the monitoring application, the factory can have direct insights into all of the data of the machines, processes, and people in the factory. In the virtual replica, all of the latest data points are stored. Based on the data in the digital twin, the factory can send an alert when a certain data point changes or is abnormal. A scenario that is commonly used within monitoring is setting an alert when a certain temperature of an engine or machine is reached. This application can also provide insight into the energy used by machines so that the factory can endeavor to use their energy more efficiently.

2.2.4 Benefits of using digital twins

Implementing a digital twin with the applications described in Section 2.2.3 can give a factory some important benefits that are not always related to sustainability. The users in factories can automate regular tasks remotely without any human intervention. This will reduce human errors and the cost of producing the product and could result in a more sustainable factory.

Digital twin implementation's advantages can be categorized into analytical, descriptive, predictive, and diagnostics values (Warke et al., 2021). The analytical value provides the ability to capture and analyze the data from the digital twin that can result in better decision making and performance. Descriptive value gives the operators the possibility of conducting off-site monitoring and control. This can help the factory be more efficient. The predictive value can help with better prediction of errors in the process with the data that comes from sensors and systems in the factory. The diagnostics value can help the factory with potential failures in machines or processes. One of the other main benefits, the ability to share data across the silos, is also one of the major challenges in manufacturing. Sustainability insight is also a significant advantage of a digital twin, as all of the data collected from the machines is displayed in the factories' performance management systems (refer to Section 2.3).

2.2.5 Challenges of using a digital twin

Implementing digital twin technology within a factory also presents plenty of challenges. One major challenge is the physical or wireless data connection with the factory (Modoni et al., 2019a). For a digital twin solution, there is a need for a real data connection between the physical object and the virtual counterpart. When enabling a digital twin, that data connection—namely, to the Internet—is needed to send the data from the physical machine to the virtual world. This can be a risk from a cybersecurity perspective (Holmes et al., 2021).

Another challenge with the implementation of digital twin technology is the unclear advantage over other technologies that are already in place in the factory—for example, the big data (Babu et al., 2021). Many factories already collect data, but it is unclear to them why there is a difference between big data and a digital twin (Qi & Tao, 2018). Related to this challenge is education regarding digital twins. Lack of knowledge and expertise about digital twins presents challenges in factories when implementing this kind of technology (Modoni et al., 2019). High-quality data is essential for a digital twin to run properly (Holmes et al., 2021).

Data that is captured from sensors can have many faults, including noise in the environment or improperly operating sensors. This data must first be pre-processed and cleaned of the noise before it can be useful to the digital twin.

One of the largest challenges of having a digital twin reach its full potential are the high and risky investments needed for technical implementation (Ogewell, 2018). It is not only buying the software that can create a digital twin of a machine or process, but also all of the components—such as sensors and machines—that must work together in the digital twin, that makes it expensive. If the factory wants to run simulations, a huge amount of computing power is needed, which can result in exorbitant costs for cloud computing or large investments and operational costs for local computing power (Talukder et al., 2010).

Factories that focus on using digital twins to improve their processes and reduce costs must transform their operation team as well (Ogewell, 2018). Currently, the operation teams of factories operate the production line; with a digital twin, the operation team must integrate multiple technology suppliers. This means that they are an orchestrator between the tech companies and their production lines, which results in different skills being needed.

2.3 Measuring performance and sustainability in a factory

How a factory is performing can be a good indicator of its sustainability (Wan Mahmood et al., 2015). Factories use several methods to calculate the performance of their operations. The OEE is the most used method in manufacturing to measure the performance drivers for improving productivity (de Ron & Rooda, 2006). It is mainly used within the production lines of factories to see where they can improve production. Factories can define the OEE score with three factors. The availability score is calculated to divide the actual production time with the planned production time. Second is the equipment performance. This is the relationship of how well the machines run and is calculated based on the actual number of products produced by the equipment against the theoretical maximum number of products that can be produced. The performance score is calculated to divide the actual output with the theoretical output. The last factor is the production quality. This factor is the number of products that are produced that meet the specifications of the product. When a product is produced and does not meet the required quality, it will be seen as a loss. The quality score can be calculated to divide the good output with the actual output.

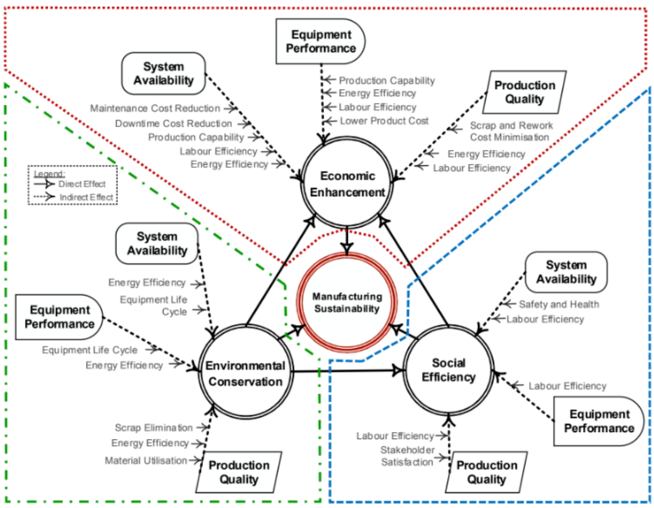
When the factors are individually calculated, the OEE score for a production line or factory can be calculated. This is possible with the following formula in Figure 8 (Ing. Jozef Glova, 2012).

$$Availability \times Performance \times Quality = OEE$$

Figure 8: OEE formula (Ing. Jozef Glova, 2012).

Wan Mahmood created a model to translate the OEE score into sustainability factors (Wan Mahmood et al., 2015). Figure 9 presents this model, in which the OEE—system availability, equipment performance, and production quality—is related to three sustainability elements: the economic enhancement, environmental conservation, and social efficiency. Every element has certain subitems that the sustainability can be related to. They indicate that any improvement in the OEE factor will result in an indirect and positive impact on the economic enhancement, environmental conservation, and social efficiency of factories, thus also reducing emissions (Warke et al., 2021).

Figure 9: Translating OEE to sustainability factors (Wan Mahmood et al., 2015).



The OEE method itself does not directly incorporate any sustainability factors, but there are two new studies that add an extra “E” to the OEE method. The first piece of research designates the extra “E” as energy (Ing. Jozef Glova, 2012). This research argues that manufacturing is the major consumer of energy and will continue to rise in the coming years. It advises creating an energy management Key Performance Indicator (KPI) based on water, air, gas, electric, and steam (WAGES). Combining that energy management KPI and the OEE calculation will result in a new calculation method—overall equipment and energy efficiency (OEEE), as shown in Figure 10.

Figure 10: Overall equipment and energy efficiency (Ing. Jozef Glova, 2012)

$$OEEE = OEE + E$$
$$OEEE = Availability \times Performance \times \times Quality \times Energy$$

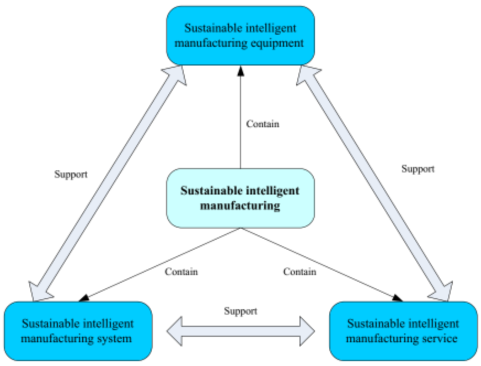
This new method concludes that their method, together with the OEE, can give insights into how the factory is performing regarding sustainability and energy usage. The challenge that they see in their study is how to collect and measure that energy consumption data from physical devices to get that extra KPI in the calculation.

The second piece of research designates the extra “E” as effectiveness (Domingo & Aguado, 2015). This research proposes executing an assessment of the OEE calculation to identify the environmental impact of every step in the process. For the measurement, the researchers used carbon dioxide (CO2) emissions, which is commonly practiced in manufacturing (European Environment Agency, 2021). With that measurement, the environmental component of OEE can be calculated by dividing the environmental impact of the workstation, the individual machine in the production line, with the total environmental impact of the initial state of the production. This number is than multiplied with the OEE outcome, with outcomes than the full OEEE score. With this method, the factories can also compare the environmental impact of two states of the production line to identity improvements or faults in the production process (Domingo & Aguado, 2015). Both new methods can be used in manufacturing to add sustainability numbers to the most important performance system, the OEE.

2.4 Sustainable intelligent manufacturing

Now that there is a comprehensive understanding of digital twins, sustainability, and the performance drivers of factories, it is time to bring the concepts together. In the literature, the term *sustainable intelligent manufacturing* is used to combine manufacturing technology, such as digital twins, with sustainability (He & Bai, 2021). Sustainable intelligent manufacturing consists of three elements: sustainable intelligent equipment, sustainable intelligent manufacturing systems, and sustainable intelligence manufacturing services. The relationship between the three elements is displayed in Figure 11.

Figure 11: Three elements of sustainable intelligent manufacturing (He & Bai, 2021) page 2.

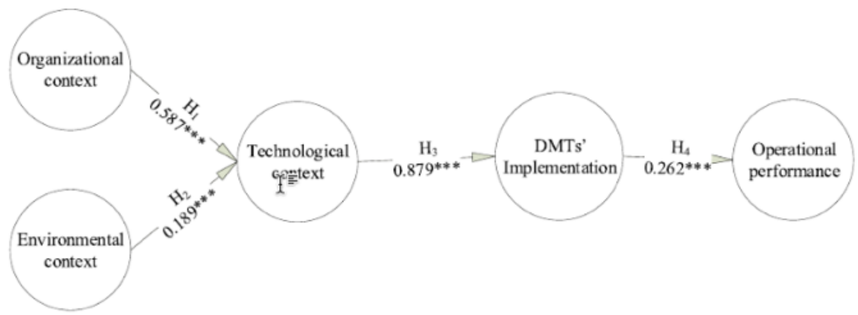


Based on these three elements, a sustainable digital twin–driven sustainable framework was proposed by He and Bai (He & Bai, 2021). The framework identifies all of the functions that are needed for a sustainable digital twin in manufacturing, including all of the standard manufacturing systems, services, and equipment. The framework consists of a basic platform—with functions such as big data, IoT, and cloud computing—and maps with the three elements of sustainable intelligent manufacturing. The framework maps the intelligent manufacturing systems, such as equipment and MES systems that operate the production lines, with the virtual prototype—that is, the digital twin. The data from the virtual replicas of the production lines and other systems is stored into a big data system based on three sustainable aspects: environmental, economic, and social (He et al., 2020). From these data sources, the sustainability of a factory can be calculated with methods like OEEE (Ing. Jozef Glova, 2012).

2.5 Implementation of digital twins in manufacturing

When new technology, such as a digital twin, is implemented in manufacturing, there are many challenges to implement and accepting that new technology in the factory (Gillani et al., 2020). Within the literature, there are different frameworks available for implementing those new technologies, many of which are focused on enabling technology and not the kind of factors or interconnections needed for implementation (Gillani et al., 2020; Liao et al., 2017). The literature search identified two technology implementation methods that are repeatedly used as implementation frameworks: the Rogers diffusion of innovations (DOI) framework (Rogers, 2003), and the technology organization and environment (TOE) framework (Depietro et al., 1990). Neither are focused on the manufacturing sector. Some researchers are skeptical about the DOI framework because it does not consist of external factors, such as environmental drivers, that play a crucial role in factories (Alshamaila et al., 2013). The TOE framework uses these external drivers, which has led to its widespread implementation across different sectors, such as retail (Zhu & Kraemer, 2005). Based on the TOE framework, Gillani et al. researched the specific implementation of the TOE framework for digital manufacturing technologies (DMTs) in the manufacturing sector (2020). Figure 12 displays the outcome of their hypothesized model.

Figure 12: Technology organization and environment (TOE) framework for digital manufacturing technologies (DMTs) (Gillani et al., 2020).



The hypothesized model shows that all direct relationships have a positive value to the implementation of technology in DMTs and the direct operational performance in manufacturing. In addition, the environmental context does influence the technology's implementation in DMTs, which is an important statement for this research.

2.6 Literature conclusion

In this section, a conclusion is written about the desk research conducted in this chapter. These themes were valuable input for the propositions that will be tested in this research (refer to Section 3.1).

After processing a lot of literature about the topics digital twin, manufacturing, and sustainability it was clear that the combination between these topics in the research almost couldn't be find. During the research, there was only one dedicated framework found that combined those three topics (He & Bai, 2021). This digital twin sustainability framework had not been tested yet in a factory and has no practical information about the usage and implementation of that framework. A very important element within a digital twin framework is how the data of a digital twin will be presented to its users. There is no research available how factory workers will use the data that is presented from a digital twin point of view in, for example, a 3D view of the production line, and if that will help with a better implementation of new technology like digital twin in the factory.

There are many applications that can be created with the use of digital twin technology that have benefits for the factories (Cimino et al., 2019). Another upcoming application is simulation with digital twin technology (Bangsow, 2016). With simulation, factories can plan for what will happen in the future if they, for example, want to change their production line process before making large investments. One of the big challenges is the implementation and standardization of data in the digital twin. When for example machine- or sustainability data is available for the factory from vendors, it is most frequently siloed into vendor-specific systems where factories not always have access to or difficulties to integrate (Babu et al., 2021). When the data is available every vendor has also their own 'data language'. Several vendors are busy with creating a standard digital twin definition language for the manufacturing sector, but that is not ready yet (Digital Twin Consortium, 2019).

Within manufacturing, performance measurement frameworks are the most used frameworks to measure the performance of a production line in the factory. OEE is the most commonly used framework in this sector (de Ron & Rooda, 2006). Currently, there is no sustainability or environmental measurement available in this framework, but there is research, not yet tested, that will add an extra "E" to the framework to give a sustainability/ energy measurement a place (Domingo & Aguado, 2015; Ing. Jozef Glova, 2012). This new measurement is not tested in practice yet.

