HUNGARIAN UNIVERSITY OF
AGRICULTURE AND LIFE SCIENCES

DOCTORAL (PhD) THESES

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HUNGARIAN UNIVERSITY OF
AGRICULTURE AND LIFE SCIENCES
KAPOSVÁR CAMPUS

2023

HUNGARIAN UNIVERSITY OF

AGRICULTURE AND LIFE SCIENCES

KAPOSVÁR CAMPUS

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IMPLEMENTATION AND BENEFITS OF DIGITAL TWIN ON DECISION MAKING AND DATA QUALITY MANAGEMENT

Written by

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2023

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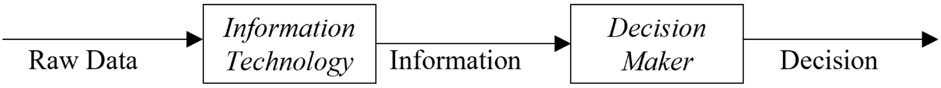
1 INTRODUCTION

"By 2021, half of large industrial companies will use digital twins, resulting in those organizations gaining a 10% improvement in effectiveness."(Gartner, 2017b)

Digital transformation is becoming a very important issue, and companies that are not able to adapt to digital transformation will fall victim to "digital Darwinism" (Helmy Ismail et al., 2018). Some companies will disappear, and only the most adaptable that respond to technological trends will survive (Schwartz, 2001). Therefore, digital transformation requires a company to develop a wide range of capabilities that vary in importance depending on the business context and the specific needs of the company (Reis et al., 2018; Stolterman et al., 2004; Yoo et al., 2010). Digital transformation at industrial level began with Industry 4.0, which includes transformation based on the use of cyber-physical systems (CPS) and the support of information and communication technology such as the Internet of Things (IoT), big data, cloud computing and artificial intelligence (AI) (Pires et al., 2019). All of these technologies are based on data, the amount of which will increase from 26 in 2017 to 180 zettabytes by 2025 (Roy et al., 2018; Vassakis et al., 2018). The quality of this data directly determines the value of these technologies as well as the quality of decisions (Pavlovich et al., 2020). For the implementation of Industry 4.0, CPS are the backbones that support the creation of a network of components with cyber and physical counterparts capable of making decentralized and autonomous decisions (E. Lee, 2008). The design principles for Industry 4.0 serve as guidelines for implementation and include decentralization, interoperability, virtualization, real-time capability, service orientation, and modularity (Pires et al., 2019). An important role is played by virtualization concepts. These are virtual copies of physical systems, creating a link between real and virtual systems (Hermann et al., 2015). The concept has evolved into a new technology, namely the digital twin (Rodič, 2017) which has received increasing attention in the development of industrial IoT-platforms (3DS, 2021; GE, 2021; IBM, 2021; Microsoft, 2021; PTC, 2021; SAP, 2021; Siemens, 2021). Digital twins have a critical role to play in the evolution of Industry 4.0, and this has been confirmed by Gartner’s “hype cycle” (Gartner, 2017a,b). Gartner rated the digital twin as one of the top 10 strategic technology trends for 2017 (Gartner, 2017a), 2018 (Gartner, 2018), 2019 (Gartner, 2019) and 2020 (Gartner, 2020). Indeed, Gartner's 2018 hype cycle predicted that hundreds of millions of objects, machines or systems would have a digital twin by 2023 (Gartner, 2018). For these reasons, the digital twin is critical to the future development of an organization and therefore should be explored. A **digital twin** is a digital representation of an entity that meets the needs of a number of use cases (Platenius-Mohr et al., 2020) through a combination of data, analytics, and visualization of insights to support decision-making (Meierhofer et al., 2020). It can be used to address three high-level priorities in industry: (1) **sustainability**, the reduction of energy consumption, and the development of green alternatives (Biewendt et al., 2020); (2) **smart innovations**, such as smart cars (Blaschke et al., 2021); and (3) health care and safety, for disease diagnosis and treatment, and occupational health and safety concepts (Apte et al., 2021). Digital twins are equipped with technologies such as IoT, BD, cloud computing, and AI that rely on data, the quality of which directly determines the value of these technologies and the quality of the digital twins (Pavlovich et al., 2020). It may be useful to begin by defining a few terms. **Data** is a collection of facts or information from various sources that influence the quality of decision-making (Sulistyo et al., 2020). **Data quality** provides data suitable for use by data consumers (Fürber, 2016). **Data quality management** defines, collects, stores, processes, and manipulates data (Glowalla et al., 2014). In this context, **decision-making** consists of a course of action, action strategy, or goal achievement strategy (Rashidi et al., 2018), where **decision support systems** help managers to understand **unstructured decisions** (Hosack et al., 2012) that cannot be solved with standard procedures (Turban et al., 2007). Here, a **process digital twin**, as a maximum expansion stage of the digital twin, could support unstructured decision-making with end-to-end process digitization (Raj et al., 2020) as **information technology** (Meierhofer et al., 2020) in the input-process-output model shown in Figure 1 (Raghunathan, 1999) to improve **operational effectiveness**.

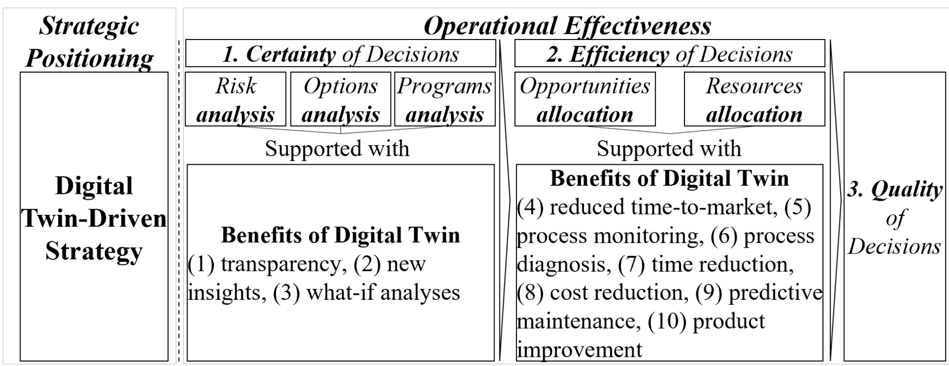
Figure 1: Input-process-output model with the digital twin



Source: Own Figure, derived from Raghunathan, 1999

However, managers should not only pay attention to effectiveness but also to strategic positioning, as strategic and basic management processes are indispensably linked (Sadun et al., 2017). **Strategic positioning** (making decisions) means doing things differently by creating a unique value proposition that is the key competitive opportunity. **Operational effectiveness** (validation and execution) means adopting, acquiring, and extending best practices by doing things increasingly better (Porter, 1996). For strategic positioning, the knowledge of data quality, the digital twin, and decision support across **management levels**, **company sizes** and **industries** is essential for understanding the current state and progress of competitors. For operational effectiveness, leveraging the **benefits** of the digital twin is particularly important. To conclude, the end product of a manager's efforts is a quality decision (Drucker, 1963), where the knowledge of strategic positioning leads to a competitive opportunity as shown in Figure 2.

Figure 2: Model of quality decision-making process with the digital twin

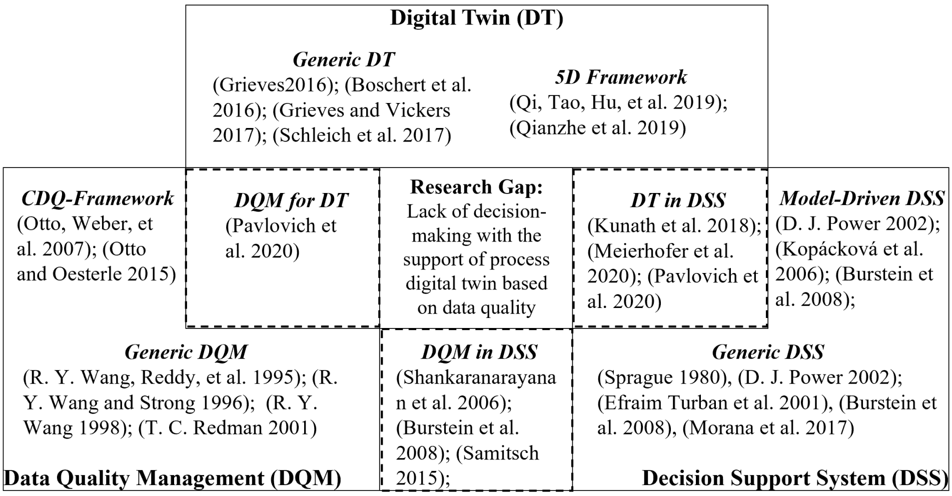


Source: Own Figure, modified and derived from Negulescu et al., 2014

2 OBJECTIVES

Based on the 212 publications, the **research gap**, the **objectives** and the **hypothesis** were derived. In examining the research areas, the focus was primarily on the **overlap** between the research areas, and a *lack of decision-making with the support of process digital twin based on data quality* was identified. Figure 3 illustrates the research gap by showing the main literature and the overlap of each topic with the literature, where available.

Figure 3: Research gap of the dissertation



Source: Own Figure

Here, the process digital twin is a possibility for end-to-end process digitization (Raj et al., 2020). This is a key objective of the digital transformation and thus of Industry 4.0, from which the end-to-end digitization of all physical assets and integration into a digital ecosystem is to be achieved (M.-X. Lee et al., 2017; Reis et al., 2018), making it a worthwhile subject for research. For this reason, the relevant literature, the current state of the art, the terminology, and the conceptual frameworks for possible integration into current industrial applications were reviewed. Emphasis was also placed on, but not limited to, the following **three objectives** from which the hypothesis was derived:

1. *Analysis and determination of differences in data quality, digital twin and decision support in terms of industry, company size and management level for strategic positioning.*

Digital twin technology is becoming one of the most important research directions and promising technologies for the realization of Industry 4.0. It can be used for strategic positioning (decision-making), where managers do things differently by creating a unique value with the digital twin that is the key to competitive opportunity (Porter, 1996). Regarding market growth and thus the value of digital twin, Infiniti Research has estimated a market growth of 24.81 billion USD by 2025 (a compound annual growth rate (CAGR) of 39.48%) (Infiniti, 2021). MarketsandMarkets Research assume a growth from 3.1 billion in 2020 to 48.2 billion USD in 2026 (CAGR of 58%) (MarketsandMarkets, 2020). Prescient & Strategic Intelligence assume a growth from 3.6 billion in 2019 to 73.2 billion USD in 2030 (CAGR of 31.9%) (Prescient et al., 2020). Research and Markets assume a growth from 5.1 billion in 2020 to 115.1 billion USD in 2035 (CAGR of 23.2%) (Research et al., 2020). This proves the importance and value of digital twin technology and explains why it is important to increase efforts in the industry to generate a viable solution (Pires et al., 2019). For the implementation of a DTDDMM, it is therefore important for managers to know the status and progress of the data quality, the digital twin technology, and the decision support of competitors and how these vary depending on **(1) management levels**, **(2) company size** and **(3) industry**. Based on these differences, the manager can then decide whether a DTDDMM also offers a unique value for his own industry and company and whether it is the key to competitive opportunity. The manager can then use these differences to negotiate the importance of the topics with various hierarchical levels. Therefore, **hypothesis 1** is as follows: **There are differences in data quality, a digital twin and decision support in terms of management level, company size and industry**.

