The human factor in operations management - understanding the influence of cognitive biases in production and risk management

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"No duty is more urgent than that of returning thanks."

James Allen

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List of abbreviations

LTS	Lead Time Syndrome
PPC	Production Planning and Control
SCRM	Supply Chain Risk Management
ORM	Operational Risk Management

Abstract

10 Jahre nach der Einführung des Begriffs Industrie 4.0 zeigt sich in der Praxis, dass dennoch viele Potenziale ungenutzt bleiben. Mit dem Konzept der autonomen, sich selbststeuernden Fabrik verbinden nach wie vor viele Unternehmen die Hoffnung nach Produktivitätssteigerungen und Effizienzgewinnen. Gerade im Bereich der Produktionsplanung und Steuerung (PPS), einem der Hauptbereiche im Operations Management, erhofft sich die industrielle Praxis durch den Einsatz digitaler Technologien zunehmende Transparenz und infolgedessen Komplexitäts- und Kostenreduzierungen. Gleichzeitig bringen diese neuen digitalen Technologien aber auch neue Risiken, wie beispielswiese im Bereich der Cybersicherheit mit sich und verändern zudem bestehende Risikoprofile. Hierfür benötigt es ein entsprechendes Risikomanagement, welches diese neuen Risiken entsprechend adressiert.

Trotz dieser zunehmenden Automatisierung bleibt der Mensch auch in der smarten Fabrik eine Schlüsselressource und nimmt als zentraler Entscheidungsträger eine bedeutende Rolle im Gelingen von digitalen Transformationsprojekten sowie dem Risikomanagement ein. Zwar hat die Forschung im Bereich der Verhaltensökonomie in den letzten Jahren deutlich zugenommen, dennoch liegt der Vielzahl an Entscheidungsmodellen im PPS und Risikomanagement die Annahme des rational entscheidenden Menschen zu Grunde. Bei der Anwendung dieser Modelle in der industriellen Praxis zeigt sich jedoch, dass dies häufig zu Problemen führt, weil der Mensch eben nicht rational entscheidet, sondern im Entscheidungsverhalten von sogenannten „kognitiven Verzerreffekten“ beeinflusst wird. Als Folge dessen werden im Risikomanagement daher Risiken häufig falsch eingeschätzt oder gar ganz ignoriert. Im Bereich der PPS kommt es häufig zu Prozessabweichungen mit der Folge einer Verschlechterung der logistischen Leistung.

Ziel dieser Dissertation ist es daher zu analysieren, wie das menschliche Verhalten, Entscheidungen im Operations Management und in der Folge die Ergebnisleistung beeinflusst. Des Weiteren sollen Empfehlungen zur Berücksichtigung der Einflussfaktoren in der menschlichen Entscheidungsfindung zur Ergebnisverbesserung erarbeitet werden. Ausgehend von einer strukturierten Literaturanalyse wurden die Erkenntnisse aus den Forschungsfeldern der Psychologie und dem Operations Management zusammengeführt. Anhand einer breiten Datenbasis von Industrie 4.0 Implementierungsprojekten konnte der Einfluss von kognitiven Verzerreffekten im Bereich der menschlichen Entscheidungsfindung beobachtet werden. Dabei wurden erste Hypothesen entwickelt und mithilfe von Verhaltensexperimenten der Einfluss von kognitiven Verzerreffekten auf Entscheidungen im Risikomanagement und PPS Umfeld nachgewiesen.

Abstract

10 years after the introduction of the term Industry 4.0, it is becoming apparent in practice that many potentials remain unharnessed. Many companies still associate the concept of the autonomous, self-controlling factory with the hope of productivity increases and efficiency gains. Particularly in the area of production planning and control (PPC) – one of the main areas in operations management – industrial practice is hoping for increased transparency and reductions in complexity and costs through the use of digital technologies. However, these new digital technologies lead to new risks, for instance in the area of cyber security, and also change existing risk profiles. This situation requires an appropriate risk management which addresses these new risks. Despite this increasing automation, the human factor remains a key resource in the smart factory and represents as a central decision maker a crucial role in the success of digital transformation projects and risk management. Although research in behavioural economics has increased significantly in recent years, the majority of decision-making models in PPC and risk management are based on the assumption of rationally human behaviour. However, the application of these models in industrial practice shows that this often leads to problems due to the fact that people do not decide rationally and tend to be influenced in their decision-making by so called “cognitive biases”. In risk management, risks are therefore often assessed incorrectly or even ignored. In the area of PPC, process deviations frequently occur with the consequence of a deterioration in logistical performance.

The aim of this dissertation is therefore to analyse how human behaviour influences decisions in operations management and subsequently the logistic performance. Furthermore, recommendations will be developed for how to consider the influencing factors in human decision making in order to improve results. Based on a structured literature review, the findings from the research fields of psychology and operations management were combined. Using a broad database of Industry 4.0 implementation projects, it was possible to observe the influence of cognitive biases in the area of human decision-making. Initial hypotheses were developed and the influence of cognitive distortions on decisions in the risk management and PPC environment was demonstrated with the help of behavioural experiments.

"The confidence people have in their beliefs is not a measure of the quality of evidence but of the coherence of the story the mind has managed to construct"

Daniel Kahneman

1. Introduction

1.1 Background and motivation

Both researchers and practitioners emphasise the benefits of digital technologies. The vision of a self-controlling, autonomous smart factory changes the entire production process. Especially industrial practice hopes for productivity increases and efficiency gains through the increasing digitalisation. In PPC – one of the core parts of operations management – practitioners further hope for complexity and cost reductions through increasing transparency by using artificial intelligence algorithms and digital twins for planning purposes. Nevertheless, almost 10 years after the introduction of the term "Industry 4.0" as a concept of an autonomous, smart and fully digitalised industry vision still tremendous potential remains untouched (Cimini et al. 2020). However, many digitalisation projects fail due to incorrectly assessed or even completely ignored risks (Brocal et al., 2019). Also, in PPC the hope of having short lead times is fading (Häußler et al., 2021). As an underlaying reason, practice shows that there is often a disconnection between the models and concepts developed and their practical implementation. One main reason is often the lacking attention to the human factor (Donohue et al., 2020). Especially in the implementation of new technologies, their success depends heavily on the understanding and acceptance by the human (Neumann et al., 2021). However, most digitalisation projects in industrial practice fail due to the lack of acceptance by the worker who should be using the digital technology (Abel et al., 2019).

Additionally, the increased collaboration required in production tasks between humans and machines. accompanied by the discussion of which decisions should be made through humans and which through machines, underpins the need for consideration of the human factor (Romero, 2016).

On this basis, the European Commission has developed a concept of the so-called Industry 5.0 vision, focusing on human needs as a further development of the Industry 4.0 concept in order

to achieve a more sustainable and resilient industry (European Commission, 2021). By paying more attention to human behaviour, industrial practice hopes to realize the untouched potential which a fully digitalised economy can offer.

Two well researched phenomena in operations management show the importance of considering human behavioural aspects with regard to the improvement of operational performance: the Lead-Time-Syndrome (LTS) and the Bullwhip Effect. As a reaction to decreasing due date reliability, the LTS describes the results of the subsequently following overreaction of production planners who adapt planned lead times too frequently. This results in an even worse schedule adherence (Selçuk, B., et al., 2009). Several researchers (see, for instance, Häussler, et al., 2021, Bendul and Knollmann, 2016, Selçuk, B., et al., 2006) identified distorted human decision-making as the cause for the occurrence of LTS. Also, the Bullwhip Effect, which describes how order variability increases as it progresses though the supply chain, can be traced back to distorted human behaviour. The underlaying reason is the systematic underestimation of the inventory pipeline by the humans involved (Udenio et al., 2017). Particularly in complex situations with time pressure, which decisions in operations management typically are, humans fail to make rational decisions and tend to systematically deviate from a rational optimum. Kahneman and Tversky (1974) were two of the first researchers to investigate how so-called cognitive biases influence human decisions. These cognitive bias effects arise as a result of mental short cuts which are used by the human brain to process information and which lead to distorted human behaviour and subsequent deterioration of operational performance.

1.2 Cognitive biases

The occurrence of cognitive biases can be traced back to different evolutionary stages of the human brain. There are two different areas in the human brain which are involved in the human decision-making process. Evans (2013, p.454) described them as “two minds in one brain”. Several researchers named them differently, such as Thaler and Sunstein (2008), who referred to the “automatic system” and the “reflective system” or Sloman (1996), who talked about the “associative system” and the “rule-based system”. Tversky and Kahnemann (1974) classified them as “intuition” and “reasoning” in their early research. The intuition system, which is the elder system in human evolution, is very fast, effortless and intuitive. Therefore, it is also called “instinct” or “gut feeling”, as it is a result of human evolution for ensuring survival. Various researchers in the fields of psychology and behavioural operations have been trying for years to describe the processes it takes for the intuition system to come to a decision, but there is as

yet no clear explanation. We only can register decisions when they the consciousness level of our mind (Arnott, 2019).

The younger system - the reasoning system - requires cognitive effort, is slow, rule-based and controlled (Evans, 2013). Decision making is not innate and must be learned through education. In later research, Stanovich and West (2000) simply named this dual process "System I" and "System II". Both systems can interact with each other and are involved in human decision-making at the same time. Depending on the decision situation and the decisional environment, such as number of involved parties, familiarity with decision situation, or also the time horizon, determine which system is dominant. Based on the initial research by Kahneman and Tversky (1974), plenty of different cognitive bias effects and their influence on human decision-making have been investigated. Also, several classification schemes have been proposed by several researchers for grouping these various effects (see, for instance, Arnott, 2006; Benson, 2016; Bendul and Zahner, 2020).

With increasing interest in behavioural economics in the field of operations management, several operational phenomena, such as the LTS (see, for instance, Selçuk et al., 2006) or the Bullwhip Effect (see, for instance, Udenio et al., 2017) were investigated with a strong focus on the influence of human behaviour. In the course of these developments, also the research on cognitive biases and human decision-making has been transferred to the field of operations management and has gained increasing interest during the last decade (Fahimnia et al., 2019).

To contribute to human needs, to lower the negative influence of cognitive biases and to contribute to more rational decisions, research in parallel has tried to investigate so-called debiasing techniques (see, for instance, Camerer and Hogarth, 1999; Larrick, 2004, Kaufmann and Carter, 2010). Various motivational, cognitive and technological methods have been developed for effective debiasing (Larrick, 2004). Particularly designers of modern decision support systems are highly interested in these effects and have proposed methods to integrate them into the user interface of digital technologies (Philips-Wren et al., 2020).

1.3 Research gap

Behavioural factors in operations management have been the subject of study for a number of years and have led to the emerging research domain of behavioural operations management (Bendoly et al., 2010; Tokar, 2010; Fahimnia et al., 2019; Donohue et al., 2020). In various operations management areas such as supplier selection, decision-support systems design, risk management and inventory and production planning and control management, the influence of humans has gained increasing research interest (Bendoly, 2006; Neumann et al., 2021).

Nevertheless, in the fields of production planning and control as well as in supply chain risk management (SCRM) and operational risk management (ORM), which are the core areas of this thesis, several research points remain open.

First, research in the field of production planning strongly focuses on behavioural estimations for the development of mathematical models that improve planning and performance (Fahimnia et al. 2019; Troutt et al, 2006). The influence of human behaviour and especially of human decision-making on production planning and control results have rarely been discussed in the literature so far (Gasser et al., 2011). The same applies for supply chain risk management literature, where only little research into the influence of human behaviour on risk management decisions has been published so far (Schorsch et al, 2017). Also, in risk management literature in the context of digital operations, the influence of human factors is sparsely considered (Tupa et al, 2017).

Although the consideration of human factors is gaining increasing interest, most PPC and risk management models still assume a rational human behaviour and neglect the influence of cognitive biases on human decision-making (Gino et al., 2008; Ghadge et al., 2012).

Second, the influence of human behaviour is often discussed in a general way in operations management literature (Katsikopoulos, 2013). However, as the results from human decision-making research in psychology show, the type of decision as well as the decisional environment, such as time frame, familiarity of decision-making situation etc., plays an important role in how cognitive bias influence decisions. Therefore, the influence of cognitive biases must be investigated in relation with the relevant decision tasks and, typically, decision environments in PPC and risk management.

Third, what holds true for both research areas, is a lack of evidence through behavioural experiments (Bendoly et al., 2010). However, if behavioural experiments are conducted, these are often based on the involvement of students and lack the involvement of practitioners in this field, which makes it hard to transfer the results to real-life situations in industrial practice (Bendoly et al., 2006)

Overall, even though the increasing research interest in behavioural operations management has also led to increasing research in the field of PPC and risk management, the influence of cognitive biases depending on the decision type remains unclear, and practical confirmation based on behavioural experiments involving practitioners is still missing.

1.4 Research objectives

To fully exploit the potential that digitalisation offers in industrial operations. it is necessary to consider human behaviour in decision-making. Particularly the described hopes of efficiency gains, cost reductions and increased operational performance require the integration of human behavioural aspects in modern PPC and SCRM models as well as in industrial practice. Current discussions in research and industry about the optimum collaboration level between humans and machines confirm this need. Therefore, this thesis aims to combine the research of psychology and operations management in order to address the research gaps in terms of PPC and risk management.

The main research question is "*How do cognitive biases influence human decision-making in operations management with regard to operational performance?*

This overall research question can be broken down into three sub-questions:

(1) *Which decision types in PPC and SCRM are affected by cognitive biases with respect to operational performance?*

Human decision making is a well-researched field of psychology. Based on the initial work by Kahneman and Tversky (1974), plenty of cognitive bias effects have been investigated in various research areas and have been described in detail in the literature. Sometimes, even different names have been proposed by different researchers for the same effects. Despite that, several classification models for the various cognitive bias effects exist. In order to create a clear and structured view, it is necessary to define the relevant cognitive bias effects which influence human decisions in operations management. Thereby, a special focus is set on these types of cognitive bias which lead to an impact on operational performance. Especially, based on the specific tasks and required decisions in PPC and SCRM, the relevant influencing factors should be identified.

(2) How do cognitive biases affect different decision-making types and situations in operations management with respect to operational performance?

Further, based on the several different decision tasks in PPC and risk management, also different decision types can be distinguished. For example, a decision made by one decision-maker faces different conditions than a decision made within a group decision. Daily business decisions with a high degree of familiarity will also be made in a totally different way from a

decision in a unique situation with a high degree of uncertainty. These different decision types also determine the effect itself as well as the intensity of the effect of the different types of cognitive biases. Therefore, it is important to understand and also to test which type of cognitive bias influences which type of decision in operations management.

(3) How can debiasing techniques be reflected in decision support systems in operations management in order to improve operational performance?

To lower the influence of cognitive bias, several debiasing techniques can be applied. An understanding of which type of cognitive bias occurs in which situation is the basis for the development of any debiasing strategies.
With the increasing level of collaboration between human and machines, decision support systems are also frequently used to assist the human in making decisions. The way in which information is presented also influences the human worker in the decision-making process. Therefore, recommendations for how the human factor can be reflected in the design of decision support systems are required by system designers, IT-programmers and industrial practitioners.

1.5 Course of research

In order to answer these research questions and sub-research questions the thesis is structured into seven main chapters based on five research papers. These are presented in the chapters 2,3,4,5 and 6. The following figure 1 shows the structure of the thesis and how the different research papers build upon each other.

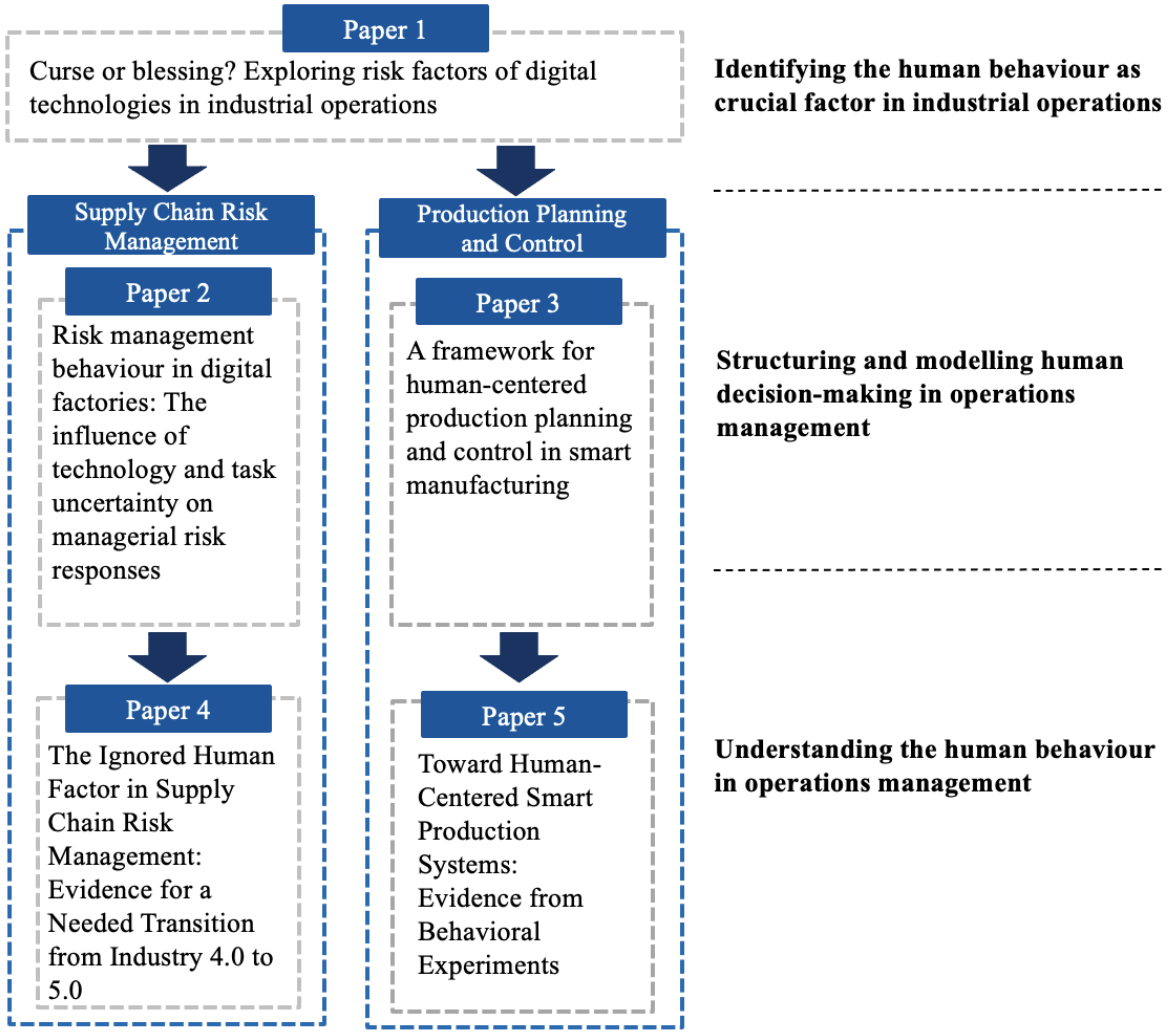


Figure 1: Thesis structure based on five research papers

The following Figure 2 gives more details about the applied research methodology, background information about the research objective and conducted work as well as further information about how the results of each paper guided the further research process of the thesis. Thereby, paper 1,2 and 4 build on the same data set of an analysis of 300 Industry 4.0 use cases as well as additional 53 expert interviews. However, each research paper sheds light

on a special aspect of the data. Paper 3 and Paper 5 are based on individual methods which are presented in the following Figure 2 in more detail.

Phase	Paper 1	Paper 2	Paper 3	Paper 4	Paper 5
Titel	Curse or blessing? Exploring risk factors of digital technologies in industrial operations	Risk management behaviour in digital factories: The influence of technology and task uncertainty on managerial risk responses	A framework for human-centered production planning and control in smart manufacturing	The Ignored Human Factor in Supply Chain Risk Management: Evidence for a Needed Transition from Industry 4.0 to 5.0	Toward Human-Centered Smart Production Systems: Evidence from Behavioral Experiments
Method	▪ Practical motivation by identification of research gap regarding the adoption of I4.0 technologies in industrial operations and associated risks ▪ Online database analysis of 300 I4.0 uses cases of German companies ▪ 53 expert interviews between 25-50 min	▪ Analysis of secondary interview data of 53 expert interviews with special focus on nature of human machine interaction	▪ Extension of structured literature review by combining the literature streams of psychology, PPC and behavioural operations management ▪ In-depth case study of a german steel case manufacturer	▪ Structured literature review by combining the literature streams of psychology, supply chain risk management and behavioural operations management ▪ Analysis of secondary interview data of 53 expert interviews	▪ Behavioural experiments with 99 participants and 75 PPC practitioners
Research objective	▪ Explore relationship between I4.0 technologies and SC risks in the implementation and operating phase	▪ Investigation of managerial responses in SCRM in the context of digitalisation projects	▪ Mapping of relevant PPC decision-making situations with cognitive bias effects ▪ Framework for human-centric PPC in smart manufacturing	▪ Identification of relevant active cognitive bias effects which distort decisions in SCRM	▪ Investigation of identified cognitive biases and their influence on PPC decisions
How research results guide further research	▪ Identification of human behaviour in decision-making as a central influencing factor in risk management especially in production technologies motivated further research	▪ Strong influence of human behaviour and cognitive biases in SCRM was identified	▪ Development of testable hypotheses of influence of cognitive biases on PPC decisions	▪ Development of six testable hypotheses ▪ Development of a framework of cognitive biases and debiasing techniques in SCRM	

Figure 2: Thesis outline, methods and course of further research

The chapters 2,3,4, 5 and 6 present the main research papers of this thesis.

The first paper in chapter two forms the basis of the further research and shows the theoretical and practical motivation for this thesis project. Relevant associated risks with the implementation of Industry 4.0 technologies and the decision-makers´ response to different types of risks are investigated. Based on empirical evidence of 300 use cases of industrial practice and fifty-three interviews with relevant managers from selected cases, this paper aims to show how digital technologies adopt existing risks and it introduces new risk profiles. In particular, human behaviour turned out to be one key success factor for the implementation of digital technologies.

Under application of Normal Accident Theory, a framework to explicate the drivers and contingency factors of supply chain risks in the context of Industry 4.0 technologies is proposed. First practical recommendations for mangers are provided to guide the implementation of digital technologies in practice.

On this basis, the paper of the third chapter (Paper 2) aims to deepen the understanding of managerial responses in risk management in the context of digitalisation projects. Therefore, the same initial data set of fifty-three interviews was analysed but with a special focus on the level of the human-machine interaction in the digital technologies. Thereby, a high influence of human behaviour on risk management decisions was identified, especially for production technologies. Further, based on the model of natural decision-making, cognitive biases were identified as a distorting factor for the information processing capabilities of the managers. This motivated, on the one hand, a deepening of the research into the influence of cognitive biases in supply chain risk management and, on the other hand, opened up a new research area of production planning and control. Especially in smart manufacturing systems, an effective PPC is essential to achieve short lead times and high due date reliability, both of which are expected by the customers. Thereby, a multitude of decisions have to be taken by production planners. These decisions are often influenced by cognitive biases, with the result of suboptimal operational performance. Therefore, the paper of the fourth chapter (Paper 3) focuses on the production planning and control process of smart manufacturing systems. As several phenomena, such as the LTS or the Bullwhip, show that distorted human decision-making often results in suboptimal operational performance, this paper focuses on developing a human-centered design of planning and control processes to mitigate biased decisions. Based on a structured literature review of behavioural operations management and cognitive biases in PPC as well as an in-depth case study of a steel producer involving 12 expert interviews, two decision-making models are explored. As a result, a framework for human-centered PPC in smart manufacturing systems comprising five testable hypotheses on the impact of cognitive biases on human decision-making and on manufacturing performance is developed.

Research Paper 4 (chapter five) builds on the data set and results of Research Papers 1 and 2. To deepen the understanding of the influence of cognitive biases in SCRM decision-making, the literature streams of psychology and supply chain risk management are combined. Therefore, the initial data set of the fifty-three interviews with experts and managers from industry was analysed with a special focus on the influence of cognitive biases in SCRM decisions. Thereby six testable hypotheses are derived. Initial recommendations for debiasing

techniques are developed which serve as a starting point for reflecting these methods in decision support systems.

The fifth paper in chapter six confirms the influence of cognitive biases on human decision-making PPC based on empirical evidence from behavioural experiments. With 99 participants, also including 75 practitioners from different industrial sectors, this paper contributes to the overarching research question and emphasises its practical relevance. Thereby, 14 typical PPC decision-making situations with 16 questions were presented to the participants. The results confirm the initial hypothesis on how cognitive biases distort human decision-making.

Finally, chapter seven presents an overarching outlook on how the findings can be applied in industrial practice. Further, it summarizes the key contributions of the papers and discusses their limitations. Additionally, potential further research fields are presented.

1.6. Thesis framework

This thesis consists of five main publications with different perspectives and areas of operations management. All papers focus on human decision-making and the different consequences for each business area. Table 1 below shows the corresponding overarching topics that the thesis covers.

	Impact of human behaviour	***Characteristics of decisions***	***Decision support systems and human-centered design***	***Technological environment and digitalisation***	***Core areas of operations management (PPC, SCRM)***
Paper 1: Curse or blessing? Exploring risk factors of digital technologies in industrial operations	×			×	×
Paper 2: Risk management behaviour in digital factories: The influence of technology and task	×	×		×	×

uncertainty on managerial risk responses					
Paper 3: A framework for human-centered production planning and control in smart manufacturing	×	×	×	×	×
Paper 4: The Ignored Human Factor in Supply Chain Risk Management: Evidence for a Needed Transition from Industry 4.0 to 5.0	×		×		×
Paper 5: Toward Human-Centered Smart Production Systems: Evidence from Behavioral Experiments	×	×	×	×	×

Table 1: Overarching thesis framework

The influence of human behaviour and the role of decision-making are investigated for several sub-areas of operations management. Thereby, the papers have a different focus of the sub-areas, namely PPC and SCRM. Based on different decision types, which can be classified by several criteria such as time frame, familiarity with the decision, involved parties etc., specific cognitive bias effects occur which are investigated in this thesis for each mentioned sub-area of operations management.

The area of decision support systems and the technological development towards digitalisation demonstrate the practical and theoretical motivation of the research. The technological

development with increasing digitalisation leads to the occurrence of various digital applications. Particularly the collaboration between human and machines intensifies - enabled by various digital technologies. Decision support systems represent such a technology which supports human in their decision-making process based on the analysis of a vast amount data. However, as human decision-making is prone to biases, this also raises the debate on how a human-centric design and the usage of debiasing techniques can be reflected within these decision support systems.

The first paper investigates this technological development and the influencing factors for the implementation of digital applications in operations management. Thereby, human behaviour is identified as a key element in risk management. The second paper deepens the understanding of the managerial responses in SCRM and investigates the influencing factor on the information processing capabilities of humans. A special focus is set on the relationship of the human-machine interaction of the implemented digital technology. As human behaviour plays a crucial role for the success of such implementation projects, research Paper 4 takes a detailed look at the influencing factors of cognitive biases on supply chain risk management.

All three papers contribute to the sub-research questions (1) and (2).

Based on the results of Paper 1, which identified in particular biased decision-making in the context of production technologies, the extension of the research process to the area of PPC was motivated. Therefore, the third paper focuses on the influencing factors of cognitive biases on another sub-area of operations management namely production planning and control in smart manufacturing systems. Additionally, to sub-research questions (1) and (2), the proposed framework also gives recommendations which should be considered in the design of decision support systems considering human needs, and sub-research question (3) is addressed. Based on the empirical testing through behavioural experiments, Paper 5 addresses all three research questions and concludes and summarizes the findings of all research papers confirming the existence of cognitive biases in the different sub-areas of operations management.

2. Paper 1: Curse or blessing? Exploring risk factors of digital technologies in industrial operations

Authors: Melanie Kessler, Julia Arlinghaus, Eugenia Rosca, Manuel Zimmermann

Status of Publication: Published in International Journal of Production Economics, Volume 243 (2022).

DOI: 10.1016/j.ijpe.2021.108323.

Contribution of Melanie Kessler to the work: Conducted the data analysis, wrote the paper, contributed to discussions about the findings.

Contribution of the co-authors: Manuel Zimmermann collected the raw data by collecting the uses cases and conducting the expert interviews. Julia Arlinghaus made the methodological selection. Eugenia Rosca and Julia Arlinghaus both reviewed the paper and helped with structuring the paper. Both also contributed to discussions on the findings.

Contribution of the paper to the PhD project: This paper is the motivational paper for the further research of this dissertation. Based on the implementation of digital technologies in business operations, several risk factors are investigated. The proposed framework based on qualitative data analysis and Normal Accident Theory shows the drivers and contingency factors of new sources of supply chain risks in the context of digitalisation projects. Human behaviour in particular turned out to be a crucial element for a successful implementation of these technologies.

Note: In the interest of uniformity, all articles have been reformatted according to the dissertation format.

Curse or Blessing? Exploring Risk Factors of Digital Technologies in Industrial Operations

Abstract

Both practitioners and scholars emphasise the benefits of Industry 4.0 (I4.0) technology implementation, such as increased transparency and the availability of real-time data in operations processes. Current literature on I4.0 technologies tends to overemphasise the positive impact and transformational capabilities of digital technologies while there is little focus on evaluating potential risks associated with their adoption in industrial operations. An understanding of how supply chain risks are perceived in digitalisation projects within industrial operations and an understanding of decision-makers' responses to different types of risks has important managerial implications. Current literature, however, lacks systematic empirical evidence on the implementation of I4.0 applications and related risk factors. This study aims to address this research gap by exploring the relationship between I4.0 technologies and supply chain risks based on empirical evidence from 300 case studies of industrial practice in Germany and fifty-three interviews with relevant managers from selected use cases and with general experts in this field. Our findings show that digital technologies are frequently adopted to address certain existing supply chain risks but that their implementation introduces new sources of risks (e.g. cyber risks). Based on qualitative data analysis and drawing on Normal Accident Theory, we propose a framework to explicate the drivers and contingency factors of new sources of supply chain risks in the context of Industry 4.0 technologies. Practical recommendations are provided for supply chain managers to guide the process of managing supply chain risks based on the technological life cycle.