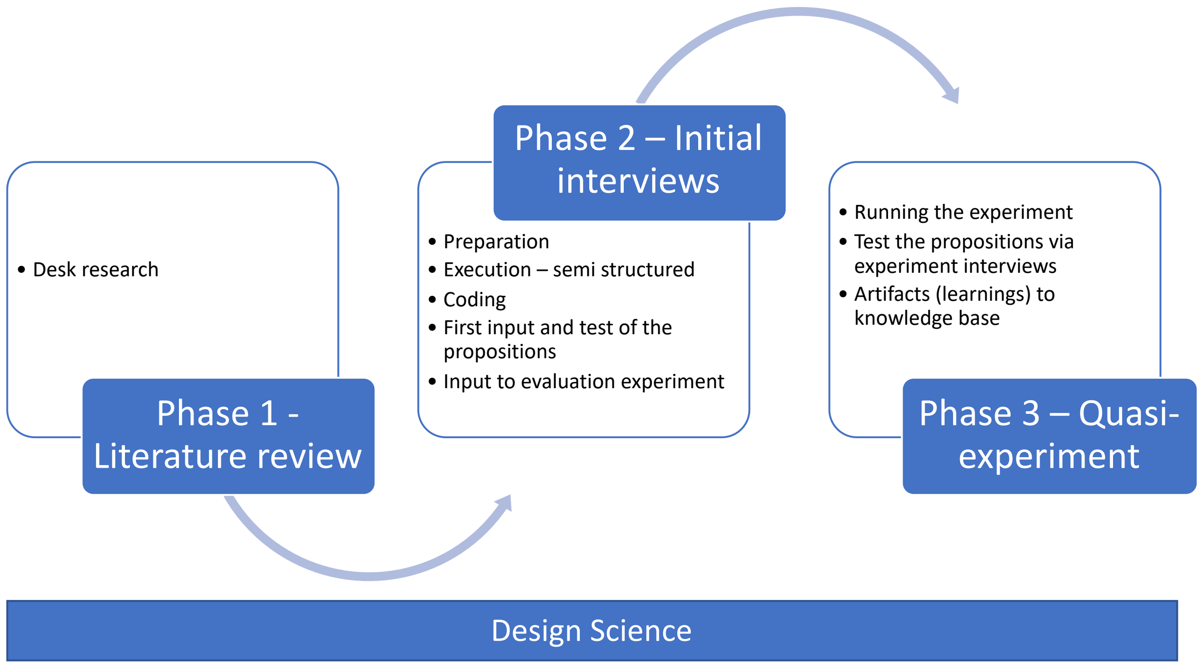
In the reviewed literature there was not a lot of practical knowledge about digital twin technologies implementations within the manufacturing sector. Specially in combination with sustainability. Off course the term sustainability was found a lot in combination with manufacturing, because they are one of the biggest emission sectors in the world. There is at the moment only two studies, not practical tested yet, that have created a model to display sustainable scores in the production process (refer to Section 2.3).

Concluded is that in the literature review there is almost no theory that practical underpins that adding environmental- or energy measurements to existing performance management systems, like OEE, can result in more sustainable insights and even reduce energy at the production line in the factory. It is also unclear whether presenting these measurements in 3D visualizations of a digital twin, where those measurements are recorded, could potentially result in a better implementation of this new technology in the production line of the factory and will add value for the factory.

3. Research methodology

In this research, the goal was to gather data not only via interviews, but also by conducting a quasi-experiment to test propositions with creating a digital twin solution for a factory like displayed in Figure 13. This quasi-experiment could give more practical information about the use of digital twin technology in manufacturing that was lacking in the literature review (refer to Section 2.6). A quasi-experiment was chosen because the test group for the experiment was selected by the researcher based on the initial interviews (Kampenes et al., 2009).

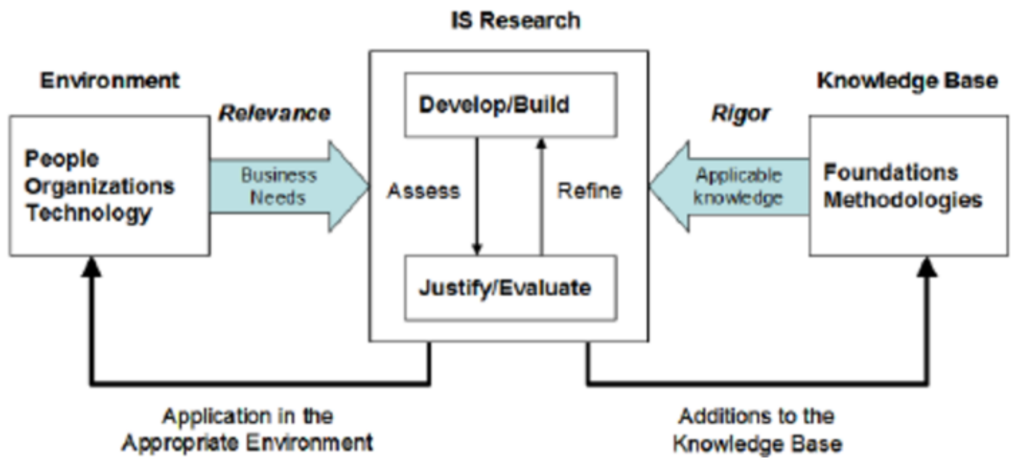
Figure 13: Research phases (Ploeg, R, 2022).



This chapter starts by explaining the underlying scientific design research method used for this research called Design Science (Hevner et al., 2004). After that, the steps of that approach are explained. The last section of this chapter describes the aspects of the experiment that was executed.

Design science is a framework used in information systems (IS) research (Hevner et al., 2004). The goal of this research method is to develop knowledge, via designing new and innovative artifacts, that can be used to design solutions for problems (vom Brocke et al., 2020). Digital twin technology is part of the IS domain in factories. This research created a quasi-experiment that provides valuable input for the manufacturing sector regarding how factories can use digital twin technology with sustainability data in their production lines. Design science helped form a scientific method of structuring the quasi-experiment and the outcome. The design science framework consists of three main elements: environment, IS research, and the knowledge base (Hevner et al., 2004). These are displayed in Figure 14.

Figure 14: Design science information systems research (Hevner et al., 2004).



The environment element defines the problems and opportunities of the digital twin technology with respect to sustainability for the manufacturers. Within this element, business needs are aligned with the company strategy pursued by the employees. This strategy information comes from the interviews conducted at the factories during this research (refer to Section 3.2).

The IS research is the element for executing the quasi-experiment. This is where the researcher has developed the experiment for a digital twin with sustainability aspects in the factory with the use of propositions (refer to Section 3.1). The learnings, or so-called artifacts, of this experiment flow back into the knowledge base.

The knowledge base element provides the raw materials to the experiment and the interviews, such as frameworks, theories, models, and methods in the development phase of the research. This knowledge base data comes from Chapter 2, but also partly from the outcome of the first interviews.

3.1 Design propositions and research timeline

With data from the knowledge base, design propositions were defined that could be tested in this research. Design propositions are statements that can be judged by true or false, but don't need to be testable or measurable like hypothesis does. A design proposition just deals with pure concepts of the research, but without the need for any laboratory test (Clay. Charles, 2018). Below the three design propositions that are based on the theoretical review and input of the first interviews are described. These propositions will be questioned in the interviews to give input to the quasi-experiment. The propositions will be also practical tested in the quasi-experiment with digital twin technology (refer to Section 3.3). The output of the quasi-experiment will be available as artifact for the literature (Offermann et al., 2010).

Proposition 1: Digital twins used for real-time control in manufacturing reduce energy consumption.

From the literature research, it is not well known whether digital twin technology can help reduce energy consumption in factory production lines. Different digital twin applications can potentially reduce energy consumption in the factory. In the interviews that have been held, these applications were questioned to get more background on these applications.

Proposition 2: Including an extra "E" for energy in OEE in a digital twin will generate sustainability insights.

OEE is a widely used framework that measures performance in manufacturing (de Ron & Rooda, 2006). Using the new OEEE method—that is, adding an extra "E" for energy—could give factories better insights into sustainability data and make them more sustainable (de Ron & Rooda, 2006). In the literature there is no practical information about the use of this new framework in factories and how factory employees will look at it.

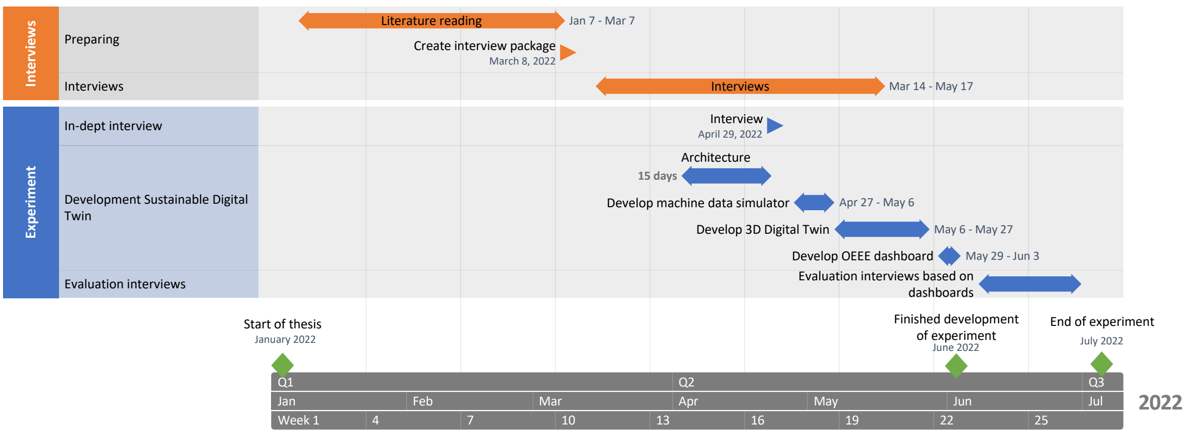
Proposition 3: The 3D visualization of a sustainable digital twin contributes to the improved use of the technology.

In the literature there was almost no information how to present the data from digital twin technology. Implementing new technology is challenging within the production line. Providing a 3D visualization of the digital twin at the production line with sustainability data could help to a better implementation and insights of new technology, like digital twin, for the workers.

In Figure 15, the overall timeline of this research is presented. The research approach is divided in two sections. First, interviews were held to validate the literature research, but also to get more insights due to lack of literature about this topic (refer to Section 3.2). The first interviews results gave a great insight between the literature and the 'real world'. This gave background information to build the propositions also for the experiment (refer to Section 3.1).

Apart from the interviews, to be able to answer these propositions for the quasi-experiment, an underlying technology environment was needed to create those sustainability digital twin dashboards of the production line (refer to Section 3.3). This development was done during the first interviews to get the deadline of this research paper and could not wait till the end of the first interviews. On the dashboards, factory workers can directly see the current status of the sustainable digital twin. The development of that technology environment was a necessary part of the research. With regard to the repeatability of the research, the software components, technical architecture, and instructions of the technical setup are open sourced for other researchers. Together with the detailed steps of the whole quasi-experiment this can be found on the researcher's GitHub page (Ploeg, 2022b).

Figure 15: Timeline of research approach (Remco Ploeg, 2022).



3.2 Initial interviews

This section describes the data collection method that was used in this research based on the interviews conducted to test the different propositions. This method was chosen to gain more background information about the factories, with a particular focus on sustainability, and the applications of digital twin technology that they can use. In the literature there was limited information found about this topic. Performing only the quasi-experiment would not have given enough information to answer the research question. Only factory employees were involved in the quasi-experiment, but more roles were involved in the interviews to give more background information about the topic.

3.2.1 Data collection initial interviews

The data collection began with qualitative data to understand how the manufacturing sector uses digital twin technology and addresses sustainability in their factories (Castillo-Montoya, 2016). Online semi-structured interviews were held due to international people and COVID-19 regulations. Because digital twins are a relatively new technology in manufacturing, the interview questions were explorative and open to obtain the most detailed information possible about this complex technology (Louise Barriball & While, 1994). The interviewees were selected based on knowledge, relevance in the market (factories), and interviewees with and without experience of digital twin technology and sustainability in manufacturing.

Summary information about the interviewees and the interviews is presented in Table 4.

Table 4: Interviewees in this research

Type	Nr.	Role	Type of company	Date	Duration
Factory	1	Global factory plant manager	Food	14/03/2022	47 min
	2	MES manager of factories in EU	Milk	12/05/2022	32 min
	3	Plant manager of factories in NL	Food	29/04/2022	41 min
	4	Plant manager	Concrete	05/05/2022	27 min
	5	Innovation manager and data scientist	Repair	11/05/2022	42 min
	6	Innovation manager manufacturing	Aircraft maintenance	28/04/2022	25 min
	7	Innovation manager—digital twin	Renewable energy	10/06/2022	54 min
	8	CIO	Publisher	20/06/2022	38 min
Experts	9	Program manager—digital twin	Software vendor	08/04/2022	20 min
	10	Leader—digital twin and edge computing	Software vendor	25/03/2022	25 min
	11	Manufacturing—digital twin	Software vendor	15/03/2022	27 min

There was a need to have in-depth information about how a factory or production line operates and performs in combination with sustainability, the plant managers and innovation managers of factories were interviewed (Bloom et al., 2014). In particular, the innovation managers offered a perspective of how innovation is embedded in the factory.

Within manufacturing, digital twin software must be created and implemented by manufacturing software vendors. Several software vendors that provide digital twin solutions to the manufacturing market were interviewed about their applications and implementation frameworks. To avoid having a sales-driven interviews, only domain experts who are well-known in the market were interviewed. Together with the factory employee interviews, this provided an end-to-end overview of sustainability and digital twin technology in manufacturing.

In Table 5, the interview questions with the themes are displayed. These themes are categorized on the TOE framework, Technology, Organization and Environmental (Baker, 2012) found during desk research, as discussed in Chapter 2. This framework was tested in the manufacturing sector and offered structured guidance in the interviews about using new technology, such as digital twins (Gillani et al., 2020).