2. *Elaboration of the theoretical DTDDMM for industries combining data quality, digital twin and decision-making.*

A theoretical DTDDMM consists of: (1) corporate data quality management, (2) process digital twin and (3) model-driven decision support systems shown in Figure 4.

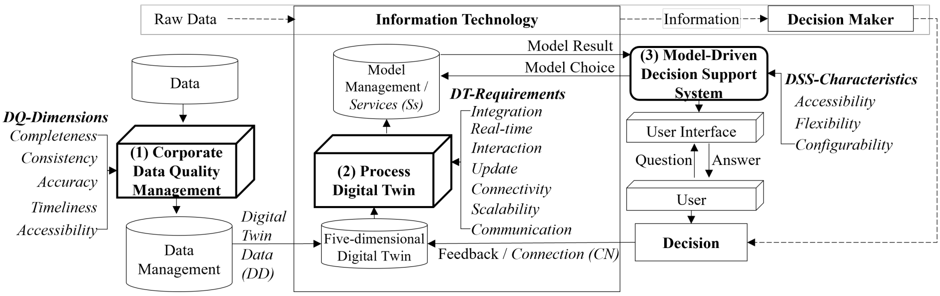


Figure 4: Basics of the digital twin-driven decision-making model

(1) Corporate Data Quality Management: **Data** are a collection of facts or information from various sources that are "dirty" and affect the quality of decision-making in an organization (Sulistyo et al., 2020). These are augmented by **BD**, which are high volume, high velocity, and/or highly varied information assets that require cost-effective, innovative forms of information processing and enable better insight, decision-making, and process automation (Mccarthy et al., 2019). **Data quality** provides data suitable for use by data consumers (Fürber, 2016). Therefore, **data quality management** is a management system for data that ensures high quality and defines, collects, stores, processes, or manipulates data (Glowalla et al., 2014) based on a coherent **corporate data quality management** (Otto et al., 2007). Lünendonk & Hossenfelder have shown that data quality in 155 companies has increased over the last five years. However, 60% of companies still rate their data quality as only average (Zillmann, 2017), although they are aware that poor **data quality** affects efficiency and is an important success criterion. The Harvard Business Review surveyed 75 managers' records to determine data quality levels. On average, 47% of 100 newly created records had at least one critical error, and 3% were considered acceptable only at the loosest standard (Nagle et al., 2017). Digital twins are equipped with technologies like IoT, BD, cloud computing and AI (Pires et al., 2019) and are based on data. Thus, data quality directly determines the value of these technologies: the quality of a digital twin as well as the quality of the ensuing business decisions (Pavlovich et al., 2020). Therefore, **hypothesis 2** is as follows: **Data quality management is a basic**

requirement for a digital twin.

(2) Process Digital Twin: A **digital twin** is a digital representation of an entity that meets the needs of a range of use cases (Platenius-Mohr et al., 2020). It is a combination of data, analytics, and visualization of insights to support decision-making (Meierhofer et al., 2020). A **process digital twin** is an enterprise-level view to measure operational aspects across the enterprise-level view to measure operational aspects across the enterprise with end-to-end visibility to optimize throughput, quality, and process performance. It enables organizations to visualize and simulate alternative approaches to redesigning entire processes (Raj et al., 2020) based on a **five-dimensional digital twin** (Tao et al., 2019b). Since the digital twin can digitize processes end-to-end (Raj et al., 2020), which is a key objective of digital transformation and thus of Industry (M.-X. Lee et al., 2017; Reis et al., 2018), it is very important for strategic positioning and provides a competitive opportunity. So, **hypothesis 3** is as follows: **The implementation of a digital twin is a competitive opportunity.**

(3) Model-Driven Decision Support System: Decisions are defined as choices in a course of action, a strategy of action, or a goal achievement strategy (Rashidi et al., 2018). **Decision support systems** are interactive computer-based systems or subsystems designed to help decision makers use communication technologies, data, documents, knowledge, and/or models to identify and solve problems, complete decision-making tasks, and make decisions (Hosack et al., 2012; Power, 2003) which are **model-driven** (Power, 2002). A process digital twin can be used as a model, supported by technologies such IoT, BD, cloud computing, and AI (Pires et al., 2019) to improve the decision-making process (Meierhofer et al., 2020). It is the **information technology** in the input-process-output model in Figure 1 (Raghunathan, 1999). Therefore, **hypothesis 4** is as follows: **Decision support systems are improved by digital twins.**

3. *Elaboration and analysis of the improvement in operational effectiveness using a digital twin for decision-making, focusing on data quality in a theoretical model.*

To achieve **operational effectiveness** (validation and execution), managers should adopt, acquire and extend best practices by doing things better and better (Porter, 1996). In this context, the **benefits** of a digital twin for decision-making based on data quality can be leveraged. In terms of a digital twin for decision-making, the end product of a manager's work are decisions that are made in business situations in three steps (Drucker, 1963):

1. **Analysis**: Managers need to analyse the facts, such as risks, options and programs, to achieve **certainty**. This can be supported by digital twins.
2. **Allocation**: Managers have to allocate opportunities and resources to achieve **efficiency**. This can be supported by digital twins.
3. **Decision-making**: Managers must base their decisions on the above analysis and allocations to achieve **quality**. This can be supported by digital twins.

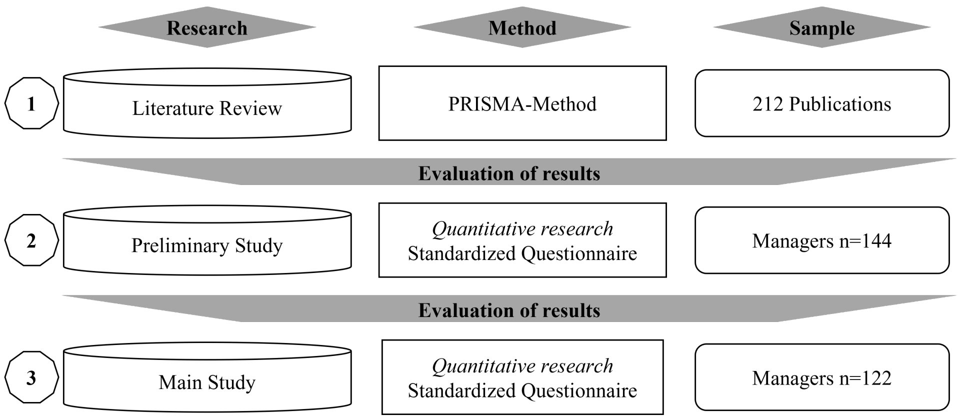
Regarding decision-making, McKinsey & Company conducted a survey of 809 managers called *"Decision Making in the Age of Urgency"*. The results were as follows: 48% of the respondents believed their companies made decisions quickly, 57% of the respondents believed their companies consistently made high-quality decisions, with managers spending 37% of their time on decision-making of which 18.5% was **ineffective**[1] (Aminov, 2019). Therefore, the **benefits** generated by a DTDDMM are to increase decision certainty through transparency, new insights, and what-if analyses. A digital twin, through realistic process models, enables large amounts of data to be linked to rapid simulations, allowing early and efficient evaluation of the impact, performance and quality of decisions on processes (Tao et al., 2019a; Zhang et al., 2017). This leads to reduced time-to-market, improved process monitoring, process diagnosis, time reduction, cost reduction, predictive maintenance and product improvement. The quality of decision-making is adversely affected by slow decisions made by the wrong people, in the wrong part of the organization, with the wrong information (Blenko et al., 2010). To sum up, distinguishing **alternatives** to gain **certainty** and allocating **resources** and **opportunities** effectively improves efficiency and thus operational effectiveness. Therefore, **hypothesis 5** is as follows: **A theoretical DTDDMM increases effectiveness by 10%.**

[1] Fortune 500 companies: 53,001 days work time and $\sim$ \$250 labour costs per year lost

3 MATERIALS AND METHODS OF DISSERTATION

This dissertation uses quantitative research (Williams, 2007) shown in Figure 5.

Figure 5: Research process of the dissertation



Source: Own Figure

The managers were divided into upper, middle, and lower management (Katz et al., 1978) and were recruited electronically via the LinkedIn business platform and email from university, personal, and professional environments. The **preliminary study** consisted of a 15-question industry-wide survey, while the main study was a 50-question industry-wide survey. It was requested that the link also be forwarded, so the actual number of link recipients is unknown. The **random sampling method** was used (Mitra et al., 1984). To validate the preliminary and main studies, 10 managers were contacted personally by email and phone prior to publication and asked about the content of the survey and to suggest improvements, which were than incorporated into the surveys. There was consistently positive feedback concerning the relevance of the topic, the theoretical DTDDMM and the content of the surveys, which were assessed as precise and targeted. The **preliminary study** survey was devised in German and English on the SurveyMonkey platform, launched in 01 August 2021, and completed in 30 September 2021. A prologue on the introduction page outlined the research intentions, and anonymity was assured when responding to the survey. Participants were asked about their experiences with the digital twin, data quality management, and decision support systems in their companies. To ensure scientific quality, only managers were allowed to participate (**quality score 1**). The survey focus on the **awareness level**, if these answered with strongly disagree or disagree, the specific questions were skipped (**quality score 2**). The **main study** survey was devised in German and English on the SurveyMonkey platform, launched in 01 December 2021, and completed in 28 February 2022. A preface on the introduction page outlined the research intentions, and anonymity was assured when responding to the survey. Managers were asked about their experiences with digital twins, data quality management, and decision support systems in their respective companies. To ensure scientific quality, only managers were allowed to participate (**quality score 1**). It focused on the automotive, healthcare, retail, transport, construction, computer and food industries. Therefore, managers from other industries were disqualified (**quality score 2**). To ensure that the awareness derived from the preliminary study did not bias the results, managers who had no experience with digital twins, data quality management, and decision support systems were excluded (**quality score 3**). The data collection procedure for the preliminary study consisted of 343 participants, resulting in a sample size of 144 managers. Therefore, 42% could be included in the survey, as 58% failed the quality assessment or didn't answer all the questions. For the main study, the data collection procedure consisted of 278 participants, resulting in a sample size of 122 managers. This meant that 44% could be included in the survey, as 56% failed the quality criteria or didn't answer all the questions. The speed of the average completion time (5 minutes for the preliminary study and 15 minutes for the main study) was due to the relevance of the topic and the simplicity of the surveys. The population of managers in Germany was set at a population of 3.16 million managerial positions (CRIF, 2018), with a margin of error for the preliminary study of 8% (confidence level of 95%) and for the main study of 9% (confidence level of 95%), which was acceptable. It should be noted, however, that both studies focused on managers from the automotive, healthcare, retail, transport, construction, computer, and food industries. The high number of managers from the automotive and retail industries was due to the fact that the author's direct network consisted mainly of managers from these industries.