Keywords: risk factors, digitalisation, technology life cycle, Normal Accident Theory, Industry 4.0 technologies, technology vendors and users

1. Introduction

New technologies, such as mobile applications, the Internet of Things (IoT), cloud services and artificial intelligence, are increasingly being adopted by industry to facilitate operations and supply chain processes. Digitalisation is driving a process of transformation into digital supply chains and smart industrial operations (Ivanov et al. 2019). This global trend is often viewed as

part of the progression towards Industry 4.0 (I4.0), an idealised vision of future industrial manufacturing. A wide variety of technology components, also called I4.0 technologies, such as cyber-physical systems, IoT applications and cloud computing, which integrate virtual space with the physical world, form the basis of this concept (Xu et al., 2018). The main benefits promised by I4.0 and other similar initiatives include productivity gains, smaller environmental footprints, higher efficiency, lower costs, greater robustness and flexibility, higher quality and shorter time-to-market (McKinsey Digital, 2015; World Economic Forum, 2017). As events in the past few years have shown, however, these technologies are also accompanied by the emergence of new risks, such as data security or cyber risks. In 2015, for instance, hackers not only halted biscuit production at a Canadian factory but also made its complete renovation necessary because of dried dough in the pipes (Ries, 2015). Another example relates to radio frequency identification (RFID) technology: substantial investments were made in the early 2000s to implement RFID technology in industry but environmental factors (e.g. humidity, nearby metals) impeded the 100% identification required, adversely affecting logistics performance and, consequently, return on investment (Bolić et al., 2010). These examples show that the implementation of digital technologies can render industrial operations more vulnerable to a variety of risks and disruptions that are highly relevant to supply chains.

Literature on supply chain risk management (SCRM) provides numerous frameworks and models for types and sources of risks as well as mitigation strategies, yet little is known about supply chain risks in the I4.0 technology landscape (Hahn, 2019). Moreover, current literature on I4.0 technologies tends to overemphasise the positive impact and transformational capabilities of digital technology while underestimating the potential risks associated with its implementation (Flyverbom et al., 2019). Therefore, there is a strong need for a systematic understanding of supply chain risks driven by digital technologies (Tupa et al., 2017; Birkel et al., 2019) in order to mitigate and minimise new sources of risks in operations management (Ivanov and Dolgui, 2020).

Subsequently, this study aims to answer the following research question: *How does the adoption of I4.0 technologies alter the supply chain risk profile in industrial operations and what is the role of the technological life cycle?* Drawing on extensive analysis of 300 case studies of I4.0 technologies used in German industry and fifty-three interviews with relevant managers from selected use cases and general experts in the field, this study identifies and classifies sources of risk inherent to I4.0 technologies arising from their adoption in industrial operations. The methodological overview of this study is presented in Figure 1.

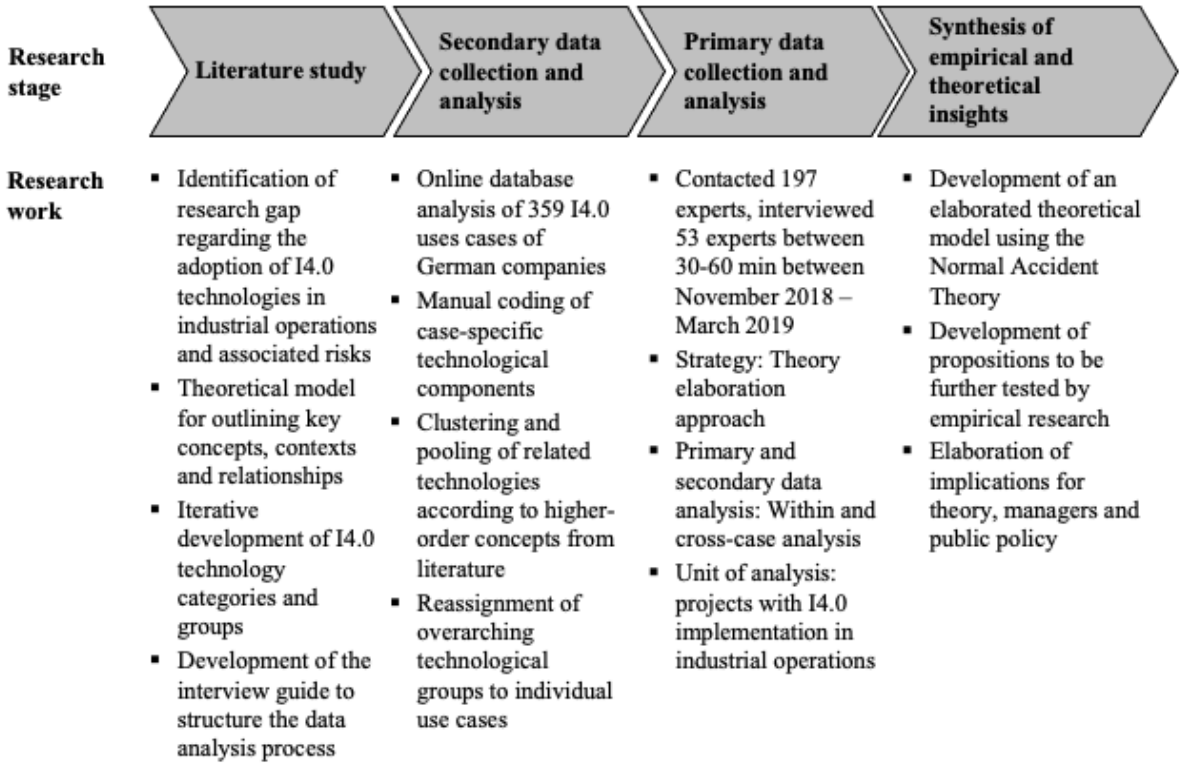


Figure 1: Methodological overview

The remainder of this article is structured as follows: Section 2 describes the theoretical background of SCRM, Industry 4.0, its risk implications, and relevant digital technology life cycle (DTLC) models. Section 3 presents the methods employed and provides an overview of the data used. Section 4 presents the findings and is followed by discussion and a conclusion in section 5.

2. Theoretical Background

The aim of this section is to provide an overview of the relevant theoretical constructs. These serve as the foundation for this study and outline the research gap addressed by this study. First, a brief overview of the supply chain risk management literature outlines the lack of frameworks and models to account for I4.0 technologies implementations in industrial operations. Second, an overview of classifications of I4.0 technologies is given. It acts as a foundation for the empirical analysis and provides the basis for linking risks with I4.0 technologies. Third, a systematic identification of studies addressing issues of supply chain risks and digital technologies is conducted in order to synthesise main insights and outline the research gap. In subsections 2.4 and 2.5, we discuss the theoretical foundations of the study, namely Normal Accident Theory (NAT) and the digital technology life cycle model. The digital technology life

cycle approach is adopted in this study to provide a more nuanced view of supply chains risks triggered by the adoption of digital technologies. Subsection 2.6 synthesises main insights and outlines the goal and intended contribution of the study.

2.1 Supply Chain Risk Management (SCRM): The need for an adapted risk management approach toward I4.0 technologies

Several authors have examined different types of supply chain risks over the past years and have developed corresponding categorisations, which are presented in Appendix A. Rao & Goldsby (2009) developed a typological model of SCRM by incorporating risk factors from the literature (environmental factors, industry factors, organisational factors, problem-specific factors, and decision-maker factors) into the standard supply chain framework. Their approach conforms with the work of Ritchie & Marshall (1993), Kersten et al. (2007) and Christopher & Peck (2004), all of whom proposed three groups of risk factors: environmental factors, internal industry/supply chain factors and organisational/corporate factors. Rao & Goldsby (2009) developed a general typological model of risk intended to serve as a guide for structuring and organising future, more specific studies of supply chain risk. Other authors, such as Chopra & Sodhi (2004) and Tang & Tomlin (2008), focus on mitigation strategies and approaches for resilient supply chain design in the context of conventional supply chain risks. Christopher & Peck (2004) identified several risk factors in their research and demonstrated the interplay between supply chain risks and internal corporate risks within the supply chain as a whole. Tummala & Schoenherr (2011) compiled categories of common supply chain risks (e.g. disruption risks) and corresponding triggers (natural disasters, terrorism and wars) from prior studies.

The phases of risk management comprise three basic activities, regardless of the SCRM framework consulted. Although the wording varies from author to author, these successive phases are essentially (1) risk identification/determination, (2) risk evaluation/assessment and (3) appropriate risk mitigation/control. The initial phase of risk identification/determination is often considered the most important since it lays the foundation for all subsequent risk management activities. It involves comprehensively screening and understanding the current risk situation in order to identify all potential risks and determine which are relevant for further assessment and mitigation. The wide and fast adoption of digital technologies changes the setting and character of industrial operations. Therefore, current frameworks and models for traditional supply chain risks may be insufficient to fully explain the changes brought about by

digital transformation. There is a strong need for research and development towards an adapted risk management approach for I4.0 technologies in industrial operations.

2.2 Industry 4.0 Technologies: What are they?

While most studies discuss individual technologies and applications under the umbrella of I4.0, a systematic classification is needed to facilitate the development of a risk profile per technology group rather than individual technologies. The literature includes several attempts to synthesise and classify current I4.0 technologies. Some studies applied higher-order technology concepts (e.g. automation and machine-to-machine communication) as criteria for developing typologies, while others employed abstract ideas (e.g. horizontal/vertical integration and predictive maintenance), linking them with specific sets of hardware and software technologies required for implementation. More specifically, Schlüter & Hetterscheid (2017) comprehensively evaluated the recent literature to list relevant I4.0 technologies. They defined thirty criteria for I4.0 technologies and clustered them into fifteen higher-order technology groups, such as augmented reality, machine-to-machine communication or smart factory. For example, wearable is a higher-order technology group which consists of two technologies: data glasses and sensor gloves. Furthermore, Alcácer & Cruz-Machado (2019) derived nine technological pillars from their analysis of recent literature on I4.0. The pillars represent higher-order concepts of technology-based solutions that are essential components of the I4.0 paradigm. Similarly, Rüssmann et al. (2015) proposed nine foundational technologies, i.e. nine pillars of technological advancement, which constitute the foundation of I4.0. In their study, Oztemel & Gursev (2018) analysed headings, abstracts and keywords of publications about I4.0 to create a hands-on library on the subject for both academics and industry practitioners. The authors identified ten basic components of I4.0 that serve as technological enablers of the paradigm. Altogether, these studies are valuable efforts to systematise the use of I4.0 technologies and related terminology. This is essential for ensuring research continuity in this field.

2.3 SCRM in the context of Industry 4.0: An important research gap

Relevant studies in the area of SCRM for I4.0 technologies applications have been identified through a systematic approach. Table 1 provides an overview of the investigated relevant

studies.[1] The analysis of current studies shows that a systematic analysis of risk management practices for I4.0 technologies implementation based on empirical data is missing.

Study	Approach	Technology Focus	Risks
Brocal et al. 2019	Literature review	Human-machine interaction, human-interaction	Accident risks, psychosocial and musculoskeletal risks, increased complexity and unpredictability of robot tasks, increased complexity in distributed instances
Hertel 2015	Literature review, case studies	Unspecified - smart factory	Cyberattacks (intentional and unintentional), errors (human, technical, organisational, force majeure)
Birkel et al. 2019	Literature review, interviews with experts	Unspecified – Industry 4.0	Economic, ecological, social, technical/IT, legal/political
Ivanov et al. 2018	Literature review	Big data, Industry 4.0 (IoT, smart products, robotics, augmented and virtual reality), additive manufacturing, advanced tracking and tracing technologies	Aggravation of the ripple effect, increase in coordination complexity, data safety issues, information disruption risk
Rossmann et al. 2017	Delphi study, fuzzy c-means clustering	Big data, big data analytics	Risk of poor validity and quality of shared data, data tampering, data security, reduced necessity of human interaction, risk of interorganisational conflicts, synchronisation throughout the supply chain impeded by different technology readiness levels among partners
Guha/ Kumar 2017	Literature review	Big data, especially applications for cloud computing, IoT/ smart city, predictive manufacturing, 3D printing, smart healthcare	Data security, high implementation costs, hidden problems and costs after completion of projects, lack of technological knowledge
Fosso Wamba et al. 2015	Literature review, case study analysis	Big data, big data analytics	Inferior and/or poor quality of data, inappropriate data, waste of organisational resources, careless handling of personal and organisational privacy; challenges mentioned: data policies, technology and techniques, organisational change, access to data, industry structures

Table 1: Overview of risk factors relevant to I4.0 technologies: Synthesis of relevant studies

While the actual range and magnitude of benefits has been discussed frequently in the literature (e.g. Müller et al. (2018), Schmidt et al. (2015)), researchers have only recently begun raising questions about new risk factors accompanying the use of the I4.0 technologies introduced. Brocal et al. (2019), for instance, dealt with the risks of I4.0 in the current operational context and designate organisational and human factors as fundamental risks. Hertel (2015) emphasised

[1] To identify the relevant literature, we used the two search engines of Business Source Complete (EBSCOhost) and Web of Science. Therefore, we combined the terms ‘risk’, ‘Industry 4.0’, ‘supply chain’ and ‘supply chain risk management’ as search strings for the title, abstract and keywords. We investigated the identified papers and focused on articles which address specific I4.0 risks.

potential technical risks in smart factories and proposed a classification model that distinguishes between cyberattacks and errors. Attacks in this context comprise malicious intentional and unintentional threats, e.g. hacking or phishing mails, while errors include human, technical or organisational failure as well as force majeure.

Based on recent literature on digitalisation applications in supply chain management (SCM), Ivanov et al. (2019) studied the influence of digitalisation and I4.0 on the ripple effect and disruption risk control analytics in the supply chain. While focusing on the opportunities of certain digitalisation applications in SCM, the authors expounded the simultaneously arising challenges and risk themes. Predictive analytics, for instance, can increase demand forecast quality or supply chain visibility but simultaneously raise challenges related to data safety or coordination complexity. Several studies have explored more specific issues subsumed by I4.0 technologies and associated risk factors. Rossmann et al. (2018), for instance, examined the future and the social impact of the use of big data analytics in SCM in general. They emphasised common cyber security risk, such as poor validity and quality of shared data and data tampering. Moreover, some authors have focused on certain industries to ascertain the risks of big data in specific areas of application. Guha & Kumar (2018), for instance, posited that big data applications in healthcare supply chains cause data security risks as well as increased implementation costs and hidden problems and costs even after projects have concluded. The authors identified privacy concerns and related legal issues as major risk factors and obstacles to big data applications. Overall, the current literature focuses on potential risks associated with the ultimate concept of I4.0 in several specific sectors using illustrative cases. Moreover, none of the literature examines the changing risk situation in companies that are introducing I4.0 applications.

2.4 Normal Accident Theory (NAT)

Various theories have been applied in the SCRM literature, with the most frequently used ones being transaction cost economics, agency theory, system theory and institutional theory (Fan and Stevenson, 2018). The incorporation of behavioural theories and models into the supply chain risks literature is an emerging and novel topic of study (Pournader et al., 2020; Arlinghaus et al., 2020; Bendul and Knollmann, 2016). While the application of theories can significantly enhance supply chain risk conceptualisations, SCRM research has not fully taken advantage of the existing body of theories (Pournader et al., 2020; Fan and Stevenson, 2018). These theories have been used to inform the conceptualisation of supply chain risks and inter-relationships among risk types, but also to guide hypotheses development and testing regarding capabilities,

resources and mechanisms needed to identify, manage and mitigate supply chain risks (Fan and Stevenson, 2018).

The focus of this study is to understand how the adoption of digital technologies influences the internal structure and decision making inside a company. To inform the conceptualisation of supply chain risks and inter-relationships with other system parameters, NAT has been chosen as a theoretical foundation. This theory has been previously used in a few supply chain risk studies to understand disruptions (e.g. Scheibe & Blackhurst, 2018; Bendul & Skorna, 2015; Skilton & Robinson, 2009). NAT focuses on the system conditions and how they are influenced by external parameters, for instance, through the implementation of new technology. Therefore, NAT is used in this study to inform the understanding of risk and the influence of external drivers, such as the adoption of a digital technology. NAT holds that a system's complexity and its tightly coupled processes increase the likelihood of failures (Perrow, 1999). Complexity can be defined broadly as 'the sum of information required to entirely describe the system*'* (Cohen & Stewart, 1994). Supply chain complexity is the product of the number of suppliers, differentiation of suppliers and the level of interrelationship between suppliers (Skilton & Robinson, 2009; Choi & Krause, 2006). Coupling of system components comprises the number of variables shared among subsystems and the strength of the coupling (Weick, 1976). Tight coupling of system components determines the ease with which disruptions spread across the entire system (Marley et al., 2014). NAT holds that even small disturbances can cause major disruptions in operations and affect the entire supply chain's functionality (Bendul & Skorna, 2015).

2.5 Digital Technology Life Cycle

The understanding, identification and mitigation of supply chain risks is closely linked with the stages of the technological life cycle. The digital technology life cycle approach is adopted in this study to provide a more nuanced view of supply chain risks triggered by the adoption of digital technologies. This is important because several risks may present strong manifestations during the implementation stage (e.g. employee resistance) but can be more easily addressed during later operational stages. The technology life cycle model serves as a guide to map interrelationships between supply chains risks occurring at different stages of technology implementation.

The literature provides numerous life cycle models for various technologies. All of them describe the readiness level at different stages over time (Jamnia, 2018; Project Management Institute, 2017). The standard life cycle consists of four stages: introduction, growth,

maturity/stabilisation and saturation/decline (Levitt, 1965; Anderson & Zeithaml, 1984). These stages follow one another in chronological order and describe a technology's interaction with its environment, for instance. One common approach depicts a product's market life cycle over time in terms of performance indicators, such as sales, revenue, profit and number of customers. The view of the life cycle varies depending on the perspective and motivation (Stark, 2015). The industrial product life cycle and the technology life cycle, for instance, address the perspective of manufacturers of (technology) products. Both concepts thus focus on processes related to the research and development, manufacture, sales, after-sales and disposal of technology products (Saaksvuori & Immonen, 2008). Variations such as the market-driven product life cycle, however, are concerned with the use and adoption of such technologies by users and operators in their own manufacturing processes. The generic project life cycle similarly comprises the essential phases of corporate projects by introducing sequential stages. Even though projects vary in content, size and complexity, a typical project can be mapped to the life cycle structure.

Companies usually initiate a project to introduce I4.0 technologies. The market-driven product life cycle and the project life cycle can be combined into a digital technology life cycle (DTLC) that describes the subsequent stages of a technology's life cycle in a company in order to identify the risk factors relevant to the implementation and operation of I4.0 technologies. Figure 2 presents the proposed DTLC model with its different phases.

The DTLC based on the market-driven product life cycle also consists of the four stages of introduction, growth, maturity/stabilisation and disposal/replacement during the two relevant technology implementation project phases, i.e. implementation and operation (Levitt, 1965; Anderson & Zeithaml, 1984). A technology is initially implemented in its area of application in the introduction stage. The growth stage includes the transition from the implementation phase to the operation phase, and thus upscaling, through operational optimisation and adaptation by employees. Once the maturity/stabilisation stage has been reached, the technology is established in its area of application and its usability and efficiency remain largely constant (Taylor & Taylor, 2012). After transitioning to the stage of disposal/replacement, the technology is done away with or replaced.

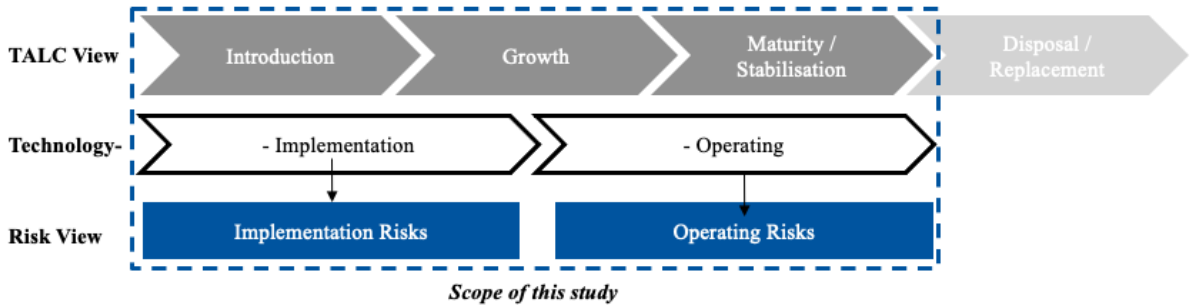


Figure 2: Scope of this study in the DTLC framework

2.6 Research Gap and Theoretical Model Guiding the Empirical Investigation

Current literature grounded in conceptual arguments suggests that I4.0 technologies curtail exposure to certain risks and introduce new risk sources (Ivanov et al., 2019). A synthesis of main concepts, main relationships and scope of the study is presented in Figure 3. This theoretical model has guided the empirical investigation. While the supply chain risk management literature and the technology life cycle literature provide an analytical basis for the external and decision-making-specific risk factors, NAT provides a foundation for understanding the problem-specific context through the lens of two constructs: system complexity and its tightly coupled processes (Perrow, 1999). These two constructs are important to further advance the understanding of risks posed by digital technologies because previous studies have shown that digital technologies can increase process complexity and enable tighter integration of value chain processes across functions and company boundaries (Ivanov et al., 2019; Hanelt et al., 2020). Regarding the research gap, most studies address these aspects conceptually or focus on specific technologies and applications (e.g. big data in healthcare) and lack exhaustive empirical evidence (Guha & Kumar, 2018). Current models and frameworks for supply chain risks fail to explain the phenomena of I4.0 technologies adequately because they depict major transformation capability across an entire organisation. Digital technologies diffuse across entire organisations and their supply chains, triggering organisational changes that are distinct from previous changes related to information technology (Hanelt et al., 2020). Since the rapid diffusion of digital technologies is changing the empirical reality, established models of supply chain risks need to be revisited (Busse et al., 2017). Empirical studies are needed to expand and theorise new frameworks and models. This study addresses this research gap with an empirical analysis of case studies of I4.0 technology implementation in German industrial operations.

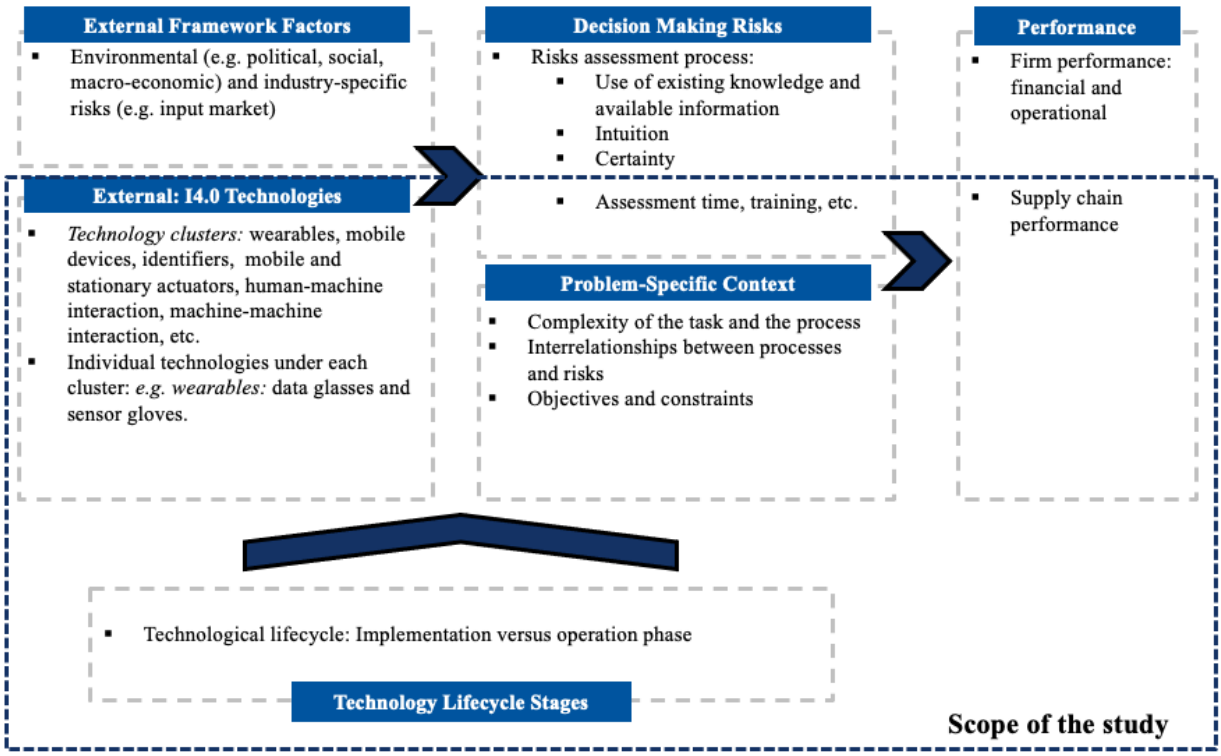


Figure 3: Theoretical model: Main variables and relationships (based on Rao and Goldsby, 2009; Tazelaar and Snijder, 2013 and other insights from the theoretical background)

3. Methodology

This study explores risk factors and their relationships to digital technologies used in industrial operations. Since this constitutes a novel empirical context, the study at hand adopts a theory elaboration approach that employs an existing theory to explore the new empirical context and to develop testable hypotheses (Ketokivi & Choi, 2014). Guided by this theory elaboration approach, we employ a five-step approach in our study that is described in the following subsections.

3.1 Use Cases: Selection, Data Collection and Data Analysis

First, we analyse a comprehensive online database with 300 I4.0 use cases, shedding light on which technologies actually are currently in commercial use and thus relevant to state-of-the-art industrial practice. Second, we conduct interviews with experts in order to explore the risks associated with the use of the identified I4.0 technologies in practice. Third, we ascertain risk themes of the different DTLC phases that emerge from the interviews with experts. Fourth, we link these risk themes of I4.0 technologies with established SCRM risk categories from the literature in order to identify interdependences between I4.0 technologies and SCRM. In the final

step of our study, we synthesise the findings by identifying patterns emerging from the data across use cases in order to develop hypotheses. Drawing on the principles of abductive reasoning, our empirical research is guided by a systematic iteration between theory and empirical data (Ketokivi & Choi, 2014). The specific projects in which a digital I4.0 technology has been applied in industrial operations are the unit of analysis in this study.

3.1.1 Selection of Use Cases: 'Plattform Industrie 4.0' Online Database

A multiple case study design has been employed in this paper to study the underlying technologies of I4.0 solutions empirically. To this end, this study initially draws on insights from 300 I4.0 use cases in Germany taken from the 'Plattform Industrie 4.0', created and managed by the German Federal Ministry for Economic Affairs and Energy in collaboration with the Federal Ministry of Education and Research (Federal Ministry for Economic Affairs and Energy and Federal Ministry of Education and Research, 2019). This platform was launched by the German government with the objective of sharing knowledge and best practices for I4.0 project implementation in German companies. The database is reliable and valid as it was launched and is maintained by an official government institution, and companies voluntarily share their best practices and insights related to I4.0. Moreover, there is a verification process prior to the publication on the website which ensures that the necessary data are included, that data are reliable, that the cases are I4.0-specific and that there are no hidden goals (e.g. it is not allowed to make concealed sales offerings). It provides standardised categories with present data field options for each case, specifically company size, region, examples of products, value creation, examples of applications and development stage. Moreover, several guiding questions are answered for each project. These questions include targeted benefits, technologies applied, approach adopted and lessons learned. This database was selected for several reasons. First, the use cases on the platform represent the current state-of-the-art of I4.0 implementation in Germany. Second, the database is comprehensive and representative since it includes projects from every region of Germany, different types of companies and industries, and the different applications and technologies employed.

By drawing on a large number of use cases, this study can develop empirical insights into technology components relevant to the implementation and operation of I4.0 solutions. Several use cases from the initial database of 359 were eliminated from this study because they lacked key information about the technologies applied. We eventually drew on a final data set of 300 use cases with complete information for further investigation. The data set has several descriptive characteristics. First, the majority of use cases are located in Baden-Württemberg,

North Rhine-Westphalia, Bavaria and Lower Saxony – Germany's four largest federal states and industrial regions. Second, as Figure 4 shows, a large share of the participating companies on the platform are small and medium-sized businesses (SMB, 1-250 employees), just as the vast majority of German businesses are. Each of the three other company size categories (250-5000, 5000-15000, >15000 employees) account for approximately 20% apiece. Altogether, the database is representative of German industry and valuable because it covers all company sizes and different industries and is not limited to certain technologies or areas of application.

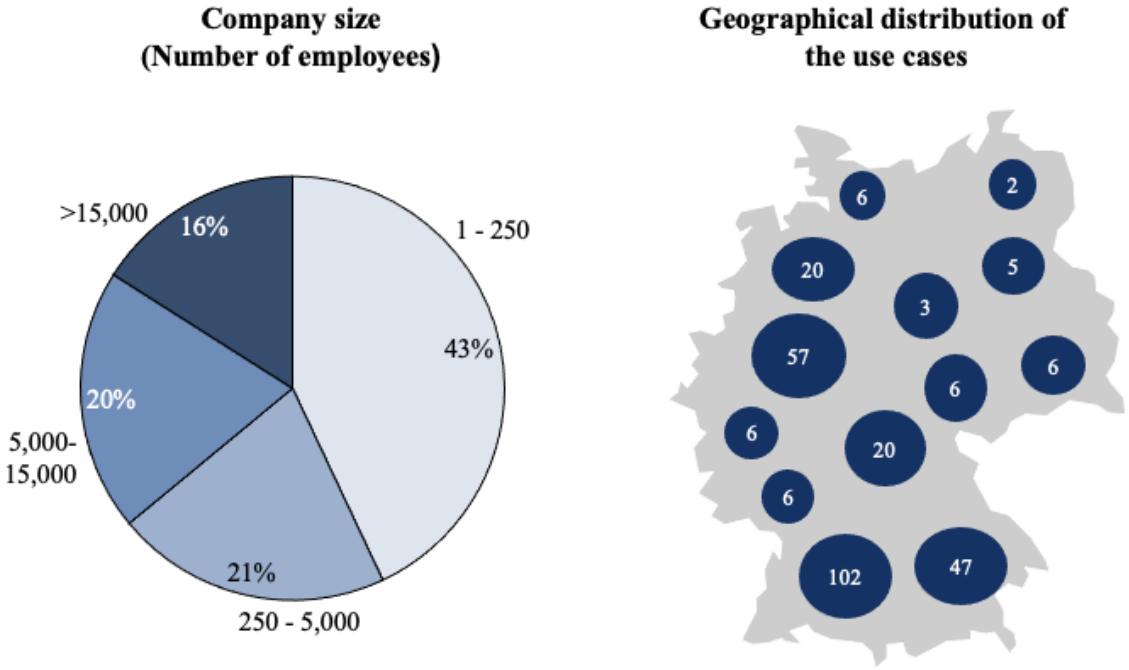


Figure 4: Descriptive statistics of the online database, N=300 (Federal Ministry for Economic Affairs and Energy and Federal Ministry of Education and Research, 2019)

3.1.2 Use Case Analysis Based on Secondary Information

A Web crawler was used to gather all information available on each case in an Excel file. Next, the information on all 300 use cases was screened using the five or fewer answer text blocks and the default filter categories. The third step entailed extensively coding the individual case data sets manually to record the I4.0 technologies applied. An overview of twelve higher-order technology groups, which covers all technology components relevant to I4.0, was developed based on Schlüter & Hetterscheid (2017), Oztemel & Gursev (2018) and Alcácer & Cruz-Machado's (2018) comprehensive studies of different I4.0 key technologies. This was used to assign as many as four of the technologies employed in the solution described to each of the use cases. The fourth step involved pooling of all the technologies from the bottom up,

following corresponding higher-order constructs from the literature. In the final step, the higher-order constructs were reassigned to the individual use cases, thus rendering them comparable and establishing a basis for exploring overarching themes of the relationships between I4.0 technologies and risks.