The interview questions were inductive because the research is about new(future) technology and there is limited literature available. The questions were based on the literature review and the selected propositions (P1, P2 and P3). Apart from the themes used, keywords were added to every question by the researcher. The keywords could give guidance to find deeper answers on the questions or topics that were not mentioned by the interviewee. The keywords came from the word cloud in Figure 3, but also from feedback of the first two interviews conducted. Some of the questions are also related to the propositions that will be tested in the quasi-experiment. These answers of these questions will give valuable input to the quasi-experiment and input of the research questions.

Table 5: Interview questions — structured with themes and keywords (Author, 2022).

Nr.	Theme	Question	Keywords	Related proposition
0	Generic	Can I record this interview?		None
1	Generic	What is your name and role in your organization?		None
2	Generic	What kind of organization do you work?		None
3	Environmental	How important is sustainability for your factory?	goals, measuring, stakeholders, services, products	None
4	Environmental	What are the challenges with your sustainability goals?	stocking, technology used, how do you calculate?	None

5	Environmental	Can you explain your current sustainable goals, and how important are they buying new technology like a digital twin?	stakeholders, decision, development	None
6	Technology	What is your view on the definition of a digital twin in your organization? What do you think about this definition of digital twin?	virtual, simulation, replica and Industrial	None
7	Technology	What are the characteristics of a digital twin in your opinion? These are the characteristics I have found about digital twin in manufacturing. What are the most important for you and why?	simulation, sustainability, costs, decision making, models, integration	None
8	Technology	What are the benefits and challenges for you with a digital twin solution in general, but also from a sustainable angle?	sustainability, use cases, energy optimization, models	None
9	Technology	What kind of applications of digital twin technology do you currently use or see being used in general, but also from a sustainable angle?	monitoring, simulation, prioritize, decision making, optimize, industrial	P1
12	Organization	Do you use PMS frameworks in your factory such as OEE? If yes, do you see any challenges with sustainability goals, and how do you measure that in your current frameworks?	OEE, sustainability, management, performance, digital manufacturing	P2
12	Environmental	Do you see that digital twin playing an important role within reaching your sustainability goals as a company?	goal, already using this?	P1

13	Organization	Has your company used any standard implementation frameworks with implementing new technology in the past years? If yes, what kind, and why did you used that framework?	implementation, challenges, technology, and blue-collar workers?	P3
14	Generic	Thank you for your time. Do you have any questions or information that is relevant for this research?		None

The interviewees received an interview package with the question list and background of this research in advance to prepare themselves (see Appendix A). This interview package was developed based on the main themes that were identified in the literature and tested in advance with one of the stakeholders in the researcher's company to evaluate the interview's flow and duration. There was also a checkpoint with the academic supervisor about the interview questions. Based on the first interview the questions were changed with input from the academic supervisor.

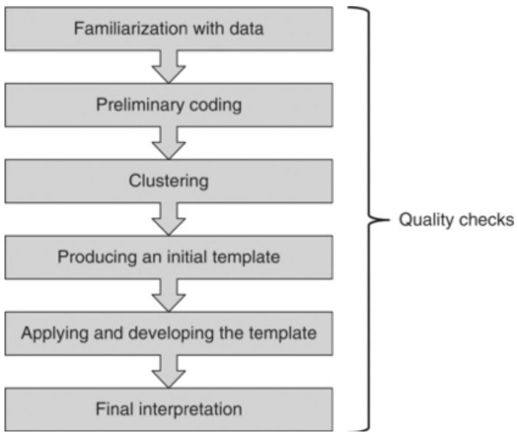
In every interview, the researcher started with the explanation and goals of the interview and the obtainment of consent to record the interview. All interviewees consented to having the interviews recorded. After the introduction of the interviewee's role, the questions were answered in an open discussion between the interviewee and researcher. The average length of the interviews was around 35 minutes, and they took place between the end of March 2022 and the middle of June 2022. The transcripts of all of the interviews can be collected from the researcher.

3.2.2 Data analysis interviews

For this research, flexibility was needed in the interviews to understand the different data that was collected. For the data analysis of the interviews, template analysis was used (King & Brooks, 2017). The main reason for choosing template analysis is that it offers flexibility because it is not related to any epistemology. After the first two interviews, the coding template was discussed with the supervisors before the other interviews were held. This led to some adaptations in the coding (see Table 13). The main steps that are recommended in the literature for the template analysis method were used in the analysis of the interviews. These steps are displayed in

Figure 16.

Figure 16: Steps in template analysis (King & Brooks, 2017).



Based on the literature review, a set of priority codes was applied as a signpost for the data analysis from a theoretical perspective (see Appendix D). This set was evaluated with the academic supervisors as input for the interview questions. After the first two interviews, the template was changed based on that input. This constituted the initial template. In Table 13 the evolution of the coding template of the interviews can be found.

3.2.3 Interview quality criteria

In the template analysis of the interviews, it was important to decide on the quality criteria before going to the results of this research (King & Brooks, 2017). There are no specific quality checks, but Tracy created the eight "Big-Tent" quality checks (Tracy, 2010). In Table 6 the quality criteria are listed in the order of the Big-Tent quality checks and connected to this research.

Table 6: Big-Tent criteria interviews (Tracy, 2010)

Big-Tent quality check	Proof in research
Worthy topic	This is covered by Section 1.1. The business challenge of this research has a significant impact on the world's emissions.
Rich rigor	This is covered with the intensive interviews and making the interview questions better after the first interview.
Sincerity	Every step in this research from the literature review to the experiment is clearly described.
Credibility	The Maxqda software is used to combine the desk research with the field research with the use of codes (*Maxqda*, 2022). Industry experts and factory employees were interviewed to have a sufficient understanding of the market and challenges. A quasi-experiment was created in which a real sustainable digital twin is tested with factories to test the three propositions
Resonance	This research goes further than only interviews, as it also gives practical advice to factories to implement digital twin technology.
Significant contribution	The experiment (refer to Section 3.3) of this research makes a practical contribution to the factories and the knowledge base of design research.
Ethical	All of the data collected in the interviews was anonymized. All recordings were deleted so that no data can be connected to any person or company, and all of the interviewees gave consent to being recorded.
Meaningful coherence	By using the design science method, a clear step-by-step method was chosen (Hevner et al., 2004).

The results of the interviews are presented in Chapter 4.

3.3 Evaluation using quasi-experiment

The goal of this quasi-experiment was to test, together with the initial interviews results and theoretical literature, the propositions of this research based on a digital twin solution that was built by the researcher (Cook, 2015). Because the test group of this experiment was already selected by the researcher in the initial interview phase, this quasi-experiment method was chosen instead of a full controlled experiment (Kampenes et al., 2009). Beside that it was unfeasible in time to find enough participants to do a full controlled experiment. In Table 7 the controlled variables and measuring instrument are described for this quasi-experiment. At the end of the quasi-experiment, the initial interviewees of factories were interviewed about the digital twin solution combined with an in-depth demo during the experiment interviews.

Conducting and evaluating an experiment within a design science framework can be challenging because of the lack of coherent frameworks for creating the artifacts (Ge & Helfert, 2014). Ge and Helfert proposed a framework for experimental research within design science (Ge & Helfert, 2014). This framework structures the experiment in a scientific manner to produce the same results by running the same experiment in another time period and by another researcher. In Table 7, the experimental research framework is adopted specifically for this experiment to control the variants. Based on the propositions, the overview of the whole experiment is captured. The following paragraphs describe the process, data collection, and data analysis of the experiment so that it can be repeated by other researchers.

Table 7: Experimental research framework for this research, adapted from (Ge & Helfert, 2014) page 152.

Artifact	Experiment	Data analysis
Digital twin technology makes an attractive 3D visualization where real-time insights on energy usage and emission output in existing performance management solutions, like OEE, are displayed for a better implementation in the production line.	Comparing sustainable digital twin emission dashboard, combined with a 3D visualization on one production line, with a standard OEE reporting in the factory	Showing emission insights of a production line will help with awareness of sustainability and maybe even reduce emissions. Compared this with the standard OEE dashboard via experiment interviews.
Practical problem: The literature review indicated that there is no real-time emission dashboard on the virtual replica of production lines available to steer emission output. A higher emission output of a production line can also indicate problems with machines or processes in the production line.	**Validation of measuring instrument:** Experiment interviews with factory workers (CDC, 2018).	**Data collection**: Simulated data (origin factory data) and sent machine data to the cloud. This data was processed in the digital twin for sustainable analytics. Interviews with selected experts to receive feedback about the new dashboard.
Research: Jozef Glova (OEEE calculations) is used (Ing. Jozef Glova, 2012).	**Control of external factors**: External factors, such as data points and real-time data, the concepts of digital twins, and dashboards, are controlled due to sample data.	**Data analysis**: Experiment interviews of the experiment dashboard were compared with the standard OEE dashboard.
Literature review: See Chapter 2—journals about digital twin technology, performance frameworks, and sustainability in manufacturing	**Concise and easy-to-operate experiment**: Conducted an experiment with machine data from one production line of a factory. All of the technical details and data points can be collected on GitHub (Ploeg, 2022b).	

3.3.1 Factory data collection

In

Figure 17, a production line layout is displayed (Koperek, 2013). This layout was used in the experiment as an outline to create the virtual digital twin with the simulated data from a factory. This line is responsible for packaging food products and the real machine data are mapped to the virtual machines in the model. On the left the product is entering the production line, where in the first machine the candy is filled in their form. In the second machine the candy is individually packaged and in the third machine the candies are grouped together. The robot on the end is moving the package from the production line on the transport bench.

Figure 17: Sample factory layout of production line (Koperek, 2013).

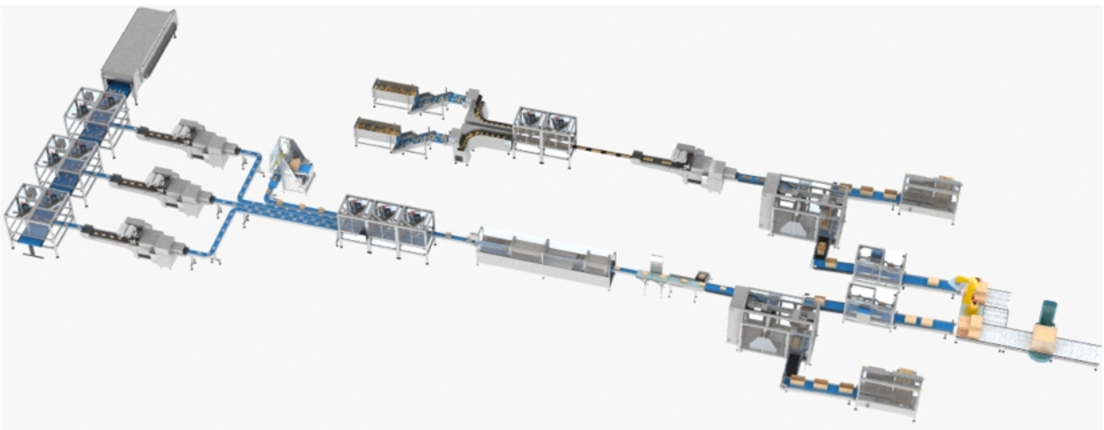


Table 8 describes the type of physical factory machines in the production line that were used in the experiment. From this information, the researcher simulated data boundaries to send simulated data to the sustainable digital twin (Ploeg, 2022a). This method was chosen because it was impossible to be directly connected to any production line due to security and compliancy challenges of several selected factories. The researcher decided to simulate the data and dashboards based on machine details of factory machines (J+P Machine Bau, n.d.).

Table 8: Machines used in the experiment.

Machine name	Machine type	Description
Machine 1	Filling	Machine packages the product
Machine 2	Packaging	Machine transports the package on the production line
Machine 3	Packaging	Machine closes the package

Machine 4	Robot	The robot moves the package from the packaging line to a pallet

To measure the sustainability factors and OEEE there are certain data points needed from machines and systems of the factory. Table 9 describes the relevant data measurement parameters that come from the literature review and interviews (Ghafoorpoor Yazdi et al., 2018).

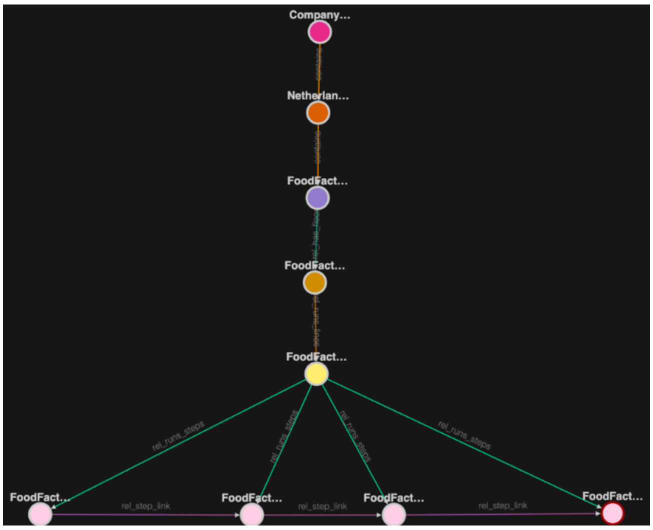
Table 9: Data fields collected for experiment.

Measurement parameter	Description
Shift number	Which and how many persons were part of the shift creating the product (Wan Mahmood et al., 2015)
kWh	The energy consumption per machine, based on the OEE (Ghafoorpoor Yazdi et al., 2018)
Total parts made	The total number of products made per shift (Wan Mahmood et al., 2015)
Defective parts made	The number of defective parts that the machine created (Wan Mahmood et al., 2015)
Batch number	The batch number of the product
Temperature motors	The temperatures of the motors in the machines (Qi et al., 2021)
Health status	The health of the machine (running, stopped, error, etc.)
Oil temperature	The oil temperature of the machine
Planned kWh (energy)	The normal kWh usage of the machine

An important element within the digital twin is the DTDL, the structure of the virtual replica of the production line. In

Figure 18, the DTDL model of the experiment is displayed in a graph. In this model, the relations between all of the elements of the production line are displayed. In this model the structure of the company and factory is described together with the selected production line for the experiment (refer to Section 3.3).

Figure 18: Digital twin model in experiment.