3.1 Preliminary study sample

19.4% of the respondents were lower-level managers, 58.3% were middle-level managers, and 22.2% were upper-level managers. Regarding age, 34.7% of the managers were between 18 and 30 years old, 30.6% were 31 to 40 years old and the remainder as follows: 41 to 50 years (18.8%) 51 to 60 years (11.8%) and 61 to 70 years (4.2%). Therefore, the majority of participants in the preliminary study were between 18 and 40 years old. Regarding gender, 66.7% were male and 33.3% were female. The average length of company affiliation in companies was 6 to 10 years, 34.7%; up to 5 years, 21.5%; 16 to 25 years, 20.8%; 11 to 15 years, 9%; 26 to 35 years, 9%; 36 to 40 years, 4.2%; and 41 to 50 years, 0.7%. This suggests that the length of company affiliation of the managers in this study was relatively short, although they may have worked in previous companies – company affiliation is calculated from the time of entry. The rather short length of company affiliation may be explained by the rather young age of the managers. Regarding **company size**, 41% worked in companies with 250 or more employees, 29.2% in companies with 50 to 249 employees, 16% in companies with 10 to 49 employees, and 13.9% in companies with up to 9 employees. So, most of the managers worked for large companies. The **industry** distribution was as follows: automotive (23.6%), healthcare (16%), retail (11.8%), transport (11.1%), computer (10.4%), construction, and food (9%). In response to the statement *"digital twin technology is known in your company"*, 37.5% answered with, "I neither agree nor disagree", 22.2% agreed, 16% strongly disagreed, 12.5% strongly agreed, and 11.8% disagreed, which indicated that the concept was partly known. Apropos the statement *"data quality management is known in your company"*, 31.9% agreed, 27.1% neither agreed nor disagreed, 22.2% strongly agreed, 12.5% disagreed and 6.3% strongly disagreed, indicating that the concept was known. Concerning the statement, *"decision support systems are known in your company"*, 31.3% agreed, 25% neither agreed nor disagreed, 18.1% strongly agreed, 18.1% disagreed and 7.6% strongly disagreed, indicating that the concept was known. Regarding digital twin implementation plans, 36.5% planned to implement digital twin within the next 3 years, 22.1% within 1 year, 14.5% within 5 years, 13.5% reported that it was already available and 13.5% reported no plans for implementation existed. This indicated that the majority of companies plan digital twin implementation within the next 3 years. Regarding data quality management implementation plans (N=117), 32.5% of the respondents reported plans within the next 3 years, 25.6% reported that it was already available, 23.9% reported implementation plans within 1 year, 12.8% within 5 years, and 5.1% reported that no implementation plans for data quality management existed. This suggests that for the majority, the concept had already been implemented or will be within the next 1 to 3 years. Regarding decision support system implementation plans (N=107), 34.6% reported plans within the next 3 years, 27.1% reported that a decision support system was already available, 19.6% reported plans within 1 year, 10.3% reported no plans for implementation and 8.4% reported plans within 5 years. This indicated that the concept had already been implemented or will be within the next 1 to 3 years. Responding to the statement that digital twin is a competitive opportunity for your company (N=104), 40.4% agreed, 28.8% neither agreed nor disagreed, 20.2% strongly agreed, 9.6% disagreed and 1% strongly disagreed. So, the majority believed that digital twin was a competitive opportunity. Regarding the statement that data quality management is a basic requirement for digital twins (N=117), 33.3% agreed, 29.9% neither agreed nor disagreed, 28.2% strongly agreed, 6.8% disagreed and 1.7% strongly disagreed. This suggested a digital twin dependency on data quality management. Regarding the statement that decision support systems are improved by digital twins (N=107), 37.4% agreed, 29% neither agreed nor disagreed, 22.4% strongly agreed, 5.6% disagreed and 5.6% strongly disagreed. This indicated that generally, decision support systems are improved by digital twin technology.

3.2 Main Study Sample

25.4% were lower management, 50.8% were middle management, and 23.8% were upper management. The average age was 37.40 years using a free text field rather than a corridor, but neither the procedure change nor the age had an effect on the dissertation. More men (59.8%) participated than women (40.2%). The average length of service in the companies was **8.40 years**, using a free text field and not a corridor. This rather short length of company affiliation could have been the result of the relatively young age of the managers, although they may have worked in previous companies – company affiliation is calculated from the time of entry. Regarding company size, most of the managers worked for large companies. The **industry** distribution was as follows: automotive (19.7%), retail (19.7%), computer (16.4%), healthcare (16.4%), construction (9.8%), transport (9.8%), and food (8.2%). The majority of companies planned to implement digital twin within 5 years: 37.7% planned implementation within 1 year, 29.5% within 3 years, and 5.7% within 5 years. In 21.3% of the companies, a digital twin was already available, and in 5.7%, no implementation plans existed (N= 122). Data quality management had been either implemented or planned within the following 3 years: 37.7% stated that it was already available, 32.7% had plans to implement it within 1 year, 24.6% within 3 years, 4.1% within 5 years, and 1.6% had no implementation plans (N= 122). Regarding the implementation of a decision support system (N=122), 35.2% stated that it was already available, 32.8% had plans to implement it within 1 year, 23% within 3 years, 5.7% within 5 years, and 3.3% had no implementation plans. So this concept had already been implemented or planned in most companies. In response to the statement that the implementation of a DTDDMM needs the full implementation of a digital twin, data quality management and a decision support system, 45.9% agreed, 23.8% neither agreed nor disagreed, 19.7% strongly agreed, 8.2% disagreed and 2.5% strongly disagreed, which shows the importance of full implementation. When asked whether digital twin provided a competitive opportunity, the majority agreed: 43.4% agreed, 33.6% neither agreed nor disagreed, 11.5% strongly agreed, 10.7% disagreed and 0.8% strongly disagreed. In response to the statement that data quality management is a basic requirement for the digital twin concept, 34.4% agreed, 33.6% strongly agreed, 20.5% neither agreed nor disagreed, 10.7% disagreed, and 0.8% strongly disagreed. So, the majority believed that there was a certain dependency. Similarly, regarding the statement that decision support systems are improved by digital twin, 43.4% agreed, 27% neither agreed nor disagreed, 23% strongly agreed, 5.7% disagreed and 0.8% strongly disagreed. In response to the statement that a DTDDMM is useful for their company, 37.7% agreed, 36.1% neither agreed nor disagreed, 16.4% strongly agreed, 8.2% disagreed, and 1.6% strongly disagreed. So, the developed model would appear to be useful for the majority of managers. Asked how important it was to have a common understanding of the process of a digital twin as defined by (Raj et al., 2020): 45.9% agreed, 29.5% neither agreed nor disagreed, 16.4% strongly agreed, 7.4% disagreed and 0.8% strongly disagreed, which suggests that the concept of a process digital twin was largely understood. Regarding the data quality management of a DTDDMM, the average data quality was rated at 65%, suggesting that there is improvement potential here. In response to the statement that data quality management must be fully anchored at corporate level for successful implementation, 52.2% agreed, 18% strongly agreed, 14.8% neither agreed nor disagreed, 11.5% disagreed and 3.3% strongly disagreed. Regarding the statement that the process digital twin is dependent on the quality of the supplied data, 41.8% agreed, 32% strongly agreed, 15.6% neither agreed nor disagreed, 8.2% disagreed and 2.5% strongly disagreed, clearly showing that the process digital twin depends on data quality. Furthermore, when asked to comment on the statement that the success of a decision support system is dependent on the delivered data quality, 42.9% agreed, 27.9% strongly agreed, 18.9% neither agreed nor disagreed, 7.4% disagreed and 3.3% strongly disagreed, clearly showing that a decision support system is also dependent on data quality. Finally, the majority of managers believed that timeliness was the most important prerequisite and that process monitoring was the greatest benefit of a DTDDMM.

3.3 Methods for Data Analysis

For the analysis of the data **IBM SPSS Statistics 28** was used focusing on two non-parametric tests in Table 1 to show **differences** (Hopkins et al., 2018; Mircioiu et al., 2017):

Table 1: Parametric and nonparametric analysis

Analysis	2 Independent Groups	2 Dependent Groups	>2 Independent Groups	>2 Dependent Groups
Parametric	Independent t test	Dependent t test	One-way ANOVA	Repeated-measures ANOVA
	N > 30	Sample sizes equal	No minimum N	No minimum N / Sample sizes equal
Nonparametric	Mann-Whitney	**Wilcoxon**	**Kruskal-Wallis**	Friedman's ANOVA
	$N \geq 8$	$N \geq 5$	No minimum N	No minimum N

Source: Own Table, derived from Hopkins et al., 2018

- Wilcoxon Signed-Ranks Test (Wilcoxon, 1945) to show differences within a group and
- Kruskal–Wallis test (Kruskal et al., 1952) to show differences across groups.

The tests are described in Sheskin, 2000: *Test 6. The Wilcoxon Signed-Ranks Test p. 143 - 156* and *Test 22. Kruskal–Wallis One-Way Analysis of Variance by Ranks p.609 - 623*. To calculate the effect sizes, the Wilcoxon signed-rank test uses the Z-score to calculate the correlation coefficients in Equation 1[2] (Fritz et al., 2011):

$$r = \frac{Z}{\sqrt{n}};\ r^2\ or\ \eta^2 = \frac{Z^2}{n} \tag{1}$$

The Kruskal–Wallis one-way analysis of variance by ranks uses Equation 2 (B. H. Cohen, 2008) to calculate the effect sizes[3]:

$$\eta_H^2 = \frac{H-k+1}{n-k} \tag{2}$$

[2] n: Total number of observations based on z

[3] H: Kruskal-Wallis test statistic; k: Number of groups; n: Total number of observations

Here, Cohen discusses the relationship between eta squared (η^2) and Cohen's f in Equation 3 (J. Cohen, 1988)[4].

$$\eta^2 = \frac{f^2}{1+f^2};\ f^2 = \frac{\eta^2}{1-\eta^2};\ f = \sqrt{\frac{\eta^2}{1-\eta^2}} \tag{3}$$

If the model is a two-group ANOVA and the number of observations in each group is the same, then the standardized range of population means, Cohen's d with small (d = 0.2), medium (d = 0.5), and strong (d = 0.8) effects shown in Equation 4[5] (J. Cohen, 1988).

$$d = 2 * f \tag{4}$$

Besides the nonparametric analysis, **percentage points** show the arithmetic difference of two percentages (Rossouw, 2013). There are differences between a percentage change and a change in percentage points, where the difference between two percentages is expressed in Equation 5 (Rossouw, 2013; Walsh, 1959):[6]

$$x * \left(1 + \frac{y}{100}\right) \tag{5}$$

In order to make the results in this dissertation comparable, three assumptions were made:

- *Assumption 1*: The actual condition was 25%, and participants indicated an increase of 15%. Then these percentages were converted to 15 percentage points (3.75%), representing an increase from 25% to 28.75%.
- *Assumption 2*: The actual condition was 25%, and participants indicated an increase of 75%. Then these percentages were converted to 50 percentage points (12.5%), representing an increase from 25% to 37.5%.
- *Assumption 3*: If the increase in assumptions 1 and 2 was above 100%, these were not considered further in the evaluation of the results.