This bottom-up approach was chosen for several reasons. First, it makes the broad range of technology components and the size of the overall database manageable without losing track of the variety of technology. Second, analysing groups of technologies instead of individual technologies makes it possible to transfer this study's findings to future technologies too. New generations of smart clothes, for instance, will still fit in the wearables technology group, based on their technical features. The insights gleaned from this study will thus be transferable to that specific new technology based on its technology grouping. Moreover, technology pooling reveals the overarching and thus most relevant risk factors of I4.0. Table 2 provides an overview of the technology groups and examples of the underlying technology components.

Technology components	**Technology groups**
AGV, UAV…	Mobile actuators
Industrial robot…	Stationary actuators
Temperature sensor, humidity sensor…	Sensors
RFID/NFC, QR-Code…	Identifiers
Smartphone, handheld…	Mobile devices
Data glasses, data gloves…	Wearables
Touchpad, motion capture…	Human-machine interfaces
Bluetooth/BLE, WLAN, 3G…	Machine-machine interfaces
Private/public cloud…	Cloud computing
ERPS, MES, dashboards…	Software solutions
Analytics, data mining…	(Big) data
Selective laser sintering…	Additive manufacturing

Table 2: Technology groups with examples

3.1.3. Interviews with Experts: Selection, Procedure and Data Analysis

Following extensive analysis of the data from the online platform, in-depth interviews were conducted with practitioners involved in the use cases from the online database and with additional experts on digitalisation and I4.0 from business and academia. Interviewing practitioners from the database cases also enables us to verify and enhance the information on solution approaches and technologies from our secondary data. Interviewing general experts on digitalisation and I4.0 provides an additional and broader look at specific technologies' impact

on risk situations. All interviews were conducted in German by phone or face-to-face between November 2018 and March 2019. Interviewees were selected based on their past or present involvement in I4.0 projects. Along with the contacts from the online database, potential interviewees were approached at conferences related to I4.0 or found through personal contacts from earlier projects in the field. We anonymised individual information, e.g. names of interviewees and companies and specific attributes, for reasons of confidentiality. We were able to conduct fifty-three of the 197 interviews that we had requested, resulting in a total response rate of 27%. All interviews were recorded, transcribed or extensively summarised (whenever interviewees did not agree to being recorded). The robust project selection strategy employed covered a wide range of organisational attributes in order to ensure representativeness and facilitate analytical generalisations (Eisenhardt, 1989).

Twenty-two interviewees work for companies classifiable as SMBs with up to 250 employees. We placed special emphasis on this group in our sample since SMBs are particularly relevant to the national economy in Germany in general and to the field of I4.0 in particular. Seventeen interviewees work for companies with 250-5000 employees, six for companies with 5000-15000 and eight for large companies with over 15000. Nineteen interviewees represent companies in the manufacturing sector, comprised of such subsectors as electrical and electronics manufacturing, automotive manufacturing, equipment manufacturing and automation equipment manufacturing. In addition, twelve interviewees work in industrial consulting and provide an outside view of I4.0 projects in various companies. Moreover, nine IT companies, eight logistics companies and five representatives of academia are involved. The heterogeneity of our sample permits overarching insights and prevents potential adverse effects from sample distortion. Figure 5 visualises the composition of our set of interviewees in terms of company size and industry.

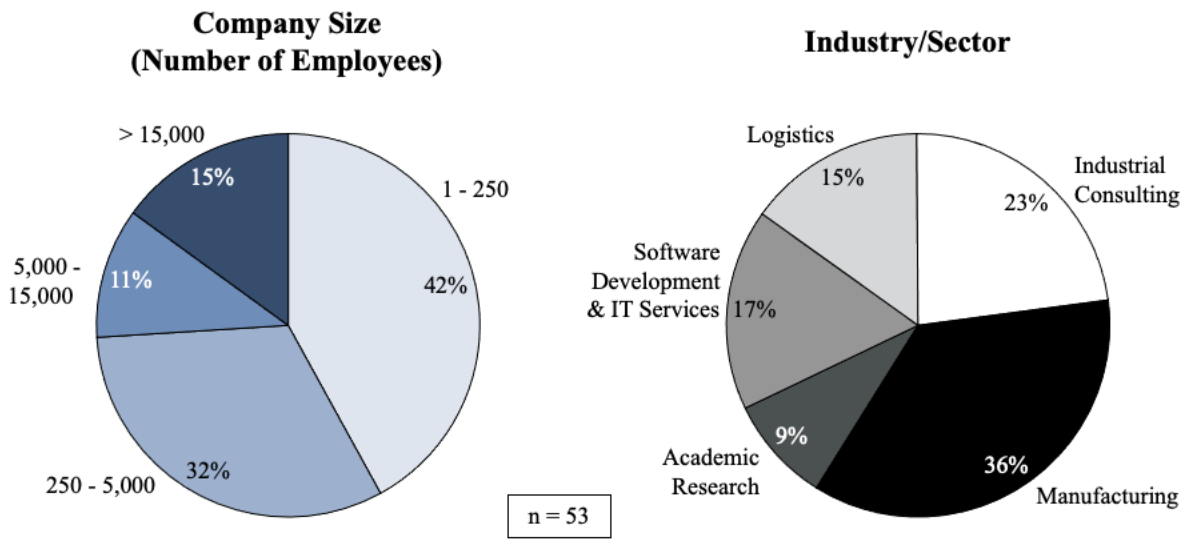


Figure 5: Interviewees' company sizes and industries, N=53

The main goal of the interviews was to identify risks associated with applying and operating the technology solutions that we identified by evaluating the online database. Table 3 provides some examples of interviewees and their backgrounds.

	Position	**Industry/Company**	**Company Size**	**Technologies**
1	Head of Engineering and Robotics Division	Metalworking	250 – 5000	Industrial robots, WLAN
2	Chief executive officer	Software development	1 – 250	AGV, identifiers
3	Project manager and support	Steel industry	> 15000	Wearables, Bluetooth
4	Head of IT manufacturing and internal logistics	Automotive industry	5000 – 15000	Apps, sensors, Bluetooth
5	Chief technical officer	IT infrastructure development	1 – 250	Data glasses, WLAN
…				
53	IoT risk analyst	Industrial consulting	250 – 5000	UAV, 4G

Table 3: Examples of interviewees

Interviews lasted between twenty-five and fifty minutes and followed a semi-structured approach, which allows gathering data in a structured way while maintaining the necessary openness to include additional and unexpected information. The questionnaire consists of three main sections. In the first section, the interviewees describe their company's I4.0 use case, specifically naming all relevant basic technologies, their areas of application, their functionalities and the desired goals. The second and main section of the questionnaire

incorporates the DTLC devised in section 2.4 and surveys potential types of risks. This overview, compiled from the literature presented in sub-sections 0, 2.2 and 2.3 combines the established risk categories of SCRM with those of I4.0. The overview thus comprises adaptation risks, the established SCRM framework factors of environmental, industry and corporate risks, and technical risks of errors and cyberattacks (Rao & Goldsby, 2009; Hertel, 2015). This ensures that interviewees cover and consider as many recent risks as possible while analysing their use cases. Interviewees could either assign actual risks from their own experiences to an existing category or add risk factors to the categories provided. The complete translated questionnaire can be found in Appendix C.

3.2 Data Analysis Strategy

The data analysis strategy followed an iterative dialogue between theory and data (Ragin, 1994). The overall empirical investigation was guided by theory in several ways. The analysis of cases from the online database used established theoretical concepts from risk management and I4.0 higher-order technologies as codes, while the interview guide used for primary data collection is based on the theoretical background. The steps undertaken for primary and secondary data collection and analysis are presented in Figure 6.

The combination of primary and secondary data enables us to conduct a within-case analysis where each case or project was evaluated based on a number of criteria (e.g. technology, implementation stage, risk) and a cross-case analysis was performed to identify emerging patterns (Miles & Huberman, 1994). Combining primary and secondary data on different projects and digital technologies employed in industrial operations enabled us to develop two deliverables. First, we proposed a typology of risks relevant to digital applications in industrial operations. This overview of technologies that are relevant in practice together with associated risks during the implementation phase and the ongoing operation phase can be found in (Appendix D: Risk Table). These risk patterns are explored by deriving 2nd order risk themes from 1st order risk factors from the interviews conducted (see Appendix E for the data structure). The distinction between technology users and vendors emerging from the risk analysis constitutes an important aspect of I4.0 technologies. Together with the data from the interviews, several contextual factors were developed which are characteristics of I4.0 technologies.

In a second step, this study explored the shifting role of risks in the different phases of introduction, growth and maturity. The emerging risk themes were linked with established risk classification schemes from the literature, especially Rao & Goldsby's (2009) comprehensive

supply chain risk model, in order to embed the results in the general and established field of SCRM. This integrated approach enhanced the validity and reliability of our findings, as suggested by prior studies (Barratt et al., 2011; Carter et al., 2020). Finally, several hypotheses and an elaborated framework combining the insights from the empirical analysis and NAT were proposed. The appendices C, D and E, which are available in the online supplementary materials, provide further evidence and details for the data analysis.

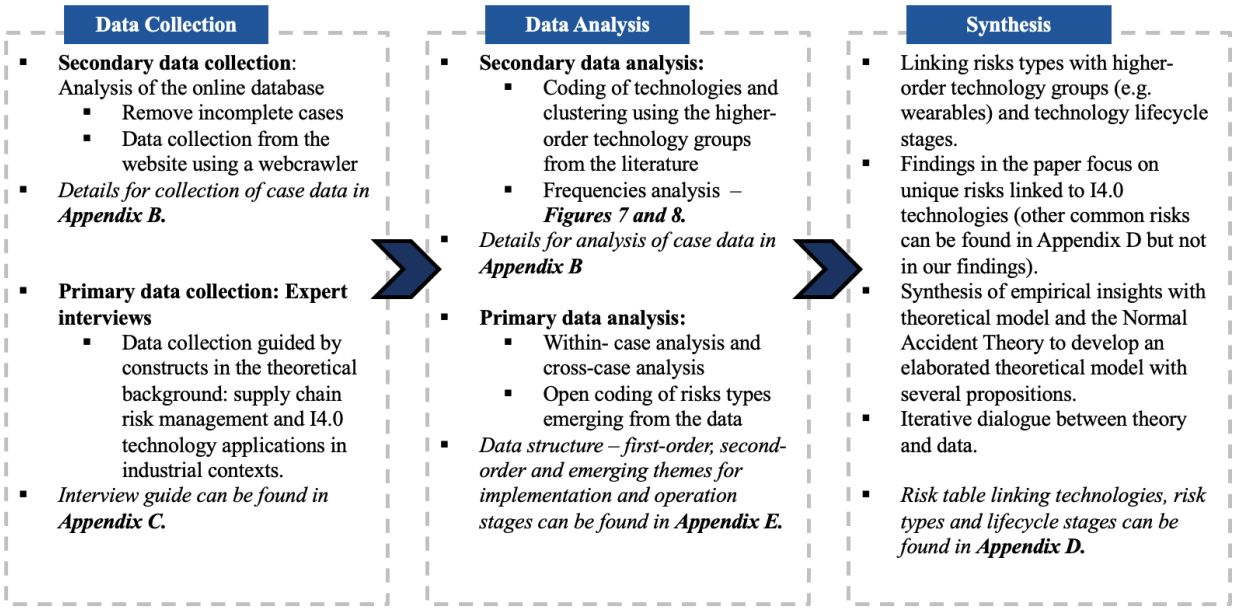


Figure 6: Data collection and analysis strategy

3.3 Validity and Reliability

By combining the insights from both primary and secondary data, this study incorporates principles of triangulation by building on multiple sources to enhance construct validity (Yin, 2003; Denzin & Lincoln, 2003). In the first step, several internal meetings were held with experts to supplement the insights gained from the literature review, to develop the procedure for the database analysis and to refine an interview guide. Secondary data were collected by Web crawling an online case database and manually coding the collected raw data. Primary data were collected by conducting semi-structured interviews with experts on I4.0, who were involved in I4.0 technology projects from the database. This method assures consistency and comparability of data among the use cases as well as flexibility to pursue information about relevant topics and contextual elements beyond the guiding questions. Moreover, the cross-case approach is an established starting point for theory development that provides a good basis for analytical generalisation (Eisenhardt, 1989). The interviews followed an interview guide developed beforehand, which incorporates insights from desk research of I4.0 technologies,

risk categories and life cycle models. Information was crosschecked with interviewees to ensure validity (Denzin & Lincoln, 2003). All interviews were recorded, transcribed and summarised extensively. The study thus adhered to criteria of internal validity, construct validity, external validity and reliability (Gibbert *et al.*, 2008), as shown in Table 4.

Methodological criteria	Components	Work performed
Internal validity	▪ Research framework derived from literature	▪ The analytical constructs employed draw on theoretical insights from SCRM models, related risk classifications and life cycle models.
	▪ Pattern matching	▪ Comparison of patterns from different contexts of various use cases and interviews during data collection.
	▪ Theory triangulation	▪ Use of different bodies of literature as research framework and as a tool to interpret findings
Construct validity	▪ Data triangulation	▪ Combination of primary (original interviews conducted by researchers) and extensive secondary data (archival data from online platform).
	▪ Review of derived data by peers	▪ Review of drafts and interview recordings by peer academics who are not co-authors of this paper.
	▪ Explanation of data analysis	▪ Structuring of collected secondary data in a database
External validity	▪ Multiple case study approach to cross-case analysis	▪ Multiple case studies included in both primary and secondary data.
	▪ Case study background	▪ All the use cases examined (compared) concern the introduction of I4.0 technology but have different backgrounds in terms of company size, industry, areas of application.
Reliability	▪ Case study protocol	▪ Data collection according to a set of guiding questions following the analytical constructs and project-specific anomalies.
	▪ Case study database	▪ Development of a case study database with all data sources (available documents, interview files, archival data, etc.).

Table 4: Components of the research design based on Gibbert et al. (2008)

4. Findings

The findings are presented in three sections. First, we argue that digital I.40 technologies are driving the transition to a new industrial landscape and several unique contextual factors therefore govern the emergence of unique risks. Second, we present three major sources of risks unique to the implementation of I.40 in industrial operations. Third, we synthesise our findings and draw on insights from NAT to propose an elaborated framework and several hypotheses on contextual drivers of I.40, unique sources of risks and outcomes.

4.1 New Landscape for Traditional Companies Adopting Digital Technologies

Our data reveal that several contextual factors are driving the transition to a new industrial landscape in which I.40 is implemented: information asymmetries between technology vendors and users and external contextual drivers related to the technology market and the attributes of digital technologies.

First, the case analysis uncovered significant differences in how users and vendors understand I4.0 technologies in terms of risks and intended benefits (see Figures 7 and 8). Technology vendors are the companies developing and selling digital technologies (e.g. Axoom, Bosch, Siemens), while technology users are all manufacturing and logistics companies in our sample that are using digital technologies for specific industrial operations (e.g. BASF, Kärcher, Pfizer). The content analysis of the 300 use cases delivered several interesting insights. Technology users of all sizes identify increasing complexity, insufficient flexibility and high production system latency as factors currently driving the adoption of digital technologies in industrial operations. Technology vendors do not necessarily view Industry 4.0 as particularly suited to mitigate these challenges. The discrepancy between vendors' and users' view of predictive maintenance and the category 'other' is striking. Both tend to be associated more with various vendor applications than with user applications. Specialised technology experts among vendors are generally more familiar with predictive maintenance than are potential users, especially in smaller companies, as the numbers show. Moreover, users do not necessarily consider predictive maintenance's positive impact on the current risk situation to be critical enough to justify the investments and expenditures required.

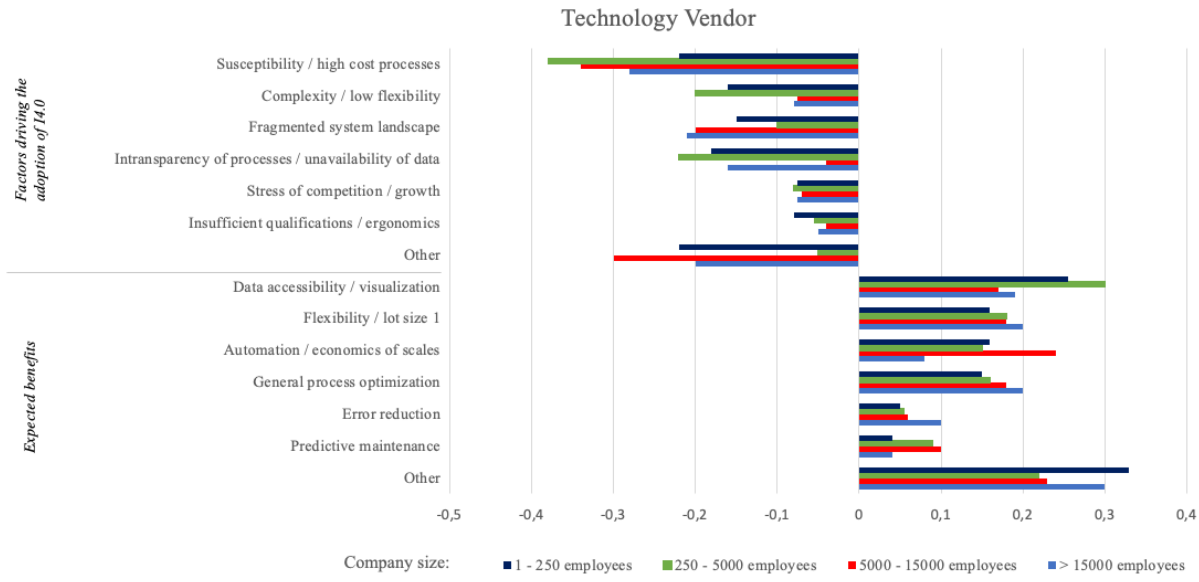


Figure 7: Drivers of I4.0 technology adoption: technology vendors' responses

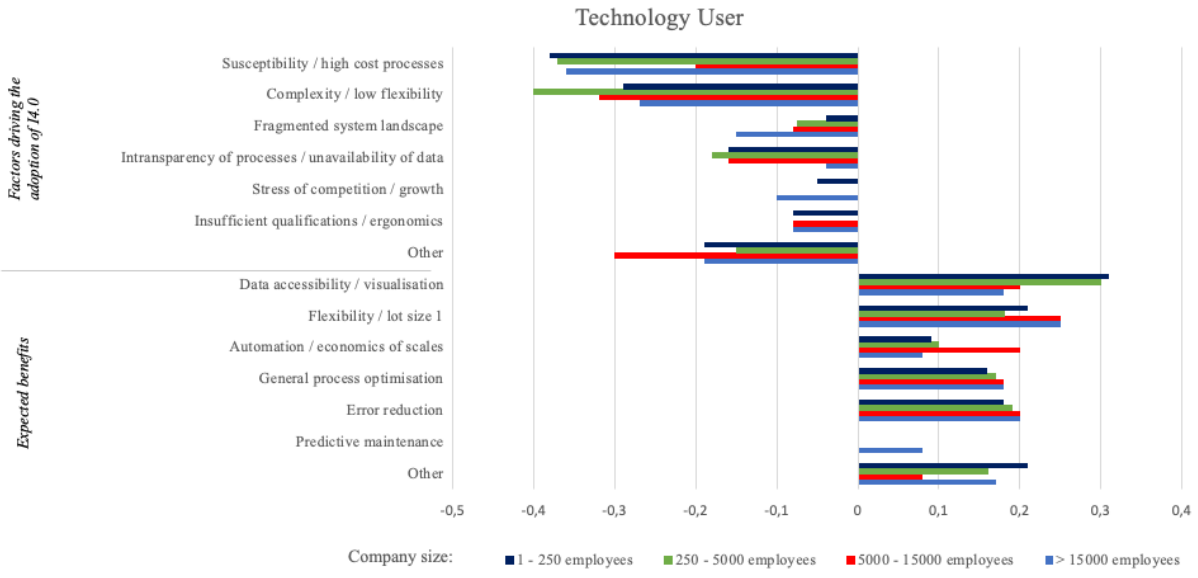


Figure 8: Drivers of I4.0 technology adoption: technology users' responses

Apart from the information asymmetries between the users and vendors, other contextual drivers make the reality of I.40 distinctive from past IT implementation. These contextual drivers include increased dependability, susceptibility to disruptions, digitalisation of individuals (workers and consumers), and increased contextual turbulence and dynamism. The interviews revealed that practitioners are being confronted with the necessity and ongoing advance of industrial digitalisation and many decision-makers are experiencing strong pressure to make use of the technologies available to improve their own business processes and performance. One project manager stated, for instance, that *'Failure isn't an option: There is*

strong pressure on us to implement the technology because we have spent a lot of money on it.' At the same time, practitioners from most sectors usually have only rudimentary knowledge of such technologies and have had few points of contact during their daily business to date. This pressure, combined with a lack of knowledge can spawn new risk sources, as one manger explained: *'There's strong pressure from unfocused innovation, and the result is risk factors being ignored.'* A lack of knowledge of technologies and technology markets and uncertainty about the utility or return on investment create hesitancy and anxiety among managers, as another project manager divulged: *'We had had no experience with I4.0 technologies until now. Our first project has shown us the weaknesses of our business processes.'*

Many decision-makers bring up uncertainties about the return on investment and technologies' long-term utility (see Table 5). Even though this financial risk does not threaten a technology's functionality or operations directly, it is a major recurring concern among practitioners during the implementation phase. Once a company commits to a certain technology, the failure und removal of that technology could be a substantial blow to the company. This is especially true for SMBs which have limited financial resources and for disruptive technologies with extensive interdependences with operations. This risk factor is exacerbated by the limited availability of practical experiences or empirical values which could be drawn on for independent study or evaluation. Management consequently exerts great pressure for projects to be implemented quickly and not allowed to fail, which often results in potential risks being overlooked.

Risk	Technology	Case/Application	Quote
Uncertainty of ROI and long-term value	(Stationary actuators) Industrial robots	Automation of manual machining (cutting, grinding)	*Of course, since a lot of parameters need to be adjusted, there are unexpected costs involved during implementation.*
	(Mobile devices) Smartphone (software solutions) app	Parameterisation and reading of machine data	*A lot of people consider it all to be just 'bells and whistles' at the beginning. And if something doesn't work smoothly at first go, it's ignored.*
	(Stationary actuators) Industrial robot	Automation of manual machining (cutting, grinding)	*For us, there's an investment risk. We're spending all this money on this [application], but you never know whether it's going to pay off or not.*

Technology clusters: All, in particular mobile and stationary actuators, wearables, additive manufacturing.

Table 5: Use cases and quotes illustrating increased uncertainty surrounding I4.0 technologies

The adoption of I4.0 technologies by traditional manufacturing and logistics companies reveals several contextual factors which make this new landscape unique and which relate to discrepancies between users' and vendors' knowledge and the uncertainty surrounding the

technology market and the attributes of digital technologies. While uncertainty is relevant for all digital technologies, it is more severe for hardware-heavy solutions (e.g. mobile and stationary actuators, wearables, additive manufacturing) since new technology is expensive (e.g. high R&D costs and low production volumes) and life cycles are short. We therefore propose the following hypothesis:

Hypothesis 1 (H1): I4.0 constitutes a unique context due to several external drivers related to the attributes of digital technologies and uncertainty of the technology market, which is relevant in particular for hardware-heavy solutions, such as mobile and stationary actuators, wearables and additive manufacturing.

4.2 Major Sources of Risks of I.40 Technologies in Industrial Operations

Content analysis of data from the interviews with experts reveals various sources of risks at different levels of analysis, specifically sources of environmental risks, organisational risks, industry risks, process risks and decision-maker risks (see Appendix E for the data structure and emerging risk categories during the implementation and operation of I4.0 technologies in industrial operations). The emerging risks fall into two categories. The first category includes traditional supply chain risks applicable to many other industrial processes, only the magnitude of which can be affected by digital technologies. Such risks include integration with existing information technology infrastructures and processes, general legal issues, operational interferences and resistance from employees. The second category includes risks that change their character in conjunction with digital technologies. Based on our analysis, we propose three sources of specific supply chain risks in conjunction with digital technologies in industrial operations: information asymmetries between technology users and vendors, legal uncertainties surrounding data security, privacy and transparency, and digital transformation at the organisation level.

4.2.1 Information Asymmetries between Users and Vendors

The information asymmetries are most pronounced in two main areas: technology-specific knowledge and technology markets. These two types of information asymmetries create risks of direct and indirect dependence in supply chains. Our data show that a lack of internal expertise increases users' dependence on technology vendors, affecting the number of errors during the implementation phase. Table 6 presents several illustrative examples and quotes from our analysis.

Pressure to adopt I4.0 without sufficient technological expertise creates various risks during the implementation phase. This risk applies in particular for software-based technologies in traditional manufacturing industries with decades of focus on non-digital products and related manufacturing processes. The decision-makers at a steel producer, for instance, were aware of the usefulness of QR codes and scanners for tracking materials in production but lacked thorough knowledge of the technology, its features and its constraints. They consequently encountered many initial problems with unscannable QR codes because of poor lighting or with scanners damaged by the high temperatures in a steel plant's harsh environment. Similarly, many practitioners frequently decide to use cloud solutions to handle customer data, for instance, because of the technology's popularity and prevalence. Those in charge often have no knowledge of the technical risks of cyberattacks or the legal obligations attendant to storing external data.

Much akin to insufficient knowledge of the technology itself, we also found a lack of knowledge of the technology market, which is especially relevant for technologies from fast-moving hardware markets, such as sensors, identifiers, mobile devices, wearables and additive manufacturing. Practitioners often do not have enough market transparency or knowledge available to them to be able to evaluate different proposals, such as price or service level agreements. Lacking similar experience, they are simply unable to assess whether services offered will actually meet their needs. The case of one company that had introduced data gloves exemplifies this. Unfamiliar with potential vendors, the company's decision-makers ultimately chose one they had met at a trade fair, only to become aware of other companies with similar products later on.

Risk	**Technology**	**Case/Application**	**Quote**
Insufficient knowledge of I4.0 technology	(Mobile actuators) AGVS	AGVS	*We didn't know enough about the requirements that need to be considered besides the technology itself, such as the requirement of having no ramps in the factory.*
	(Stationary actuators) Industrial robot	Automation of manual material processes (cutting, grinding)	*The lighting was good enough for a human eye but too dark for a camera.*
Technology clusters: Mobile and stationary actuators, human-machine interfaces, cloud computing, software solutions, (big) data.			
Insufficient knowledge of technology markets	(Mobile actuators) AGVS	AGVS	*The CEO was unaware of the complexity of the technology selection.*
	(Wearables) Data gloves	Order picking assistance for	*We bought them from a company we met at a trade fair. We thought it was the only relevant company on the market.*

		employees in warehouse processes	
Technology clusters: Mobile actuators, sensors, identifiers, mobile devices, wearables, additive manufacturing.			
Direct and indirect dependence	(Mobile actuators) AGVS	Internal logistics	*The AGV is hard to replace with an alternative product from a different vendor.*
	(Wearables) Data glasses	Order picking assistance for employees	*If the technology failed, I wouldn´t be able to maintain my operations.*
	(Identifiers) QR codes	Material identification in steel production	*Of course I'm growing dependent on the system! If it failed at a technological level, I'd immediately need to implement some sort of plan B.*
	(Stationary actuators) Industrial robot	Automation of manual machining (cutting, grinding)	*Hardly any of the software solution are really open. The controls are often quite different. If you've become accustomed to one specific robot and it´s then discontinued, you´ve got a problem.*
Technology clusters: hardware from small, fast-moving markets (mobile actuators, wearables, identifiers) and complex software-based solutions (human-machine interface, cloud computing, software solutions, big data).			

Table 6: Use cases and quotes illustrating information asymmetries as a major source of supply chain risk from I4.0 applications

Insufficient knowledge of both the technology and the technology market can result in direct dependence on a vendor both for hardware from fast-moving hardware markets and complex software-based solutions. While some technologies, such as tablets or routers, are easily replaced with commercial alternatives without much effort or many drawbacks, numerous solutions require vendor-specific hardware, software and know-how. This makes users directly dependent on the vendor when they need to service or replace hardware components or want to upscale or restructure their operations. The vendor's prices, items in stock, product strategy and market success can affect a technology's availability and functionality for users. Many vendors of I4.0 solutions, for instance, are small, highly innovative and flexible start-ups operating in highly volatile markets. Should a start-up go out of business or discontinue product lines, users most likely have to abandon or replace their technologies. Moreover, users that have outsourced their digitalisation activities to vendors and have not developed extensive internal expertise over time grow dependent on vendors' know-how and innovativeness in many cases.

Based on the evidence and conclusions presented above, the following hypothesis is proposed: *Hypothesis 2a (H2a): The information asymmetries between technology vendors and users concerning technologies' functionalities and the technology market lead to direct and indirect dependence on technology vendors and an increase in errors and mishandling.*

4.2.2 Legal Uncertainty Surrounding Data Security, Privacy and Transparency

Significant legal uncertainty surrounding data security, privacy and transparency as they relate to I4.0 technologies constitutes a major source of supply chain risk for industrial applications (see Table 7). These issues are generally relevant for technologies which collect, process or handle customer/employee data, namely cloud computing, software solutions or big data. The creation of digital twins of human-machine systems is the biggest driver of legal risks and adaptation problems of many applications. Use cases reveal that practitioners frequently have insufficient knowledge of legal issues, such as data security regulations and employee council issues and liability. SMBs in particular lack the financial resources to hire legal experts, rendering them unable to navigate the complex interrelationships and hidden pitfalls of legal issues and regulations. Some companies in our use cases implemented new, connected machines capable of communicating over the company's own WLAN. While the decision-makers examined all the relevant issues related to cyberattacks and other things, they overlooked the fact that the remote maintenance function requiring encrypted employee data needed to comply with the European Union's General Data Protection Regulation (GDPR).

Legal issues frequently arise during the implementation phase and primarily involve aspects of workplace law, data privacy and data protection. The most common risks in this context are impending conflicts with employee councils that are apprehensive about additional workloads and demands, disadvantages for employees and violations of data privacy. Individual employees in companies without employee councils might raise concerns about labour law themselves, thus delaying or averting the implementation. Monitoring solutions in particular are often suspected of exposing employees and their performance to corporate surveillance or, at the least, of being gateways for potential leaks of employees' personal data.