To implement this adjusted digital twin–driven sustainable framework, a complete technical environment was needed. For that implementation, several Microsoft and open-source software components were used in the experiment to simulate data from the machine in the factory, create a digital twin environment, and display the sustainability data in reports and in a 3D model. The technical architecture of the total solution is described in Appendix G. The source code and detailed documentation are available on the researcher's page in the GitHub repository so that other researchers can repeat the experiment (Ploeg, 2022b).

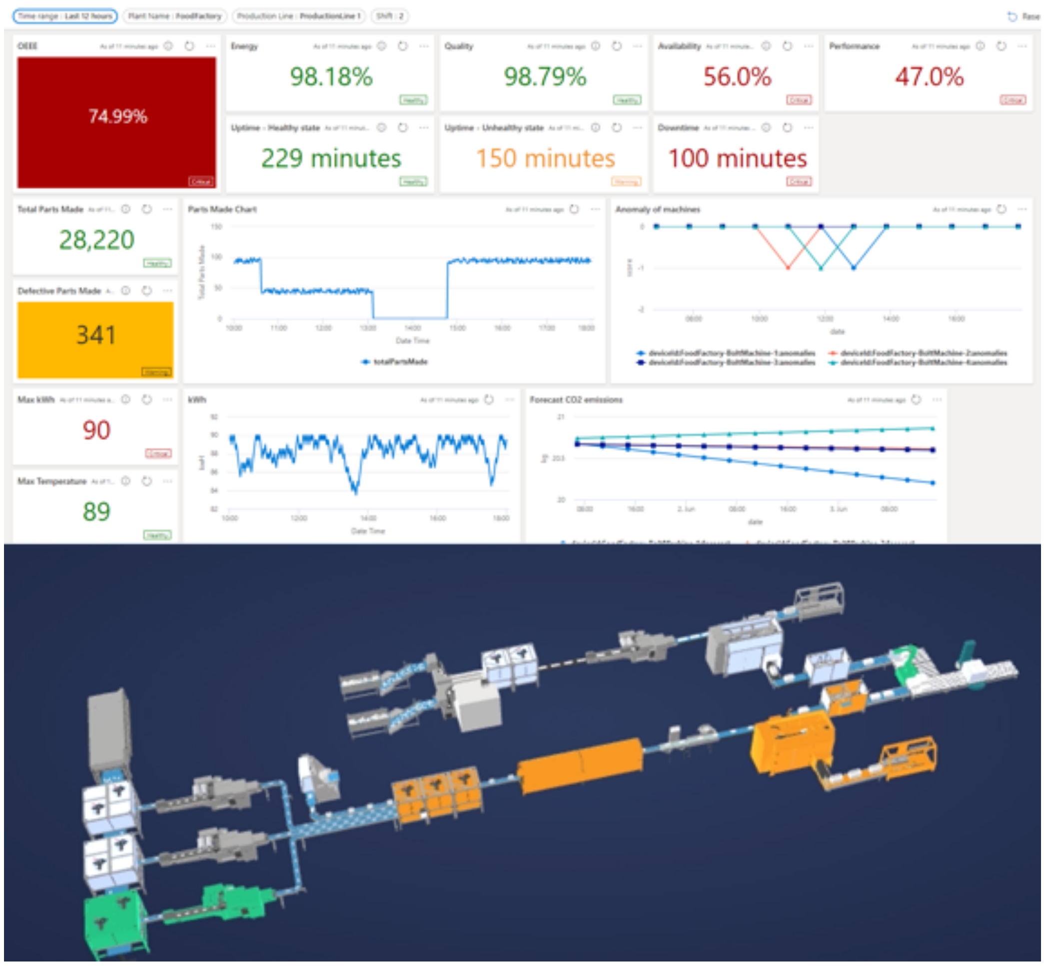
3.3.2 Data analysis of the experiment

The experiment used the sample machine data from the factory machines (J+P Machine Bau, n.d.). This sample data can be downloaded from GitHub page of the researcher (Ploeg, 2022a). With that data, the energy and emissions calculations were created for the experiment dashboard. To give this a valuable and known outcome, the OEEE method was chosen because it is widely used in factories (Ing. Jozef Glova, 2012). The standard OEE measures the general performance of a production line. The OEEE framework adds an extra "E" to measure energy in the production line.

The result of this experiment was an artifact of a digital twin with simulated emission data in a OEEE dashboard that could be compared with a standard OEE dashboard (see Appendix H). In Table 7 the validation framework and controlled factories are described. These results were presented in experiment interviews to answer the propositions.

Figure 19 displays the experiment dashboard with the OEEE and 3D-based production line based on the sustainable digital twin.

Figure 19: OEEE dashboard used for interviews, Remco Ploeg (2022).



The information produced by the digital twin was presented in the experiment interviews to answer the three design propositions (refer to Section 3.1). The experiment interviews were held online, and they were semi-structured to have an open discussion with the interviewee and provide guidance to have a common outcome of the experiment results (Louise Barriball & While, 1994). This method was chosen to quickly collect responses to the propositions and to ask the questions behind the questions. In Table 10, the list of interviewees of the experiment interviews is displayed.

Table 10: Experiment interviewees

Type	Nr.	Role	Type of company	Date
Factory	1	MES manager of factories in EU	Food	10/06/2022
	2	Factory manager	Concrete	14/06/2022
	3	CIO of a factory	Publisher	23/06/2022

In Table 11, the semi-structured questions are described based on the two dashboards and the interview output discussed in Section 4.2. Related to every question also the proposition is connected.

Table 11: Questions during experiment result interviews

Nr	Question	Description	Related proposition
1	What do you think about OEEE calculations with the extra E of Energy, what will be the effects if you use it?	In the dashboard, an extra "E" is calculated. Based on the planned kWh per machine and the actual usage a percentage is calculated.	2 - Including an extra "E" for energy in OEE in a digital twin will generate sustainability insights.
2	What do you think about the forecast of CO2 emissions? Does it affect your organization?	Based on the actual kWh usage, a forecast algorithm runs to predict the calculated kWh usage in the production line.	1 - Digital twins used for real-time control in manufacturing reduce energy consumption.
3	What do you think about the anomaly detection based on kWh usage of the machines? Will your maintenance department use this data?	Based on the historical data, an anomaly algorithm checks anomalies of the machines and warns the operator.	1 - Digital twins used for real-time control in manufacturing reduce energy consumption.
4	What do you think about the usability of 3D OEEE information and alerts?	Is there any value showing 3D digital twin data, and will that better explain the value of digital twin?	3 - The 3D visualization of a sustainable digital twin contributes to the improved use of the technology.
5	What do you think about showing alerts of the machines in the 3D model? Will the workers react to them?	Is there any value to showing alerts in the model? If yes, what is the audience for that?	3 - The 3D visualization of a sustainable digital twin contributes to the improved use of the technology

The full outcome of this quasi-experiment is presented in Chapter 4.2.

3.3.3 Experiment quality criteria

To be accepted as a credible and repeatable experiment, certain quality criteria needed to be used (Lincoln et al., 1985). In Table 12, these quality criteria for the execution of this experiment are described.

Table 12: Criteria used for experiment (Lincoln et al., 1985).

Criterion	Actions of researcher
Dependability	The scope changes of the experiment are logged in the Logbook of Maxqda (*Maxqda*, 2022) The technical data and logbook for the experiment is placed in GitHub, and the changes are recorded with versioning (Ploeg, 2022b).
Credibility	The results (input and output) of the experiment will be shared and discussed with selected experts of factories.
Transferability	The development of the experiment is documented in GitHub so that other researchers can repeat the same experiment (Ploeg, 2022b). The development code, example data and instructions are documented for other researchers (Ploeg, 2022b).
Authenticity criteria	The outcome of this research flows back into the knowledge base. All of the data that is recorded is anonymized so that it can be shared with a wider audience in the market.

3.3.4 Give back to the knowledge base

The output of the propositions was returned as an artifact to the knowledge base in the design science framework. This paper will become available for factories to learn about digital twins and sustainability. Furthermore, the experiment was made available for everybody via GitHub, so every factory can try it themselves (Ploeg, 2022c).

4. Results

This chapter presents the results of the initial interviews (refer to Section 3.2) and the experiment (refer to Section 3.3). First, the results of the initial interviews are shown to improve the understanding of the theory and insights in factories (refer to Section 4.1). The results of the experiment interviews are then presented based on the experiment (refer to Section 4.2). In the experiment, the propositions are tested. Both sections explain the results regarding the empirical examination of the three propositions.

4.1 Initial interview results

In all of the interviews, sustainability at every factory and vendor was considered an important topic of the strategy, mostly driven by government regulations and the current increase in gas prices due to the war between Russia and Ukraine (Reynolds, 2022). Most of the interviewees could describe digital twin technology, but their definitions differed. Most of the factories did not have any implementation of digital twin applications, and only one factory was busy with the implementation of a monitoring digital twin application.

In the software tool MAXQDA, a coding system was used for supporting the analysis of the interviews (see Appendix E). The most important topics are outlined in this section to present the results of the interviews and the relevant quotes.

The evolution of the coding template that was used for the initial interviews is shown in Table 13.

Table 13: Evolution of the initial interview coding

A-priori topics	Description	First template (transcripts 1–2)	Final template (rest of the transcripts)
Importance of sustainability	How important is the topic of sustainability for the factories? Are they already implementing sustainable solutions?	- Sustainability - Focus - Implementation	- Focus - Reduce
Understanding of the definition of digital twin	What is the interviewees' definition of digital twin technology?	- Definition - Use cases - Characteristics	- Definition - Characteristics
Sharable data	How important is the sharing of data? Do they recognize any challenges?	- Challenges - Scattered data - Data models - Investment	- Scattered data - Data models
Clear insights into the reduction of energy	Do the interviewees have insights into energy consumption and the ways to reduce it?	- OEE - Measurement - Consumption	- OEE - Insights into energy
Digital twin applications	What types of digital twin applications are already used (or contemplated) by the interviewees?	- Efficiency - Maintenance - Simulation - Quality - Inspection	- Monitoring - Efficiency - Simulation

Aside from answering the questions, the interviewees also gave their direct inputs to the propositions of the quasi-experiment (refer to Section 4.2).

4.1.1 Importance of sustainability

All of the interviewees considered sustainability as among the key priorities in their business agenda. This observation is partly driven by government regulations in recent years that companies must report their current sustainability numbers, consumer demand for more sustainable products, and need to reduce emissions to attain sustainability goals. For most of the interviewees, the sustainability agenda is difficult to achieve because they lack insights into the sustainability numbers of their factories. For example, most of them are only aware that the energy usage is on a contractual basis with the energy company, the so-called purchased energy. Furthermore, they have no idea about the energy usage per machine or production line or the amount of CO_2 emissions per production line to determine the areas where they can reduce their footprint. In addition, most of their data are scattered in different systems or on paper. As Interviewee 4 stated, "Ultimately our clients will ask more and more of us." The clients of the factories also increasingly ask about the sustainability indicators of their produced products. Every company must eventually report its emissions from the products it manufactures. If the factories produce products with a high emission output, then those high emissions will also reflect on their clients' sustainability goals.

In the interviews, the sustainability discussion was primarily focused on the insights into the emissions output of a factory, especially CO_2. However, for factories, reducing CO_2 emissions is not the only means of becoming more sustainable; for instance, packaging products more efficiently or with more sustainable materials will result in a more sustainable factory.

4.1.2 Lack of a clear understanding of digital twins

Most of the interviewees acknowledged the difficulty of understanding the precise meaning of a digital twin. Although they could provide a high-level definition, they all differed in the details. The definition ranged from a digital reflection to a "connected dot" system. According to Interviewee 1, a digital twin "is a digital reflection of an asset or a business process. With a digital twin, you are better able to properly follow processes [and] to simulate and thus anticipate not only possible problems but also improvements." Interviewee 7 noted that "You get to it as a kind of graph database and all the little dots in there, and I love this idea and I need to see it for myself. I love this idea that you can make those connections, this kind of hard physical connection between some of those dots." Most of the interviewees provided a high-level definition that a digital twin is a copy of a real asset in the factory.

Most of the interviewees underscored the challenge of explaining the story of a digital twin within their own companies and insisting upon the value of its implementation. Such observation is indeed also related to the different detailed definitions of a digital twin during the interviews. One of the solutions mentioned in the interviews was the visualization of the digital twin as a story-telling mechanism. As Interviewee 8 indicated, "I think virtual views have a significant value; [especially] at the leadership level, it removes the challenge of understanding what people are going to do with the data." This method was also tested in the experiment (refer to Section 4.2 for the results).

4.1.3 Sharable data within the factory

According to the interviewees, sustainability data are currently scattered around and within the factory walls, thus presenting a significant challenge. As Interviewee 9 noted, "To really get the value out of the data, which is a huge investment, it needs to be [thoroughly] simplified." The identification and extraction of sustainability data and subsequent use for the digital twin can be a substantial investment for the factory. Without those investments, obtaining insights into sustainability within the factory can be challenging. Sharing the (machine) data within or outside the walls of the factory requires standardized data models for efficient data sharing. However, these data models are not implemented in factories, and most of these factories are unaware of any industry standards. In the factories where the interviewees work, most of the machines are not connected to internal systems, thus rendering the impossibility of extracting data from all the machines. This situation presents a challenge, particularly if these data must be accessed to gain insights into sustainability numbers from a machine or to optimize a production process.

4.1.4 Clear insights into the reduction of energy

Most of the interviewees did not have any insights into the amount of energy that their production lines or machines utilize throughout the day. They stated that they use the main utility bill from the whole factory building to obtain insights into energy, but they cannot undertake the same action at the production line or machine levels. At this level of insight, determining the areas where a factory can reduce energy becomes difficult. Most of the interviewees considered this factor as a major challenge and acknowledged that they can only act on the numbers of the main utility bill. They added that some of the factories operate old machines that render the unfeasibility of measuring energy or other datapoints and underscored the need to invest in new machines or technology to measure energy.