The results were compared using the mean value (all values were added and the sum was divided by the total number of values), here the actual state (%) was compared with the newly calculated state (%).

[4] f^2: Square of the effect size; η^2: Partial eta-squared; f: Effect size

[5] f: Effect size

[6] x: Percentage Value; y: Percentages Point

4 RESULTS AND EVALUATION

4.1 Data Analysis - Preliminary Study

Management Levels: To sum up, there were no significant differences between the management levels, regarding whether digital twin were known about or unknown (*Mdn* = 3.00 [1.20, 4.00]). Furthermore, at least 50% of managers said they had either implemented digital twins already or would do so within the next 3 years and 75% of managers said they had either implemented digital twins already or would within the next 5 years. Overall, the digital twin was seen as a significant competitive opportunity (*Mdn* = 4.00 [3.00, 5.00]) and the concept of data quality management was understood (*Mdn* = 4.00 [2.00, 5.00]). At least 50% and 75% of managers said they had either implemented data quality management already or would within the next 3 years. Data quality management was also seen as a basic requirement for a digital twin (*Mdn* = 4.00 [2.00, 5.00]). Decision support systems were neither known nor unknown (*Mdn* = 3.00 [2.00, 5.00]). At least 50% and 75% of managers saying that they had either implemented decision support systems already or would within the next 3 years. The resulting improvement to decision support systems by the application of a digital twin was acknowledged (*Mdn* = 4.00 [3.00, 5.00]).

Company Size: It can be concluded that there were significant differences depending on company size in **(3)**, **(6)** and **(8)**. However, digital twins were both known about and unknown (*Mdn* = 3.00 [1.20, 4.00]). Furthermore, at least 50% and 75% of managers said they had either implemented digital twins already or would do so within the next 5 years. Data quality management was known, with *Mdn* = 4.00 [2.00, 5.00], and at least 50% and 75% of managers said they had either implemented data quality management already or would do so within the next 3 years. Decision support systems were both known about and unknown (*Mdn* = 3.00 [2.00, 5.00]). Here, at least 50% and 75% of managers said they had either implemented decision support systems already or would do so within the next 3 years.

3. There were significant differences concerning the perception of the extent to which

digital twins provided competitive opportunity **H(3)= 16.74, p<.001, d=0.83** between 50 to 249 and 250 or more employees, up to 9 and 250 or more employees, and 10 to 49 and 250 or more employees.

Here, differences were found between the 250+ group and all other groups. By contrast, no statistically significant differences were found between the groups with fewer than 250 employees. The mean for the 250+ group was *Mdn* = 4.00 [3.00, 5.00], for 50-249 *Mdn* = 3.00 [2.60, 4.00], for 10-49 *Mdn* = 4.00 [3.00, 4.00], and up to 9 *Mdn* = 3.00 [2.00, 5.00]. The statistical significance of the difference between group 250+ and groups 50–249 and 1–9, can be attributed to the higher mean value in group 250+. However, regarding the statistically significant difference between the 250+ and 10–49 groups, this was more likely a result of the spread of values around the mean, as the mean was the same in both groups. Here, the spread between the 16th and 84th percentiles in the 250+ group indicated that 68% of the responses fell within the value range of 3 to 5, whereas in the 10–49 group they fell between 3 and 4. As a result, agreement in the group 10–49 was less positive than in the group 250+.

6. There were significant differences regarding data quality management being a basic requirement for a digital twin application: **H(3)=10.01, p=.018, d=0.55** between 10 to 49 and 250 or more employees, up to 9 and 250 or more employees, and 50 to 249 and 250 or more employees.

Differences concerning this were found between the 250+ group and all other groups. By contrast, no statistically significant differences were found between the groups with fewer than 250 employees. The mean for the 250+ group was *Mdn* = 4.00 [3.00, 5.00], for 50-249 *Mdn* = 4.00 [3.00, 4.00], for 10-49 *Mdn* = 3.00 [2.56, 5.00] and for up to 9 *Mdn* = 4.00 [2.00, 5.00]. The statistical significance of the differences between the 250+ group and the other groups, can be attributed to the spread of values around the mean, as the mean was the same in 3 out of 4 groups. The scatter between the 16th and 84th percentiles of group 250+ indicates that 68% of the responses here were in the 3–5 value range. The spread in the 50–249 group here indicates a lower level of agreement and even disapproval. For the groups 10–49 and 1–9, on the other hand, there were only negative attitudes.

8. There were significant differences regarding the implementation level of decision support systems: **H(3)=10.96, p=.012, d=0.61** between 250 or more and 50 to 249 employees, 250 or more and 10 to 49 employees, and 250 or more -and up to 9 employees.

Differences here were found between the 250+ group and all other groups. In contrast, no statistically significant differences were found between the groups with fewer than 250 employees. The mean for the 250+ group was *Mdn* = 2.00 [1.00, 3.00], for 50-249 *Mdn* = 3.00 [1.00, 5.00], for 10-49 it *Mdn* = 3.00 [2.00, 4.00], and for up to 9 *Mdn* = 3.00 [1.40, 4.60]. The statistical significance of the differences between the 250+ group and the other groups, can be attributed to the lower median value, as the median was the same in 3 out of 4 groups and was lower only in the 250+ group. The spread between the 16th and 84th percentiles of group 250+ indicates that 68% of the responses were in the 1–3 value range. The dispersion in the other groups indicates a lower number of disapproving and a higher number of approving attitudes due to the partly higher 16th and 84th percentile values.

Industries: It can be concluded that there were significant differences between the industries in **(1)**. However, the digital twin was both known and unknown, with *Mdn* = 3.00 [1.20, 4.00]. Furthermore, at least 50% of managers said they had either implemented digital twin already or would do so within the next 3 years, and 75% of managers said they had either implemented digital twin already or would do so within the next 5 years. Data quality management was known with *Mdn* = 4.00 [2.00, 5.00]. Here, at least 50% and 75% of managers said they had either implemented data quality management already or would do so within the next 5 years. Decision support systems were both known and unknown, with *Mdn* = 3.00 [2.00, 5.00], and at least 50% and 75% of managers said they had either implemented decision support systems already or would do so within the next 3 years.

1. There were significant differences in the level of digital twin awareness between the retail industry and all the other industries with the exception of the healthcare industry: **H(6)= 14.79, p=.022, d=0.55**

By contrast, no statistically significant difference was found between the other industry combinations. The mean values were, *Mdn* = 2.00 [1.00, 3.16] for the retail industry, *Mdn* = 3.00 [2.00, 5.00] for the automative industry, *Mdn* = 3.00 [2.00, 4.00] for the transport industry, *Mdn* = 3.50 [2.44, 4.00] for the computer industry, *Mdn* =3.00 [1.56, 5.00] for the construction industry, *Mdn* = 3.00 [3.00, 4.76] for the food industry, and *Mdn* = 3.00 [1.00, 4.00] for the healthcare industry. The statistical significance of the differences between the industries can be attributed to the lower median value of the retail industry, since the median was 3 in all the other industries. The dispersion between the 16th and 84th percentiles of the retail industry indicates that 68% of the responses here fell within the value range of 1.00 to 3.16 and thus within the range of low agreement. The scatter in the other industries indicates a tendency towards higher agreement and lower disagreement due to the partly higher percentile values.

The **implementation level** is the most important part for a DTDDMM, showing that at least 50% of managers said they had either implemented digital twins (N=104) already or would do so within the next 3 years, and 75% of managers said they had either implemented digital twins already or would do so within the next 5 years. At least 50% and 75% of managers said they had either implemented data quality management (N=117) and decision support systems (N=107) or would do so within the next 3 years. Making it worthwhile to investigate further in the **main study**. For the DTDDMM, this meant that data quality management was a basic requirement for the digital twin (H_2) with *Mdn* = 4.00 [3.00, 5.00], that digital twins were a competitive opportunity (H_3) with *Mdn* = 4.00 [3.00, 5.00], and that decision support systems were improved through digital twin application (H_4) with *Mdn* = 4.00 [3.00, 5.00].

4.2 Data Analysis - Main Study

Management Levels: Thus, it can be concluded that there were no significant differences. At least 50% of managers said they had either implemented digital twins already or would do so within the next year, and 75% of managers said they had either implemented digital twins already or would do so within the next 3 years. Digital twins were seen as a competitive opportunity with *Mdn* = 4.00 [3.00, 4.00]. At least 50% of managers said they had either implemented data quality management already or would do so within the next year, and 75% of managers said they had either implemented data quality management already or would do so within the next 3 years, and data quality management was seen as a basic requirement for digital twins *Mdn* = 4.00 [3.00, 5.00]. At least 50% of managers said they had implemented decision support systems already or would do so within the next year, and 75% of managers said they had either implemented decision support systems already or would do so within the next 3 years. The improvement of decision support systems through digital twins was acknowledged with *Mdn* = 4.00 [3.00, 5.00]. With regard to the DTDDMM, its usefulness was also acknowledged with *Mdn* = 4.00 [3.00, 5.00] and the definition of process digital twin was understood with *Mdn* = 4.00 [3.00, 5.00]. Regarding data quality for the model, the managers believed that corporate data quality management had to be implemented with *Mdn* = 4.00 [3.00, 5.00], and that there was a relationship between process digital twin and data quality with *Mdn* = 4.00 [3.00, 5.00], and decision support systems and data quality with *Mdn* = 4.00 [3.00, 5.00]. The full implementation of digital twin, data quality management and decision support systems was seen as a basic requirement for the model with *Mdn* = 4.00 [3.00, 5.00].