Moreover, the latest developments in legal policies such as the GDPR frequently have implications that are perceived as a major source of risk. Again, these uncertainties often put SMBs at a disadvantage. The complexity of such regulations is simply overwhelming in practice, making them impossible to implement in their entirety. One company, for instance, agreed with a client upon a particular channel of communication about the information

technology system. All the data platforms and cloud storage systems for the use case were so well established that the client expected that all their data would be deleted, but the company was unable to name all the locations where client data were stored whenever established procedures were not followed, e.g. when the client sent an email instead of ordering directly through the system.

Several legal conflicts put technology users at risk during the operation phase. The most common risks arise from collecting, storing and processing either supply chain partner or employee data. Since the legal situation of such activities is constantly changing and promises to remain challenging and uncertain in the near future, practitioners view legal issues as an ongoing risk of many technologies. In several cases, companies have had to guarantee certain security measures and that they are able, for instance, to delete certain types of data completely and promptly upon request. Since many companies fail to address and meet these requirements adequately, they are constantly at risk of lawsuits in the event of related incidents.

Risk	**Technology**	**Case/Application**	**Quote**
General lack of knowledge of legal issues	(Software solutions) Remote maintenance	Remote maintenance	*We didn't realise we were granting access to employee data by using the remote maintenance function.*
Technology clusters: cloud computing, software solutions, big data.			
Workplace law issues	(Wearables) Data glasses	Order picking assistance for employees	*I'm having problems with the employee council. As soon as you start digitalising, you are allowed to track a CNC lathe but not an employee.*
Technology clusters: sensors, mobile devices, wearables, human-machine interfaces.			
Compliance issues	(Wearables) Data glasses	Order picking assistance for employees	*The first question is always 'where's my data being stored?'.*
	-	Consulting	*Especially smaller companies and start-ups aren't capable of signing a complex data protection agreement. […] They just can't handle it.*
Technology clusters: wearables, cloud computing, software solutions, big data.			
Legal issues	(Sensors)	Automated material requisition for Kanban systems	*The main issue is that of monitoring. We monitor our warehouses with this solution and our workplaces too, of course.*
	(Cloud computing)	Remote maintenance	*You have to be aware of which data you're allowed to store, and which not […] Now, you've got all this data. Who's allowed to do what and when with which data? What happens if the customer wants the data deleted? […]Management is liable for this.*

Technology clusters: cloud computing, software solutions, big data, sensors.

Table 7: Use cases and quotes illustrating legal uncertainty as a major source of new supply chain risks

Based on the evidence and conclusions presented above, the following hypothesis is proposed: *Hypothesis 2b (H2b): The legal uncertainty surrounding data security, privacy and transparency as they relate to I4.0 technologies can create new types of legal risks at the organisation level and supply chain level, especially for technologies which collect, process and handle data (cloud computing, big data, software solutions) and for technologies which directly or indirectly monitor employee performance (sensors, mobile devices, wearables, human-machine interaction).*

4.2.3 Digital Transformation at the Organisation Level

Our findings reveal that the implementation of I4.0 technologies entails digital transformation at the organisation level and supply chain level, causing significant spillover at different levels of analysis (see Table 8). These spillover effects can be either positive or negative and decision-makers face difficulties mapping them. The increased connectivity and linkages inside and outside the organisation heighten vulnerability to cyber risks.

First, I4.0 technologies require making organisational adjustments to the processes involved. A company that automated its reordering process for C-parts, for instance, had to change the process steps themselves so that the process conformed to the technology's functionalities and requirements. Changing the entry process ultimately caused errors in the subprocesses. Since the numerous interdependences characterising the information technology landscape and the process landscape make them sensitive to external changes and newly introduced elements, the initial introduction of such technologies can compromise the stability and reliability of day-to-day operations. In addition, introducing new processes or modifying existing ones to conform to the technologies employed often causes subsequent interferences related to aperiodic or unexpected events, such as special orders or vendor changes. In several cases, technologies have resulted in an ossification of processes and diminished flexibility – since desired process changes inevitably entail changes in the technology solution too. This increases costs and/or requires technological knowledge that users often do not possess. Organisational transformation and increased supply chain interdependences are driven by technologies which

impact the whole organisation (e.g. mobile devices) and collaboration-based software (e.g. big data, cloud computing).

Second, cyber risks emerge as an omnipresent theme from the experts' statements. The most relevant threat identified by the practitioners in the interviews that we conducted is that of corporate data espionage and theft over wireless connections such as WLAN or mobile communications. They consider the probability and severity of such events to be quite low in most cases, though, since they assume that their data would be of little interest to attackers. The cyber risks are linked more to the interconnectedness of assets (IoT) than to the connected technologies themselves. Experts with a greater wealth of experience especially warn as well against unauthorised access to physical facilities through digital interfaces, undetected data tampering and malicious encryption of data by ransomware. The use of common and pervasive mature technologies, such as smartphones with Android OS or iOS, exposes applications to such threats in the form of equally common and pervasive mature malware. In addition, many experts consider most technologies to be enticing and rewarding targets of cyberattacks. This is because the range of vulnerable infrastructure grows along with a company's level of digitalisation. Facilities that were completely 'offline' previously become vulnerable to the new threat of cyberattacks as soon as I4.0 technologies link them to the Internet or a corporate intranet. Many experts see a need to address cyber risks in hitherto unaffected areas.

Risk	**Technology**	**Case/Application**	**Quote**
Organisational transformation	(Stationary actuators) Industrial robot	Automation of manual machining (cutting, grinding)	*You have to take care that the robot doesn't damage its environment during the first runs.*
	(Cloud computing)	Remote maintenance	*The biggest problem is the modification of business processes. You're changing the way your operations work. This is one of the threats. […] We underestimated this back then.*
Technology clusters: software solutions, big data, cloud computing, mobile devices.			
Organisational and supply chain interdependencies	Software solutions	Software for evaluating and ordering transportation services	*Of course they became dependent on you as a company. We contractually obliged our suppliers to use our software.*
	Software solutions	Supplier portal	*You have to be careful about what data is relevant to your business and needs to be hosted by your company to keep your business running. […] It´s important for our production planning that we have our article master data in our own*

			system rather than spread across several vendor portals by our clients
	(Big data) Supply chain data	I4.0 solutions consulting	*I had an interesting project: An OEM and a first-tier supplier were both offering each other a cloud solution for storing all their supply chain data and both of them wanted the other one to subscribe to it. It's normal in supply chains for only one party to dominate and for the other one to become dependent.*
Technology clusters: cloud computing, software solutions, big data.			
Cyber risks	(Sensors)	Automated material requisition for Kanban systems	*The IT department is scared that someone will access the process from outside and that data will be stolen or tampered with in some way.*
	(Mobile devices) Smartphone	Parameterisation and reading of machine data	*Anything wireless is not allowed in the production area. They're afraid of someone hacking the system.*
	(Cloud computing)	Remote maintenance	*Every gateway you open increases your risk of an attack. We use all the available state-of-the-art encryption technologies. But if you look at the hacking of that uranium enrichment facility in Iran, there are always going to be ways and means to access our data if someone really wants to do so.*
Technology clusters: cloud computing, mobile devices, sensors.			

Table 8: Use cases and quotes illustrating digital organisational transformation as a major source of new supply chain risks

Based on the evidence and conclusions presented above, the following hypothesis is proposed: *Hypothesis 2c (H2c): Organisational transformation, increased interdependences among supply chain actors, and cyber risks driven by mainly collaboration-based software increase the likelihood of major disruptions that have a significant impact on the entire supply chain.*

4.3 Elaborated Framework

The empirical qualitative analysis of use cases and interviews with experts reveals that I4.0 technologies are employed in industrial applications in response to certain existing challenges and risks but that they also create new sources of risks. Based on the empirical findings and drawing on insights from NAT, we propose an elaborated theoretical framework that explicates drivers, contingencies and outcomes of digital technologies in industry while focusing on risk management (see Figure 9). The proposed framework identifies two groups of drivers aligned with the two analytical dimensions of NAT, e.g. complexity and tight coupling of system

components, a series of contingencies, and outcomes found in our empirical data. We conceptualise increased complexity in I4.0 technologies as the interaction between a highly dynamic and uncertain external environment (technology market and attributes of technologies), information asymmetries between technology vendors and users, and legal uncertainties surrounding data security, privacy and transparency. The second driver suggested by NAT relates to the interdependence between system components at both the organisation and the supply chain level. In keeping with NAT's underlying logic that high complexity and tight coupling of processes increase the likelihood of accidents, we link the drivers and contingency factors with several outcomes. We identified several outcomes resulting from procurement risks, specifically an increased probability of occurrence of supply chain risks and disruptions, errors and mishandling; and increased dependence on technology vendors.

Several contingency factors emerging from the data affect the identification and management of sources of risk. These include the technology life cycle stage, technology type, and company size and resources. Different risks arise at different stages of the technology life cycle. Our data show that the adverse effects of unaddressed implementation risks grow in the operation phase. We additionally found significant differences between SMBs and larger companies in their perception, identification and management of risks, largely because SMBs' lack of internal resources affect their options significantly. Our analysis of risk factors also shows that sources of risk manifest themselves slightly differently for different types of technologies (see Appendix C). The overview of contingency factors invited the following hypothesis: *Hypothesis 3 (H3): The likelihood of accidents caused by sources of risk from I4.0 technologies is contingent on several factors, specifically company size and resources, technology type and technology life cycle stage.*

Figure 9 presents the elaborated framework with every hypothesis proposed.

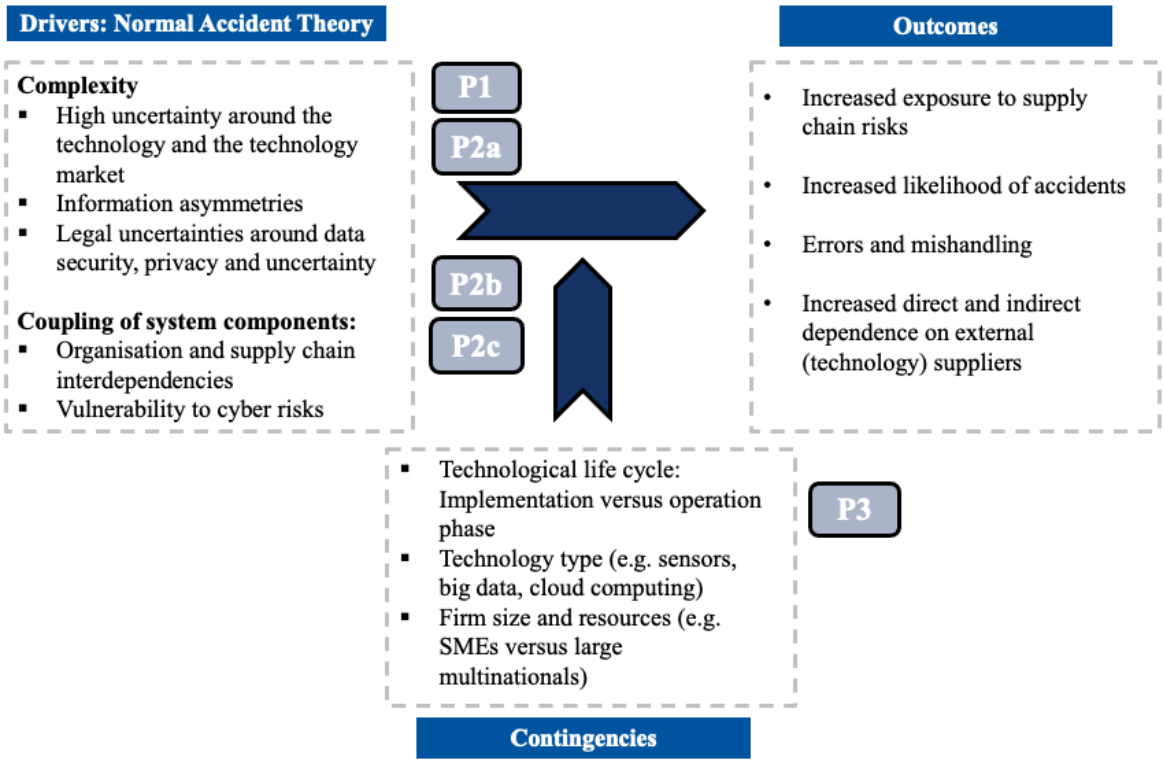


Figure 9: Elaborated framework: Drivers and contingencies of new sources of supply chain risks of I4.0 digital technologies in industry

5 Discussion and Conclusion

The overarching goal of this study is to identify and map risks associated with the implementation and operation of I4.0 technologies. Drawing on NAT and using a unique data set of interviews with experts and 300 case studies, we argue that digital I4.0 technologies are driving the transition to a new external and internal industrial landscape. This landscape is dominated by strong uncertainty about the technology market, the attributes and functionalities of digital technologies and the spillover effects upon organisations and supply chains. Three major risk sources are hypothesised: information asymmetries between technology users and vendors, legal uncertainties and organisational transformation, each predominant for different technology clusters. An elaborated framework is developed and several hypotheses about the drivers and contingencies of risk management in the context of I4.0 technologies are proposed.

5.1 Theoretical Contributions

The study makes several important theoretical contributions. First, it provides an exploratory empirical analysis of emerging phenomena. The analysis reveals that the application of I4.0 technologies in industrial operations is unique in several ways and is therefore accompanied by

several unique risk sources. Previous studies have demonstrated that the implementation of I4.0 technologies in practice is concomitant with greater connectivity between humans, systems and objects and can create new and modified risks (Tupa et al., 2017). Digital technologies diffuse across entire organisation and their supply chains, triggering organisational changes distinct from earlier changes related to IT (Hanelt et al., 2020). Our study corroborates these findings and expands them with an eye towards supply chain risks linked with technology clusters, showing that greater interdependence at the supply chain level, increased complexity, and digital transformation of organisations and supply chains can create new sources of supply chain risks. This important implication requires further study to gain a more nuanced understanding of the vulnerability at firm and supply chain level brought in by I4.0 adoption, and the required resources and capabilities needed by firms to cope with this. The increased inter-connectedness at both firm and supply chain level needs to be further studied through in-depth investigations and empirical data to evaluate whether the benefits outweigh the risks from the perspective of focal firms and at supply chain level. Moreover, the increased level of complexity, uncertainty around I4.0 technologies as well as increased interconnectivity at firm and supply chain level creates a unique set of challenges for human decision makers. Therefore, an important research direction relates to the incorporation of behavioural theories (Pournader et al., 2020) to understand how this increased complexity impacts the decision-making process (e.g. intuition, use of information, certainty, knowledge) around identifying and assessing supply chain risks for digital technologies. Second, based on our empirical study, we propose three major risk sources for I4.0 applications: information asymmetries; legal uncertainties surrounding data security and privacy; and interdependences between organisations and supply chains that are relevant for different technology clusters, as shown in the findings. This aligns with earlier literature demonstrating that digital technologies' disruptive effects compel companies to reorganise their internal organisational processes and external supply chains (Porter & Heppelmann, 2014). We also expand on the studies by Guha & Kumar (2017), Fosso et al., (2015), Ivanov et al., (2018) and Rossmann et al., (2018) to start systematically linking supply chain risks with digital technology clusters. The impact as well as suitable mitigation strategies for these novel sources of risks can be further analysed in future studies.

Third, the emerging concept of information asymmetries between technology vendors and technology users as a major source of risk in this context is novel. The underlying idea is in line with Orlikowski's (1992) concept of the duality of technology, i.e. technology development and technology implementation represent distinct processes that therefore require different capabilities to be completed successfully. We demonstrate, however, that the high level of

complexity of technology use, functionality and uncertainty about the technology market amplify this duality in the context of I4.0. Understanding the duality of digital technology and the capabilities required by firms to manage technology development and implementation while minimising the gaps and risks between the different stages represents an important avenue for further research.

Lastly, the study has employed Normal Accident Theory (NAT) to conceptualise novel sources of risks triggered by I4.0 technology adoption in industrial operations, thereby expanding the use of this theory in the supply chain risk literature. With this, we contribute to existing literature by employing NAT in a novel context triggered by the use of digital technologies in operations and supply chains. Our findings show that digital technologies aggravate the system complexity through various mechanisms, such as increased uncertainty, information asymmetries, increased direct and indirect dependences on technology suppliers, and emergence of new risks, e.g. cyber risks. Our findings also show that digital technologies, in particular collaborative software solutions, enable tighter integration of value chain processes across functions and company boundaries, but also increase the vulnerability of supply chains by creating stronger interdependences among processes across companies and supply chains. Together, this leads to increasing risk of accidents and therefore dedicated mitigation and prevention strategies need to be developed aligned with the particularities of digital technologies.

5.2 Managerial and Public Policy Implications

Our findings show that companies are facing numerous challenges and are having to deal with a number of risks while they implement current I4.0 technologies. The proposed elaborated framework is intended to help practitioners understand the different types of risks and the ways they arise at the different stages of a technology implementation project. More specifically, our findings present a few implications for managers. First, the study guides managers dealing with I4.0 technologies adoption in industrial operations to distinguish between risks occurring during the development and implementation stages in order to develop nuanced mitigation strategies. Second, managers need to focus on establishing regular knowledge exchange with the technology vendors or to hire internal technology experts in order to reduce the uncertainty and lack of expertise related to I4.0 technologies. Moreover, a better understanding of the technologies can also provide new opportunities for managers. Third, managers need to develop proactive mechanisms to address cyber risks and potential interferences with operations and production processes. For example, there needs to be clear guidelines about what types of

devices are allowed for use by employees on the shop-floor or the policy regarding the use of external devices by internal employees. Fourth, managers need to be aware that the adoption of I.40 technologies triggers changes at organisational and supply chain level and specific assessment needs to be performed to evaluate the benefits of increased connectivity versus the risks arising from this new situation.

The study also contains implications for public policy. First, the increased legal uncertainty around the adoption of I.40 creates extra challenges for firms. Governments need to provide extra support regarding the legal aspects related to the implementation of these technologies. Moreover, our findings show that these risks are especially challenging for SMBs as these often lack a varied set of experts with special know-how for the specific technology. Therefore, our study emphasises the need for governmental programs in order to reduce the market uncertainty for I4.0 products and to facilitate the access to knowledge (e.g. through platforms, educational funding) especially for SMBs.

5.3 Limitations and Further Research

Even though it makes important contributions, our analysis has its limitations, which open avenues for further research. First, the exploratory nature of our qualitative study limits its generalisability. The foundation for our study is the database of cases launched and maintained by the German government. While this database is valuable for exploratory research, it also presents a bias towards successful cases and towards SMBs. Further research should expand data collection efforts via surveys, Delphi studies and other secondary databases to evaluate the representativeness of this database. Large-scale empirical studies can be employed further to test hypotheses. Moreover, the applicability of our study conducted in an empirical German context to other major industrial contexts, such as the United States or Japan, still has to be established.

Second, the focus of our analysis on a wide range of I4.0 technologies keeps our findings general. Other specific groups of technologies deserve study. Smart products that exchange information independently, trigger actions and control each other may have very different risk profiles, for instance (Pereira & Romero, 2017). Third, our study reveals that humans play a crucial role in the implementation and use of I4.0 technologies. Recent review studies (e.g. Hanelt et al., 2020) have identified the digitalisation of individuals and key decision-makers as an opportunity for further research. Further research could explore the impact the digitalisation of decision-makers has on the identification, management and mitigation of supply chain risks. A growing stream of research drawing on insights from behavioural economics is exploring the

impact of human behaviour and cognitive biases on processes and operational performance (Loch & Wu, 2007). Previous studies of supply chain and operations management have examined the role of human factors and cognitive biases in decision-making in inventory management, procurement, forecasting, yield management and resource management. Interest in supply chain risk management is growing as well (Fahimnia *et al.*, 2019). An understanding of risk perception and of decision-making in the event of disruptions to the supply chain is essential for supply chain risk management since such disruptions can have major managerial implications (Fahimnia et al., 2019; Ellis et al., 2010).

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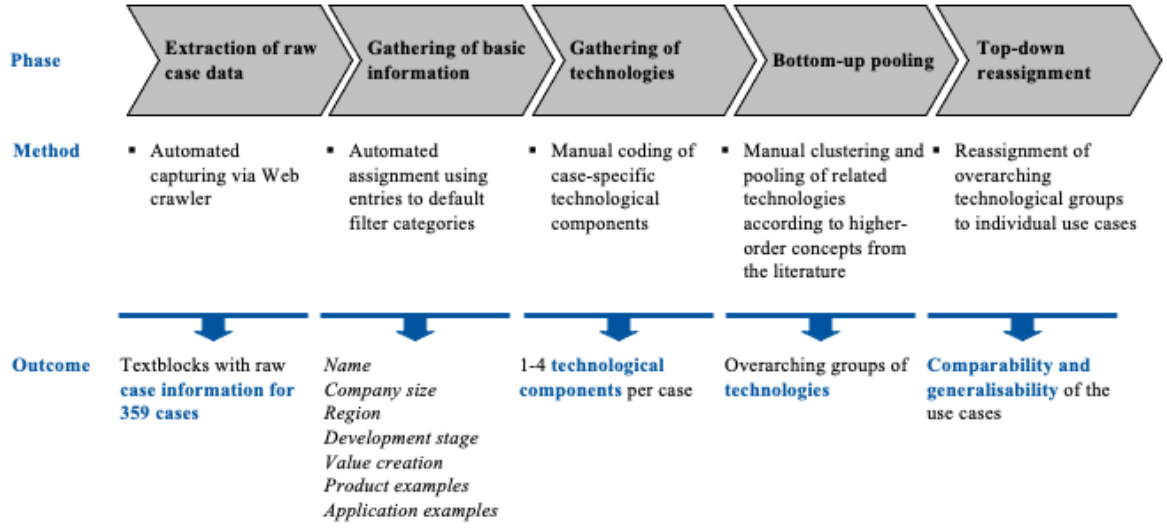
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Supplementary Material for Review

Appendix A: *Definitions and Categorisations of Supply Chain Risks*

Authors	Definition of Supply Chain Risk	Source of Supply Chain Risks
Christopher and Peck (2004)	"In this work we use risk in line with common usage in the sense that it relates to supply chain vulnerability, as '*at risk: vulnerable; likely to be lost or damaged*."	Inside the company – process and control Outside the company but inside the SC network – demand Outside the company but inside the SC network – supply Outside the SC network – environmental
Chopra and Sodhi (2004)	"Supply chain risks result from natural disasters, labour disputes, supplier bankruptcy, acts of war and terrorism, and other causes. They can seriously disrupt or delay material, information and cash flows, any of which can damage sales, increase costs - or both."	Disruptions Delays Systems Forecasting Intellectual property Procurement Receivables Inventory Capacity
Tang and Tomlin (2008)	"…risks that are inherent to all supply chains. […] There are two common measures of risk: the likelihood of the occurrence of an (undesirable) event, and the negative implications of the event."	Supply and demand Processes Intellectual property Behaviour Political/social situation
Rao and Goldsby (2009)	"…a situation is risky when it entails exposure to two essential components: exposure to an event and the uncertainty of possible outcomes – both of which are necessary in completing a risky situation."	Environmental factors Industry factors Organisational factors Problem-specific factors Decision-maker factors
Tummala and Schoenherr (2011)	"…we conceptualize supply chain risk as an event that adversely affects supply chain operations and hence its desired performance measures, such as chain-wide service levels and responsiveness, as well as cost. Regardless of the area of interest, risk is associated with an undesirable loss, i.e. an unwanted negative consequence, and uncertainty."	Demand Delays and Disruptions Inventory Manufacturing (process) breakdown Physical plant (capacity) Supply (procurement) System Sovereign risks Transportation

Appendix B*: Steps and methods of the online database analysis*



Appendix C: *Translated Interview Questionnaire*

Interview guide 'Risks in the context of Industry 4.0 applications'

Interview partner:
Company:
Date:

Part 1: Information regarding Industry 4.0 applications in your company

Application area:

- In which area is the Industry 4.0 application used in your company? (e.g. procurement, production, sales, administration, etc.)
- Which processes are specifically involved? (e.g. master data, picking, assembling)
- How many employees are affected by the Industry 4.0 application? (Individuals, employee groups, departments, company-wide)

Functional principle and objective

- Briefly describe the application. What is the general principle of the Industry 4.0 use case?
- What is the concrete objective of the application? What are the expected benefits?

Technological components

- Which technological components constitute the basis for the Industry 4.0 application? (e.g. cloud-computing, data glasses, RFID, additive manufacturing, drones, etc.)
- Does the application necessarily require an Internet connection? (e.g. online plant monitoring, qualification platform, pick-by-light)
- Is the application connected to existing systems? If so, to which ones? (e.g. ERP, MES, SCADA, PLC etc.)
- Does the application involve the use of transmission standards? If so, which ones? (e.g. WLAN, Bluetooth, 4G, 5G, etc.)
- Who is the manufacturer or provider of the technologies used?

Part 2: Existing and potential risks of Industry 4.0 applications

During the **implementation phase**, are there or were there...

- …adaptation problems among employees? (e.g. rejection, dissatisfaction, unexpectedly flat learning curves etc.)
- ...organisational risks or deficits? (e.g. unexpected costs, delays in the schedule, negative influence on operational processes, etc.).

During the **operational phase**, are there or were there potential risks….

- …through targeted attacks? (e.g. data theft, attack on infrastructure, malware, hacking etc.)
- …through untargeted attacks? (e.g. phishing, terrorist attacks etc.)
- …through human error? (e.g. operating errors, programming errors, rejection etc.)
- …through technical failure? (e.g. defect, failure etc.)
- …through organisational failure? (e.g. insufficient maintenance, missing updates etc.)
- …regarding procurement or sales markets? (e.g. availability of critical technical components, system breaks/ deviating standards, failure of special communication channels etc.)
- …regarding the competitive environment? (e.g. alternative to widespread industry solution etc.)
- …due to force majeure? (e.g. power failure, fire, flood etc.)
- …due to political or legal implications? (e.g. uncertainty regarding data protection regulations, personal rights, etc.)

Other:

- Do you see any risks outside these categories?

Part 3: Risk management measures and mitigation strategies

If risks **during the implementation phase** were mentioned in Part 2, were appropriate risk management measures or mitigation strategies applied? If not, why not?

- Proactively or in response to adaptation problems of employees? (e.g. early involvement of affected staff, information measures, etc.).
  >If not, why not?
- Proactively or in response to organisational risks or deficits? (e.g. iterative implementation, scenario development, time/cost buffers etc.).
  > If not, why not?

If risks in the **operation phase** were mentioned in part 2, were corresponding risk management measures or mitigation strategies applied? If not, why not?

- Against targeted attacks? (e.g. firewall, IDS/IPS, etc.)
  >If not, why not?
- Against untargeted attacks? (e.g. segmentation of networks, physical protection, etc.).
  >If not, why not?
- Against human errors? (e.g. authorisation management, integrated security mechanisms, etc.).
  >If not, why not?
- Against technical failure? (e.g. backup systems & processes, wear and tear monitoring, spare parts management, etc.).
  >If not, why not?
- Against organisational failure? (e.g. auditing, update/patch management, monitoring by external service providers, etc.).
  >If not, why not?
- Regarding the constellation of procurement or sales markets? (e.g. inclusion of suppliers/customers in the selection of technology or interfaces, etc.)
  >If not, why not?
- Regarding the constellation of the competitive environment? (e.g. competitive analyses etc.)
  >If not, why not?
- Against force majeure? (e.g. revision/adjustment of fire protection, division of circuits, UPS etc.)
  >If not, why not?
- In the context of political or legal implications? (e.g. inclusion of legal advice etc.)
  >If not, why not?

If **other risks** were mentioned in Part 2, were corresponding risk management measures or mitigation strategies applied? If not, why not?

Appendix D: *Data structure: Risks (implementation and operation stages) emerging from the data*

Risk Category	1st Order Risk Factors	2nd Order Risk Themes
Implementation risks	Unknown return on investment; unexpected costs during implementation; innovative but unfamiliar functionality; unknown coverage and network quality during early stages; unknown market situation for certain technologies; high capital expenditures for untried and untested technology; unknown training requirement, no experienced internal staff	Insufficient knowledge and uncertainty
	Resistance from employee councils; accusation of surveillance from employees; violation of employment contract; violation of legal regulations such as the GDPR	Legal issues
	Difficult integration with the industrial IT environment; adaptation of operational processes necessary and expensive; interference caused by initial integration in the shop floor infrastructure, objects and/or workflows; operational interference caused by necessary adaption of processes and infrastructure; mutual interference with other wireless standards	Integration with the IT landscape and processes
	Innovative but unfamiliar use; flat learning curves; technology initially distracts and preoccupies users rather than assisting them; hostile or dissatisfied workers; employees ignore or overlook new components and their implications for their jobs; autonomy and lack of control possibilities hamper people's acceptance; fear of replacement of jobs; strong enticement to experiment for fun	Human adaptation
Operation risks	Many interfaces for highly sophisticated cyberattacks; targeted cyberattacks; theft of data; data tampering; untargeted cyber threats; technology opens new gateways for potential attackers	Cyber risks

Low maturity; technology frequently fails to meet industrial standards, loss of devices and data stored on them, constant errors because of the large number of components employed, technical failures because of low maturity and extreme conditions of industrial use	Operational inference
Legal issues related to employee customer and supply chain partner data handling; ongoing legal debate, future restrictive laws possible	Legal issues
Strong enticement to misuse; human operating errors, unauthorised physical intervention by workers, operating errors because of poor usability; deliberate workarounds; health or comfort issues from constant wearing	Human factors
Rapid hardware obsolescence, rapid software obsolescence; dependence on a specific technology vendor; lack of standard interfaces for easy access; unclear state of the technology market; external service outage, dependence because of low expertise in the company and the high complexity of the technology	Direct and indirect dependence

3. Paper 2: Risk management behaviour in digital factories: The influence of technology and task uncertainty on managerial risk responses

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Contribution of Melanie Kessler to the work: Conducted the data analysis, wrote the methodology and findings sections, contributed to discussions on the findings.

Contribution of the co-authors: Eugenia Rosca wrote the literature review as well as the discussion part. She helped to structure the paper and gave advice about presenting the findings. She reviewed the paper intensively and provided feedback. Julia Arlinghaus conceptualised the research, reviewed the paper and contributed to discussions on the findings.

Contribution of the paper to the PhD project: The paper has a closer focus on the managerial response in risk management in the context of digitalisation projects. Based on 53 expert interviews, the paper provides a nuanced view of how technology and task uncertainty impact the perceived risks by managers and how this is attenuated by the nature of human-machine interaction. In this context, managers respond in paradoxical and unexpected ways to risk management, which are far removed from recommended approaches. Therefore, the influencing factors on human decision-making which affects individuals risk perception are investigated. The paper particularly contributes to the first research question.

Note: In the interest of uniformity, all articles have been reformatted according to the dissertation format.

Risk management behaviour in digital factories: The influence of technology and task uncertainty on managerial risk responses

Abstract

Purpose: This study advances a behavioural approach towards understanding how managerial perception impacts the enactment of responses to risk management during the implementation of digital technologies in industrial operations and supply chains. The purpose is to investigate the influence of (digital) technology and task uncertainty on the risk perception of managers and how this impacts risk responses adopted by managers.