According to the interviewees, all of them use the OEE method for measuring the performance of their factories and gaining insights into energy usage where possible (de Ron & Rooda, 2006). However, all of them are not aware of the OEEE method (Ing. Jozef Glova, 2012). For the interviewees, including an "E" in their current OEE method can add significant value. As Interviewee 2 explained, "The only a problem we have with the OEE [method] is that we do not get any context with OEE; [however, the fact that] extensions are also coming is great [news]." The existing frameworks are capable of calculating the OEE score to sustainability numbers to obtain context from a sustainability angle, but the interviewees were unaware of those calculations (refer to Section 2.3). Nonetheless, most of the interviewees acknowledged that the current OEE method does provide insights into sustainability.

If a factory manufactures broken or low-quality products during the production process, then the sustainability score of the factory is directly affected. According to the interviewees, they are not yet reporting these sustainability scores to the factory floor or in their company sustainability reports.

4.1.5 Applications for a digital twin

Many digital twin applications were discussed during the interviews (refer to Table 14). The most frequently mentioned application was the monitoring application, with which the factory can acquire direct insights into the current condition of the entire factory or a specific production line. Interviewee 14 described this application as follows: "In all contexts, the first and most basic [use case for us] is genuinely one [that provides] as close to a real time view of our inventory [as possible]. In an ideal world, collaborating with our partners [is facilitated]."

The current challenge with this application is that data are scattered around the factory or at partners, hence presenting the challenge of deploying a digital twin application in the factory. For the interviewees, starting with implementing on one production line with gaining sustainability insights can be the initial first step toward a monitoring digital twin application in the factory. This application is tested in the experiment of this research (refer to Section 4.2). The most frequently mentioned digital twin applications during the interviewees are listed in Table 14.

Table 14: Digital twin applications mentioned in interviews

Application name	Application description	Number of times mentioned
Overall monitoring and real-time overview	Full oversight of all the information of the entire factory or production line	11
Energy monitoring	Insights into the current energy usage of the factory and areas where energy can be saved	6
Simulations/efficiency	Testing of new settings of machines or procedures with simulations	5
Insights into the partner (supply) chain	Insights into not only the factory or production line but also the whole supply chain with partners to obtain a complete overview of the processes involving a product	2

The interviewees agreed that the monitoring application is a first step for other digital twin applications. The lack of monitoring of the current status of machines and production lines would create the challenge of implementing other digital twin applications. This element constitutes the basis of every digital twin application.

The interviewees found that the simulation application could have the most impact within their factories. With this application, the interviewees could work on optimizing the production lines to reduce energy via the simulation technology in the digital twin. For example, they can test the new settings of a machine to determine whether the production will, in the real world, work more efficiently or use less energy to optimize it for sustainability scores. However, none of the interviewees had implemented this application yet.

One of the feedback items in the interviews is the implementation of those digital twin applications in the factories. As Interviewee 10 stated, "Enabling those technologies in manufacturing is difficult, especially with blue-collar workers." Most of the interviewees had an experience with implementing a new technology for blue-collar workers, and they acknowledged that an effective implementation plan is key to a successful digital twin application.

4.2 Experiment results

After evaluating and acquiring further information about the proposition by using the initial interviews in Section 4.1, a quasi-experiment was conducted to test the three propositions through the building of a digital twin solution. This solution was demonstrated to the experiment interviewees in the experiment phase (refer to Figure 14). All the experiment interviewees were enthusiastic about the digital twin demonstration that they had seen during the experiment interviews. In general, they noted the advantage of using this new digital twin technology in their factories, but they also provided useful feedback to further improve the application.

In this section, the results of the quasi-experiment are presented. It consists of two subsections. The first subsection includes the results and challenges of creating a sustainable digital twin as an experiment, as well as the challenges that the researcher encountered while building this experiment before conducting the experiment interviews. The second subsection covers the results of the experiment interviews that were based on the digital twin sustainability dashboards described in Chapter 3. For the experiment, an online video is created in which the full experiment is explained, and a full demonstration of the sustainable digital twin is presented (Ploeg, 2022c).

4.2.1 Including an extra "E" for energy in OEE in a digital twin will generate sustainability insights

For the interviewees, the real-time OEEE dashboard of the sustainable digital twin offers valuable added information about the real-time usage of the energy indicator against only the OEE dashboard that they used to work with in the factory. Especially in the current global energy crisis, monitoring energy to optimize production lines will position the sustainable digital twin as a significant advantage. According to experiment interviewee 1, "In any case, everything in the field of energy monitoring is very current if you look at the costs that simply go through the roof, and we are also affected by this worldwide [situation]." Most of the interviewees cited the same aspect, stating that monitoring will be the most value-added digital twin application (refer to Section 4.1).

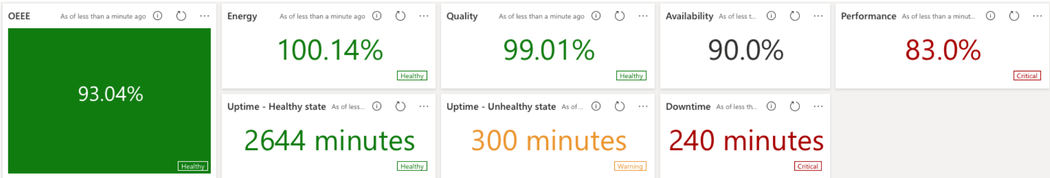
The dashboard with data from the sustainable digital twin itself provided everybody with a clear overview of how sustainability data from a production line can be displayed together with the operational data and structure of the machines, especially because the dashboard had real-time data with color marking. Hence, in case problems emerge in the production line with emission data, the color coding will prove very useful and function accordingly. As experiment interviewee 3 noted, "As soon as the technology team identifies a way to measure something and put it on a dashboard, then it improves the understanding of all parties, and not least the ability to tell people that things are green almost all the time."

Showing the extra "E" for energy with OEEE was similarly beneficial, as it offered a clear overview of how the energy is used and whether it is more or less than planned. One of the challenges with this model is that against the standard OEE indicators, the energy indicator can be more than 100%. The reason is that if the production line is using less energy than planned, then the calculation of the energy indicator will be more than 100% (see

Figure 20 as an example).

One idea that emerged from the interviews is that the maximum value of energy cannot be higher than 100%; otherwise, a wrong picture of the total OEEE score would arise.

Figure 20: Energy score higher than 100% (Author, 2022)



Giving this number for the energy score likewise provided the interviewees with the notion that if the number is below 100%, then the production line is running in a less sustainable manner than expected. With this information becoming available in the dashboards, the interviewees obtained clarity regarding the potential steering on the sustainability outcome of the production line. Furthermore, the interviewees indicated that they could disable machines when they are not used or explore any ensuing problems with the machines; more importantly, they could gain insights into the current baseline of their production line and the scenarios that had never occurred before the implementation of the sustainable digital twin.

Interviewee 1 mentioned a concern about the calculation of the CO_2 outcome of the production line: "There is no world standard for calculating one kWh to CO_2." In this study, a standard calculation model was employed to calculate CO_2 emissions in combination with the kWh consumption of the machines (United States Environmental Protection Agency, 2022). The interviewee cited the different calculation models used for transforming the kWh energy to CO_2 emissions throughout the world. Hence, addressing this discrepancy to properly compare production lines is necessary. Another example of how the CO_2 calculation can be incorrect is the manner in which the energy is bought by the factory. If the factory buys energy from a coal-powered energy plant, then the CO_2 emission output per kWh is much higher than buying renewable energy from windmills or solar parks. As this information was not collected by the researcher in the experiment, it requires attention in further research.

4.2.2 Digital twins used for real-time control in manufacturing will reduce energy consumption

In the dashboard of the sustainable digital twin, an energy forecast for the coming five days becomes available. Based on the historical data, the digital twin predicts the amount of energy that will be used for the production line. For experiment interviewee 2, "Predictability with regard to energy consumption is good because with it you can also make plans to minimize or reverse energy consumption." One of the business scenarios that the interviewees envisaged involves buying the energy in advance for a lower price if a factory realizes that it needs more energy in the coming days for the production line. This approach can positively impact the operational costs especially in these times of rising energy prices. Another use case that the interviewees mentioned pertains to the utilization of more energy in the production line, which can also indicate functionality issues with one of the machines in the production line. In the sustainable digital twin demonstration, an anomaly detection algorithm was similarly created, which is capable of checking any unpredictable energy usages in the production line, thereby denoting issues with a machine. All the interviewees stated that this function within the digital twin has a significant business value, although none of them presently use it.

4.2.3 The 3D visualization of a sustainable digital twin works for the improved use of the technology

The sustainable digital twin in the experiment likewise featured an interactive 3D visualization of a production line. One of the goals of the experiment was to verify if 3D visualization had any added value for factory employees. For experiment interviewee 1, "The 3D model can light up the operator's screen when there is a problem somewhere, [prompting him to] immediately know where to look." All the interviewees were enthusiastic about the possibilities of displaying sustainability data and the standard OEE in a 3D environment. The factory employees, when they receive an alarm for using an excessive amount of energy, can easily see the specific area in the production line that triggered the alarm. According to the interviewees, this situation can be much more challenging in the current screens where they simply see a list of alarms, without any visualization of the area in the production line where the problem occurs. An interactive 3D visualization can accelerate the process of solving potential problems and ensuring that the production line runs, especially in cases where only a few operators are working on the production line.

The 3D visualization also offers an attractive overview of all the data related to the production line. With regard to the 3D view, Interviewee 7 noted, "A lot of that is because stuff is buried in various different systems and then someone inevitably grabs some stuff in a spreadsheet and then manipulates it to tell the story that he wants to tell, which is not the way to run a business." In most of the cases, data are scattered around systems and thus cause difficulty in creating an objective sustainability story to the management of the factory; even people can manipulate those data to make the objective story even better. With this tested 3D dashboard, an objective story can be told by the operator in an attractive manner, but such story is based on the integrated data of the production line in the factory, without the chance to manipulate the data, because the sustainable digital twin is an exact virtual copy of the real production line.

4.3 Conclusion of the results

Sustainability is high on the agenda for every factory, which is both partly driven by the government and driven by factories that intend to become more sustainable entities in society. At the factories of the interviewees, no sustainability numbers are measured at the detailed level of the factory. The main meter is normally used for measuring the power or gas that is utilized in the factory, but not at a detailed level.

The interviewees do not provide an overlaying definition of digital twin. Most of them understand the meaning of digital twin at a high level, but they have difficulty in explaining its characteristics. All of them acknowledge the benefits of digital twin technology in their factories, of which the monitoring of the production line is the most essential one. Digital twin technology is used at the factory of only one interviewee, in which the implementation of the technology has merely started. Even without digital twin technology, one of the major challenges is the sharing of data of a production line within a factory. This aspect is a key characteristic of digital twin technology, whereby the data of machines will be synchronized with the physical and virtual assets of the factory. None of the interviewees are aware of any standardized data model for exchanging data between suppliers and the digital twin.

In the quasi-experiment, the three propositions are tested with the building of a digital twin solution. In this digital twin solution, the OEEE framework is tested with the interviewees (Glova, 2012). The interviewees recognize the direct advantage of using this new framework, in addition to the usage of their existing OEE framework (de Ron & Rooda, 2006). This new energy measurement allows them to directly acquire real-time insights into the energy usage of the entire production line (i.e., between the expected energy usage and real energy usage). The data could be used for informing the worker on the production line or the factory manager. As the energy measurement an addition to the framework that every factory is using, its implementation is simple. The energy usage numbers provide factories with other possibilities to reduce energy. In the experiment, an algorithm was built to predict future energy needs (refer to Section 3.3), therefore offering the factory the possibility to produce fewer products when prices are high in the market. An important element of sustainability is the need for machines that produce the products to operate and be efficient. In the experiment, an algorithm was built to investigate the anomalies of machines. These anomalies could indicate problems with the machines, and such aspect proved useful for the interviewees. The factory could send the data to the manufacturing of the machine or own maintenance department for further investigation.

An essential element of the implementation of digital twin technology is showing it in a useful manner. In the experiment, a 3D dashboard was built that displays the data within the digital twin. The dashboard was a virtual copy of a production line with datapoints from several machines. It demonstrated in real time the OEEE numbers, and factory employees could directly identify the problems in specific areas of the line. The dashboard would help factory workers to rapidly resolve problems with fewer people on the production line.

In Table 15, the three propositions are described with the summary of the results based on the interviews and the quasi-experiment.

Table 15: Results of the propositions

Design proposition	Results
Digital twins that are used for real-time control in manufacturing will reduce energy consumption.	Certain algorithms have been developed to optimize the energy usage of the production line. The interviewees have expressed optimism about the possibilities to reduce energy. However, controlling the machine in this experiment in real time was not possible due to regulations and restrictions on access to factories. Thus, further research is needed to test this proposition even better.
Including an extra "E" for energy in OEE in a digital twin will generate sustainability insights.	All the interviewees believe that including OEEE in their existing performance framework will yield additional sustainability insights, thus allowing the steering on the energy consumption of the production line. The challenging aspects of the implementation include the diversity of emission calculation methods that are used per country and the acquisition of energy data from the machines.
The 3D visualization of a sustainable digital twin contributes to the improved use of the technology.	The interviewees are enthusiastic about the usage and possibilities of the 3D visualization based on the production line. According to the interviewees, the 3D dashboard will help with the use of this new technology in the factory. A proper user design research needs to be executed to investigate if 3D will help with a better implementation of technology.

5. Discussion

In the literature review about the research topic, the number of academic papers found was limited because this area is a new, emerging one. In this chapter, the results of the interviews and three tested propositions are discussed with the literature.

5.1 Sustainability real-time insights as an added value

All the interviewees underscore the importance of sustainability for their factories. Although insights into the detailed sustainability figures as a factory are yet to be obtained, they are highly essential to save energy in specific areas. This result differs from the theory that has been reviewed (ICE, 2022; Manufuture High-Level Group, 2018). For compliance, governments currently focus on the summary report of the entire company instead of on a factory or even a production line (Murphy & McGrath, 2013). If the sustainability numbers in the report are ultimately correct, then the government becomes pleased. This aspect is probably one of the direct reasons for the lack of any drive to steer the production line in factories based on the sustainability numbers.