Across Company Size: It can be concluded that there were significant differences depending on company size with **(2)**, **(4)**, **(6)**, **(7)**, **(9)** and **(11)**. However, at least 50% of managers said they had either implemented digital twin already or would do so within the next year, and 75% of managers said they had either implemented digital twin already or would do so within the next 3 years. At least 50% of managers said they had either implemented data quality management already or would do so within the next year, and 75% of managers said they had either implemented data quality management already or would do so within the next 3 years. Furthermore, at least 50% of managers said they had implemented decision support systems already or would do so within the next year, and 75% of managers said they had either implemented decision support systems already or would do so within the next 3 years. With regard to the DTDDMM, the definition of process digital twin was understood, with *Mdn* = 4.00 [3.00, 5.00]. Regarding data quality for the model, the relationship between process digital twin and data quality with *Mdn* = 4.00 [3.00, 5.00] was acknowledged. The full implementation of digital twin, data quality management and decision support systems was seen as a significant and basic requirement for the model, with *Mdn* = 4.00 [3.00, 5.00].

2. There were significant differences regarding the extent to which managers viewed digital twin technology as a competitive opportunity: **H(3)= 10.86, p=.012, d=0.57** between up to 9 and 250 or more employees, 10 to 49 and 250 or more employees, and 50 to 249 and 250 or more employees.

Differences here were found between the 250+ group and all other groups. By contrast, no statistically significant differences were found between the groups with fewer than 250 employees. The mean value for the group 250+ was *Mdn* = 4.00 [3.00, 5.00], for 50–249 *Mdn* = 3.00 [2.00, 4.00], for 10–49 *Mdn* = 3.00 [2.84, 4.00], and for up to 9 *Mdn* = 3.00 [2.00, 4.00]. The statistical significance of the differences between the 250+ group and the groups with a lower number of employees could be attributed to the higher mean value in the 250+ group. The spread between the 16th and 84th percentiles of the 250+ group indicated that 68% of the responses here laid in the value range of 3 to 5.

4. There were also differences regarding the importance of data quality management being a basic requirement for digital twins: **H(3)=13.78, p=.003, d=0.66** between 10 to 49 and 50 to 249 employees, and 10 to 49 and 250 or more employees.

These differences were found between the 250+ group and all other groups. By contrast, no statistically significant differences were found between the groups with fewer than 250 employees. The mean value for the group 250+ was *Mdn* = 4.00 [3.00, 5.00], for 50–249 *Mdn* = 3.00 [2.00, 4.00], for 10–49 *Mdn* = 3.00 [2.84, 4.00], and for up to 9 *Mdn* = 3.00 [2.00, 4.00]. The statistical significance of the differences between the 10–49 group and the 50–249, and 250+ groups can be attributed to the lower mean score of the 10–49 group. The spread between the 16th and 84th percentiles of group 10–49 indicates that 68% of the responses here, were in the 2–4 value range. The scatter in the other groups, due to the higher percentile values, indicates a higher approval, or a lower number of disapproving attitudes.

6. There were significant differences regarding the extent to which digital twins improved decision support systems: **H(3)=9.50, p=.023, d=0.52** between up to 9 and 250 or more employees, and 10 to 49 and 250 or more employees.

Here, differences were found between the group 250+ and both groups up to 9 and 10–49. The mean value for the group 250+ was *Mdn* = 4.00 [3.00, 5.00], for 50–249 *Mdn* = 4.00 [3.00, 5.00], for 10–49 *Mdn* = 3.00 [3.00, 4.00], and for up to 9 *Mdn* = 3.50 [3.00, 4.00]. The statistical significance of the differences between the group 250+ and both groups 1–9 and 10–49, can be attributed to the lower mean. The scatter between the 16th and 84th percentiles of group 250+ indicates that 68% of the responses here were in the value range of 3–5. The spread in the 1–9 and 10–49 groups indicates a smaller number of high agreements due to the lower 84th percentile values.

7. There was a significant difference in opinion regarding the usefulness of a DTDDMM: **H(3)=10.12, p=.018, d=0.54** between up to 9 and 250 or more employees and 50–249 and 250 or more employees.

These differences were found between group 250+ and both groups 50–249 and up to 9. The mean for group 250+ was *Mdn* = 4.00 [3.00, 5.00], for 50–249 *Mdn* = 3.00 [3.00, 4.00], for up to 9 *Mdn* = 3.00 [2.00, 4.00], and for 10–49 *Mdn* = 3.00 [3.00, 4.00]. The statistical significance of the differences between the 250+ group and both the 50–249 and 1–9 groups, can be attributed to the lower mean. Although the difference between the 250+ group and the 10–49 group was not statistically significant, it can still be assumed on the basis of the descriptive statistics that there was also a difference with this group. This assumption is derived from the fact that the 16th, 25th, 50th, 75th, and 84th percentile values for group 10–49 were identical to those for group 50–249, to which again a statistically significant difference was found. However, the two groups differed in group size, which was 33 respondents for group 50–249 and only 23 respondents for group 10–49. The p-value for the difference between group 250+ and 10–49 also confirms this assumption due to its proximity to the significance level, p = .061. The spread between the 16th and 84th percentiles of group 250+ indicates that 68% of the responses here were in the 3–5 value range. The spread in the 1–9, 10–49, and 50–249 groups indicates a smaller number of high agreements due to the lower 84th percentile values.

9. There were significant differences regarding the importance of implementing corporate data quality management for the model: **H(3)=14.95, p=.002, d=0.70** between up to 9 and 250 or more employees, 10 to 49 and 250 or more employees, and 50 to 249 and 250 or more employees.

These differences were found between the 250+ group to all other groups respectively. By contrast, no statistically significant differences were found between the groups with fewer than 250 employees. The mean for the 250+ group was *Mdn* = 4.00 [4.00, 5.00], for 50–249 *Mdn* = 4.00 [2.00, 5.00], for 10–49 *Mdn* = 4.00 [2.00, 4.16], and for up to 9 *Mdn* = 3.50 [1.40, 4.00]. The statistical significance of the differences between the 250+ group and the groups with a lower number of employees can be attributed to a higher number of negative attitudes and a partly decreasing number of positive attitudes in the groups with a lower number of employees. The spread between the 16th and 84th percentiles of the 250+ group indicates that 68% of the answers here laid in the value range from 4–5. This shows a particularly homogeneous picture in the responses, which is significantly more heterogeneous in the groups with a lower number of employees.

11. There were significant differences of opinion regarding the extent of the dependency of decision support systems on data quality: **H(3)=9.40, p=.24, d=0.52** between 10 to 49 and 250 or more employees, and 50 to 249 and 250 or more employees.

These differences were found between group 250+ and both groups 10–49 and 50–249. The mean for group 250+ was *Mdn* = 4.00 [4.00, 5.00], for 50–249 *Mdn* = 4.00 [2.00, 5.00], for 10–49 *Mdn* = 4.00 [3.00, 5.00], and for up to 9 Mdn = 4.00 [1.80, 5.00]. The statistical significance of the differences between the 250+ group and both the 10–49 and 50–249 groups, can be attributed to the increase in negative attitudes. The scatter between the 16th and 84th percentiles of the 250+ group indicates that 68% of the responses here were in the 4–5 value range. The spread in the 10–49 and 50–249 groups indicates a higher number of negative attitudes due to the lower 16th percentile values. This trend was also found in group 1–9. The fact that the difference with this group was not statistically significant, despite a fairly similar distribution, can also be attributed to a significantly lower group population. This was 33 respondents in group 50–249, 23 respondents in group 10–49 and only 14 respondents in group 1–9.

Industries: Thus, it can be concluded that there were no significant differences. At least 50% of managers said they had either implemented digital twins already or would do so within the next year, and 75% of managers said they had either implemented digital twins already or would do so within the next 3 years. Digital twins were perceived as providing a considerable competitive opportunity with *Mdn* = 4.00 [3.00, 4.00]. At least 50% of managers said they had either implemented data quality management already or would do so within the next year, and 75% of managers said they had either implemented data quality management already or would do so within the next 3 years. Data quality management was seen as a basic requirement for digital twins with *Mdn* = 4.00 [3.00, 5.00]. At least 50% of managers said they had implemented decision support systems already or would do so within the next year, and 75% of managers said they had either implemented decision support systems already or would do so within the next 3 years. Where the improvement of decision support systems as a result of digital twin implementation was acknowledged, with *Mdn* = 4.00 [3.00, 5.00]. Regarding a DTDDMM, its usefulness was also acknowledged, with *Mdn* = 4.00 [3.00, 5.00], and the definition of a process digital twin was understood, with *Mdn* = 4.00 [3.00, 5.00]. Regarding data quality for the model, most managers believed that data quality management had to be implemented at corporate level, with *Mdn* = 4.00 [3.00, 5.00], and that there was a relationship between a process digital twin and data quality with *Mdn* = 4.00 [3.00, 5.00] as well as between decision support systems and data quality with *Mdn* = 4.00 [3.00, 5.00]. The full implementation of digital twin, data quality management and decision support systems was seen as a basic requirement for the model, with *Mdn* = 4.00 [3.00, 5.00].

The **implementation level** is the most important part for a DTDDMM, showing that at least 84% of managers *(N=122)* said they had either implemented digital twin, data quality management and decision support systems already or would within the next 3 years. For a DTDDMM this means that data quality management is a basic requirement for digital twin implementation (H_2) with *Mdn* = 4.00 [3.00, 5.00]. However, there were industry differences in the **data quality score** where the average data quality score was rated with **64.88%** as shown in Equation 6, meaning that there is potential for significant improvement potential across the industries.

$$DataQualityScore = \frac{7915}{122} = 64.88\% \tag{6}$$

Furthermore, it was acknowledged that digital twins provide a competitive opportunity (H_3) with *Mdn* = 4.00 [3.00, 4.00] and decision support systems are improved by digital twins (H_4) with *Mdn* = 4.00 [3.00, 5.00]. There were no differences across industries regarding **requirements** and **benefits**. There were three requirements of data quality management among the top five requirements: timeliness, with *Mdn* = 4.00 [3.00, 5.00]; consistency, with *Mdn* = 4.00 [3.00, 5.00]; and accuracy, with *Mdn* = 4.00 [3.00, 5.00]; as well as integration, with *Mdn* = 4.00 [3.00, 5.00] and update, with *Mdn* = 4.00 [3.00, 5.00]. This proves the importance of data quality management for a DTDDMM. The ranking can be seen as requirement priorities, corresponding to the descriptions from the literature review. As two of the top five benefits related to process improvement: process monitoring, with *Mdn* = 4.00 [3.00, 5.00]; and diagnosis, with *Mdn* = 4.00 [3.00, 5.00]. The others were time reduction with *Mdn* = 4.00 [3.00, 5.00], new insights with *Mdn* = 4.00 [3.00, 5.00] and transparency with *Mdn* = 4.00 [3.00, 5.00]. This all proves the importance of the process digital twin for DTDDMM – and *rank 1*, process monitoring and *rank 3*, process diagnosis – further show that the intention of a DTDDMM was understood by the managers. The benefits correspond to the descriptions from the literature review, although the rapidly changing digitization may create more benefits. The main study demonstrated the effectiveness of the digital twin-driven decision-making model (H_5). These were achieved through the benefits of digital twins regarding (1) decision certainty – through transparency, new insights and what-if analyses – and (2) decision efficiency – through reduced time-to-market, process monitoring, process diagnostics, time reduction, cost reduction, predictive maintenance and product improvement. Decision certainty and efficiency led to an improvement of **11.13%** in decision quality, and a corresponding improvement in operational effectiveness. The results are shown in Equation 7, where the percentages of unstructured decisions (high uncertainty) in each company were queried (*Is-StateUnstructuredDecisions*) as well as the increases of **certainty** of unstructured decisions, where both the new state (*New-StateStructuredDecisions*) and the improvement (*Improvement Certainty*) were determined.