Design/methodology/approach: Following an exploratory theory elaboration approach, we collected more than 80 hours of interview material from 53 expert interviews. These interviews were conducted with representatives of 46 German companies that have adopted digital technologies for different industrial applications within manufacturing, assembly and logistics processes.

Findings: Our findings provide nuanced insights on how individual and combined sources of uncertainty (technology and task uncertainty) impact the perception of decision makers and the resulting managerial responses adopted. We uncover the important role played by the interaction between the digital technology and the human being in the context of industrial operations. Our exploratory study shows that the joint collaboration between humans and technologies has negative implications for managerial risk responses regardless of positive or negative perception and therefore requires significant attention in future studies.

Originality: This paper focuses on the managerial risk responses in the context of digitalisation projects with practical insights of 53 expert interviews.

Research limitations/implications: The empirical base for this study is limited to German companies (mainly small and medium size). Moreover, German culture can be characterised by a high uncertainty avoidance and this may also limit the generalizability of our findings.

Practical implications: Managers should critically revise their perception of different types of digital technologies and be aware of the impact of the human-machine interaction. Thereby, they should investigate more systematic approaches of risk identification and assessment.

Keywords: digital technologies, technology and task uncertainty, risk perception, managerial risk responses

INTRODUCTION

Digital technologies are being adopted at high speed in industrial operations. These novel technologies, such as smart connected products, cyber physical systems, or cloud computing, enable a transformation process across operations and supply chains (Xu *et al.,* 2018). The literature tends to overemphasise the expected benefits of applying these technologies in industrial operations and to focus on efficiency gains, visibility, transparency and effectiveness (Koh *et al.,* 2019, Rehman *et al.,* 2022). Yet, there is increasing recognition among academics and practitioners that digital technologies present substantial uncertainty for managers. This increased uncertainty stems from multiple sources, namely unexpected and unknown impacts by enabling complex product-process interactions and by enabling data availability within and across supply chains (Holmström *et al.*, 2019). The collection and processing of real-time data in volatile, uncertain, complex and ambiguous environments represents a new source of uncertainty even though the availability of real-time data is supposed to enhance transparency (Lechler *et al.*, 2019). These sources of uncertainty create vulnerability and thereby increase the chances of risk and disruption along supply chains (Ivanov *et al.,* 2019; Brocal *et al.,* 2019; Tupa *et al.,* 2017). For instance, the use of Artificial Intelligence in ordering processes is changing the way of working between customers and suppliers and is also transforming data availability throughout the supply chain (Mithas *et al.,* 2022). These changes in technology and the way of working leads to two important sources of uncertainty: (digital) technology and task uncertainty. While (digital) technology uncertainty refers to the lack of knowledge about the use and function of the technology (Chai *et al.,* 2019); task uncertainty relates to the adapted way of working due to the usage of these digital technologies that can lead to the inability to predict the input and output factors, goals and affected processes regarding the work (Griffin *et al.,* 2007).

The handling of (digital) technology and task uncertainty present major challenges for decision makers who often make decisions based on individual cognition and perception rather than systematic, objective analysis (Ellis *et al.,* 2010). Decisions based on the individual risk perception of managers can be biased and thereby lead to suboptimal risk strategies (Markman and Krause, 2016; Sato *et al.,* 2020). For instance, in a study by PricewaterhouseCoopers (PwC) from 2021, six out of ten companies indicated a dismissive attitude towards the usage of cloud services. The main reason provided by every second participant in the study was the lack of confidence in the corporate data security in relation to cyber risks. As a result of this distrust, most companies prefer data storage on their own servers (PwC, 2021). However, in most cases, data security, intrusion protection and disaster recovery are significantly higher for professional

cloud services firms compared to internal data storage on a company's own servers (Nehmer, 2019; Digital business, 2020). This example illustrates how managers often respond to uncertainties based on their own perceptions, instead of assessing actual risks and choosing the adequate mitigation strategies. As a result, more researchers focus their attention on investigating the risk perception of decision makers and the influences on the supply chain flexibility to cope with these risks (Sreedevi *et al.,* 2017; Yu *et al.*, 2018; Sato *et al.,* 2020).

Inspired by these intriguing insights, our aim is to explore how technology and task uncertainty influences the perception of the managers to emerging risks that are triggered by the implementation of digital technologies in industrial operations. This research focuses on common risks which frequently occur during the implementation of digital technologies and influences the company's operations as well as the whole supply chain, e.g., human factor risks or data security risks. As the human factor plays a crucial role for the success of the implementation of digital technology, this research focuses on technologies which have a higher level of interaction between the human and the technology such as data glasses (Kessler and Arlinghaus, 2022).

While the literature on supply chain risk management provides a rich foundation for understanding and managing risks, it often assumes that managers act in a rational and objective manner, viewing risks in accordance with classical decision theory (Ellis *et al*., 2010). Based on a fundamental literature review, Pournader *et al.* (2020) confirm that most existing models in supply chain risk management are based on the assumption of a rational human behaviour. Earlier behavioural studies have shown that people confronted with decisional conditions of high uncertainty, tensions and time pressure are influenced in their information processing capabilities (Wickens et al., 2021). Already in the 1970s, Tversky and Kahneman (1974) showed in their pivotal study on so-called cognitive biases that these conditions often result in a systematic deviation from an optimum of logic, leading to risk ignorance or the misinterpretation of the likelihood of risk occurrence. However, recent developments in behavioural operations management as well as in supply chain risk management advance the idea that managerial perception is more influential in the decision-making process than an objective assessment of the situation is (Fahimia *et al.*, 2019; Tazelaar and Snijders, 2013), and that managerial cognition is very important in determining the responses to supply chain disruptions (Reiman *et al.,* 2017; Kessler and Arlinghaus, 2022). DuHadway *et al.* (2018) found out in their study that even the way of communicating risks impacts the managers risk perception and their decision-making strategies. Therefore, we aim to answer the following research question: *How does technology and task uncertainty influence the individual risk*

perception of managers during the implementation of digital application and how does this influence the managerial response related to risk management?

To answer this question, we first develop a theoretical model based on the naturalistic decision-making process (Kahneman and Klein, 2009) and draw on the information processing theory (Simon, 1978) in order to theoretically explicate how task and technology uncertainty can impact the risk perception of managers and thereby trigger responses to risk management, in terms of risk identification, assessment and mitigation. Second, we employ a qualitative theory elaboration approach and conduct 53 expert interviews involving more than 80 hours of interview material with managers from 46 companies across several of Germany's industry sectors. We sampled small and medium sized businesses (SMEs) from a production-intense setting (e.g., Germany) to better understand how uncertainty influences risk perception in the case of digital technologies. This is especially relevant because SMEs are typically characterised by lower hierarchy levels where a single manager takes on larger responsibility for risk management, thereby, the risk perception of the decision maker is crucial.

Our findings contribute to the ongoing discussion of uncertainty and the implementation of adequate risk management in the context of digital technologies in operations and supply chain management in several ways. First, we elaborate a behavioural approach to managing risks of digital technologies in industrial operations and supply chain management. We explain managerial responses with two different sources of uncertainty which are namely technology and task uncertainty and the role of human-machine interaction. We provide support for the claim that managerial decision-making in the context of digital technologies is largely driven by perceptual assessments which are directly affected by the perceived technology uncertainty and task uncertainty arising from the nature of human-machine interaction. Further, we propose that cognitive biases act as the main determinants which influence the risk perception of managers when the latter are exposed to digital technologies. Second, we uncover the important role played by the interaction between the digital technology and the human being in the context of industrial operations. Our exploratory study shows that the joint collaboration between humans and technologies has negative implications for managerial responses regardless of positive or negative perception and therefore requires significant attention in future studies.

THEORETICAL BACKGROUND

We draw on several research streams to develop the theoretical foundation for this study. We review the risk management literature on digital technologies and we argue that the nature of digital technologies and their application in industrial operations have created a unique context

which calls for novel risk management approaches. Then, we develop a theoretical framework to guide the study.

Risk management for digital technologies in industrial operations

The supply chain risk management literature is well-established and offers significant managerial guidance on how risks should be identified, assessed and mitigated. There are numerous categorisations of risks, their triggers and implications (e.g., Tummala and Schoenherr, 2011; Rao and Goldsby, 2009; Kersten *et al.,* 2007; Christopher and Peck, 2004), studies offering mitigation strategies and their effectiveness for achieving resilient supply chains (e.g., Tang and Tomlin, 2008; Chopra and Sodhi, 2004) or frameworks providing guidance on how risk management activities should be structured (e.g., Tummala and Schoenherr, 2011). Risks are the combination of exposure and impact of any probable event which results in a damage, loss or any unintended negative consequences (Wicaksana *et al.,* 2022). Taken together, these studies offer rich insights for understanding and managing supply chain risks, yet, they view risks in the way suggested by classical decision theory and therefore assume that managers act in a rational and objective manner and (Ellis *et al.,* 2010). Recent studies in behavioural operations management advance the idea that managerial perception is more instrumental in the decision-making process rather than the objective assessment of the situation is (Fahimia *et al.,* 2019; Tazelaar and Snijders, 2013) and that managerial cognition is very important in determining the responses to supply chain disruptions (Reiman *et al.,* 2017).

The wide adoption and diffusion of digital technologies in industrial operations presents a suitable context for theory elaboration in various areas of supply chain and operations management. The new technological implementation transforms supply chains and requires new and adapted risk management measurements (Ivanov et al., 2019). On the one hand, the new technologies can lead to changing risk profiles (for instance legal aspects around data security) as well as to the occurrence of new risks such as cyber risks (Kessler *et al.,* 2022; Ivanov *et al.,* 2020). Human behaviour can play a crucial role for the successful implementation of digital technologies (Sodhi *et al.*, 2019). In this context, the lack of knowledge about the use and functions of the technology as well as resistance to new ways of working and technologies can lead to new risks (Ghadge *et al.*, 2020; Kessler *et al.,* 2022). Drawing on insights from recent studies, we argue that the application of digital technologies in industrial contexts presents a unique context and requires novel approaches in risk management for several reasons.

First, the adoption and diffusion of digital technologies spans traditional organisational boundaries and goes beyond supply chains, triggering novel and unexpected changes at the technological, managerial and societal level (Hanelt *et al.,* 2020). Maghazei *et al.* (2022) studied the adoption of drones in operations management and found that previous technology management models and frameworks have not accounted for the particularities of emerging digital technologies and their technology adoption patterns have not always followed a linear logic of technology fit. As the boundaries between physical and digital structures become more blurred, there is more interaction between product, processes and consumers, opening up opportunities but also threats. Digitalisation is heightening operational risks and it is also spawning new risks (Gottlieb *et al.,* 2019).

Second, human factors are coming to the forefront and can serve as fundamental risks in this new operational context (Brocal *et al.,* 2019). Sodhi *et al.* (2019) show that supply chain managers tend to perceive emerging digital technology very differently in the early stages of adoption from how they do later, and this tendency significantly influences their goals and any benefits expected from the technology. The digitalisation of individuals, such as workers, also raises concerns for organisations (Gregory *et al.,* 2018). Human-machine interaction, or the lack of, can influence the current way of working and individuals' perceptions (Scott *et al.,* 2021). Moreover, there are various concerns and issues emerging from the interaction between humans and the digital technologies, namely privacy, security, legal protection, workers and consumers' welfare, human rights and health problems (Choi *et al.,* 2022). However, the human factor in the context of digital technologies is still under-researched (Sgarbossa *et al.,* 2020).

Third, digital technologies affect traditional supply chain and operations in multiple unexpected and unknown ways by enabling product-process interactions, access to real-time information within and across supply chains and identifying bottlenecks in new ways (Holmström *et al.,* 2019). These factors lead to unprecedented levels of vulnerabilities for firms and their supply chains. Especially, for SME`s which represent the backbone of the European economy this is highly relevant, as they often have to deal with scarce resources. Moreover, in SMEs, decision making around risks and their mitigation strategies often revolves around single managers (Ferreira et al., 2020).

Theoretical model for risk management of digital technologies in industrial operations

The naturalistic decision-making process model considers human behaviour when individuals make a decision. The way in which humans perceive and experience their environment, their own experiences and their personal attitude influence the decisional result (Klein, 1997).

Additionally, psychological stress and time constraints lead to distorted decision-making. Tversky and Kahneman (1974) describe in their research the systematic deviation from a rational optimum by so-called cognitive biases when decision-makers are confronted with stress and time pressure. Thereby, the naturalistic decision-making process can be classified into four steps (1) Situation, (2) Perception, (3) Choice response selection and (4) Response execution. First, the decision maker recognizes the situation for which a decision has to be made. Second, the perception of the decision-maker regarding the decisional environment, time constraints and also personal experiences influences and distorts the impression of that individual. Third, the final choice is selected and executed in the fourth step (Kahneman and Klein, 2009). During this decision-making process, several influencing factors occur which distort the decisional result and can lead to a biased decision (Tversky and Kahneman, 1974). Inspired by the early research of Tversky and Kahneman (1974), several researchers have investigated various cognitive bias effects. However, in the context of technology implementation projects especially judgment biases such as the pro-innovation bias or the bandwagon effect are relevant (Philips-Wren et al., 2019).

Stump et al. (2022) show that during the recognition and experience of the decisional environment by managers when implementing digital technologies in industrial operations, two major sources of uncertainty occur: (1) technology and (2) task uncertainty. Uncertainty thereby is characterised as the inability of a decision-maker to predict the probability of future events as well as the consequences of the decision (Zimmermann *et al.* 2020). Regarding technology uncertainty, fast and multiple changes in technologies lead to an increasing level of technological uncertainty which can then lead to an increasing level of transparency regarding unforeseen developments, new functions, and also new chances and risks. Moreover, the lack of transparency in market conditions and the inability to compare solutions with different functions increase the level of technological uncertainty (Ellis *et al.,* 2010). Regarding task uncertainty, unknown input and output factors result in an increasing level of task uncertainty. Especially with increasing interlinked parameters, which lead to higher complexity, it becomes more difficult for humans to acquire a complete overview of the affected processes and involved parties, which can result in an increasing level of task uncertainty (Griffin *et al.,* 2007).

The two sources of uncertainty may impact the risk perception of managers. In this conceptualisation, we refer to perceived rather than actual risk and we define this risk as a perceived chance of danger and feelings of uncertainty (Ellis *et al.,* 2010). The perceived risks can lead to a preliminary assessment of a potential event occurrence with detrimental effects (Zsidisin and Smith, 2005). There is more research suggesting that managers' decision-making

is guided more often by perceptual rather than by objective risk assessment measures and even when there is objective data available, the interpretation of risks may be biased (Yates *et al.,* 1994).

Information processing theory describes human behaviour in solving problems. Thereby, the human not only responds to the original stimuli, but rather the information is processed through the human mind, which takes the decision maker's perception of the environment and also her personal experiences into consideration (Miller, 1956). Three different stages in the human mind are involved in this throughput of information. First, the sensory memory collects all available impressions through every sense and, second, it filters the information into the short-term memory. Several factors and influencing factors (such as amount of information, time constraints, personal experiences or preferences) decide whether the information is worth processing into the long-term memory (Simon, 1978).

Based on the perceived risks, managers need to develop adequate managerial risk responses. Following structured supply chain risk management frameworks, these responses can take three forms: risk identification, risk assessment and risk mitigation. The identification of risks consists of scanning the environment for potential risks, and taking into account various activities and interdependencies in the supply chain (Chopra and Sodhi, 2004). Risk assessment refers to the likelihood of the identified risk's occurrence. Its potential impacts are established in this step in order to deliver detailed information on whether and how the risk can be prevented and whether its likelihood of occurrence and impact can be controlled, or whether the risk has to be accepted and contingency plans need to be developed (Kern *et al.,* 2012). Risk mitigation refers to the development of adequate mitigation strategies and this also involves defining potential countermeasures and subsequently evaluating the potential mitigation strategies (Kleindorfer and Saad, 2005). We combined insights from the literature on behavioural psychology and risk management to develop the underlying framework guiding this empirical study which is summarised in Figure 1.

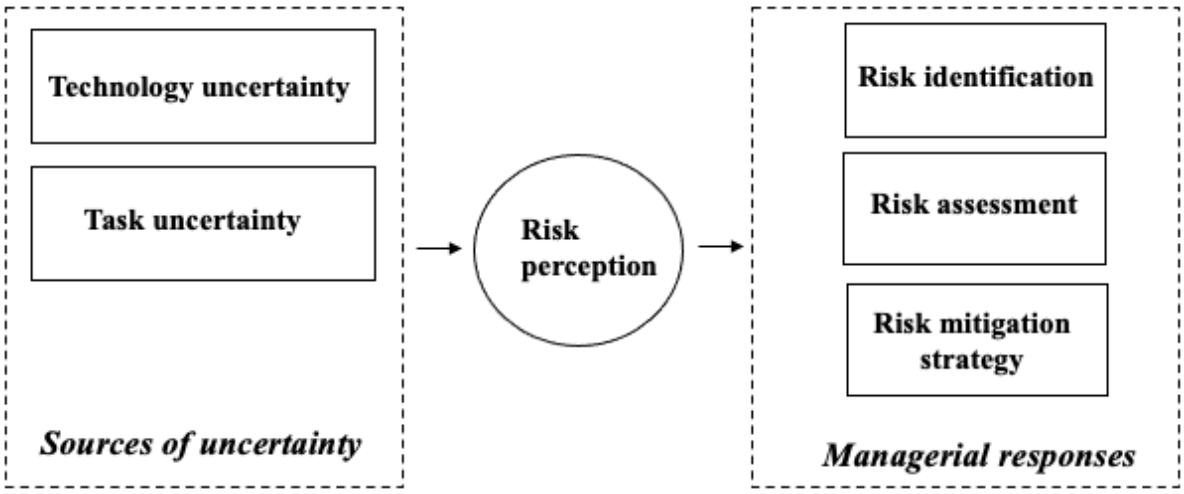


Figure 1: Theoretical Framework

METHODOLOGY

This study aims to investigate the managerial responses to risk management in the new context of digital applications in industrial settings using a theory elaboration approach. Theory elaboration in a novel context is suitable for this study because the risk management approach is a more established theoretical approach, while the application of digital technologies provides a novel empirical context to expand existing theories. The unit of analysis is the specific I4.0 technology implementation project of the analysed use cases: this is always a combination of a digital technology, a specific task in industrial operations, perceived risks and managerial actions. Our focus is on understanding how the technology-task combination presents new sources of uncertainty and impacts the risk perception of risk managers who in turn develop responses for risk identification, assessment and mitigation.

Sampling and data collection

Primary data were collected via 53 semi-structured interviews and more than 80 hours of recorded interview minutes with managers and consultants involved in implementing digital technologies in different operational contexts in Germany. Due to several reasons, Germany provides a suitable setting for this study. The focus on Germany as an empirical context was intended to reduce the influence of contextual factors, but also to enable the study of managerial responses in the context of a major industrial setting and of significant experience regarding digital technologies. As Kagermann *et al*. (2016) confirm, Germany provides an interesting setting, as there are a lot of different production-intensive sectors that are also strongly

technology driven. It is also notable that the majority of the German companies have already started to execute digitisation projects (Deloitte, 2020). Therefore, the findings may be transferable to other technology and production intense nations. In addition, Germany has a significant number of SMEs which entail the majority of its economy and therefore allowed us to sample and study the implementation of digital technologies and risk perception in SMEs. However, it is important to note that Germany is characterised with a high uncertainty avoidance score (Hofstede, 2011). Therefore, some of our findings may be bound to this cultural context and less applicable to empirical contexts characterised by a different uncertainty culture.

The initial starting point for the sampling was the data platform *"Plattform Industrie 4.0",* created by the German Federal Ministry for Economic Affairs and Energy in collaboration with the German Federal Ministry of Education and Research (Federal Ministry for Economic Affairs and Energy and Federal Ministry of Education and Research, 2019). This platform was launched with the aim of creating knowledge and sharing experiences between companies regarding the use of digital technology. Any company willing to share their project undergoes a verification process and fills in a structured questionnaire before their I.40 use case is published online. Out of the 359 cases available on the platform in October 2018, 197 cases were selected: First, we selected cases with a contact person who had an active participating role in the project and was in charge from the initial idea until the final implementation, to ensure information gathering throughout the project. Second, we aimed for a balanced sample across technologies, industrial sectors and sizes of the companies. We contacted all 197 respondents and 39 agreed to participate in this study, resulting in a response rate of 20%. In addition, using a snowball effect, we contacted 14 consultants who agreed to take part in the study. We involved consultants in the study to get a higher level perspective. Out of these 14 consultants, 7 had general experience with digital technologies, and the other 7 were directly involved in a project with a given technology implemented in an industrial context. This resulted in a final sample of 46 cases comprising a digital technology-task application, and we used this sample for the final analysis.

In several cases, the invitation was forwarded to the manager responsible for the digital technology project. Figure 2 gives an overview of the respondents' characteristics. The sample is balanced with regard to industries. Respondents were either at the top, middle or operational level and had intimate knowledge of the project. The data set covers a large range of small and medium-sized companies (1-250 and 250-5000 employees), which is representative of companies in Germany, in particular regarding the created jobs for the German economy.

Further small and medium-sized enterprises have a significant role in the development and implementation of industry 4.0 technologies within Germany (Kagermann *et al.,* 2016). Further, especially SME's are often characterised by low hierarchical processes where typically one manager is solely responsible for the complete decision making regarding the applied risk strategy and mitigation actions. In contrast, large multinational companies often have stricter and rule-governed decision-making processes with a lot of people involved. Therefore, the risk perception plays a crucial role for the applied risk mitigation actions. However, larger (5000-15000 employees) and even multinational companies (>15000 employees) are represented with approximately 20% each. While our focus was on SMEs, these cases provided a basis for comparison.

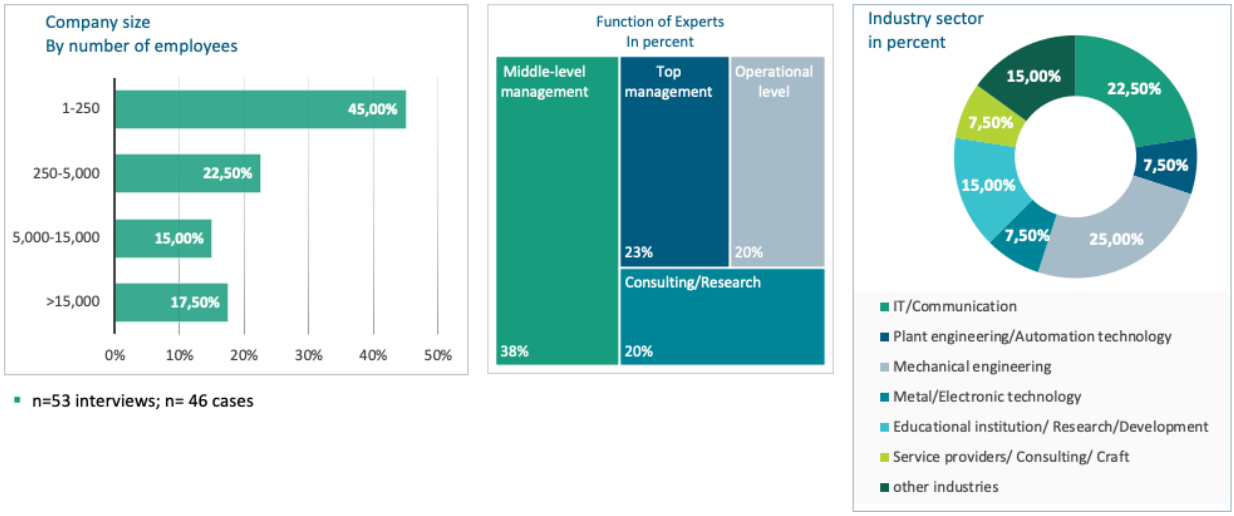


Figure 2: Overview of the sample – Characteristics of respondents

Interviews were conducted face-to-face or by phone between November 2018 and March 2019. Interviews lasted on average between twenty-five and fifty minutes and followed a semi-structured approach based on our developed interview guide. The interview questionnaire[2] consists of three main parts. In the first section, general information about the technology and its industrial use as well as about the company in general were queried. The second part focuses on the technology and its specific characteristics as well as on risks identified by the managers. The applied risk management processes, such as the types of risk identified, the process of risk assessment as well as the definition of risk mitigation action, are asked in section three. Figure 3 provides an overview of the distribution of digital technologies studied. Especially technologies which facilitate the production and the material flow are widely used in industrial

[2] The interview questionnaire used for this study can be found as appendix in Kessler et al. (2022). While the interviews serve as a basis for both papers, Kessler et al. (2022) uses an additional base of 300 case studies and the focus in that study is on exploring various risks emerging from the implementation of digital technologies.

practice, as also our analysed cases confirm. Depending on the characteristics of the technology as well as on the specific process for which the technology is used different risk profiles occur. Therefore, we classified digital technologies according to the higher-order concept of Alcácer and Cruz-Machado (2019), which is based on the involvement of essential components of the Industry 4.0 vision. In their research, they present a detailed characteristic of each of the enabling Industry 4.0 technologies and a classification of the digital technologies. We employed this classification to classify the technologies which we found in the use case. Based on these explanations, we categorized the use cases to the corresponding technology.

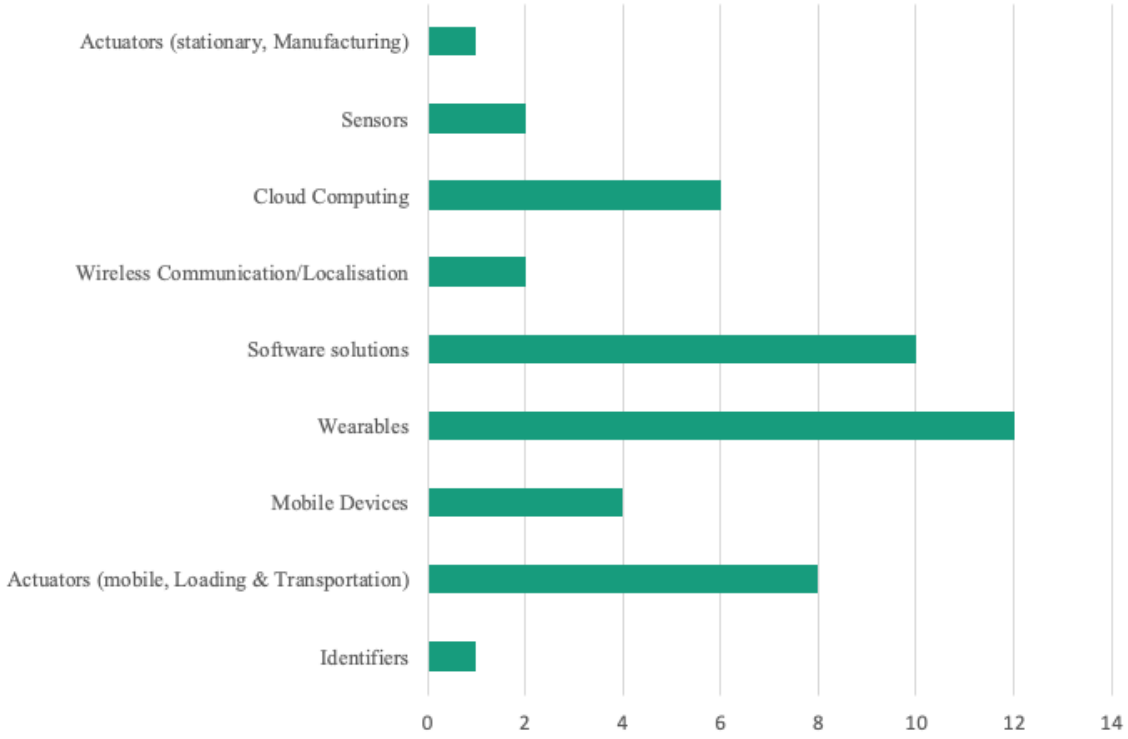


Figure 3: Overview of digital technologies in the sample (N=46)

Data analysis

Data analysis was conducted in three steps. First, an exploratory, open coding strategy was adopted for the initial investigation. During this stage, we linked types of digital technologies with different tasks based on typical tasks in supply chain management. Exemplarily, the task of material movement can be supported or done by mobile actuators such as automated guided vehicles. One theoretical dimension emerged from the data as highly relevant, namely the nature of the interaction between the digital technology and the workers. We grouped the cases into two categories based on the role of the digital technology and relationship with the human: the first group consists of cases where the technology enables the autonomous behaviour of the human and the second group consists of cases where there is an engagement between the human

and the machine in order to perform the task (Simpson *et al.,* 2020). Table 1 provides illustrative evidence for this step.

During the data analysis we found out that the technologies in group one are used differently when they come from the consumer sector or from industrial practice. Especially technologies such as mobile devices or drones that are frequently used in private life, risk managers treat them differently in their risk assessment process than technologies which are designed for industrial usage. Based on that, we decided to differentiate our analysis in group 1 between consumer technologies and industrial technologies.

Table 1: Linking digital technologies, and tasks with two dimensions of human-machine interaction - Evidence

Dimension – Group of cases	**Definition**	**Relevant digital technologies and their definition (according to Oztemel and Gursev, 2018)**	**Technology examples**	**Examples of tasks (operations and supply chain)**
The machine engages actively with the human to perform a task (n=29)	The technology and the human worker perform tasks in close cooperation and work together	● **Sensor:** An instrument which reacts to certain physical conditions such as light etc. It is often used in areas where a fast and sensitive reaction is needed. It supports humans in their work. ● **Identifiers:** The use of e.g. RFID or barcodes to identify, localize, and track and trace parts along the supply chain. ● **Mobile devices:** These include smartphones, handhelds etc., which interact with humans and provide data and information. ● **Wearables:** These include technologies such as data glasses, sensors, or data gloves. The term stands for "wearable computing", which are computer systems that are worn on the human body and give data support to humans in several activities, ● **Software solutions:** These include ERP systems and apps and help humans to structure processes and present information in a structured way.	▪ Sensor gloves ▪ Motion capture ▪ RFID/NFC ▪ Barcode/QR ▪ Smartphone ▪ Tablet ▪ Smartwatch ▪ Data glasses ▪ Data gloves ▪ Data brackets ▪ ERP (enterprise Resource Planning System) ▪ Manufacturing Execution System MES ▪ Apps	● Support in identifying the right information, such as in warehouse picking processes, quality control processes ● Decision support information, such as for definition of order quantity and time based on inventory stock level, resource planning based on the current resource utilisation for the whole supply chain
The technology enables	The technology takes over	● **Actuators (mobile):** Parts of a device or of a machine which enable movement. They	▪ Automated guided vehicle ▪ Drone	● Internal material transport

autonomous behaviour by the human (n=17)	tasks from the human worker and therefore enables the human to perform other, often more strategic and creative tasks whereas the technology focuses on more operational tasks.	thereby imitate the human body, which creates motion by using muscles. Actuators include drones, automated guided vehicles, etc. and are often used to support or replace the human workforce in logistical tasks. ● **Actuators (stationary):** Similarly, to the mobile actuators, also the stationary actuators enable movement. They are not movable around the factory. Robots, which are in the group of actuators, are fixed and localized in one place in the factory and support or replace human tasks. ● **Cloud Computing**: The provision of delivery hosted services over the internet, which makes data available from anywhere. ● **Wireless Communication/Localisation :** GPS, W-LAN etc. represent transmission standards which enable the exchange of data and enable communication.	▪ Industrial robot ▪ Control valve ▪ Private Cloud ▪ Public Cloud ▪ Platform as a Service (PaaS) ▪ 5G ▪ WLAN ▪ Bluetooth	● Assembly tasks ● Simple production tasks ● Communication internally and externally throughout the supply chain e.g. automatic EDI exchange of data and orders with suppliers ● Localisation of delivery along the supply chain via technology

Second, emerging codes were connected deductively to constructs emerging from the theoretical framework presented in Figure 1. During this step, data for each case were coded following these theoretical codes. Several themes emerged as relevant for driving the managerial responses, namely the role of familiarity with the technology, the role of top and operational managers, bargaining power of supply chain partners, technology customisation, necessary work adaptations due to technology implementation as well as task specific issues. Relevant definitions, an analysis guide and illustrative quotes are presented in Tables 2 and 3. All the data was coded by several researchers and we had multiple discussions to discuss emerging disagreements. Moreover, we presented the findings and the data to multiple industrial partners who also provided feedback. Parts of the interviews were coded in NVivo by two researchers and we had a very high inter-reliability score (mostly above 0.9 for the different parts in the coding, such as risks, responses).