Based on the interviews, the OEE method is currently the main performance measurement method within every factory. This result also underpins the literature. All the interviewees use this method in their factories, sometimes in real time, at other times after several hours. In the researched literature, Jozef Glova extended the OEE method by including an extra “E” for energy, and the method was subsequently denoted as OEEE (Ing. Jozef Glova, 2012). Energy is indeed an important element for sustainability, especially in the current period with the war between Russia and Ukraine, causing high energy prices for factories (Reynolds, 2022). Reducing the energy usage in factories will directly result in lower operational costs and less emissions. However, the OEEE method is only advocated on paper (Ing. Jozef Glova, 2012). In the experiment of the present research, this new method began to work with factory data and feedback from factory employees and with the building of a digital twin solution (refer to Section 3.3). In the aforesaid experiment, the proposition “Including an extra ‘E’ for energy in OEE in a digital twin will generate additional sustainability insights” was tested during the experiment interviews; the results confirmed that the new OEEE framework works in practice (Ing. Jozef Glova, 2012). All the interviewees were highly enthusiastic that this framework would work in their own factories to steer more toward sustainability outcomes, resulting in a lower energy price.

The OEEE framework is also straightforward in terms of its incorporation into the current OEE process of a factory if the energy data are available from the machines, as explained in Section 4.2.1. The availability of these data for factories likewise creates the possibility to create other applications, aside from the digital twin. The energy monitoring of the digital twin application was mentioned in the experiment interviews, which was similarly found in the literature (Kamble et al., 2022). At the machine level, this application provides real-time insights into the energy usage of every single machine, and based on algorithms, the factories can predict the maintenance need of a machine.

The focus of the literature is on the monitoring of the energy in the factory; however, the experiment in this research shows that many more digital twin applications are possible when the energy production line data are recorded (refer to Section 4.2.1). In the tested proposition ("Digital twins that are used for real-time control in manufacturing will reduce energy consumption"), controlling the digital twin with those data was also deemed to optimize the energy usage for the factory (refer to Section 4.2.2). In the quasi-experiment, a part of the sustainability dashboard was forecasting the energy usage for the production line in the coming days (refer to Section 3.3). The experiment interviewees were enthusiastic about this new possibility due the ability to reduce the production planning during the hours that the kWh usage is high.

5.2 Implementation remains a challenge

A common high-level understanding of the meaning of digital twin technology is evident in the literature and the interviews; however, a major difference between the literature and the interviews is the deeper understanding and characteristics of digital twin technology in the factory. In the literature, the most important characteristic is the synchronization with physical systems or processes, which is related to a virtual replica that the interviewees mentioned (Warke et al., 2021). Nonetheless, the other two main characteristics (i.e., simulation and behavior prediction) are almost not mentioned in the interviews. The reason is that most of the interviewees have yet to implement digital twin technology. However, when a factory implements digital twin technology, the understanding of what a factory can do with digital twin technology is enhanced, thereby improving the technology implementation. This factor is also observed in the experiment interviews when the experiment was tested with the interviewees. As soon as the interviewees saw the experiment in real life, they directly observed other possibilities such as energy monitoring with digital twin technology (refer to Section 4.2). However, this was not mentioned in the literature.

In the literature, information is limited regarding the most effective means of showing digital twin technology to its users because the focus of most of the digital twin use cases is on the background processes and not their primary users. A vital element of the experiment in this research was how to obtain the “face” of the digital twin application for the workers and how this “face” can be an advantage. Therefore, the following proposition was tested: “The 3D visualization of a sustainable digital twin contributes to the improved use of the technology.” The tested 3D visualization of the digital twin solution in the experiment was highly useful for factory employees; according to the interviewees, this process would improve the implementation of this new technology (refer to Section 4.2). One of the principal advantages of the improved implementation of the 3D view for factory employees is that they can identify in one overview the specific problems in the production line. Factories are confronted with the difficulty of hiring new employees due to labor market challenges. With this new technology, fewer people can work on the production line because they can oversee the entire production line on one 3D visualization and thoroughly investigate into the specific machine when a problem occurs.

The TOE framework in Section 2.5 had no mention about how telling a story with the use of data emanating from technology can improve the implementation of the new technology. One interviewee noted that with digital twin technology, everybody can tell a true story about the status of the sustainability of a production line (refer to Section 4.2). This process is undertaken to combine data from several sources (i.e., machine data and ERP systems) in the production line into one digital twin environment that was mentioned in the literature; however, the matter of what kind of technologies most of the factories are working with remains unclear. According to the interviewees, their employees are periodically combining data manually in mainly Microsoft Excel, which can result in unclear overall sustainability reports due to the manual interaction (SustainIT, 2022). The digital twin has that one, fully automatic and real-time overview of (sustainability) data around the factory, but also on a more detailed level such as the production line.

5.1 Technology integration is a challenge in the factory

In his conclusion for the OEEE framework, Glova (2012) mentioned the challenge of obtaining energy data from older machines in factories. In the experiment of the present research, obtaining machine data from factories was likewise challenging due to the regulations and restrictions on access to those data. As the interviewees indicated, their factories use a mix of old and new machines in the production lines, and this case underlines Glova's theory that the acquisition of data is difficult. Aside from machine data, other data such as ERP data are difficult to obtain from factories. The reason for such difficulty is twofold: regulations and integration (i.e., highly complex). Most of the factories utilize closed systems from which data are difficult to obtain, especially context driven data. The implementation of a standardized data model for exchanging data between systems is highlighted in the literature (Jacoby & Usländer, 2020). Interestingly, this topic was not mentioned in the interviews. Although the interviewees understand the challenges of data integration and acquisition of data from machines, they did not talk about possible solutions (i.e., digital twin definition language) that can help facilitate the implementation of those solutions (refer to Section 2.2). The quasi-experiment in this research underscores the critical importance of those standards to drive the success of digital twin implementation. The suppliers of digital twin solutions in the sector indeed focus on standardized data models to drive the improved implementation of the technology; by contrast, their clients' stance on such standardization remains ambiguous (Microsoft, 2021). This standardization is key to the effective implementation of digital twin technology, such that the machines can "talk" not only with each other in a standardized manner but also with other systems in the factory. The outcomes include improved implementation and the added values of digital twin technology. The value-added benefits of digital twin technology in manufacturing are listed in Table 16.

6. Conclusion, limitations, and recommendations

This chapter comprises four sections. The first section presents the answers to the three sub-questions that are combined with the tested propositions from the quasi experiment (refer to Section 4.2). That follows in the second section where the answer to the research question is described. The third section focuses on the limitations of the research. The recommendations for further research are outlined in the final section of this chapter.

6.1 Answers to the sub-questions

In this section, the three individual sub-questions are answered with input from the interviews and the quasi-experiment that will be followed by answering the main research question.

6.1.1 What is the definition of a digital twin in manufacturing, and what are the characteristics of this technology?

Clear definitions of digital twin technology are found in the literature and in some sectors, including manufacturing. However, the implementation of digital twin technology in manufacturing remains limited, and the possibilities of this technology have yet to be fully explored. The interviewees differ in their definition of digital twin technology. Nonetheless, based on data from the literature, interviews, and the quasi-experiment, the following definition of digital twin technology for manufacturing is developed in this research: "Digital twin in manufacturing monitors, optimizes, and simulates the production processes based on virtual copies of assets, combined with data sources within or outside the borders of the factory".

Several elements of the digital twin need to be implemented in factories to maximize its benefits. The first one is the synchronization of data between physical assets, processes, and systems with their virtual copies in the digital twin. The digital twin has no business value without an up-to-date synchronization because it will be all based on old data.

The second element of the digital twin is the simulation or behavior prediction. Combined with the data synchronization in the digital twin, simulations can be created to test how a production line can run in a more sustainable manner without directly undertaking this step in the production systems. Factories can simulate new processes in the digital world without investing in the physical world; thus, not change expensive machines without knowing in front if it runs in a more sustainable way or not.

The third element of the digital twin is the visualization for humans (however, this component is not mentioned in the literature). The quasi-experiment reveals the importance of the digital twin "face": a digital twin with a "face" adds value to factory employees due to a simplistic overview. This aspect also helps to boost the understanding of the business value of the digital twin, thereby facilitating the implementation of this new technology on the factory floor or in the management room. Furthermore, it gives a "face" to data emanating from several sources (i.e., machines, sustainability data, ERP data, and external partners' data) and simplifies these data in a context-driven 3D dashboard.

Based on the interviews and the quasi-experiment, the added values of digital twin technology are presented in Table 16. These added values can help with explaining the benefits of digital twin to factories.

Table 16: Added values of digital twin technology in a factory

Added value	Description
Real-time remote monitoring of the production lines	This added value pertains to the possibility to run production lines with remote operators. With monitoring, the factory also obtains real-time insights into the present conditions of a production line and subsequently steers better.
One place, one truth	Provides the factory with a true story of the occurrences in the production line for internal and government reporting purposes.
Collaboration with partners and ecosystems	The data sit in the virtual copy of the production line, thus facilitating their integration with partners or ecosystems.
Simulation for more efficient production lines	In the virtual replica of the digital twin, the factory can test against low costs with a simulation of how the line can become more efficient.
Real-time OEEE for insights into sustainability	Steering on a more sustainable production line provides production line workers with more influence on sustainability.
Data-driven decision-making	This added value pertains to the ability to make decisions on data from the production lines.

Visualization of production line processes	This added value gives both workers and management the ability to understand how the production line process works via visualization.
Predictive maintenance	It denotes a shorter downtime of production lines due to the maintenance of machines before they break down.

6.1.2 What are the frameworks for obtaining sustainability insights and benefits from digital twin technology in manufacturing?

During the literature research, only three existing frameworks were found; the frameworks are focused on sustainability, specifically sustainability in the manufacturing sector. The emphasis of one framework is on digital twin and sustainability; hence, the model is referred to as the sustainability digital twin framework (He & Bai, 2021). The other two frameworks are centered on sustainability in manufacturing, but not combined with digital twin technology. These frameworks are instead combined with the existing performance management systems of factories (de Ron & Rooda, 2006). One of the frameworks, OEEE, is based on the major frameworks that is used in manufacturing; however, it has yet to be tested with digital twin technology. In the quasi-experiment of this research, this new framework was successfully tested with proposition number two (refer to Section 4.2). None of the interviewees use their existing frameworks to gain insights into sustainability with digital twin technology in manufacturing. They also have no existing frameworks for sustainability insights without digital twin technology, especially not focused on the factory.

6.1.3 What elements are required for the successful implementation of digital twin technology in manufacturing, which will result in higher sustainability?

The successful implementation of digital twin technology in a factory requires several elements. These elements are listed and grouped by perspective in Table 17.

Table 17: Requisite elements of the successful implementation of digital twin technology

Context	Element
Technology	Standardized data models
Technology	Access to real-time (machine) data
Organization	Strategy
Organization	Governance
Organization	Knowledge about possibilities
Environment	Easy-to-explain sustainability digital twin story

From a technology context, several elements are needed to start the implementation of digital twin technology in manufacturing, like mentioned in the TOE framework (refer to Section 2.5). The TOE framework mention that incremental innovations will have the least amount of change in organizations. Digital Twin is an incremental change, because it builds up on existing technology that factories already have but combine them together into one virtual replica. But this research indicates that combining those existing systems together is a big technology implementation change. Based on the initial interviews, but especially the quasi-experiment, the most important element for a technology implementation is the agreement on data models (refer to Section 5.1). The digital twin requires real-time data from machines and other data sources. Hence, the efficient sharing of data on a standardized model is strongly needed; otherwise, the implementation costs will become excessively high. Different vendors are busy with creating a standardized data model. One example is the digital twin Definition Language, in which vendors agree on how certain elements in the digital twin are standardized, such as temperature and energy (Microsoft, 2021). This model facilitates the implementation of a digital twin because the factory can directly focus on the business value and not worry about data standardization and integration.

Another perspective that is required for the successful implementation of digital twin technology in the factory pertains to a clear business strategy and governance. Only a few interviewees could clarify the types of applications that are useable with digital twin technology. However, most of them could explain that monitoring is an important application and that many other applications will add significant business value to the factory. Knowing these different applications will help the wider implementation, especially on the investment side, of digital twin technology.

The final perspective that is critical for technology implementation in the factory concerns the face of the digital twin. In the quasi-experiment, proposition number three was used to test with creating a 3D dashboard of the entire production line. In the experiment interviews, the feedback was that this dashboard can help with the implementation of this type of new technology in the production line. The 3D dashboard also offers a clear understanding and overview of the digital twin with the latest information over the whole production line.

6.2 Answer to the main research question

In this section, the answer to the main research question is provided:" How can digital twin technology be used in factories to improve sustainability insights?".

The results of this design science research show that through digital twin technology and the OEEE framework for measuring the energy usage of a production line, factories can benefit in terms of improving their sustainability insights (refer to Section 5.1). With the use of digital twin technology, all the energy data collected from machines can be combined into the virtual replica of the production line in the factory. With this virtual replica, the factory acquires insights into the conditions and sustainability status of the production line, as shown in the quasi-experiment (refer to Section 4.2). Factories can benefit from these sustainability insights into the production line by gaining inputs for the sustainability reporting (the so-called ESG reporting) that the government requires (Murphy & McGrath, 2013).

These sustainability insights can also be beneficial, in that energy data can be used for executing simulations to enhance the efficiency of the factory and to save energy without making physical changes in the factory (Bangsow, 2016). Changing the physical process and machine settings is excessively costly for factories; simulations can help in this regard, thereby enabling the factory to virtually perform those changes in the digital twin before executing the changes in the physical world. Another advantage is the use of energy data for predicting the energy usage in the production line depending on the products that are manufactured. With this prediction, factories can reduce their energy price, and they can produce more products when the energy price is low.

6.3 Limitations of the research

The limitations of this research are outlined in this section. The frameworks used in this research constitute a limitation due to the inadequate amount of scientific literature on sustainability and performance management systems combined with digital twin technology (see Chapter 2). Nonetheless, a sufficient amount of literature is found in this research, hence allowing the identification and examination of connections between the different topics and the testing of the propositions to provide valuable input to the knowledge base. The full list of research limitations is shown below.