$$\begin{aligned} Is-StateUnstrcturedDecisions &= \frac{4527}{93} = 48.68\% \\ New-StateStructuredDecisions &= \frac{5583.46}{93} = 60.4\% \\ ImprovementCertainty &= 60.4\% - 48.16\% = 11.36\% \end{aligned} \tag{7}$$

Here, the manager needed to analyse certainty – the facts such as risks, options and programs, which can be supported by digital twins. The important factor in the context of uncertainty, is the improvement of certainty, so that unstructured decisions become structured decisions through transparency, new insights and what-if analyses. The DTDDMM reduced the proportion of unstructured decisions in the company from 48.68% to 37.32%, which means that unstructured decision decreased by 11.36%. The results are shown in Equation 8, where the percentages of **efficiency** in decision-making in each company were queried (*Is-StateEfficiencyDecisions*) as well as the increases of efficiency in decision-making, were both the new state (*New-StateEfficiencyDecisions*) and the improvement (*ImprovementEfficiency*) were determined.

$$\begin{aligned} Is-StateEfficiencyDecisions &= \frac{5430}{94} = 57.77\% \\ New-StateEfficiencyDecisions &= \frac{6541.67}{94} = 69.59\% \\ ImprovementEfficiency &= 69.59\% - 57.77\% = 11.83\% \end{aligned} \tag{8}$$

Here, the managers had to allocate opportunities and resources, which can be supported by digital twins. The DTDDMM improved the efficiency of decisions through reduced time-to-market, process monitoring, process diagnostics, time reduction, cost reduction, predictive maintenance and product improvement in the company from 57.77% to 69.59%, which means that decision-making efficiency increased by 11.83%. The results are shown in Equation 9, where the percentages of quality in decision-making in each company were queried (Is-StateQualityDecisions) as well as the increases of quality in decision-making, where both the new state (New-StateQualityDecisions) and the improvement (ImprovementQuality) were determined.

$$\begin{aligned} Is-StateQualityDecisions &= \frac{5474}{94} = 58.23\% \\ New-StateQualityDecisions &= \frac{6520.63}{94} = 69.37\% \\ ImprovementQuality &= 69.37\% - 58.23\% = 11.13\% \end{aligned} \tag{9}$$

Here, the manager had to evaluate quality based on analysis (**certainty**) and the allocation of resources (**efficiency**), that could be supported by digital twins. The DTDDMM improved the quality of decisions in the company from 58.23% to 69.37%, which meant that decision quality and thus operational effectiveness increased by **11.13%**.

5 CONCLUSIONS AND RECOMMENDATIONS

RQ 1 Are there differences in data quality, digital twins and decision support in terms of management level, company size and industry for strategic positioning?

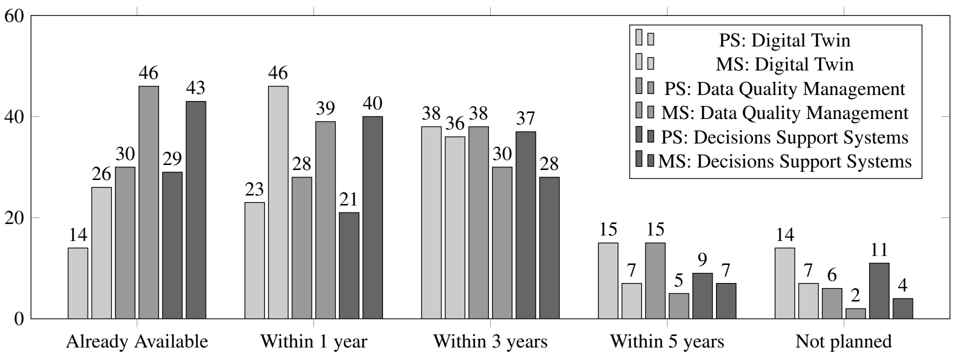
For H_1, it can be noted that there were differences **across company sizes** in both the preliminary and main studies and **across industries** in the preliminary study, which were mainly due to company size. The differences in digital twin awareness level **across industries** (**H(6)= 14.79, p=.022, d=0.55**) showed that awareness tended to be lower in the **retail industry** than in the other industries. The transport, automotive, construction, computer and food industries, on the other hand, were not statistically significantly different from one another in this respect, and the difference in the healthcare industry was relatively minor. Regarding the awareness level, therefore, it is recommended that digital twins be anchored in the Industry 4.0 strategy of every company. Next, the difference **across company sizes** will be focused on, with the differences discovered in the preliminary study being addressed first. Here, a significant differences for digital twin as competitive opportunity emerged in both the preliminary study, **H(3)= 16.74, p<.001, d=0.83**, and main study, **H(3)= 10.86, p=.012, d=0.57**, where agreement in the group 250+ tended to be higher than in the groups with fewer employees. The groups with a lower number of employees, on the other hand, did not differ statistically significantly from one another, although it was striking that the number of negative attitudes increased with a decrease in the number of employees. Based on these findings, it can be concluded that the digital twin was seen by 250+ companies as a competitive opportunity. Similarly, regarding data quality management being a basic requirement for digital twins, differences were discovered in both the preliminary study, **H(3)=10.01, p=.018, d=0.55**, and main study, **H(3)=13.78, p=.003, d=0.66**. Again, the trend was seen in the 250+ companies. However, in the preliminary study, it was noted that agreement tended to be higher in the 250+ group than in the groups with a smaller number of employees, which were not statistically significantly different from each other, although descriptive statistics indicated that the number of negative attitudes increased as the number of employees decreased. By contrast, in the main study, it was noted that agreement in the group 10–49 tended to be lower than in the other groups, although this difference was not statistically significant with respect to the group 1–9, it differed with respect to the smaller companies. It can be concluded, however, that data quality management was seen as a basic requirement for digital twins in companies with 250+ employees. Now the differences that occurred only in the preliminary or main study will be examined. A difference emerged in the preliminary study regarding the implementation level of decision support systems, **H(3)=10.96, p=.012, d=0.61**, where agreement tended to be lower in the 250+ group than in the groups with fewer employees. On the other hand, there was no statistically significant difference between the groups with a low number of employees. From this, it can be concluded that decision support systems are more relevant in smaller companies. Subsequently, there were three differences that occurred only in the main study. The first concerned the usefulness of a DTDDMM,

H(3)=10.12, p=.018, d=0.54, where the level of agreement in the 250+ group tended to be higher than in the other groups. So, even the difference with the 10–49 group was not shown to be statistically significant in this case. From this, it can be concluded that a DTDDMM is useful for companies with 250+ employees. The second concerned the implementation of corporate data quality management, where differences occurred for the model **H(3)=14.95, p=.002, d=0.70**, and where agreement in the 250+ group tended to be higher than in the groups with fewer employees. The groups with a lower number of employees, on the other hand, did not differ from each other in a statistically significant way, although the number of negative attitudes increased with a decrease in the number of employees. It can therefore be concluded that corporate data quality management must be implemented for the model in companies with more than 250 employees, which is consistent with the statement about the usefulness of the model. The third difference concerned the dependency of decision support systems on data quality, where a difference was noted: **H(3)=9.40, p=.24, d=0.52**. Agreement tended to be higher in the 250+ group than in the 10–49 and 50–249 groups. Descriptively, this also appeared to be true for the 1–9 group, but the differences with respect to this group were not shown to be statistically significant. It can be concluded that the quality of data in decision support system is most important in companies with 250+ employees. *H_1: There are differences in data quality, a digital twin and decision support in terms of management level, company size and industry.* **Conclusion: Accept H_1**

RQ 2 What could a theoretical model look like that relies on a digital twin for decision-making while focusing on data quality?

Based on the literature review, a theoretical DTDDMM was developed (shown in Figure 7 and defined as *"A process digital twin, with usable data through data quality management, analytics and the visualization in decision support systems"*. In this context, the implementation level played a crucial role where 84% of managers (N=122) said they had either implemented digital twin, data quality management and decision support systems already or would do so within the next three years. Here, the theoretical DTDDMM could only be implemented if data quality management, digital twin, and decision support systems had been fully implemented, which was confirmed with *Mdn* = 4.00 [3.00, 5.00]. Table 30 compares the preliminary and main study, where a shorter implementation period of the digital twin from five years (PS) to three years (MS) could be observed, which was due to the focus on digital twin experts (quality Score 3) in the main study.