Third, we employed a within- and cross-case analysis strategy (Miles & Huberman, 1994) to analyse the two groups individually and then compare and contrast them. The within-case analysis focused on understanding each case, the nature of technology uncertainty, task

uncertainty and the impact on the risk perception of the managers. To better illustrate this step in the data analysis, we provide a brief example here. One company wanted to implement automated-guided-vehicles (AGV) for their internal material transport. As a competitor already had successfully implemented this technology with a lot of efficiency gains, there was high pressure from the top management to get the AGV implemented fast. The responsible production manager confessed that he did not know much about the technology and its functionalities, thereby facing high technology uncertainty. Based on this combination of uncertainty, time and organisational pressure, he pushed the project and did not consider all the relevant parameters carefully. This has resulted in a situation where the manager neglected multiple relevant risks, for instance, he did not consider that there are ramps in the factory where the AGV was not able to drive.

The cross-case analysis focused on comparing and contrasting the two groups regarding the managerial responses and developing a deeper understanding of the role of human-machine interaction and the perception and management of risks in industrial operations. The within-case analysis led to the development of a series of observations, while the cross-case analysis synthesises these observations into a set of propositions where insights from previous studies are also integrated. The findings are presented following this structure and include several tables with evidence from the data.

Table 2: Theory-based data analysis - Theoretical constructs, definition and evidence from the data

Theoretical construct	**Definition**	**Analysis Guide**	**Classification**	**Illustrative Quotes**
Technology uncertainty	The inability to predict something accurately regarding the function and results of the technology. One major reason is the lack of knowledge regarding the function of the technology and the rapidly changing conditions of the technology (Chai et al, 2019)	Based on the case description (section 1 in interview guide) we analysed the characteristics of the technology and the required know how to use the technology correctly. We further analysed the problems that interviewees mentioned when using the technology.	Low: Managers are familiar with the technology and have already experience with the use and function of the technology Medium: Managers have already first knowledge about the technology. However, they are unsure about the usage and functionalities of the technology High: Managers lack knowledge and	*"With some technologies, the statistical data are so sparse and the rate of innovation is so high that it's very hard – if not impossible – to judge the risks, and the insurance costs are then obviously high" (Development Manager, Mechanical Engineering)* *"We didn't know enough about the requirements that need consideration besides the actual technology itself, like the requirement of not*

			experience about the technology and their functionalities	*having any ramps in the factory" (Head of Digital Innovation, Manufacturing)*
Task uncertainty	The inability to predict the input and output factors, goals and affected processes regarding the work performed (Griffin et al., 2007)	We analysed the affected processes and the corresponding stakeholders as well as potential influencing factors for input and output factors	Low: Managers are familiar with the tasks and are also able to assess the changes of working in correspondence with the new implemented Industry 4.0 technology. Medium: Managers are familiar with the tasks but they lack knowledge how the current way of working should be adapted in correspondence with the new implemented Industry 4.0 technology. High: Managers lack knowledge about the current task as well as how the way of working should be adapted in correspondence with the new implemented Industry 4.0 technology.	*"We were surprised about the low acquisition rate of the RFID technology. We simply hadn't considered the fact that our warehouse workers wouldn't use the RFID gate if they needed to get the material very quickly". (Production Manager, Automotive)* *"More automation also requires more consistency from our workers. For example, work pieces may need to be placed in a certain position. so that labels don't block any identifying markers. Simple things like that can be easily overlooked if they're not part of the routine." (Head of IT Manufacturing & Intralogistics, Automotive)*

Table 3: Theory-based data analysis for risk management process- Theoretical constructs, definition and evidence from the data

Risk identification	Identification of potential risks. This step is critical, since all other risk management activities are contingent on it. The focus is on scanning the environment for potential risks (Kern *et al.,* 2012). The range and interdependencies of different activities in the supply chain tasks have to be factored in order to devise suitable risk management strategies (Chopra and Sodhi, 2004).	Based on the responses of the interviewees to section 2 in the interview guide, we analysed the identified risks as well as the process that was applied for risk identification	*"We've already had one cyberattack, and nothing really bad happened, so I think we're well prepared." (Head of IT, Mechanical plant engineering)* *"Of course I'm growing dependent on the system! If it failed at a technological level, I'd immediately need to implement some sort of plan B." (Technical Sales and Distribution, Manufacturing)*
Risk assessment	The likelihood of the identified risk's occurrence and its potential impact are established in this step. Detailed information is thus acquired on whether and how the risk can be prevented and its likelihood of occurrence and impact can be controlled, or whether the risk has to be accepted and contingency plans need to be developed (Kern *et al.,* 2012).	We analysed the process and the steps taken to evaluate the likelihood of occurrence of the risks identified by the managers.	*"The people in charge didn't report the exoskeleton's problems immediately and we then lost time fixing them." (Head of Innovation & Digitisation Projects,* *"IT security now has the potential to break well-established, basic concepts of [physical] safety." (Senior Advisor, Electronical manufacturing)*
Risk mitigation mechanism	Describes the development and the implementation of adequate mitigation strategies. This also involves defining potential countermeasures and subsequently evaluating potential mitigation strategies. The capital expenditure for and the value of each mitigation action have to be determined (Kleindorfer and Saad, 2005).	We analysed the steps taken and the defined risk mitigation actions. We further analysed how successful the chosen risk mitigation strategy was in solving the risk.	*"We realised that at some point we wouldn't be able to completely prevent attacks anymore, and so we developed measures for reinstating our systems as quickly as possible in case something does happen." (Head of Research & Innovation Management, Logistics)*

Validity and reliability

We employed several tactics to adhere to the criteria of validity and reliability. We adhered to internal and construct validity by drawing on existing theoretical constructs and codes from the literature to collect and analyse data, and we engaged in pattern matching by conducting a within-case and cross-case analysis (Gibbert *et al.,* 2008). The theoretical model from Figure 1 was developed on the basis of existing literature on decision-making, and the risk management process serves as the basis for the empirical study. Moreover, case selection was guided by our aim to achieve a balance between different types of technologies, industries and company sizes in order to ensure comparability while enabling a contrasting tactic for case analysis.

To ensure reliability, we followed a theory-based interview guide for data collection, we created a case study protocol with rich descriptions of the cases, we conducted checks between the researchers who were coding the data and we engaged in multiple discussions to address any differences. The transcription was cross-checked with the interview partners to ensure validity (Denzin and Lincoln, 2003). Moreover, we focused our selection on managers with in-depth experience and expertise. To enable external validity, we created diverse samples to allow a comparison across industries and specific applications of digital technologies, and we analysed a large number of cases (46) and triangulated the insights with several consultants with a wider range of experience. Illustrative quotes and examples are shown throughout the manuscript, and additional evidence is available upon request from the corresponding author. We conducted a within-case and a cross-case analysis to enable the systematic comparison of the cases, as suggested by Miles and Huberman (1994). The within-case and cross-case analysis and comparison with previous literature ensures generalisation of the developed hypotheses (Eisenhardt, 1989).

FINDINGS

We present the findings in two parts. First, we present key insights for each of the two groups based on the nature of human-machine interaction. Second, we conduct a systematic comparison of the two groups and develop propositions on how different sources of uncertainty trigger managerial responses to risk management of digital technologies in industrial operations.

Group 1 - The machine engages actively with the human to perform a task

The companies from this group implemented digital technologies in their operations which led to an active engagement between the machine and the human in task performance.

Technologies enable a close collaboration between humans and machines. Both perform the specific tasks together. More specifically, machines support humans in information and data registration and processing as well as in supporting assembly processes involving heavy weights. Twenty-nine cases, such as RFID for warehouse processes, data glasses, data gloves and brackets for picking, digital worker assistance and exoskeletons, were summarised in this group with different technologies such as identifiers, mobile devices, software solutions and wearables. These technologies were especially used in material picking and warehousing processes as well as for supporting tasks in assembly processes.

During the analysis, we found that there are two main sub-groups with distinct characteristics and important implications for the risk management process: digital technologies from the consumer sector, such as smartphones, tablets and drones; and non-familiar technologies which were specifically designed for industrial usage. The technologies were treated differently by managers and employees regarding the risk management activities therefore we grouped them separately.

Technology uncertainty. Technology uncertainty for the technologies arising from the consumer sector is perceived to be low because employees and managers are very familiar with such technologies, their functions, usage and user interface from their private lives. As one consultant suggests: "*Technologies which are frequently used in practice were rated as more secure, and so a real analysis was missing".* In contrast, industrial technologies present a high level of uncertainty because there is little knowledge about the use and functions of these technologies. Moreover, very frequently, the technologies were customised for specific industrial applications and used for a particular company and context, which limited the availability of information and increased specificity. The high degree of technology customisation, which also means high costs, is accompanied by significant top management pressure on managers. These aspects increase the perceived technology uncertainty for industrial technologies.

Task uncertainty. The task uncertainty for technologies from the consumer sector is perceived to be very low, mainly because the industrial application is usually very similar to the private-life application of these technologies. High familiarity with consumer technologies creates a pleasant atmosphere and a low level of uncertainty. Additionally, the close collaboration with the technology reinforces this impression, as the humans engage in playful behaviour and favour working with these technologies. Only older personnel occasionally require special training and assistance. For the industrial technologies, we assessed a medium level of task uncertainty. Although the task is often clear, the joint work between the human

and the technology creates tensions, which serve as a source of uncertainty. Several issues arise from the joint, task-specific cooperation between humans and the technologies. First, workers often shift to the old working style, ignoring the new joint human-machine process because the older process was perceived to be faster and more accurate. The technology, then, is used to confirm the end-outcomes. Second, workers have a local view of the process and do not consider the human-machine interaction from the system perspective for the whole company which is often needed.

Frequently, the usage of the industrial technology requires adaptations in the industrial processes, leading to new sources of uncertainty. For example, in one case, managers found new sources of risks in the application of RFID technologies due to changes in the workflow. As the manager explains: *"We were surprised about the low acquisition rate of the RFID technology. We simply hadn't considered the fact that our warehouse workers wouldn't use the RFID gate if they needed to get the material very quickly".*

Risk perception: Our analysis uncovered several determinants with an impact on the risk perception of managers in this context. Interestingly, while the degree of uncertainty differs between consumer and industrial technologies, the information processing capabilities are negatively affected in both cases which leads to a distorted risk perception. On one hand, for consumer technologies with low perceived uncertainty, the high degree of familiarity and playful behaviour leads employees to feel safe and to the belief that they are in control. The positive perception arising from the playful human-machine interaction reinforces further the subjective assessment of managers. Additionally, as consumer technologies tend to be frequently covered by the media, this media visibility has a strong impact on managers' cognitive functions. As one consultant explains: "*There was a malware attack and people were soon reading and hearing about it everywhere. The result was that everybody was talking about nothing but cyber risks".* These determinants lead to biased and subjective risk perception of managers. On the other hand, for industrial technologies, the high level of perceived uncertainty leads managers to rely heavily on heuristics by searching for anchors, experiences of others and expert opinions. Their risk perception seems to also be strongly influenced by confirmation biases where previous negative experiences dictate new approaches. An overview of insights for group 1 can be found in Figure 4.

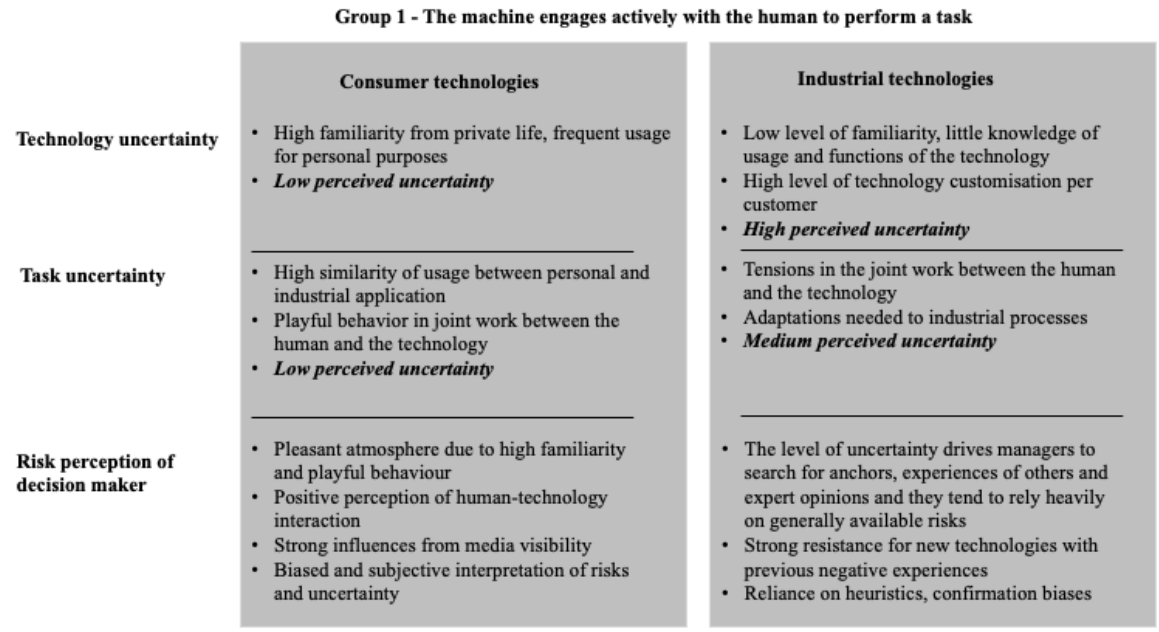


Figure 4: Group 1 - The machine engages actively with the human to perform a task

Group 2 - The technology enables autonomous behaviour by the human and often replaces humans by fulfilling human tasks

The digital technologies implemented in the second group enable autonomous behaviour by the human. They often replace the human in the task fulfilment and enable the human to fulfil more strategic tasks, because the technology takes over any repetitive tasks. Twenty-nine from our sample are used in this category and they include examples of stationary and mobile actuators, such as robots and automated guided vehicles (AGVs), which are used for material transports as well as for repetitive assembly and manufacturing processes.

Technology uncertainty. The technology uncertainty is high for this group because these technologies are customised for the company's individual needs: for instance, the AGVs are usually programmed for a specific factory layout and the robots are customised for the company's individual products. This high degree of specificity increases uncertainty due to a lack of general knowledge about the specific requirements, functions and adaptations. Moreover, there are no best practice examples or experiences from other companies. Quite frequently there is the lack of knowledge about the consequences of the general parametrization for the specific use case. One manager explains more about the AGVs *"We didn't know enough about the requirements that need consideration besides the actual technology itself, like the requirement of not having any ramps in the factory"*

Task uncertainty. The task uncertainty can be assessed as high for two reasons. The high degree of specificity and customisation of the technology for a particular industrial application leads to a high degree of parameters which need to be adjusted, as the CEO of an

automotive company explains:" *Of course, as a lot of the parameters need to be adjusted, this means that there are unexpected costs involved during implementation".* This also leads to significant changes in the business processes and thereby the way tasks are performed by different employees. One manager of a company explains that "*The biggest hurdle when you're setting up remote maintenance isn't the technology itself but managing the radical changes to business processes".*

Risk perception. Several factors impact the risk perception of managers for this group. First, the workers feel threatened by the technology and are afraid of losing their jobs or feel that they are becoming superfluous. One manager stated: *"There's often mistrust among the workers with regard to new technologies. They think that they might lose their jobs because robots will be replacing them. [...] Getting this mindset to change can require a much bigger effort than simply adapting your processes to the new technology".* As technology takes over the task, the workers feel that they are losing control of the task and of the outcome, and this has a negative influence on their perception of the technology and on the accurateness of the outcome. One manager explains that *"The process for shop floor workers is becoming less transparent because they now get a notification from the system based on a QR-code that some camera has read, and they have to accept this, even if they have the feeling something has gone wrong".*

Second, high investment costs and high pressure from top management results in managers having a tendency to rate the existing risks much higher in order to reduce the uncertainty and to avoid getting blamed in case something goes wrong. Third, high customisation of the technology and its application leads to high dependency on the technology supplier and a lack of benchmark solutions for managers. Overall, the human's impression of threat and of losing control coupled with high pressure from top management and dependency on a single technology supplier leads to a higher rating of the identified risks, as the managers tend to find arguments for avoiding the technology implementation. In this way, managers intentionally or unintentionally aim to protect themselves against possible negative outcomes. An overview of insights for group 2 can be found in Figure 5.

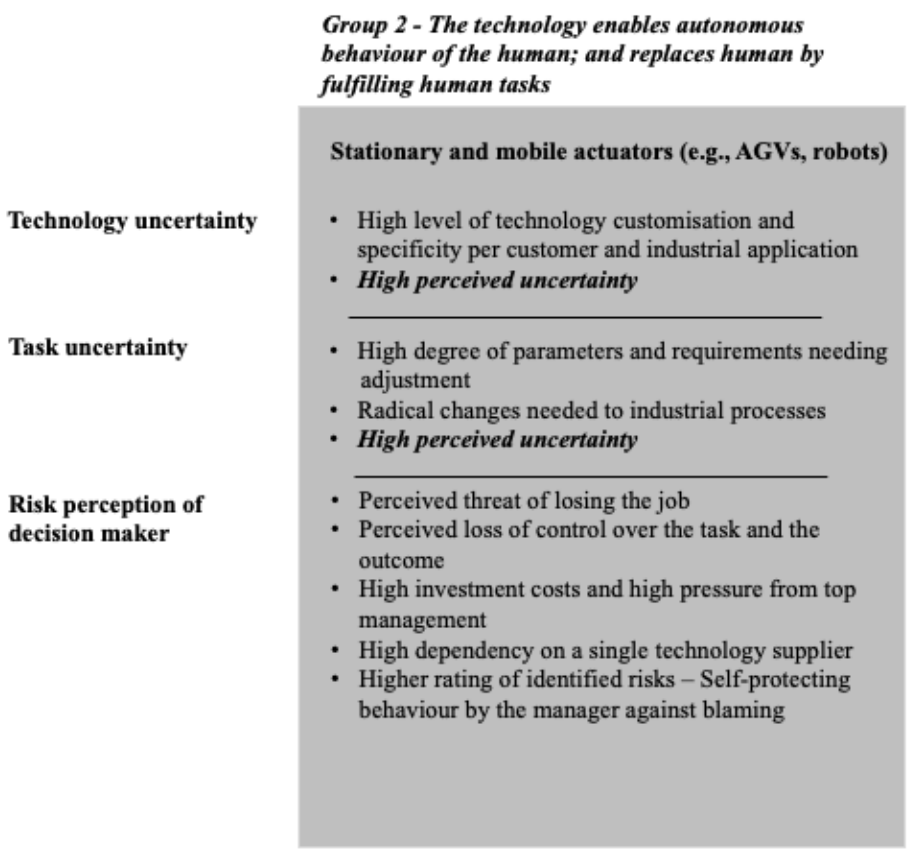


Figure 5: Group 2 - The technology enables autonomous behaviour by the human and often replaces humans by fulfilling human tasks

Cross-group comparison and development of propositions

Our findings reveal several new sources of uncertainty: high top management pressure, high pressure from external partners with bargaining power, customisation of technology, adaptations of the work environment as a result of the technology implementation and uncertainty arising from task-specific cooperation between workers and machines. The systematic comparison of the two groups enables the development of a set of observations which serve as key insights per group (see Table 4). While explaining the managerial responses found, the insights suggest that the relationship between the technology and the workers has significant influences on the perceived levels of uncertainty, and this influences managerial responses. Several propositions based on the analysis of the data are put forward to explain managerial responses induced by individual or combined sources of uncertainty. Based on the

observations and the combination of the level of technology and task uncertainty as well as the new sources of uncertainty, we developed the propositions regarding the influence on managerial responses during the risk identification and assessment phase as well as on the risk mitigation phase.

Table 4: Developing observations and key insights from the group comparison

	Group	**Technology uncertainty**	**Task uncertainty**	**New sources of uncertainty emerging from the data**	**Influence on risk perception of decision maker**	**Managerial response to risk identification and risk assessment**	**Managerial response to risk mitigation**
Group 1: The machine engages actively with the human to perform a task	Sub-Group 1 consumer technologies	Low (high familiarity from daily life)	Low (only little changes to current way of working)	● High top management pressure	Biased and subjective interpretation of risks and uncertainty	Ignorance of risks and low rating of likelihood of occurrence ○ Pro-innovation bias focuses on technological benefit and ignores risks	Trust in already existing risk mechanisms and security standards
	Observation 1a: Technologies from the consumer sector have a high acceptance rate; therefore, management favours these solutions, leading to often ignored risks for industry-specific use as well as a high trust in already existing risk mitigation mechanisms.						
	Sub-Group 2 Industrial technologies	High (customised for industrial usage)	Medium (way of working is changing due to new technology)	● Customisation of technology ● Bargaining power of technology vendors	Reliance on heuristics, confirmation bias	Missed risks, high ranking of risks for which already negative experiences exist ○ Confirmation bias and bandwagon effect	Apply risk mitigation action recommended by others without analysing whether this fits with company individual processes
	Observation 2a: Technologies from industrial applications have high perceived uncertainty and managers tend to rely heavily on heuristics, leading to missed risks and a high ranking of those risks which they have already negatively experienced. *Observation 2b: Technologies from industrial applications have a high degree of customisation and this raises the perceived uncertainty. Yet, managers tend to rely heavily on recommendations without adequate analysis, as they are influenced by the confirmation bias and the bandwagon effect.*						
Group 2: The technology enables	-	High (unclear functionalities and	High (completely new way of	● Customisation of technology	High rating of identified risks – self	Missed company-individual risks and higher	Favouring current status and avoidance of implementation

autonomous behaviour by the human; and often replaces humans by fulfilling human tasks		features of technology)	working is required)	• Adoptions of work environment	protecting behaviour by the manager	ranking of identified risks ○ Status quo bias	
	Observation 3a: The high perceived uncertainty level and the tendency towards a self-protecting behaviour leads managers to rank existing identified risks very high while missing the company-specific risks. *Observation 3b: The general personal resistance of workers and managers towards the new technology leads managers to favour the status quo.*						

First, the cross-case analysis of the use cases and the interview data uncovers how the degree of familiarity with the technology and a strong internal orientation leads managers to ignore relevant risks. Here, risks which lead to disruptions within the supply chain and business operations are defined as relevant. The high degree of familiarity which was investigated for technologies coming from the consumer industry in group 1 showed that managers tend to ignore risks. As previous literature shows, especially innovative technologies with a high acceptance rate by humans are often "glorified", and a critical review is missing (Godin and Vinck, 2017). As there is a hype around the technology, we posit that managerial cognition is affected by a pro-innovation bias which serves as an influencing factor, making managers focus only on the technological benefits and hide negative information.

Therefore, we propose:

Proposition 1a: Low perceived technology uncertainty leads managers to ignore risks.

Proposition 1b: A strong company-internal focus and perceived high organisational pressure leads managers to ignore risks.

Second, tensions arising from human-machine interaction significantly influence the managerial responses especially regarding risk assessment. Several researchers investigated the perceived threats regarding the fear of job loss and loss of autonomy (see, for instance, Stein *et al.,* 2019, Zlotowski *et al.,* 2017). We took this as a starting point for our analysis of the use cases and the interview data and we extend this with the aspect of the level of human-machine interaction. As workers feel threatened by the technology and the loss of control, they tend to assess identified risks as very high with the aim to stop the implementation of the technology. Therefore, we propose:

Proposition 2: High perceived technology and task uncertainty between workers and machines centred around loss of control leads managers to assess risks as very high with the aim of breaking off the project.

Third, we identified in our analysed data set that when the perceived distance between the technology and the workers is high, managers tend to adopt a self-protection behaviour in

the face of uncertainty. Behavioural studies have confirmed that perceived threat leads humans to adopting a self-protecting behaviour (Tversky and Kahneman, 1974, Simpson *et al.,* 2020). We extended this research by applying this aspect in the digitalisation environment, in particular regarding the human-machine interaction intensity. This self-protecting behaviour can either entail managers maintaining the status-quo, as they feel threatened by the technology or tending to adopt insufficient mitigation strategies, e.g. the trial-and-error method, which actually leads to more and higher risks for companies. Self-protecting behaviour by managers is attenuated by high pressure from top management to have the projects succeed. Therefore, we propose:

Proposition 3: Higher perceived distance between the technology and the workers in combination with high technology uncertainty leads managers to develop self-protection responses, which leads to reinforced risks.

Fourth, the degree of familiarity with the technology and the customisation to the work environment often leads managers to avoid any proactive mitigation strategy, thereby often employing reactive, high-cost mitigation strategies. Behavioural literature has been investigating this human tendency for years (Russo, 1996; Simpson *et al,* 2020). We extended this research to include the degree of familiarity in the context of digitisation projects in the analysis of our use cases and the interview data. Especially technologies with a high degree of customisation lead to a low level of familiarity, as a lot of functions are company individual or product specific. As a result, managers often apply inadequate risk mitigation strategies or miss risks entirely, which ultimately requires reactive and cost-intensive mitigation strategies when a risk does occur. Therefore, we propose:

Proposition 4: High perceived technology and task uncertainty and a high degree of customisation leads to reactive (cost-intensive) mitigation strategies.

THEORETICAL CONTRIBUTIONS

Our findings bring to the forefront the major role that human perception plays in enacting responses to risk management of digital technologies in industrial operations. With this, our study makes three notable theoretical contributions.

First, our research advances the study of risk management in a novel context which is triggered by the application of digital technologies in industrial operations as well as for supply chains. Our findings indicate that a behavioural approach is highly relevant to understanding how managerial perception impacts the enactment of responses to risk management. More specifically, our findings show that technology and task uncertainty and tensions arising from

the human-machine interaction can lead to the rise of numerous biases which impact responses to risk management. Studies in behavioural economics have shown that when people are confronted with uncertainty and time pressure, the systematic deviation from an optimum of logic appears to lead to risk ignorance or the misinterpretation of their likelihood of occurrence (Tversky and Kahneman, 1974). We provide nuanced manifestations of this phenomena in the context of digital technologies applied in industrial contexts with implications for the whole supply chain. We provide support for the claim that managerial decision making in the context of digital technologies is largely driven by perceptual assessments which are directly affected by the perceived technology uncertainty, task uncertainty and tensions arising from the nature of human-machine interaction.

While risk management research has largely focused on objective risk assessments and evaluation, our insights expand the behavioural viewpoint that suggests that perceptions of risk are guiding the managerial decision-making behaviour rather than objective risk assessments are (Reimann *et al.,* 2017; Tazelaar and Snijders, 2013; Ellis *et al.,* 2010). With this, our findings echo earlier insights from risk management studies (Qualls and Puto, 1989) in suggesting that risk assessment by managers in the context of digital technologies is more influenced by organisational factors such as uncertainty, pressure and employee-technology tensions, than by risk attitudes. Further, our research confirms the claims of other authors (see Markman & Krause, 2016; Sato et al., 2020) that biased decisions based on the individual risk perception leads to the adoption of suboptimal risk management responses. Both the technology and the task uncertainty in combination with tensions linked with different types of human-machine interaction lead to biased risk perception of managers who, in turn, adopt inadequate mitigation strategies.

Second, we show the important role played by the nature of interaction between the digital technology and the human in the context of industrial operations. Studies in information systems have suggested that a successful interaction and collaboration between humans and digital technologies is needed for digital technologies to succeed (Neumann *et al.,* 2021). Moreover, digital technologies will not replace humans, but rather processes will be redesigned to divide tasks and have the humans and the digital technology working together jointly (Cimini *et al.,* 2022). Our exploratory study shows that the joint collaboration between humans and the technologies has negative implications for managerial responses, regardless of a positive or a negative perception, and needs significant attention.

Third, we show the determinants which influence the risk perception of managers when the latter are exposed to digital technologies. Thereby, we have identified several cognitive bias

effects which have been investigated in behavioural operations management literature (Tokar, 2010; Duhadway *et al.,* 2018; Neumann *et al.,* 2021). These effects distort the managerial risk management response and have a significant influence on the defined risk mitigation strategies by managers. The following table summarises the cognitive bias effects identified during our study.

Table 5: Cognitive biases in managerial responses identified in this study and previous literature

Identified cognitive bias effect	Description	Role of human-machine interaction	Reference
Pro-innovation bias	Focus and novelty, while hiding potential risks	Tends to occur when there is a close human-machine collaboration (e.g. wearables, mobile devices, drones)	Godin et al., 2017
Confirmation bias	Individuals' tendency to seek information that confirms their own opinions and to ignore information that contradicts their own beliefs	Tends to occur when there is a high complexity of customised technologies (e.g. robots, smart maintenance technologies)	Heath, 1996; Russo, 1996
Bandwagon effect	Individuals' tendency to do things because many other people are doing the same	Tends to occur when there is a high complexity of customised technologies (e.g. robots, smart maintenance technologies)	Carter et al., 2007; Bindra, 2022
Status-quo bias	Fostering of human resistance	Tends to occur when humans feel threatened by the technology (e.g. AGV`s, actuators, RFID conveyor)	Kahneman and Thaler, 1991

Managerial implications

Our findings entail valuable implications for managers overseeing the implementation of digital technologies in industrial operations. The managerial insights are particularly relevant for SMEs where decision making tends to revolve around key individuals rather than more formal and rule-governed practices in multinational corporations. First, managers should be aware of and avoid situations in which their actions are simply responses to uncertainty caused by digital technologies or tasks performed. Instead, the focus should be on developing an in-depth understanding of the digital technology and its application context. The risk profile should be developed based on company processes and individual risks rather than imitating competitors or emulating events from the media. For this particular context, debiasing techniques can be applied in order to identify, assess and evaluate risks and to develop contextualised mitigation strategies.