(1) The focus of the quasi-experiment was solely on one production line of a factory. This limitation was due to the constraint of accessing factories within the timeframe for this research. Nevertheless, the selected production line data were representative of a normal production line in food manufacturing.

(2) The researcher was unable to interview the respondents from all types of factories in the manufacturing sector. Every factory has its own agenda on sustainability; however, only five types of factories were featured in this research, which mainly focused on Europe and with international digital twin suppliers.

(3) Another limitation pertained to the impossibility of accessing available real-time data from the factory and control machines to test the experiment in the factory itself. This limitation was due to restrictions on access to the factory and ICT systems. A time-series data copy was made to showcase the data in the quasi-experiment to the interviewees. Although showing real-time data from the factory was not needed for the experiment, such data play an important role in digital twin technology. This limitation is also typical for research involving only one experiment.

(4) The 3D model used in the quasi-experiment was not obtained from a factory that was covered in this research; a sample model was instead utilized. Furthermore, the factories included in the research had no available 3D model of their production line, particularly a 3D model that is sharable. The 3D model used in the experiment had a similarity to the production line sample data.

(5) Only one experiment with data from one factory was executed in this research. If this experiment was executed more than once with other factory datapoints, other recommendations could have been provided in this research.

6.4 Recommendations for further scientific research

The literature on the relationship between digital twin technology, performance management systems, and sustainability is lacking, thereby leaving room for further research on these topics. In response to this gap in the literature, several recommendations are proposed in this research.

From the technology perspective, integration and data exchange are some of the key challenges for implementing digital twin technology in the factory. As this research indicates, numerous vendors are busy with creating their own standards to exchange data in a standardized manner (Microsoft, 2021). A better approach would be the development of data standards by the industry. Therefore, an investigation into the types of standards that are currently used in the industry and the areas requiring the governance of manufacturing standards would be recommended.

From the perspective of factories, this research shows that at the production line level, digital twin technology can help factories to gain sustainable insights integrated with existing performance management systems. This awareness could improve the ESG reporting that every company needs to conduct in compliance with government regulations (Murphy & McGrath, 2013). ESG reporting is a companywide sustainability reporting tool, and it does not solely relate to production lines in the factory. Meanwhile, at the companywide level, further research is needed to verify if digital twin technology can assist in the provision of more accurate and automated insights into the whole sustainable understanding of a manufacturing company.

Furthermore, the quasi-experiment revealed a focus on 3D visualization, aside from digital twin, to ascertain the benefit of implementing this type of new technology (refer to Section 4.2.3). This viewpoint emerged from the limited responses of factory employees (refer to Table 10). Involving a different type of factory employee in a study on 3D visualization could reveal how this truly supports the implementation and creation of new digital twin applications. Additionally, scientific research on user interaction design will help improve the understanding of why and how users will accept these types of 3D views to implement digital twin technology.

Finally, digital twin technology can be complex for implementations (refer to Section 5.2). Such complexity relates to all kinds of topics such as technology, business, and user acceptance. Complexity in technology can also result in the expensive implementations of technologies. Therefore, the recommendation is to examine the forms of investments that are needed for a factory and to determine if such investments provide sufficient advantages to reach its goals (i.e., costs versus benefits).

6.5 Management recommendation

The acceptance of digital twin technology starts with its understanding in manufacturing. In the manufacturing sector, the meaning of digital twin and its benefits are depicted in various ways. Therefore, digital twin technology should gain more "fame" in the sector, especially the sustainable benefits that this technology can bring to production lines and entire factories. The recommendation is to share more public information about the work that the digital twin Consortium is performing with the manufacturing sector to enhance the understanding of the benefits of digital twin technology (Digital Twin Consortium, 2019).

This research showed that data models and standards are important for an implementation of digital twin technology within the manufacturing sector. Recommendation for manufacturing companies is that when they buy new machines for their factories ensure to meet the same data models and standards. This will help them to connect the machines on a standardized way and focus on the business value of digital twin technology.

6.6 Building the artifact

A time-consuming part of this research was technically building the artifact, a digital twin solution, with a focus on sustainability, which could be used in the quasi-experiment interviews (refer to Section 3.3). First, building this solution was challenging, particularly in the aspect of acquiring machine data from the factory within the short timeframe of this research to eventually create a virtual replica of a machine. Therefore, a copy machine data set was used for running the quasi-experiment due to regulations, but especially timeframe challenges. Second, in the data modelling process, the received data were not in a format that could directly be used in Digital twin technology and needed manipulation to load into the virtual replica of the digital twin. Third, the addition of any 3D dashboards to the production line for the quasi-experiment was not possible. Thus, the experiment interviews were created to showcase the 3D dashboard via an experiment interview.

Furthermore, a considerable amount of coding was needed to integrate the simulated data streams into the digital twin before a 3D dashboard could be created. Microsoft released in during the research a new preview software of Microsoft 3D Scenes Studio, a piece of software in which the 3D dashboards of the production line could be created without any coding (Microsoft, 2022).

The full building of the artifact is described via a logbook (see Appendix B). The artifact is open sourced and documented by the researcher, and it can be used by other researchers or factories to further build with this digital twin technology (Ploeg, 2022c).

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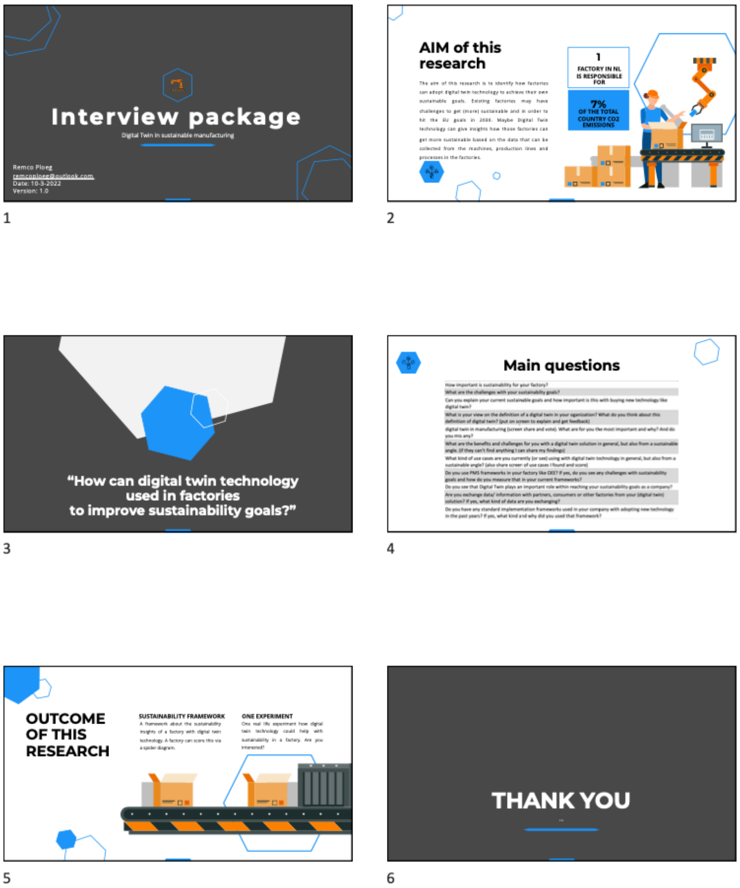
Appendix A: Interview package

The interview package slides that have been shared with the interviewees are presented in Figure 21. Slide 1 is the introduction of the researcher. Slide 2 outlines the aim of this research and Slide 3 lists the research questions. Slide 4 shows a summary of the interviewee questions. Finally, Slide 5 provides the outcome of the research.

Figure 21: Interview package



Appendix B: Logbook of building the digital twin solution

In Table 18, the logbook of building the digital twin solution is described in detail.

Table 18: Logbook of building the digital twin solution

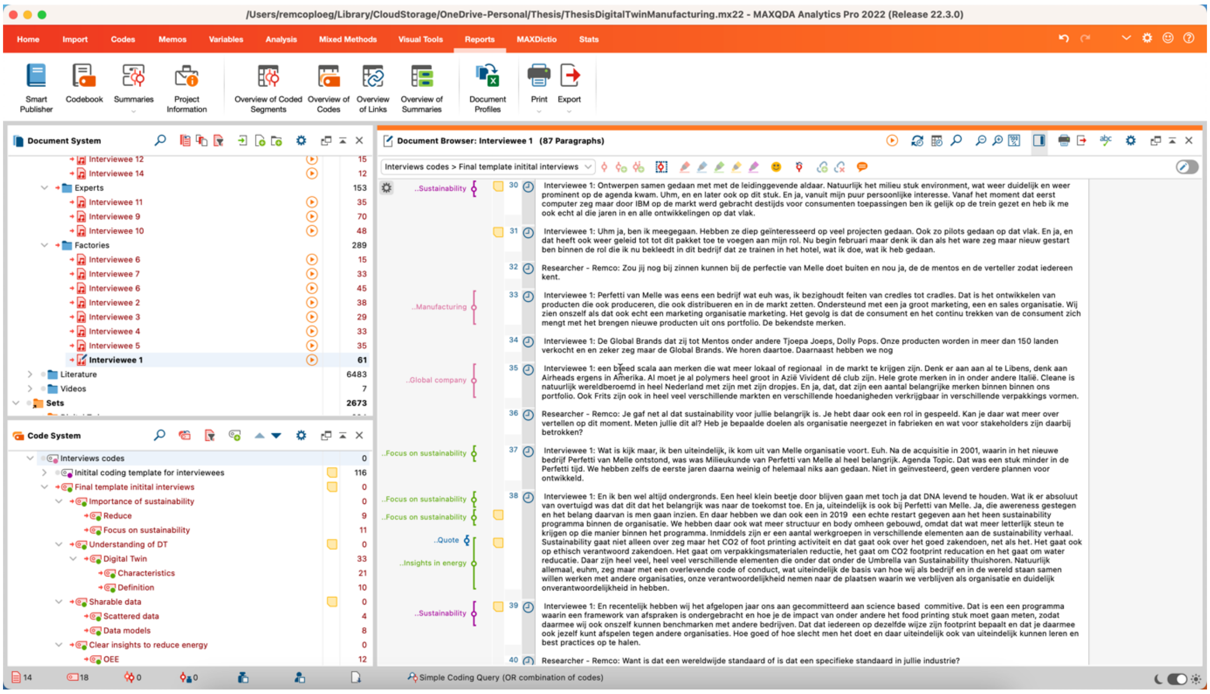
Date	Description
16-04-2022	Created the first blank project for my thesis
17-04-2022	Found an example that I can use for the OEE calculation that I can extend to OEEE
21-04-2022–24-04-2022	Created the blank technical environment with IoT Central, Azure Digital Twins, Azure Data Explorer, and more (see the installation documentation)
23-04-2022	Published the first release of the project to GitHub on 27-04-2022
	Found a sample simulator that I can reuse to send data to the digital twin
04-05-2022–08-05-2022	Set up the GitHub documentation and README file to share the documentation
12-05-2022	Created a function with Sander between IoT Central and Azure Digital Twin; all the fields are exporting to ADT
13-05-2022–15-05-2022	Configured machine templates in IoT Central with sustainability data; created a dashboard in IoT Central to display the raw data
18-05-2022	Found a great food packaging line 3D file to use in this thesis
19-05-2022	Set up the simulators to send data based on the production line
20-05-2022	Created the ontology for the digital twin in ADT based on the production line
21-05-2022	Created the first video of the demo solution to share with the professor
22-05-2022	Changed the OEE dashboard (columns + dashboard) to also display the kWh usage of the motors of the production line; the current solution has no kWh
23-05-2022–26-05-2022	Started with the documentation of the configuration manual

01-06-2022	Added the calculations of the E to the dashboard
	Added the 3D scenes changes with the extra E
	Updated the documentation of the installation steps
02-06-2022	Added documentation around the configuration of ADT
	Added documentation about the simulator
	Changed the main page with links to all the individual components' pages
	Added a logbook link
09-08-2022	Added a link to the full YouTube video of the experiment: https://www.youtube.com/watch?v=BS9UeIwKyzI

Appendix C: MAXQDA details

Maxqda is a tool where data like literature and interviews transcripts can be analyzed. All the literature, transcripts and coding system of this research is embedded in this tool as can been seen in Figure 22. The complete Maxqda file can be requested at the researcher.

Figure 22: Maxqda screenshot of research



Appendix D: Coding template interviews

In Table 19 the evolution of the coding template is described.