Figure 6: Implementation level comparison of the preliminary and main study



Source: Own Figure

For H_2, it was important to consider whether data quality management is seen as a basic requirement of digital twins, as data quality management will be implemented by 84% of companies within the next 3 years. For this reason the result of the preliminary study: z=6.59, <.001, d=1.54 with *Mdn* = 4.00 [3.00, 5.00] and the result of the main study: z=7.20, p<.001, d=1.71 with *Mdn* = 4.00 [3.00, 5.00] corresponded closely. Therefore, data quality management can be considered a basic requirement, and that without it a theoretical DTDDMM would have no practical use. So, regarding data quality for the model, corporate data quality management must be implemented with *Mdn* = 4.00 [3.00, 5.00]. Again, agreement in companies with 250 or more employees tended to be higher than in companies with fewer employees. Concerning the relationship between process digital twin and data quality, with *Mdn* = 4.00 [3.00, 5.00], this applies to all company sizes as well as decision support systems and data quality, with *Mdn* = 4.00 [3.00, 5.00], which tended to have a higher level of agreement in companies with 250+ employees. On this basis, data quality is an essential part of the theoretical DTDDMM, which means that a continuous corporate data quality management must be present, specifically for companies with 250 or more employees, because both the process digital twin and decision support system depend on the supplied data quality. If this were not the case, the theoretical DTDDMM would have no practical use because the data it uses would not be correct (data quality-proved). Due to the average data quality score of only 65%, it is extremely necessary to improve data quality, even if data quality management has already been implemented. *H_2: Data quality management is a basic requirement for a digital twin*. **Conclusion: Accept H_2**

For H_3, it was important to consider whether digital twins are seen as a competitive opportunity, as they will be implemented by 84% of companies within the next three years. For this reason, the result of the preliminary study: z=5.98, p<.001, d=1.45 with *Mdn* = 4.00 [3.00, 5.00] and the result of the main study: z=5.82, p<.001, d=1.23 with *Mdn* = 4.00 [3.00, 5.00] corresponded closely. On this basis, the digital twin can be considered a competitive opportunity, whereby there was a difference in the preliminary as well as the main study, with the level of agreement in companies with 250 or more employees tending to be higher than in companies with fewer employees. However, this does not mean that companies with fewer employees did not perceive the competitive opportunity provided by digital twins; otherwise, they would not consider it worthwhile to integrate a digital twin within the next three years. *H_3: The implementation of a digital twin is a competitive opportunity*. **Conclusion: Accept H_3**

For H_4, it was important to consider whether the decision support systems were improved by digital twins, as decision support systems will be implemented by the majority of companies within the next three years. For this reason, the results of the preliminary study: z=5.11, p<.001, d=1.14 with *Mdn* = 4.00 [3.00, 5.00] and the results of the main study: z=7.32, p<.001, d=1.76 with *Mdn* = 4.00 [3.00, 5.00] corresponded closely. Accordingly, decision support systems are improved by digital twins. Decision support systems can be implemented into the five-dimension digital twin as the service layer, which interacts with users directly. If this were not the case, the theoretical DTDDMM would have no practical use since decision support systems would not choose a process digital twin in model management to generate an enterprise-level view and provide end-to-end visibility for process transformation. H_4*: Decision support systems are improved by digital twins*. **Conclusion: Accept** H_4

For the DTDDMM, the theoretical implementation requirements and benefits are important. For this reason, the results of the main study concluded that the top five requirements for DTDDMM were timeliness, consistency, accuracy, integration and update and that the top five benefits were process monitoring, time reduction, process diagnosis, new insights and transparency. Accordingly, data quality is an essential requirement, as are the benefits to processes (process digital twin). If this were not the case, the theoretical DTDDMM would have no practical use because the top three requirements: timeliness, consistency and accuracy, relate to data quality management, and of the top three benefits, two relate to processes, with process monitoring (process digital twin) forming the core of the model. This can be regarded as an initial prioritization of requirements and benefits, which should then match the descriptions from the literature review. However, requirements may vary from use case to use case, and benefits should be taken as needed. Furthermore, it is important to consider whether the theoretical DTDDMM increases effectiveness.

RQ 3 Does the theoretical model, using digital twins for decision-making and focusing on data quality, increase operational effectiveness?

For H_5, it was important to consider whether the DTDDMM increases operational effectiveness. Here, the managers needed to analyse (**certainty**) the facts, such as risks, options and programs, which could be supported by digital twins. The important factor in the context of uncertainty, is the improvement of certainty, so that unstructured decisions become structured decisions through transparency, new insights and what-if analyses. The DTDDMM reduced the proportion of unstructured decisions in the company from 48.68% to 37.32%, which meant that unstructured decisions decreased by 11.36%. Furthermore, the manager had to allocate (**efficiency**) opportunities and resources, which could be supported by digital twins. The DTDDMM improved the efficiency of decisions through reduced time-to-market, process monitoring, process diagnostics, time reduction, cost reduction, predictive maintenance and product improvement in the company from 57.77% to 69.59%, which meant that decision-making efficiency increased by 11.83%. Finally, the managers had to evaluate quality based on the analysis (**certainty**) and the allocation of resources (**efficiency**) that could be supported by digital twins. The DTDDMM improved the quality of decisions in the company from 58.23% to 69.37%, which meant that decision quality, and thus **operational effectiveness**, increased by 11.13%. Therefore, the DTDDMM increased the certainty of unstructured decisions by 11.36%, the efficiency of decision-making by 11.83% and the quality of decision-making by **11.13%**, which all to an increase in operational effectiveness. If this were not the case, the model would have no practical use because it should increase effectiveness to justify the implementation. *H_5: A theoretical DTDDMM increases effectiveness by 10%.* **Conclusion: Accept** H_5.

Due to the quality score of 3, only managers in the main study who were familiar with all three topics were included. However, the awareness levels from the preliminary study should still be considered due to the implementation of the digital twin, data quality management and decision support systems. For strategic positioning, and due to the results of H_3, digital twins should be added and anchored in the industry 4.0 digitization strategy of companies with 250+ employees, although companies with fewer employees should also consider implementation. Due to the average data quality score of 65%, it is urgently necessary to address and improve data quality, even if data quality management has already been implemented. Both can be achieved by raising awareness and addressing digital twins and data quality through seminars, education and training from experts. Therefore, the **recommendation** of this paper is as follows:

- Companies should add and anchor digital twins as part of the Industry 4.0 digitization strategy.
- Companies should be aware of, and engage with, digital twins, as well as data quality, through seminars, training and educational programs with experts.

In addition, as only 84% of managers *(N=122)* said they had either implemented already or would do so within the next 3 years full implementation may need to be carried out, with new and consistent organizational structures, processes and methods, architectures and application systems. Therefore:

- Companies should fully implement digital twins, data quality management and decision support systems, if necessary, with new and consistent organizational structures, processes and methods, architectures and application systems.
- Companies should undertake the practical and technical implementation of a DTDDMM with new and consistent organizational structures, processes and methods, architectures and application systems.

Due to the usefulness of a DTDDMM, especially for companies with 250 or more employees, the DTDDMM should be integrated into existing information systems and digitizing and linking processes to increase operational effectiveness. Whereby all relevant data (quality-proved) is integrated and updated through consistent corporate data quality management. In addition, a process digital twin should be fully integrated to enable real-time representation of processes for monitoring and diagnostics in the model management of decision support systems. Here, automatic model generation and updating for specific decision situations and the application of self-learning and controlling algorithms in the model management of decision support systems are particularly important. Therefore:

- A DTDDMM should be integrated into the existing information systems and digitization and linking of processes.
- All relevant data (quality-proved), through consistent corporate data quality management should be updated and integrated.
- A process digital twin enabling real-time representation of processes for monitoring and diagnosis in the model management of decision support systems should be integrated.
- Automatic model generation and updating for specific decision situations in decision support systems should be integrated.

- Self-learning and control algorithms for the model management of decision support systems should be applied.

The **practical implications** of digital twins identified 46 potential industries. Accordingly, Siemens AG, PTC Inc, Dassault Systèmes, IBM, Microsoft Azure, SAP and General Electric have already built a corresponding industrial IoT-platform for digital twins. However, the connection to data quality management, specifically data quality and digital twin for decision making, is also necessary to set up a DTDDMM. Regarding data quality management, Lünendonk & Hossenfelder have shown that although data quality in 155 companies has increased over the last five years, the average **data quality score** is only 60% (Zillmann, 2017), which is consistent with the results of a 64.88% industry-wide data quality score. Although companies are aware that poor data quality affects efficiency and is an important success criterion, Harvard Business Review surveyed 75 managers to determine data quality levels and discovered that, on average, 47% of newly created records had at least one critical error, and 3% were considered acceptable only by the loosest standards (Nagle et al., 2017). This dissertation also used the Friday Afternoon Measurement method (Redman, 2017), showing that on average 35% of newly created records had at least one critical error, showing an increase in industry-wide data quality. The financial cost of bad data quality (the rule of ten) in Equation 10 (Nagle et al., 2017) should be kept in mind.

$$\begin{aligned} 100\%\ DQScore &: 100\$ * 1\$ = 100\$ \\ HBR : 53\%\ DQScore &: 53\$ * 1\$ + 47\$ * 10\$ = 523\$ \\ Dissertation : 65\%\ DQScore &: 67\$ * 1\$ + 35\$ * 10\$ = 417\$ \end{aligned} \tag{10}$$

To achieve the improvement of data quality, the implementation of continuous data quality management in the form of corporate-level data quality management is recommended for companies using a DTDDMM. With regard to **decision making**, McKinsey & Company conducted a survey with 809 managers titled, *"Decision Making in the Age of Urgency"* (Aminov, 2019). Regarding speed and thus efficiency, only 48% of respondents agreed that their organizations made decisions quickly (Aminov, 2019), which is not quite consistent with the results of 57.77%. The difference, however, can be explained in that only time was considered and not the costs. To achieve efficiency in decision making, a DTDDMM is recommended, as it increases efficiency by 11.83%. In terms of the quality of decision making, 57% of respondents believed that their companies consistently made high-quality decisions (Aminov, 2019), which is consistent with the results of 58.23%. To achieve quality of decision making, a DTDDMM is also recommended, as it increases quality by 11.13%. As managers spend 37% of their time making decisions, of which 18.5% are ineffective[7] (Aminov, 2019) a DTDDMM is recommended to counteract this and effectively use time and minimize costs. The remaining % should be analysed and offset with other measures. Based on the results of the above studies, which were strengthened and confirmed by the preliminary and main studies of this dissertation, the implementation of a DTDDMM as a virtual model of a process digital twin, with usable data by data quality management, analytics, and the visualization in a decision support system, is recommended, as it increases operational effectiveness by 11.13%.

Three aspects of this dissertation were affected by **limitations**. Firstly, the theoretical DTDDMM; secondly, the sample size; and thirdly, the methods used. In connection with the theoretical DTDDMM, it is important to mention that the elaborated dimensions, requirements, characteristics and benefits were theoretical, which may vary from use case to use case and from company to company. In addition, there are no widely accepted standards and specifications, so combining data from different sources with different interfaces and data formats was a major challenge (Adamenko et al., 2020). This limited the ways of closing the information loop between digital physical entities and virtual entities (Durão et al., 2018). Regarding the sample size, it should be noted that both studies focused on managers in the automotive, healthcare, retail, transport, construction, computer, and food industries. To validate the survey of the preliminary and main studies, ten managers were previously interviewed, and there was consistently positive feedback concerning the relevance of the topic, the theoretical DTDDMM, and the conciseness of the survey. As a result, the number of managers surveyed for the preliminary study with (N=144)(average

[7] Fortune 500 companies: 53,001 days work time and $\sim$ \$250 labour costs per year lost