Second, regarding different types of human-machine interaction groups, managers should critically revise their perception of consumer technologies and the application and the industrial contexts of these technologies by shifting to a more systematic approach of risk identification and assessment. For technologies which enable autonomous behaviour by humans and often

replace them, we encourage managers to challenge the current assumptions behind risk ranking and to use more specific debiasing techniques. For digital technologies spanning organisational boundaries, managers should move away from risk management at a company-level towards a supply chain-level. While this advice is not new, we show that digital technologies span transformation across the supply chains, thereby creating different known and unknown sources of vulnerability for firms and their supply chains. Therefore, it is of paramount importance that these supply chains are designed and managed from a systematic viewpoint.

Third, our findings suggest that the tensions arising from joint collaboration can have significant implications for the task and process outcomes. Given the high investment costs and strategic importance of these projects in organisations, managers should pay particular attention to this issue and develop conditions, training and awareness sessions to address the joint collaboration between humans and digital technologies. By raising awareness and explicitly developing tactics to improve the task distribution and role allocation between workers and the technologies, managers can improve the success chances of their digitalisation projects. Moreover, engaging in these activities can help managers themselves become aware of key issues and streamline their own decision-making process in relation to risk management.

Limitations and further research

Research on the nature and approaches for risk management in the context of digital technologies is in its infancy. Our exploratory study has unpacked the role of human perception in understanding and responding to digital technologies and their application in industrial contexts. Yet, the qualitative nature of our study does not allow causal inferences. Further research should employ experimental approaches to test the influence of behavioural factors, more specific cognitive biases, on risk management approaches and the impact on operational performance. Moreover, in this study, we adopted a manager's viewpoint in perceiving and responding to digital technologies and their applications, but further studies should explore this relationship from a triadic view point: employee – digital technology – manager. In this context, especially the role of bounded rationality and its influence on the risk perception should be investigated. While we have shown that the interaction between the employee and the digital technology in a specific task context can influence managerial responses to emerging risks, further research should explore the dynamic interaction and feedback loops between managerial responses, digital technologies and the employees either working with the technology or being replaced by the technology.

Our study has been conducted in the context of Germany, which is a major industrial context with major progress for the application of digital technologies. This is also a cultural context with high uncertainty avoidance tendencies. Managerial responses might be strongly influenced by cultural dimensions and therefore limited for that cultural aspect, and therefore it would be interesting to expand this research to other contexts with lower uncertainty avoidance tendencies and also to other industrial nations. As this study has a strong focus on German SMEs, further research should explore to what extent the findings are transferable to SMEs beyond Germany and larger organisations.

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4. Paper 3: A framework for human-centered production planning and control in smart manufacturing

Authors: Melanie Kessler, Julia Arlinghaus

Status of Publication: Published in Journal of Manufacturing Systems, Volume 65, 220-232, (2022).

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Contribution of Melanie Kessler to the work: Conducted the data analysis, wrote the paper, contributed to discussions on the findings.

Contribution of the co-authors: Julia Arlinghaus conceptualised the research, reviewed the paper, helped with structuring the paper and contributed to discussions on the findings. She also streamlined section 2 and added information about the case study design.

Contribution of the paper to the PhD project: The paper has a closer focus on another sub-area of operations management, namely Production Planning and Control (PPC) in smart manufacturing.
First, the conducted literature review in the paper investigates the relevant decision types and tasks within PPC. Further, the relevant cognitive bias effects are described in detail. Based on an in-depth case study with an additional 12 expert interviews, a framework for a human-centred PPC is developed. The paper contributes to all three research questions.

Note: The article has been published in Journal of Manufacturing Systems, Volume 65, 220-232, (2022) in a different version.
In the interest of uniformity, all articles have been reformatted according to the dissertation format.

A framework for human-centered production planning and control in smart manufacturing

Abstract

Smart manufacturing systems have to meet high performance expectations in form of customer individual products, short lead times, high due date reliability and resilience by the integration of new technologies and by intelligent process design. The planning and control of such smart manufacturing systems necessitates several instances of human decision-making. The latest research at the nexus of operations management and psychology reveals that human decision-making in such fast-paced, dynamic and complex environments is often biased, resulting in suboptimal operational performance. Human-centered design of planning and control processes can mitigate biased decisions, thus boosting performance in smart manufacturing systems. Current research is silent about the impact and mitigation of cognitive biases in operations management, though.

We intend to close this research gap. We combine systematic reviews of literature on behavioral operations management and cognitive biases in operations management, particularly in production planning and control with an in-depth case study based on 12 expert interviews. We explore two decision-making models and combine them in a PPC framework. We create a framework for human-centered PPC in smart manufacturing systems, which includes the main impact factors, challenges and performance capabilities. Based on a detailed case study of a steel producer, we present a framework of human-centered PPC comprising five hypotheses on the impact of cognitive biases on human decision-making and on manufacturing performance.

Keywords: behavioural operations management, decision types, cognitive biases, production planning and control, smart manufacturing, decision support systems

1. Introduction

Digital technologies, such as cyber-physical systems and artificial intelligence, simplify various production processes and create smart manufacturing systems. The planning and control of such systems is frequently still a manual activity in part or whole. Production planning and control (PPC) coordinates all relevant production processes to enhance logistics performance at an efficient cost level. While digitalization enabled by smart technologies has generated tremendous productivity gains in smart manufacturing systems, human-centeredness has been

sparsely examined [1]. The realization that humans remain a key enabler of further technological development that fully harnesses the capabilities of Industry 4.0 is shifting discussion toward new concepts that focus on human needs [2]. Although data analytics and intelligent planning algorithms support PPC in smart manufacturing systems, several human decisions are nevertheless required during various activities. Depending on the time horizon, human decisions can be divided into long-term strategic decisions, medium-term tactical decisions and short-term operational decisions. In this paper we focus on the operational and tactical decisions in PPC which are the main part of the daily business [3].

Although human behavior has been studied intensively in the fields of psychology, anthropology and sociology and behavioral factors have become an integral part of economics research [4], very little research has actually been done in the fields of production, manufacturing and PPC, particularly in smart manufacturing environments [5]. Various models that shorten lead times, maximize schedule adherence, lower inventory levels and increase capacity utilization, all of which are key logistics performance indicators for production systems, have been developed to facilitate decision-making processes in PPC and optimize production logistics performance [6]. The theory of *homo economicus* typically underlying these models assumes that human behavior is perfectly rational [7]. [8] challenged this assumption, demonstrating that human decisions are biased and systematically deviate from rational judgment. A universal approach to human-centered PPC does not exist yet, though. Fully harnessing the capabilities of smart manufacturing systems will require intelligent collaboration between humans and smart technology.

The quite well-researched phenomenon of so-called lead time syndrome (LTS) underscores the need to integrate human factors in the planning and control of smart manufacturing systems to enhance performance. Production planners tend to overreact to decreasing schedule adherence and adjust standard lead times too often, eventually exacerbating the decrease in schedule adherence and thus diminishing logistics performance [5].[5] identified five cognitive biases active in the planning and control of smart manufacturing systems.

Our research is intended to advance understanding of the role of cognitive biases in decision-making in the planning and control of smart manufacturing systems. We develop an initial framework of human-centered PPC in smart manufacturing systems and provide initial hypotheses on the interplay of smart manufacturing system, human decision-making, decision types and production performance. Our research is intended to answer the following research question: *How can the influence of cognitive biases on PPC decision-making in smart manufacturing systems be factored into the design of human-centered PPC systems?*

To this end, we combine systematic reviews of the literature on behavioral operations management, decision types and the impacts of cognitive biases. We underpin and corroborate our findings with a detailed case study of a steel producer based on 12 expert interviews and extensive data and document analyses. We use the implementation of a PPC system based on big data to demonstrate how disregard for biased human decision-making can jeopardize digitalization projects in manufacturing environments and how human-centered design of the PPC system can enhance logistics performance.

The remainder of this paper is structured as follows: In section two, we present the research process applied. In section three, we discuss the impact of digitalization and artificial intelligence on decisions in PPC. We outline the typical decision-making process and present the various types of decisions. We also examine different categories of cognitive biases. In section four, we combine models of decision types in a new framework and correlate decision types with the phases of an established PPC model. In section five, we formulate initial hypotheses on the impact of cognitive biases on specific decision-making situations in PPC based on a detailed case study of a steel producer and contingent on the type of decision. Finally, we discuss our findings and suggest further avenues of research.

2. Research design

This study pursues an answer to the research question by analyzing the impact of cognitive biases on typical PPC decisions in smart manufacturing systems. To this end, we combine the literature review and the situations analyzed in the detailed case study of a German steel producer to formulate initial hypotheses on the impact of cognitive biases on decisions in PPC. Figure 1 presents an overview of the methodology applied.

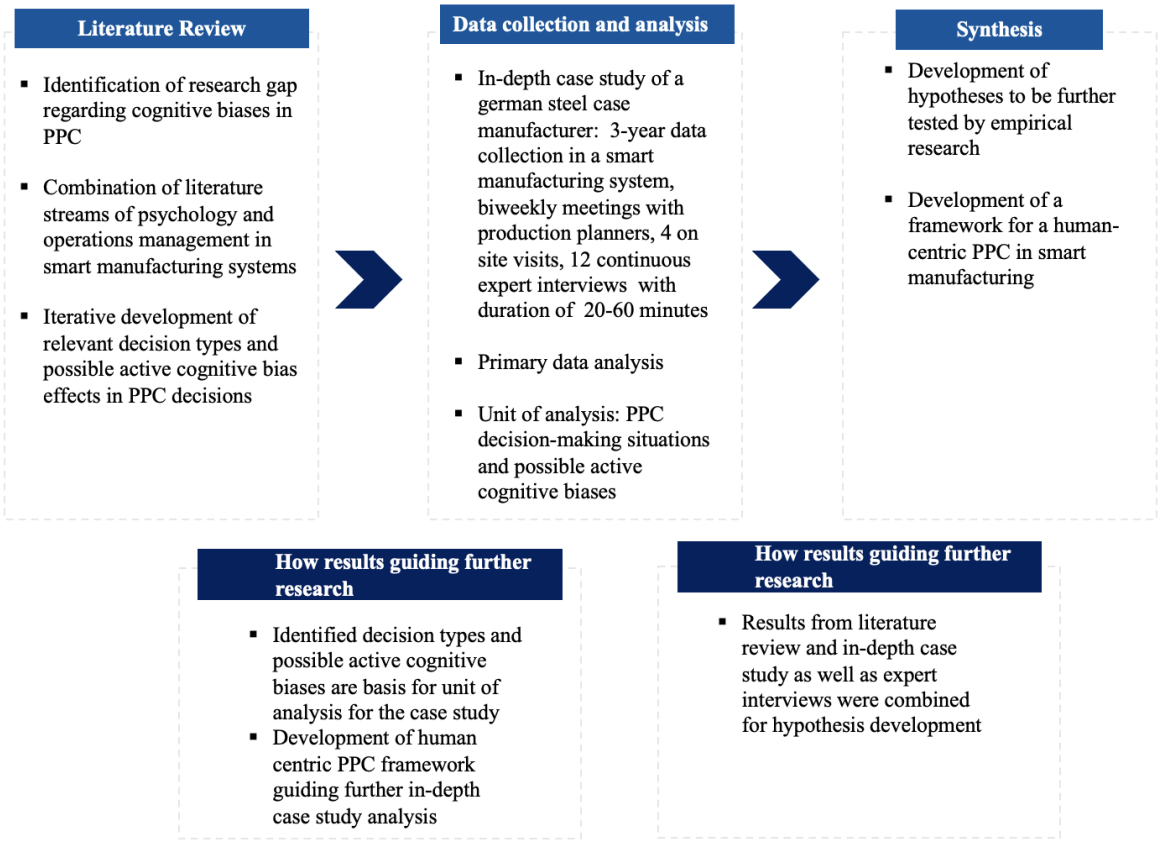


Figure 1: Applied research design

2.1 Literature review

We conducted a structured review of literature in the fields of operations management and psychology and combined the findings to obtain a comprehensive overview.

We began by creating research strings, listed in the table below, to identify relevant papers in the Web of Science and Scopus, employing a rigorous process of trial and error to define the keyword set.

Search strings applied for Web of Science and EBSCOhost
Scopus search strings: **1st search string:** TITLE-ABS-KEY ("Cognitive Bias*" OR "Human Behavior*" OR "Human Behaviour*" OR "human decision making" OR "Human factor" OR "judgement under uncertainty" OR "Human error*" OR "decicion types*") AND (LIMIT-TO (DOCTYPE,"ar")) AND (LIMIT-TO (LANGUAGE,"English")) **2nd search string:** TITLE-ABS-KEY ("Cognitive Bias*" OR "Human Behavior*" OR "Human Behaviour*" OR "human decision making" OR "Human factor" OR "judgement under uncertainty" OR "Human error*" OR "decicion types*") AND TITLE-ABS-KEY ("manufacturing" OR "production" OR "production planning and control" OR "production planning") AND (LIMIT-TO (DOCTYPE,"ar")) AND (LIMIT-TO (LANGUAGE,"English")) **3rd search string:** TITLE-ABS-KEY ("Cognitive Bias*" OR "Human Behavior*" OR "Human Behaviour*" OR "human decision making" OR "Human factor" OR "judgement under uncertainty" OR "Human error*" OR "decicion types*") AND TITLE-ABS-KEY ("manufacturing" OR "production" OR "socio-cyber-physical systems" OR "deicion support systems") AND (LIMIT-TO (DOCTYPE,"ar")) AND (LIMIT-TO (LANGUAGE,"English"))

Web of Science search strings
1st search string:
TOPIC: ("cognitive biases" or "human behaviour*" or "human decision-making" or "human factor" or "human decision-making" or "judgement under uncertainty" or "human error" or "decision types") Refined By: DOCUMENT TYPES: (ARTICLE)
2nd search string:
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3rd search string:
TITLE-ABS-KEY ("Cognitive Bias*" OR "Human Behavior*" OR "Human Behaviour*" OR "human decision making" OR "Human factor" OR "judgement under uncertainty" OR "Human error*" OR "decicion types*") AND TITLE-ABS-KEY ("manufacturing" OR "production" OR "socio-cyber-physical systems" OR "deicion support systems") AND (LIMIT-TO (DOCTYPE,"ar")) AND (LIMIT-TO (LANGUAGE,"English"))

Table 1: Applied research strings

Only journal articles published in English, regardless of the publication date, were included. We excluded articles on human behavior, which are unrelated to decision-making. We analyzed the remaining 60 articles' relevance to PPC decision-making situations, decision types and cognitive biases. The results are presented in Table 2.

Research area	Identified number of relevant papers
PPC tasks	9
Decision-making situations in PPC	5
Decision types	13
Human decision-making model	7
Cognitive biases	14
Cognitive biases in PPC	4
Socio-cyber-physical systems	8

Table 2: Identified papers for each research area

The analysis of the publishing year per each research stream shows further interesting details which are presented in Figure 2.

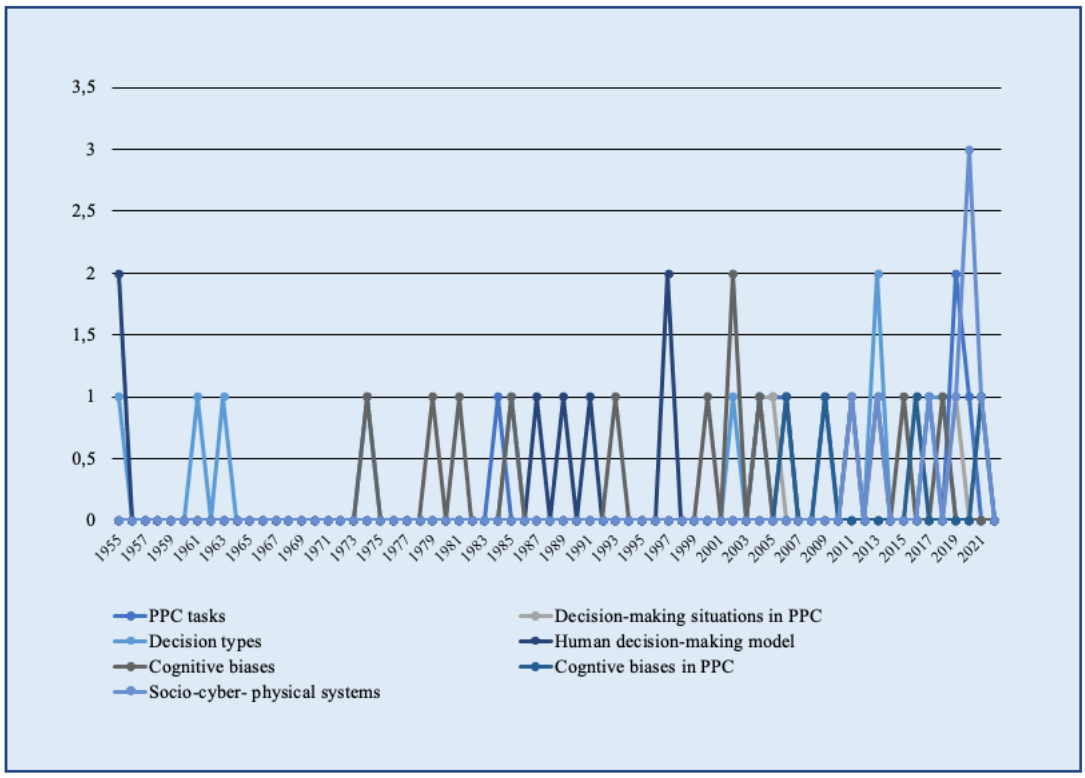


Figure 2: Results of publication trend of the analyzed papers

In psychology already in 1955 started first examinations of the human decision-making process and different decision types. With the famous publication of both nobel prize winners [8] in the mid of the 1970´s the research of cognitive biases and their influence on human decision-making marked the starting point of a growing research area. Only later, starting in the 2000´s, research in the traditional production area investigated that the human behaviour has a tremendous influence on the performance of production systems and first human related topics were part of the research interest. With the introduction of the concept of the Industry 4.0 vision also the research about socio-cyber-physical systems started.

The regional breakdown of the analyzed papers confirms the research landscape which is shown by Figure 3.

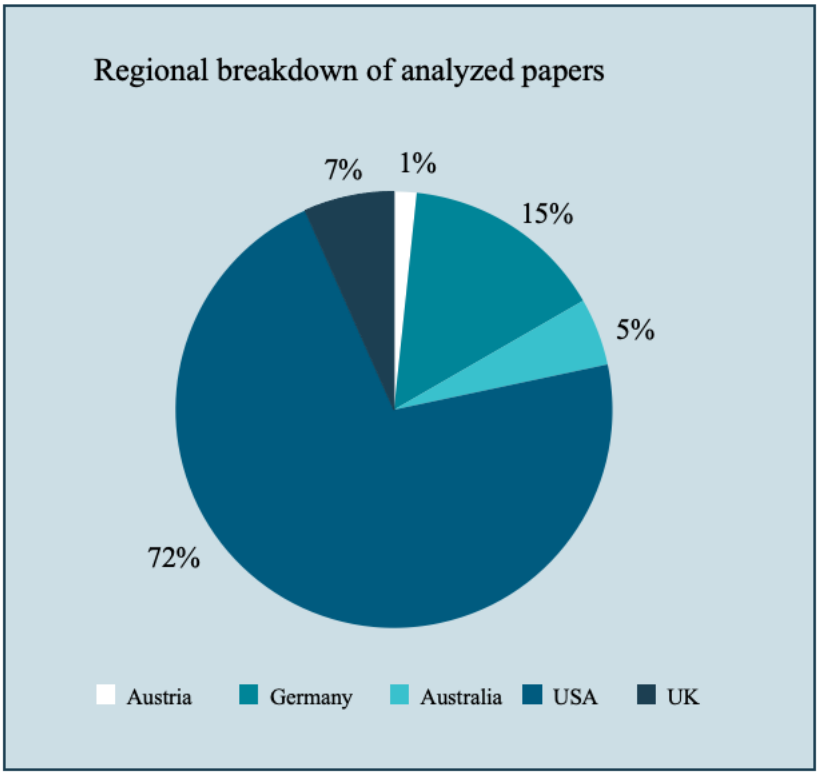


Figure 3: Results of regional breakdown of the analyzed papers

[8] published their research in the USA which created an awareness for the importance of the human behaviour and motivated further researchers in the english-speaking region for further research in this topic. This is also confirmed by the high publication rates in these countries. As Germany with its german-speaking surrounding neighbour countries have a traditional strong production-intensive economy also research in this area has a major focus.

We synthesized the results of our literature review in a theoretical model intended to guide our further research, see Figure 4.

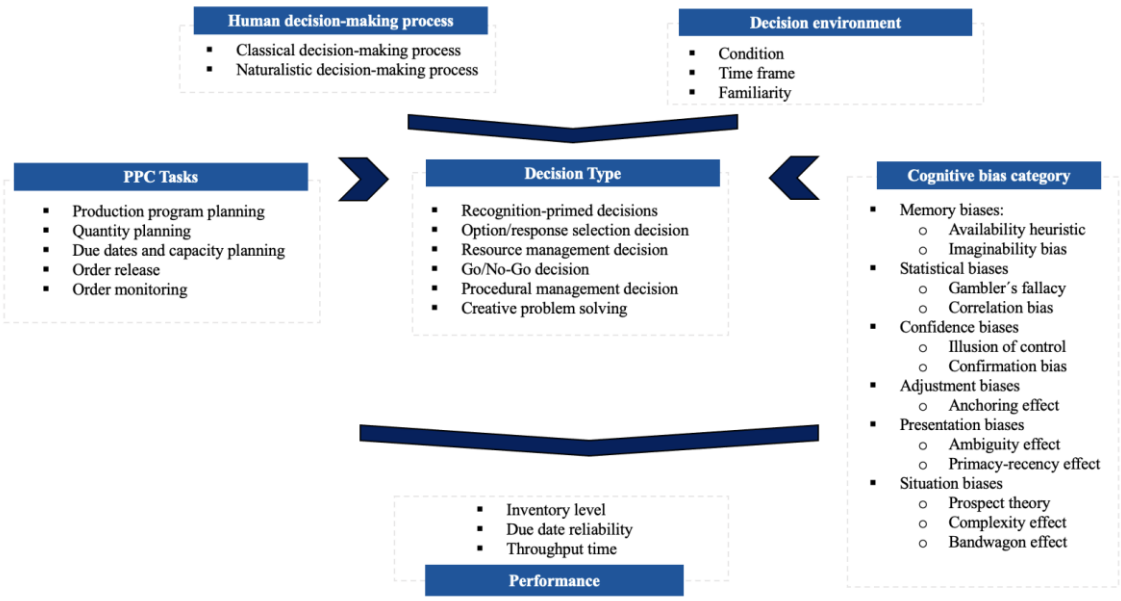


Figure 4: Theoretical model guiding further research

2.2 Case Study Design

Case studies are employed to formulate recommendations for real management situations and to develop testable hypotheses [9]. [10] argues that a typical or representative single case study can by sufficiently representative of a wider group. The following Figure 5 shows the applied research design for the case study approach by [11] and [10].

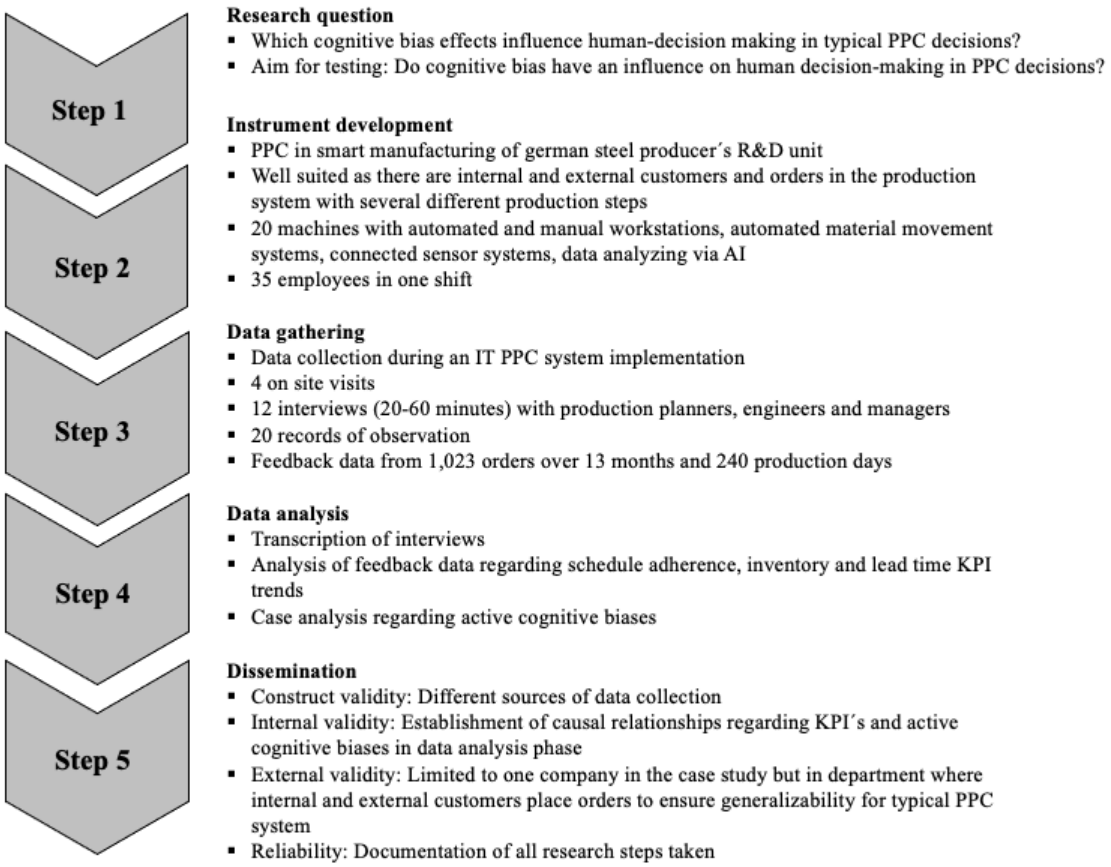


Figure 5: Applied research design for case study approach

We selected PPC in the smart manufacturing environment of a German steel producer's R&D unit as our unit of analysis in our case study. The R&D unit deals with of new alloy samples from the product development unit, quality control samples from current production and product quality complaints from customers (e.g. carmakers). Samples must run through several preparation, manufacturing, testing and quality control processes before a report on their material properties can be issued. We collected data during the design and implementation of a new PPC system to facilitate forward and backward planning based on average lead times and customer due dates. As is typical in a smart manufacturing system, numerous interconnected parameters have to be factored in to achieve high schedule adherence. Moreover, the production lot size is very small and customized. Orders are either released following a backward planning approach based on due dates set by customers or the system sets the due dates for orders based on the lead time information in the master data.

The production system with twenty machines and workstations includes several automated and connected workstations, automated material movement systems and connected sensor systems that collect data. Data from the wide array of sensors at the different test stations are analyzed

using data and AI analytics to facilitate new material and product development, provide feedback for production processes and to develop advanced testing procedures. Thirty-five employees work in one shift. Four on-site visits, twelve twenty- to sixty-minute interviews with production planners, engineers and managers and over 20 records of observations served as the basis of our case study. Feedback data from 1,023 orders over thirteen months and 240 days of production were analyzed to evaluate schedule adherence, inventory and lead time KPI trends [12].

The case selected covers three of the five activities of smart manufacturing planning and control.

2.3. Hypotheses development

The results of the two research streams of the literature review as well as the in-depth case study were combined for a structured hypotheses development. The following Figure 6 shows the detailed research steps and the conducted research work.

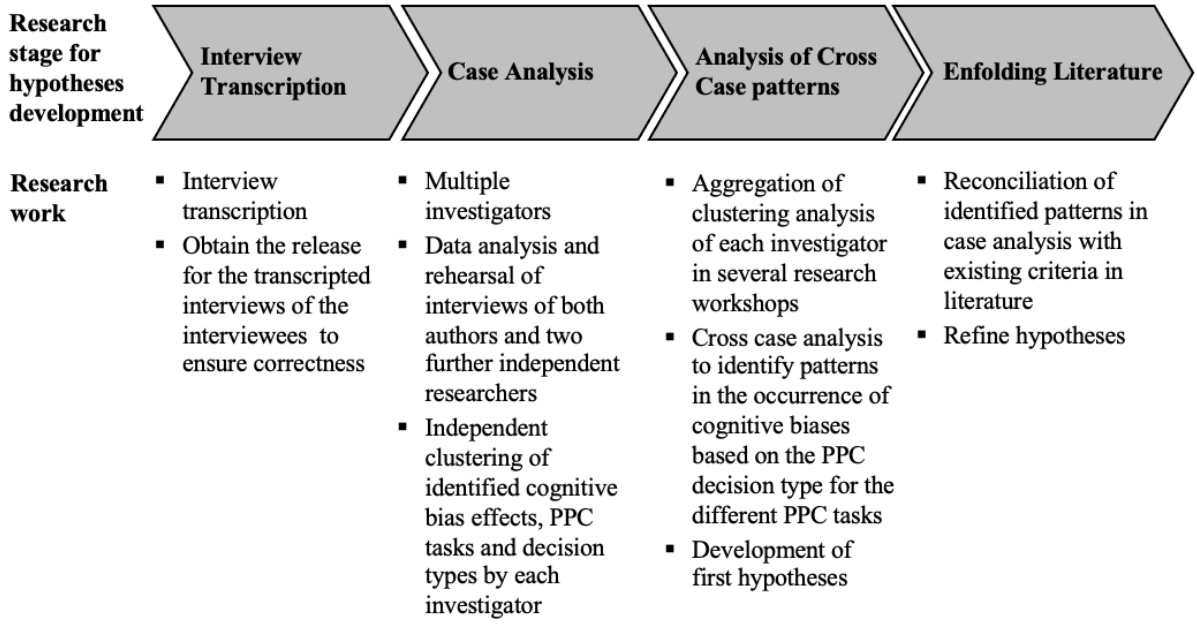


Figure 6: Conducted research steps for structured hypotheses development

Thereby, the criteria to ensure rigor in the hypotheses development of [13] were the basis of our research work. First, all conducted interviews were transcripted and the approval of the interview partners was obtained to ensure the correctness of the data. [14] and [15] described this as the "heart of the research" and the most important step for further analysis. To ensure data triangulation as proposed by [10] several research methods such as the interviews

transcriptions, the data analysis of the PPC feedback data, observation records as well as the data from the sensors were analyzed in detail. Following the suggestion of [13] multiple investigators were involved to ensure the exploitation of the richness of the data by different perspectives and opinions as well as to ensure the confidence in the data. Thereby the two authors as well as two further independent researchers reheard all the interviews and analyzed the data to develop an independent cluster of the active cognitive biases, the corresponding PPC tasks and the decision type. To further analyze cross case patterns several research workshops were conducted to discuss the findings of each investigator and to develop first initial hypotheses. Thereby, the PPC tasks based on the identified models in literature, the classification of cognitive biases as well as the decision types described which were also the result of the conducted structured literature were the basis for the dimensions and the group building. Each investigator presented the identified findings and the other participants discussed the results. Based on the different data sources the results were analyzed. If one data source corroborated the results of another data source the findings are according [13] even stronger. Following this approach, we combined the different data sources of the literature review as well as on the interview data of the in-depth case study of the steel case manufacturer and derived the initial hypotheses. Based on a further detail analysis as well as the reconciliation with the existing criteria in literature the hypotheses constructs were refined. There was a constant iterative cycle between the data found in the case and the literature review results.