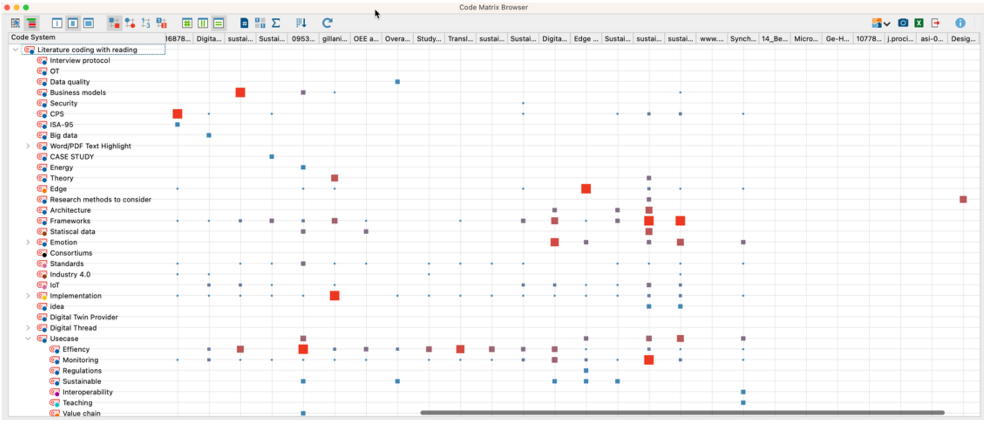
Table 19: Evolution of the coding template interviews

A-priori topics	Description	First template (transcripts 1–2)	Final template (rest of the transcripts)
Importance of sustainability	How important is the topic of sustainability for the factories? Are they already implementing solutions for this purpose?	- Sustainability - Focus - Implementation	- Focus - Reduction
Understanding of the definition of digital twin	What is the interviewees' definition of digital twin technology?	- Definition - Use cases - Characteristics	- Definition - Characteristics
Sharable data	How important is the sharing of data? Do they recognize any challenges?	- Challenges - Scattered data - Data models - Investment	- Scattered data - Data models
Clear insights into the reduction of energy	Do the interviewees already have insights into energy consumption and the ways of reducing it?	- OEE - Measurement - Consumption	- OEE - Insights into energy
Digital twin applications	What types of digital twin applications are already used (or contemplated) by the interviewees?	- Efficiency - Maintenance - Simulation - Quality - Inspection	- Monitoring - Efficiency - Simulation - Partners

Appendix E: Coding analyses literature

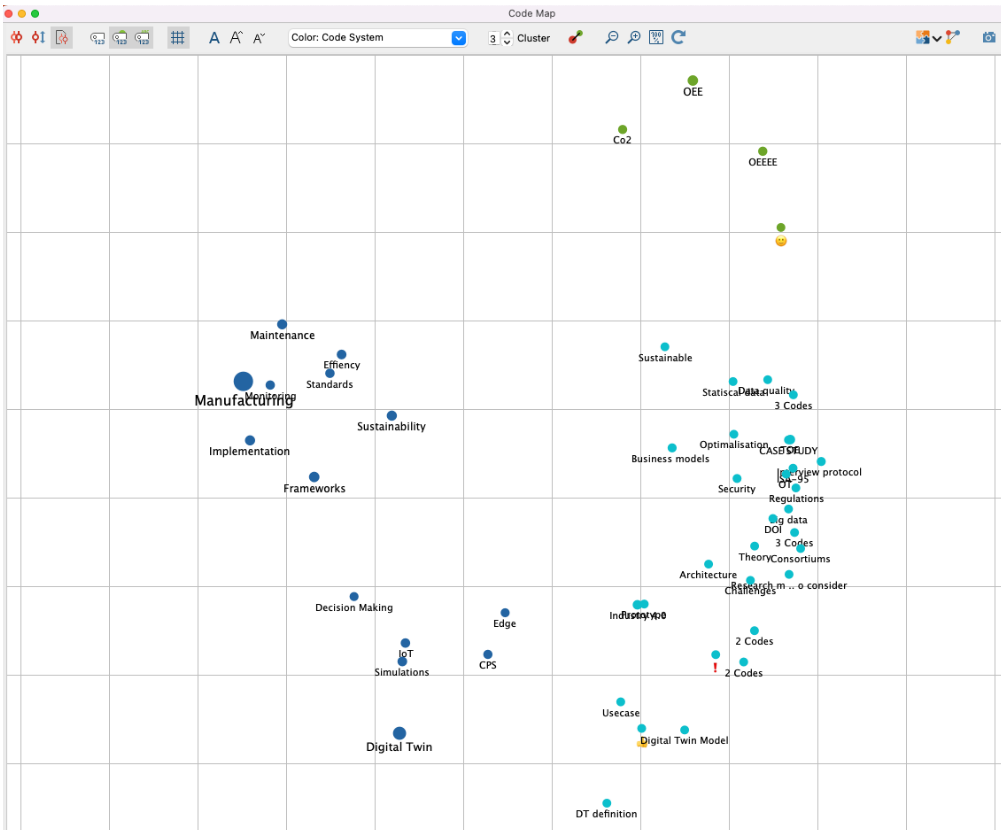
The analyses of codes with the literature that was used for this research are shown in Figure 23 (*Maxqda*, 2022).

Figure 23: Codes related to the literature



A clustered code map of the literature is depicted in Figure 24 that is used for topics in the literature.

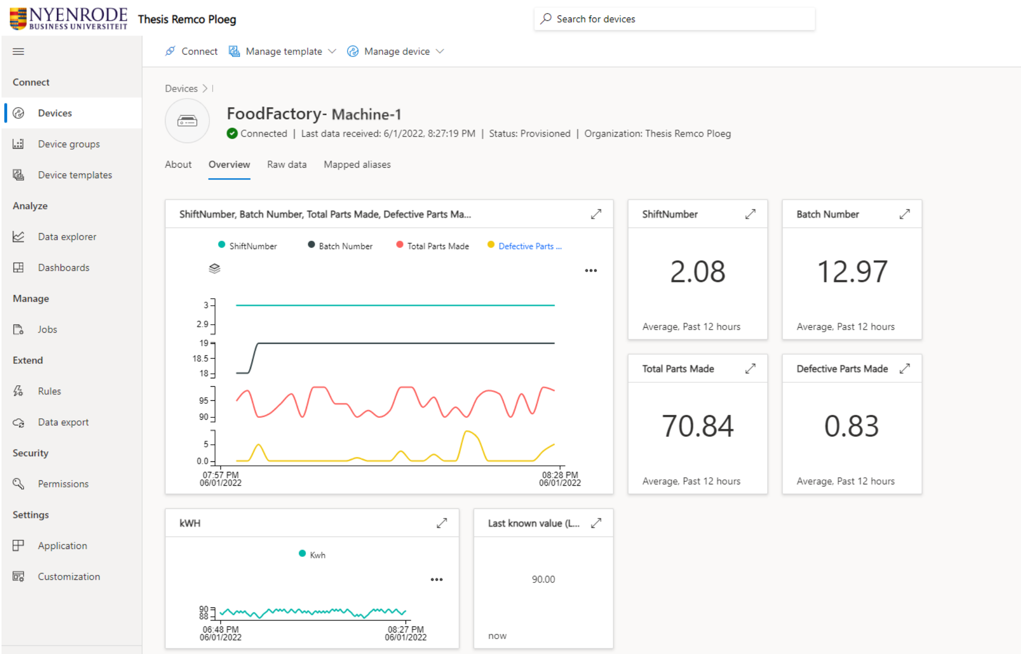
Figure 24: Clustered code map of the literature



Appendix F: Screenshots of the quasi-experiment

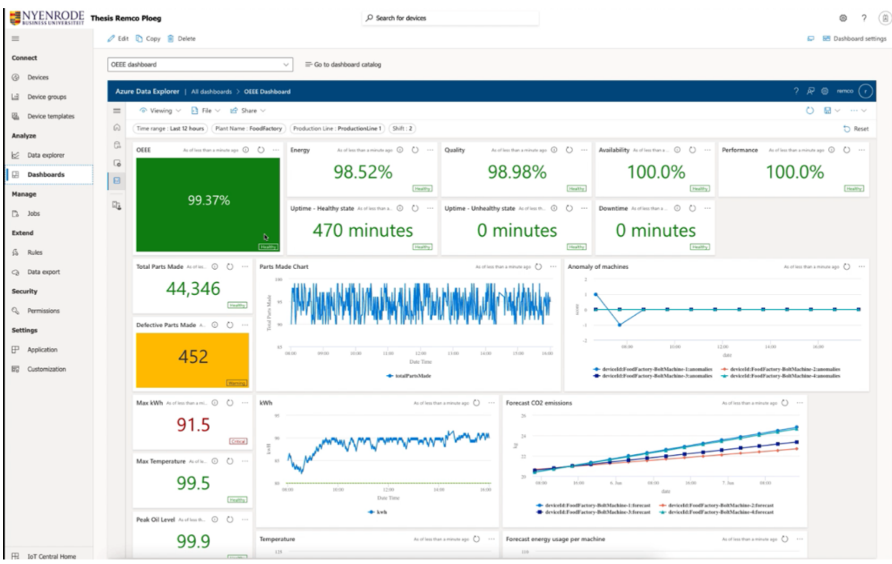
In this section, the screenshots of the experiment are collected. A full video of the experiment is uploaded on YouTube (Ploeg, 2022c). In Figure 25, the raw data of the machines are shown in a simple dashboard.

Figure 25: Azure IoT Central dashboard with the raw sensor data (Author, 2022)



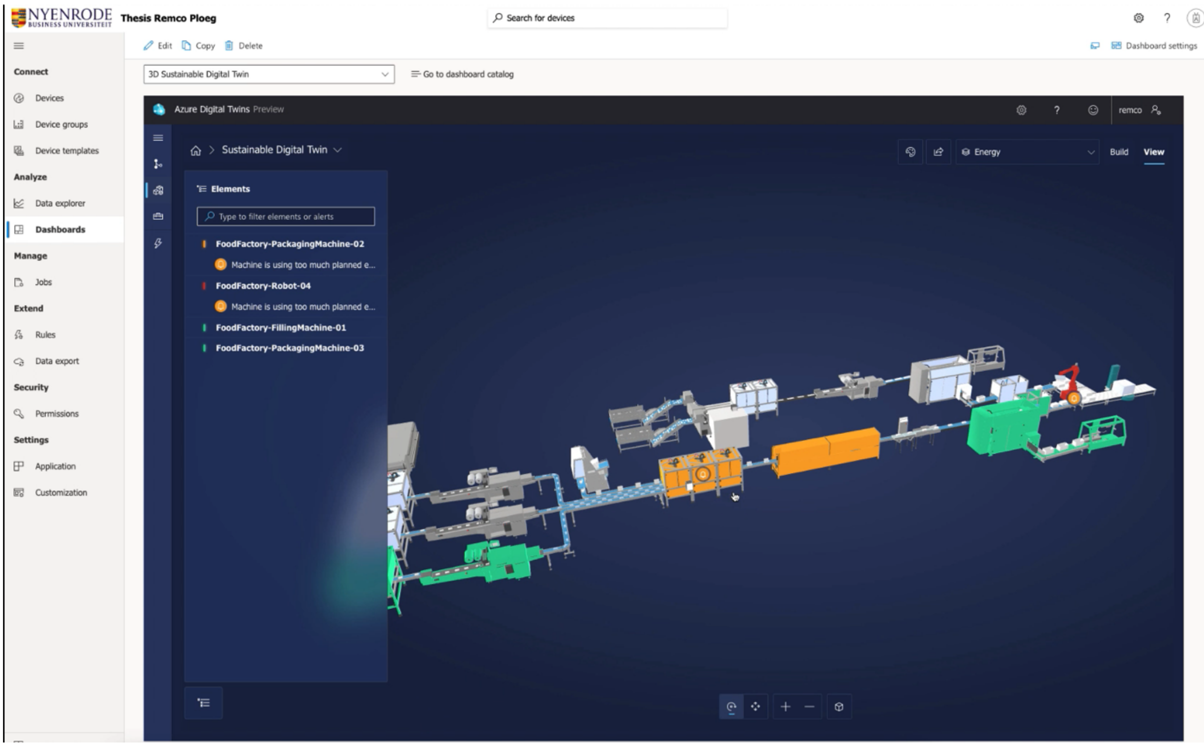
The OEEE dashboard of the experiment is illustrated in Figure 26. In this dashboard, all the key performance indicators and sustainability data are presented.

Figure 26: OEEE dashboard in the experiment (Author, 2022)



The 3D model of the sustainable digital twin is shown in Figure 27. The colors of the machines depend on the energy usage of every machine. An orange color, as in this example, indicates that the machines are using more energy than planned.

Figure 27: 3D digital twin dashboard (Author, 2022)



A full video of the experiment can be found here:
https://www.youtube.com/watch?v=BS9UeIwKyzI

Appendix G: Detailed technical architecture of the experiment

The whole technical architecture and installation steps of the digital twin application are recorded on a GitHub repository (Ploeg, 2022b). In Figure 28, the first page of the GitHub repository is displayed.

Figure 28: First page of the GitHub repository of the researcher

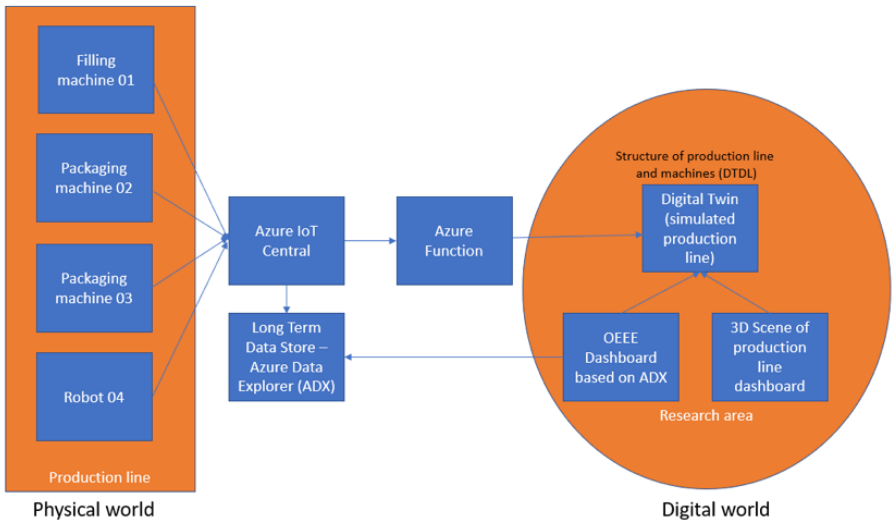
Thesis Digital Twin and sustainability in manufacturing

Welcome! This repo describes the installation and configuration of the sustainable digital twin used for my thesis. Please contact me if you have any questions!

All the steps that I have taken are noted here in my logbook.

High Level Architecture

Below you can see the high level architecture of the sustainable digital twin



1. Machines in productionline - are simulators of machine data
2. Azure IoT Central is used to receive the raw machine data
3. Azure Data Explorer is used for long term storage and machine learning (forecast energy and anomaly)
4. Azure Digital Twins for latest data points of machine and placing it in the context of the production line
5. Azure Functions sends data from Azure IoT Central to Azure Digital Twins
6. Azure Digital Twins 3D scenes is used to create the 3D view of the sustainable digital twin
7. OEEE dashboard is created on Azure Data Explorer to calculate the OEEE and showcase the forecasts of energy and problems in the production line

Installation of base infrastructuur

On the following page you can find the installation of the Azure components used in the sustainable digital twin
https://github.com/rploeg/thesisdigitaltwinsustainability/blob/main/documentation/install.md

Appendix H: Standard OEE dashboard

A standard OEE report is shown in Figure 29; it is commonly used in factories worldwide.

Figure 29: OEE dashboard (Lauzier, 2022)