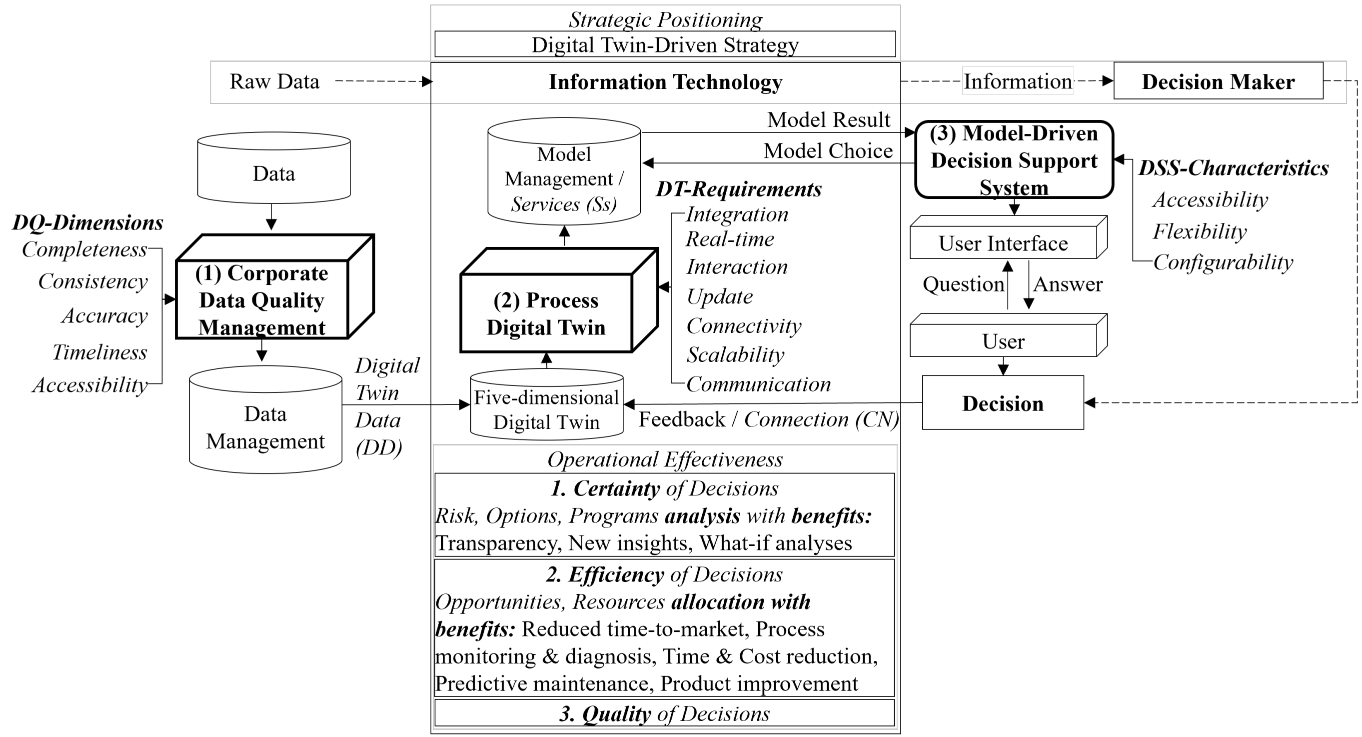
processing time: 5 minutes), and main study with (N=122) (average completion time: 15 minutes), was due to the relevance of the topic and the simplicity of the surveys. Furthermore, the 3.16 million managerial positions in Germany (CRIF, 2018) meant a margin of error for the preliminary study of 8% (confidence level of 95%) and for the main study of 9% (confidence level of 95%), which was acceptable. However, the number of managers and the selection of the automotive and retail industries were due to the fact that the author's direct network consisted mainly of managers from these industries. Furthermore, only German-speaking managers were involved – English-speaking managers were not represented in the samples, so the questions were not answered in English. Furthermore, with regard to percentage points, it should be mentioned that some managers answered the questions with percentage points instead of percentage values and others with percentage values instead of percentage points; here, no clear pattern emerged from the evaluation. In retrospect, it was not possible to clearly differentiate which managers thought in percentage values and which in percentage points. For this reason, the author made the assumptions 1–3 in Chapter 3.3 so that the results could be standardized. It is also important to note, in this context, that the focus lay exclusively on unstructured decisions and their share in a company. Thus, the focus was on increasing the certainty of unstructured decisions with high uncertainty. Note that unstructured decisions were answered with 50%. The remaining 50% may have referred to structured or semi-structured decisions where a clear assignment was not possible.

6 NEW SCIENTIFIC RESULTS

This chapter outlines the scientific results of this dissertation. Although this dissertation is not the first publication to address this issue (Figure 3), its novelty lies in the combination of topics that have either not been considered at all or have been considered in an undifferentiated manner in previous research. It empirically obtained the following six new results:

1. The development and validation of a theoretical DTDDMM (Figure 7) for the automotive, healthcare, retail, transport, construction, computer and food industries, and potentially for 39 other industries.
2. The identification and analysis of differences between the industries. This revealed a lower awareness level in the retail industry and a higher acceptance level in companies with 250 or more employees. The acceptance level concerned the following areas: the competitive opportunity provided by digital twins; data quality management as a basic requirement for digital twins; the implementation level of decision support systems; the improvement of decision support systems through digital twin implementation; the usefulness of; the implementation of corporate data quality management for the model; and the dependency of decision support systems on data quality.
3. The identification and analysis of the implementation level of 84% managers who reported that they had either implemented digital twins, data quality management and decision support systems already or would do so within the next three years, recognizing that this was a basic requirement of DTDDMM.
4. The identification and definition of the DTDDMMs top five requirements – timeliness, consistency, accuracy, integration, and update – and the top five benefits – process monitoring, time savings, process diagnostics, new insights, and transparency.
5. The identification of a potential increase of 11.13% in operational effectiveness by combining and using the benefits of digital twins.
6. The identification of 65% average data quality score in automotive, healthcare, retail, transport, construction, computers and food industries.

Figure 7: The Digital Twin-Driven Decision-Making Model



Source: Own Figure

7 SUMMARY

Based on the literature review, a theoretical DTDDMM was developed. It is important to research digital twins as they offer promising technologies for strategic positioning and the realization of Industry 4.0 using cyber-physical systems (CPS) and information technology. CPS form the backbone to support the creation of a network for decentralized and autonomous **decision-making**. The design principles for Industry 4.0 serve as guidelines for digital twins: these provide a virtual copy of the physical world in order to collect data and monitor processes. The theoretical model of this dissertation revealed differences within and across management levels, company size and industry, focusing on the automotive, healthcare, retail, transport, construction, computer and food industries. These results will help managers understand the differences between data quality management, digital twins and decision support systems for **strategic positioning**. To an extent, these differences are a result of varying levels of digital twin awareness: this being lower in the retail industry. However, the primary factor is company size, with a higher acceptance level in companies with 250 or more employees. These largely recognize and accept digital twin implementation as a competitive opportunity, and they acknowledge that data quality management is a basic requirement for digital twins, as is the implementation level of decision support systems. There is additionally considerable acceptance level of the extent to which decision support systems are improved by digital twin implementation, the usefulness of a DTDDMM, the need for corporate-level data quality management for the model, and the dependency of decision support systems on data quality. Due to an average data quality score of only 65%, it is imperative that this be addressed and improved, even if data quality management has already been implemented, ignoring can be very expensive for companies (rule of ten). A theoretical model was developed by combining corporate data quality management, a process digital twin and model-driven decision support systems. The model creates, tests, and builds a process in the virtual world to support decision-making by combining data, analytics, and visualization of insights. It prioritizes 14 requirements – the top five being timeliness, consistency, accuracy, integration, and update – all highlighting the importance of the relationship between digital twins and data quality. It also prioritizes 10 benefits, the top five being process monitoring, time reduction, process diagnostics, new insights, and transparency, all highlighting the importance of the relationship between digital twins and processes. The model identified the data quality dimensions of accuracy, completeness, consistency, timeliness, accessibility, real-time properties, integration, interaction, communication, connectivity, update and scalability for digital twin, and accessibility, flexibility and configurability for decision support systems. The benefits generated by digital twins for the model were projected onto decision-making. Through realistic process models, digital twins enable the linking of large amounts of data with rapid simulations for the early and efficient evaluation of the impact, performance, and quality of decisions (Tao et al., 2019a; Zhang et al., 2017) identifying reduced time-to-market, process monitoring, process diagnosis, time reduction, cost reduction, predictive maintenance and product improvement as beneficial factors in efficient decision-making. Conversely, the quality of decision-making is negatively affected by a longer decision-making time, decisions made by the wrong people, in the wrong part of the organization, or with the wrong information (Blenko et al., 2010). Using risk avoidance to gain certainty with the above mentioned benefits of digital, allocating resources and opportunities efficiently, and using the above mentioned benefits of digital twins all improve decision quality and thus operational effectiveness. To conclude, the model improves certainty in unstructured decisions by 11.36%, the efficiency of decision-making by 11.83%, and the quality of decision-making by **11.13%**, and thus **operational effectiveness**.

The task of future research is to first implement data quality management, digital twins and decision support systems and to practically link these three topics. In addition, it is necessary to validate the 39 other industries in terms of data quality management, digital twins and decision support systems to assess whether the theoretical model is also relevant. The second task of future research is the practical implementation of the model (Figure 7), so that all organizational and technical challenges of data quality management, digital twins and decision support systems can be further explored.

A LIST OF PUBLICATIONS

Peer Reviewed Journals

1. Biewendt, M., Blaschke, F., Böhnert, A. (2020). The Rebound Effect – A Systematic Review of the Current State of Affairs. European Journal Of Economics And Business Studies, 6(1), 106-120. doi: https://doi.org/10.26417/134 nvy47z
2. Biewendt, M., Blaschke, F., Böhnert, A. (2020). An Evaluation Of Corporate Sustainability In Context Of The Jevons Paradox. SocioEconomic Challenges, 4(3), 46-65. https://doi.org/10.21272/sec.4(3).46-65.2020
3. Blaschke, F., Biewendt, M., Böhnert, A. (2020). The Repercussions of the Digital Twin in the Automotive Industry on the New Marketing Logic. European Journal of Marketing and Economics, 4(1), 68–73. doi: https://doi.org/10.26417/229 eim64f
4. Biewendt, M., Blaschke, F., Böhnert, A. (2021). A Review of Contemporary Challenges in Business Culture. International Journal of Applied Research in Business and Management, 2(1), doi: https://doi.org/10.51137/ijarbm.2021.2.1.1
5. Biewendt, M., Blaschke, F., Böhnert, A. (2021). Motivational Factors in Organisational Change. SocioEconomic Challenges, 5(3), 15-27, doi: https://doi.org/10.21272/sec.5(3).15-27.2021
6. Böhnert, A., Blaschke, F., Biewendt, M., (2022). Impact of Sustainability on the Strategic Direction of Luxury Companies . European Journal of Marketing and Economics, 6(1), 69–82. Retrieved from https://revistia.org/index.php/ejme/article/view/6043

Conference / Poster

1. Wohllebe, A. Blaschke, F. (2022). Description and Implementation of an Experiment With Randomly Assembled User Groups Investigating the Effect of App Push Notification Frequency. doi: https://doi.org/10.13140/RG.2.2.25764.35202