3. State of the Art

Figure 4 constitutes the theoretical foundation of our further research in which we combine the literature streams of psychology and PPC.

3.1 Digitalisation and the role of decision support systems within PPC in smart manufacturing

Novel technologies such as mobile applications, the Internet-of-Things (IoT), cloud services and artificial intelligence, are increasingly being adopted in industrial practice to facilitate production processes in so-called smart manufacturing systems.

Current developments in AI and machine learning are focused on algorithms that copy complex human decision-making techniques [16]. PPC systems already assign orders to machines and approve material movement and inventory levels according to predefined performance

indicators and customer due dates. PPC systems can recalculate a production order in the event of resource loss, e.g., a material flow interruption, an extraordinary rush order, a machine breakdown or an unforeseen employee absence, but additional adjustments still require human action. Employees can contribute additional and strategic information, e.g., a customer's importance, a material shortage's severity, alternative production resources, etc. The importance of collaboration between IT systems or machines and the human workforce is growing as digitalization spreads.

Especially, AI based decision support systems are introduced to support human in their decision-making and to relieve the worker from repetitive tasks [17].

Even the traditional decision support systems were constantly evolving and with the enhancing integration of AI algorithms turning more and more into intelligent decision support systems still human decisions are required in the evaluation and final action decision of the proposed options from the decision support system [18]. In this context a socio-cyber-physical systems perspective gains increasing interest in current research. Hereby, the cyber physical system research and human behavioral aspects are combined with the potential to transform current production and logistic networks. [19] investigate that the human- machine interaction in cyber physical systems constantly increases. Unless the human as a decision-maker remains important supporting activities through decision support systems are evolving. As the human behavior and decision-making plays a crucial role for the effectiveness and the outcome of the implementation of cyber physical systems and the corresponding technologies it is important to understand the human decision-making process [20]. Further, especially to for the design of these decision support systems a detailed understanding of the influencing effects of cognitive biases is necessary.

Various decisions about due dates, capacities, production sequences, etc. have to be made in PPC. The diverse dependences, complex causal-relationships and abundant variables in PPC operations not only make optimization problems challenging but also require rapid responsiveness and updates since unplanned events, such as machine breakdowns or material delays, are frequent occurrences. Heuristics, optimization models, simulation technics and AI approaches are increasingly being applied to improve the performance of PPC systems [21]. Whereas these analytical approaches are based on processing vast quantities of data, human planners take more intuitive approaches to PPC decision-making [22]. Human-decision making based on complex data and done under time pressure has been shown to be inconsistent and suboptimal, causing manufacturing performance to diminish [5]. A study by [23] confirms the need for a more human-centered PPC system. More than 70% of production planners saw room

for improvement in their current PPC system to incorporate human needs. They were dissatisfied with the information provided, the presentation of the data and the user friendliness and designated this a major risk for misinterpreting information. Also, in the field of decision support systems, research criticizes the focus on technical and computational issues and the overlooked human behavioral issues [18]. [24] claimed the lacking knowledge and design guidelines for decision support systems considering the human behavioral aspect of decision-making which confirms the need for a design framework for these systems.
This shows how important it is to understand the human decision-making process in PPC activities and how more human-centered factors can be integrated in future PPC and decision support systems.

3.2 Decision-Making in Operations Management

Decision-making has been a primary field of research interest in operations management since the 1980s [25]. The process of decision-making has been studied in several research areas, such as psychology and strategic and organizational management. Several models have been proposed, which are largely based on the work of [25]. Decision-making has been defined as "[…] the process of selecting the course of action that best meets the decision criteria, subject to the constraints inherent in the decision-making situation." [26].
[25] identified three phases of decision-making. These apply to PPC too. In the first phase, *intelligence*, the problem requiring a solution from the decision maker is identified and prioritized. Moreover, initial success rates are defined and corresponding data collection is initiated. In the second phase, *design*, a general action plan, which include action alternatives, expected outcomes and initial evaluation criteria, is formulated. In the third phase, *choice*, the decision-maker selects the best action from all the alternatives evaluated. Several models based on the early work of [25] have been developed to explain the decision-making process. Several authors [26], [27] suggest extending the framework of [25]. They propose a fourth phase, *implementation*, in which the decision outcome is implemented. In a fifth phase, *learning*, lessons learned are compiled and shared in the organization to improve future decision-making and decision outcomes [28].
Psychology distinguishes between standard and naturalistic decision-making. This distinction can be applied to decisions in PPC. Since most PPC models assume that human behavior is rational, they neglect natural human behavior dictated by bounded rationality. The standard decision-making models assumes that the decision-maker's behavior is fully rational [29]. It

additionally assumes that the decision-maker is aware of all possible solutions to and all consequences of the decision to be made. Standard decision-making ignores time constraints and psychological stress, although research has shown that these two important factors have a huge impact on the decision outcome. [30] observed that decision-makers consider far fewer possible alternatives and dimensions when they are under psychological stress than when they are not. [31],[32] ascertained that decision-makers under time pressure and stress deviated from the standard decision-making approach even if they were trained in the method of standard decision-making to adhere to rational judgment.

Since human decisions are often biased by perceptions of and experiences with environments as well as personal experiences and attitudes rather than being fully rational [32], the naturalistic decision-making paradigm (NDM) was developed. Dynamic and constantly changing conditions, rapid responsiveness to changes, time pressure and dependent parameters, which have immediate consequences when mistakes are made, are all typical features of the NDM environment [33] and the production planners' decision environment.

Studies of NDM [34] break the decision-making process down into the following steps:

(1) Problem detection: identifying an incident that requires an action
(2) Interpretation of information: gathering data about the situation and evaluating contextual information
(3) Sensemaking: merging the available data to diagnose the current situation and possible future system state
(4) Identification of options: considering possible alternatives
(5) Evaluation of competing goals: considering and prioritizing potentially competing goals
(6) Selection of appropriate action: defining the action to achieve the goal
(7) Development of a procedure: defining the actions and the sequence in which they should be completed

The sequence of decision-making steps is the same in PPC, as the following example of a machine breakdown in production demonstrates.

First, the production planner detects the disruption in production. This identification can also be supported by the use of a decision support system such as the occurrence of some warning alerts in the IT systems for the production planner. Then, the requisite situation data, e.g., the malfunctioning part, details of the malfunction, duration of repair, etc., have to be collected and evaluated. A decision support system can facilitate the evaluation by providing the data needed and specifying the most suitable solutions in order of preference. The production planner uses the data to assess responses to the situation and options for resolving it, e.g., having production

wait until the machine has been repaired or switching current production orders to another machine. The production planner also considers potentially competing goals during the evaluation Switching machines would mean postponing other orders. A decision support system could provide scenarios of the different options and potential consequences. The production planner selects the best option based on the information and defines immediate actions. The rationality of human behavior is bounded in every step of the decision-making process and influences the decision outcome. This decision-making process and its steps are applied to various types of decisions, presented below.

3.3 Types of decisions in operations management

Various models from different fields of psychology exist to classify decision types based on the decision environment, the parties involved and the decisions-maker's skills.

In conjunction with their research on the effects of cognitive biases, [35] also studied decision situations and external circumstances in the decision-making process. They established that people tend to make wrong decisions systematically, especially in uncertain and complex situations. They classified decisions in three categories *(1) decision under uncertainty (2) decision under risk* and *(3) decision under certainty*. " [36] proposed a similar classification of *(1) uncertainty (2) time pressure* and *(3) familiarity and expertise.* Focusing on the parties involved and the environment, [37] proposed four categories: *(1) Group decision-making:* Multiple decision-makers are involved in the decision-making process, e.g., several production planners make decisions about the production program. *(2) Dynamic decision-making*: The results of current decisions affect future decisions, something often found in quickly changing environments, e.g., decisions about the production sequences in PPC. *(3) Routine decision-making*: The decision-maker is familiar with the decision environment and can apply knowledge and experience from past decisions, thus expediting decisions, e.g., on due date scheduling in the PPC environment. *(4) Conflict driven decision-making:* The decision-maker must resolve various conflicts before making a decision, weighing the situation assessment against actions, e.g., a machine breakdown forces the production planner to reevaluate the priority of production orders and reschedule machines.

Since aircraft pilots have to make numerous decisions quickly, flexibly and based on interdependent parameters, which have a huge impact on many people, human behavior research has attracted interest in aviation literature, spawning numerous models for classifying decision types. Decisions in PPC have similarities with decisions in aviation. Time pressure,

changing environmental conditions and several interdependent parameters are typically features of the decisions made by production planners in PPC in smart manufacturing systems too. We therefore adopt and apply models from aviation literature to decision situations in PPC. [34] proposed a classification with six categories of decision types: *(1) Go/no go decisions:* This decision type has only two options, continuation or termination of an action. Order release constitutes such a decision in PPC. *(2) Recognition-primed decision*s: The decision-maker recognizes a cue pattern and can match it to a familiar decision type to employ standard decision-making procedures, e.g., a capacity planning decision always follows the same sequence of steps, such as checking available resources and matching them with the planned production input factors. *(3) Option/response selection decisions:* The decision-maker has to choose between various legitimate options and therefore has to evaluate the options in terms of the expected requirements first. Quantity planning is such a decision type in PPC. The production planner has to evaluate which of several options, such as focusing on a smaller quantity to produce only the quantity needed or on a larger quantity to fill inventory, fits the requirements best. *(4) Resource management decisions:* The decision-maker has to coordinate various actions required to meet an expected due date. This is a typical resource planning decision based on the expected customer delivery date in PPC. *(5) Procedural management decisions:* These are typically made in risky situations that require rapid problem diagnosis and a quick decision. The decision-maker can follow standard procedures in the ensuing decision-making process. Several decisions have to be made in PPC when a machine breakdown occurs. Since breakdowns occur frequently in production, standard responses and steps can be followed to restart production. *(6) Creative problem-solving:* Since there are no guidelines, the decision-maker first has to define the decision problem and possible ways to arrive at a decision. New situations in which the production planner cannot follow standard procedures often arise in the order monitoring phase of PPC, e.g., a specific material has an unidentified defect that causes machine breakdowns.

We combined the various models of decision types in the holistic framework presented in Figure 7.

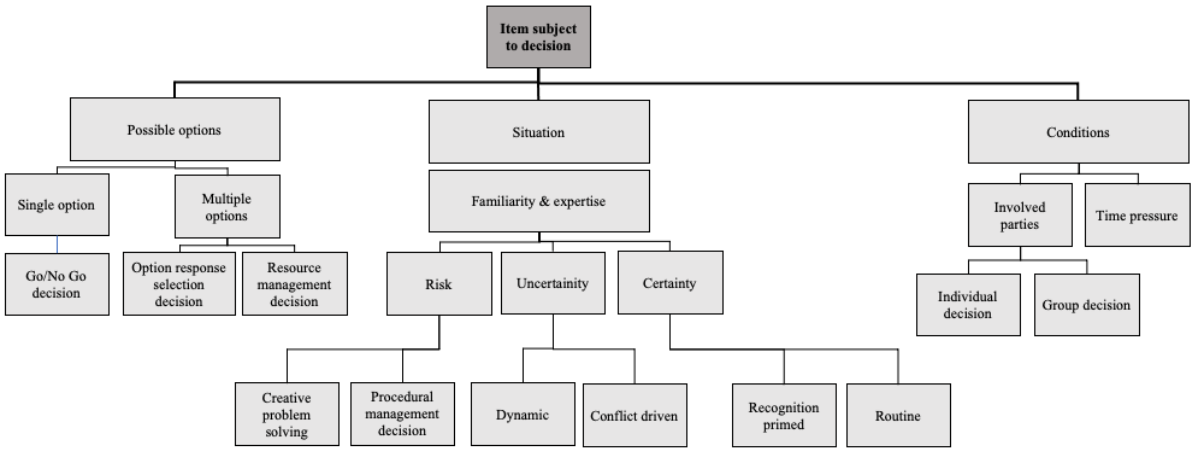


Figure 7: Decision type framework

We identified the three main features of *(1) options (2) situation* and *(3) conditions* as the basis for classifying decision types. In a second step, we classified each decision type in one of these categories. We correlate these decision types with the phases of PPC in section three.

3.4 Decision-making in PPC

Human decisions are required in several phases of PPC. The relevant processes and steps are presented in the PPC model in Figure 8, which is based on [38] model. Since this model includes every single relevant PPC activity in a logical production process sequence, we used it as the basis for refining other PPC models, such as the established Aachen PPC model. Only [38] original model truly examines every single relevant activity in PPC in detail.

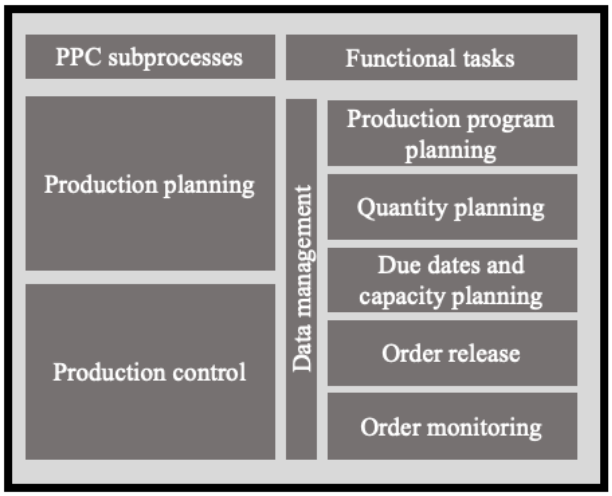


Figure 8: PPC model based on [38]

PPC encompasses two subprocesses: production planning and production control. Each of them contains several activities that require several decisions. Whereas production planning focuses on developing the basic plan for establishing the product, the production sequence and the due date and the quality, production control plays a general monitoring role to meet production targets by using different control methods.

Production program planning involves several decisions about production sequence and requisite materials, thus establishing the basis for *quantity planning,* which defines production quantities and lot sizes. *Due date scheduling and capacity planning* focus on decisions about capacity plans and due dates for specific production steps. *Order release* marks the starting point of production. Since unplanned disruptions, such as machine breakdowns, delays in material supply or quality problems, can occur during production, continuous *order monitoring* is necessary. Data validity is essential to all process steps. Continuous *data management* ensures the validity of master data, e.g. due dates, production lots, material properties, etc.

3.5 Cognitive biases

Human decisions are far from rational, as the naturalistic decision-making model shows. [8] demonstrated that the rationality of human decision-making is bounded and introduced the term cognitive bias. They observed that humans making decisions systematically make errors, especially in complex and uncertain environments. [39] deepened their research of the underlying factors in further experiments and described the cognitive processes of intuition and reasoning. Their seminal study formed the basis for further research in this field. Several authors [40], [41], [42] subsequently investigated the interplay between these two processes further, developing the dual-process or dual-system theory. [43] described this duality succinctly as *"*two minds in one brain*"*. These minds evolved at different stages in human evolution. While the "old" mind (intuition or System I) unconsciously processes information automatically and acts automatically, fast, emotively and effortlessly, the conscious, controlled "young" mind (reasoning or System II) acts relatively slowly, reflectively and assiduously [40], [43]. System I generates spontaneous impressions and beliefs, which form the basis for further decisions and actions in System II. This dual-system view is the basis for [44] assumption that impressions are generated in System I and judgments are reached in System II. These two systems coexist. The decision environment influences which of the two systems predominates, e.g., system I plays a greater role in decisions under time pressure, system II a greater role in decisions that require an evaluation of multiple options.

[8] early research spawned numerous studies of the impact of cognitive biases. [45] classified biases in six categories:

(1) *Memory biases:* biases that influence individuals' retention and recall of information
(2) *Statistical biases:* individuals' tendency to over- or underestimate certain statistical parameters
(3) *Confidence biases:* individuals' confidence in their own decision-making skills
(4) *Adjustment biases:* individuals' tendency to adhere to the first available information or to a reference point when making decisions
(5) *Presentation biases:* the influence of the presentation of information on individuals' decision-making
(6) *Situational biases:* individuals' responses to a general decision situation.

We discuss the impacts of these six categories of cognitive biases and correlate them to specific decision types in the following section.

Memory biases: The *availability heuristic* and *imaginability bias* are two memory biases. The availability heuristic describes individuals' tendency to overestimate the likelihood of the occurrence of events about which they can readily recall information [41]. They consequently tend to give undue weight to the outcome of their last decision as a basis for their decision-making in a current situation. The imaginability bias describes individuals' tendency to assume that an event is more probable if they can readily imagine it [46]. These memory biases mainly appear in recognition-primed decisions. Different parameters have to be considered to recognize cue patterns and select the correct standard procedures.

Statistical biases: The *gambler's fallacy* and the *correlation bias* are two statistical biases. The gambler's fallacy describes individuals' tendency to assume that future events are determined by past events [47]. Correlation bias describes individuals' tendency to overestimate the probability of two events occurring together if this has happened in the past [41]. Statistical biases are mainly found in option/response-selection decisions or go/no go decisions in which the decision-maker must evaluate several options.

Presentation biases: The *ambiguity effect* and the *primacy/recency effect* are two presentation biases. The ambiguity effect describes individuals' tendency to prefer options that appear simple and to avoid options that appear complicated [48]. The primacy/recency effect, the human tendency to recall the first and last items in a series best and items in the middle worst

[49]. These biases have a strong impact on resource management decisions in which several activities have to be coordinated to meet a due date and the presentation of information influences decision-making.

Adjustment biases: The *anchoring effect* is one adjustment bias. It is the tendency to rely too heavily on initial information [8]. [50] demonstrated that anchoring can cause systematic errors in decision-making situations. Adjustment biases have an impact on recognition-primed decisions. Several parameters must be considered during decision-making to recognize a cue pattern but individuals tend to adhere to the first information available.

Confidence biases: The *illusion of control* is a confidence bias. It describes individuals' tendency to overestimate their ability to solve difficult [51]. The *confirmation bias* describes individuals' tendency to seek information that confirms their own opinions and to ignore information that contradicts their own beliefs [52]. These biases are mainly found in conflict-driven and dynamic decisions with rapidly changing decision environments in which decision-makers must resolve some conflicts before making a decision. Humans overestimate their own decision-making skills in such situations.

Situational biases: *Prospect theory* holds that people tend to prefer a certain but smaller benefit when events are positive but a greater uncertain loss over a smaller certain loss when events are negative [8]. The *complexity effect* describes how individuals are particularly biased in their decision-making when they are under time pressure or overloaded with information [53]. The *bandwagon effect* describes individuals' tendency to do things because many other people are doing the same [54]. These biases influence procedural management decisions and creative problem-solving. Such decisions are made under conditions of risk and high time pressure.
Moreover, these decisions are often quite complex since several parameters and their potential impacts have to be considered. Research has revealed that the decisions made under these general conditions are influenced by situational biases [35].

3.6 Research gap

Current literature on smart manufacturing planning and control neglects human decision-making [55]. To our knowledge, our study is one of the first to combines the hitherto isolated research areas of decision-making psychology, decision types and PPC activities to demonstrate

the impact of cognitive biases in smart manufacturing based on the decision situation. Our findings, which guided our empirical study, are synthesized in Figure 4. Current literature merely describes the influence of cognitive biases in specific decision environments of production planning and control activities without any explanatory analysis [56]. [57] additionally criticize the current literature's tendency to focus on single biases in instead of analyzing a variety of biases, thus ignoring the biases' interaction and overlap.
This study addresses this research gap by combining different research streams and analyzing a variety of cognitive biases in a case study of a smart manufacturing system.

4. Decisions and human decision-making in smart manufacturing planning and control

Although various technologies support decision-making in smart manufacturing, human decision-making remains crucial to planning and control activities. We present our findings in two sections. Thereby, we applied an iterative process between theory and data. First, we correlate the typical PPC activities defined by [38] model with the various decision types described in psychology literature by [34], [36]. We enriched our findings from theory based on the data of our in-depth case study with a special focus on smart manufacturing. Then, we formulate our hypotheses on the impact of cognitive biases on human decision-making in smart manufacturing based on the specific decision situations.

4.1 Types of Decisions in PPC

In this section, we correlate decision types with the PPC activities in the case study of the German steel producer, which require decisions, and present our findings in Table 3.

PPC activities	Decision type	Smart manufacturing decision situation at the case company
Production program planning	▪ Recognition-primed decisions ▪ Option/response selection decision	▪ Determining the right mix of customer orders and new R&D orders
Quantity planning	▪ Resource management decision	▪ Sizing production lots for customer orders and R&D orders

Due date scheduling and capacity planning	▪ Resource management decision	▪ Scheduling production due dates to meet customer and internal demand and designating which of the 20 machines to use.
Order release	▪ Go-/no go decision	▪ Prioritizing order release to production based on backward planning
Order monitoring	▪ Procedural management decision ▪ Creative problem-solving	▪ Continuously monitoring customer and R&D production orders

Table 3: Correlation of decision types with PPC activities

Production program planning: Planning the production sequence, products and corresponding options produced often requires a number of human decisions, e.g., about the specific order quantity of production material and the exact production sequence [58]. The production planners at the case company have to decide on the optimal mix of customer orders and internal orders from the R&D unit. The different decision parameters, such as requested delivery date and throughput time, and options have to be evaluated to select the best option. Since these are recurring decisions, production planners are familiar with the decision situation and apply standard procedures. Decisions in production program planning are therefore often recognition-primed decisions. Decisions in production program planning are option/response selection decisions since they always involve the evaluation of several options.

Quantity planning, due date scheduling and capacity planning: Production lot sizing, due date scheduling and capacity planning are typically resource management decisions. Several activities have to be coordinated to meet scheduled customer delivery dates [59]. The production planners at the case company calculate backward based on expected customer or R&D delivery dates and decide when to start production on which machine with which employees.

Order release: Decisions on order release are go/no go decisions since there are only two options. The production planners at the case company only decide whether to release production orders to the production unit or to postpone them. They have to ascertain the availability of the type of steel needed and machine capacity to before making this decision.

Order monitoring: Order monitoring involves procedural management decisions or creative problem-solving. Machine breakdowns, delays in material deliveries and production or quality

issues are common disruptions in production, which require a response from the planner [60]. Such decisions typically have to be made under time pressure. They constitute procedural management decisions when planners can make decisions based on standard procedures because the disruption is common. When the delivery of material is delayed, for instance, the production planner has to decide whether waiting for the material or retooling the machines to complete a different order would be more efficient. Since such events occur frequently in production, standard aids, such as checklists, frequently exist, which help production planners focus on the correct parameters when making decisions. Uncommon disruptions might require creative problem-solving since the decision-maker cannot draw on prior experiences and solutions. A material quality problem, for instance, requires the production planner to decide whether to proceed with current production orders or to postpone upcoming orders.

These decisions may be made by a single individual or a group, depending on the company's organizational structure [47] and each is dynamic, routine or conflict-driven, depending on the conditions under which it is made [46]. Production planners who have to resolve conflicts, such as available capacity versus expected customer delivery date, are making a conflict-driven decision. Production planners who can draw on their experiences with prior decisions or follow a standard procedure to arrive to a decision are making a routine decision [46]. Since PPC decisions in smart manufacturing systems are contingent on numerous interdependences, e.g., decisions about lot sizes affect capacity planning and inventory level, current decisions always influence future decisions and are part of a multistage decision process [68]. Initially estimated parameters can change very quickly, e.g., the originally production sequence planned must be adjusted because of a machine breakdown. Smart manufacturing systems require fast response and throughput times [61]. This confronts production planners with changing environments and the decision-making process is dynamic.

5. Framework and Hypotheses Development: Toward a Human-Centered Design of Smart Manufacturing

In the following section, we combine the derived mapping of the PPC tasks resulting from our literature study with the decision types with practical insights from the case study of the German steel case company and derive first hypotheses for the influence of cognitive biases on different decision-making situations in PPC and on operational performance. Thereby the hypotheses development followed a structured approach suggested by [13] which is described in detail in section 2.3.

Recognition-primed decisions: Recognition-primed decisions are often made during production program planning. Production planners have to make a number of decisions about the production sequence based on available capacity, due date and product options [3]. Especially in smart manufacturing systems typified by high demand uncertainty, planners have to consider several different parameters and a variety of information during the decision-making process. They often have to extract relevant information from a plethora of other less relevant information and data [5]. [8] described how the information overload in combination with time pressure leads to the occurrence of memory and adjustment biases. We observed that the *availability heuristic* and *imaginability bias* exerted a strong influence and also detected the *anchoring effect* at work. Schedule adherence was the important key performance indicator for the production planner at the case company. It acts as an anchor independent of other relevant variables and the production planners tend to do everything possible to obtain the desired value. They responded to decreasing schedule adherence by updating planned lead times based on their intuition and adjusted the production sequence based on their "gut feeling". They considered external effects, e.g., production disruptions, the cause of deteriorating schedule adherence and started updating the planned lead times again. The same happened in production program planning. The production planner has to decide on the production sequence based on available capacity and the expected customer delivery date. The most efficient production sequence in terms of throughput time and inventory level would be A;D;E;C;B (each letter representing one product type). Since a machine had broken down the last two times, the production planner decided to change the production sequence to D;C;E;A;B based on the assumption that the past event would recur, even though this meant a poorer throughput time and a higher inventory level.

We therefore hypothesize that

H1: The higher the uncertainty and the information overload for production planners in recognition-primed decisions the more planners are distorted by adjustment and memory biases in their decision-making the more thy stick to initially given information or information which they can easily remember by themselves.

Responding to and putting this influence in a more human-centered perspective would entail presenting data to the production planner in a structured form. Moreover, concentrating on a few relevant key performance indicators facilitate categorizing the plethora of available information as relevant or irrelevant.

Procedural management decisions and creative problem-solving: Production planners often have to make procedural management decisions during order monitoring and are sometimes required to solve problems creatively too. Since disruptions in the production process generally occur unexpectedly, production planners have to analyze the situation and come up with a decision very quickly [6]. Smart manufacturing systems' highly connected parameters and vulnerability to disruptions because of individual lot sizes with low inventory levels make rapid decisions essential. Such decisions are made under conditions of risk and high time pressure. Moreover, they are often quite complex since several parameters and their potential impacts have to be considered. Research has shown that prospect theory describes the decision-making process under these general conditions [35]. It holds that past experience with gain or loss influences individuals' decision-making, regardless of the actual situation. We observed this behavior during the management of disruptions to production. Since humans prefer a greater but uncertain loss over a smaller but more likely loss in negative situations, the production planners assumed that a more severe but uncertain disruption to production is more likely and consequently failed to take sufficient precautions, resulting in a decrease in schedule adherence.

We therefore hypothesize that

H2: The more parameters production planners have to consider in procedural management decisions and creative problem solving decisions, the more the planners decide venturesome in case of negative expectations and risk-avers for positive expectations.

Contributing to this issue and taking it as a point of departure for more human-centered design of smart manufacturing PPC systems would necessitate making the correlation between these parameters transparent to the production planners. Linking this information with the potential consequences based on different scenario simulations would help production planners when making decisions and when evaluating different ideas, especially in situations that require creative problem-solving. Smart forecasting and data analytics would be helpful here [62].

Conflict-driven and dynamic decision-making: Since PPC decisions are either conflict-driven or dynamic depending on the situation, we did not correlate their decision conditions to specific phases of PPC. In dynamic decision-making, the outcomes of earlier decisions influence future decisions according to [34]. In conflict-driven decision-making, the decision-maker has to resolve various conflicts before making a decision. Literature about cognitive biases confirms the occurrence of confidence biases and situational biases in this decisional environment [45].

We assert that *confidence biases* and the *complexity effect* and *bandwagon effect* influence decisions made under these conditions. We observed that production planners remain convinced of their decision-making skills even in conflict situations. The situation is complex since planners have to consider various parameters and key performance indicators in their decision-making. Lead time syndrome describes the phenomenon of planners' behavior as schedule adherence diminishes [5]. When the production planners in our study were confronted with decreasing schedule adherence, they started to update the planned lead times by releasing waiting orders earlier and by adding additional safety lead times whenever the original lead time was too short to meet the scheduled due date. This increased the level of work-in-progress (WIP) in production, resulting in even lower schedule adherence than before the lead times had been updated. The planners were under pressure to improve the current situation. This reinforced the cycle of lead time updating, thus further exacerbating the due date situation. The planners' confidence bias led them to assume that their own actions were more appropriate than the standard planning procedures. They consequently tended to rely on information that validated their own view and ignored information that did not. Moreover, they acted as if the stable forecast of future incoming orders from customers and the R&D unit was predetermined rather than just a forecast. They used the planned lead times to raise the level of WIP to keep the production system running empty since this affects inventory levels. We additionally determined that PPC decisions were often made under time pressure. These decisions are frequently interdependent, the outcome of one decision directly affecting another. A decision about production lot size, for instance, directly influences decisions about inventory level. This example also illustrates the frequently conflicting objectives of such decisions. An increase in production lot size not only decreases fixed costs as the resource utilization rate rises but also increases the inventory level. The sheer number of interdependences overloaded the production planners in our study case with information when they were analyzing options. The bandwagon effect became came into play as one production planner started updating planned lead times and his colleagues followed suit since they considered this the simplest option.

We therefore hypothesise that

H3: The smarter in terms of implemented digital production technologies a manufacturing system is, the more production planners have to take conflict-driven and dynamic decisions and the more production planners have to consider the interrelationships between their taken decisions and therefore tend to ignore standard planning procedures and either stick to their own identified procedures or adopt them from their colleagues.

The relevant parameters' interdependences have to be presented clearly here too. Identifying whether individual parameters have conflicting goals or are mutually supportive would also be helpful.

Resource management decisions: The production planners have to make several resource management decisions during quantity planning, due date scheduling and capacity planning in PPC. They have to coordinate different information and parameters to make decisions. The expected customer delivery date, which might conflict with the target of a low inventory because of available capacity, limited resources or cost-efficient production lots, might diverge from the feasible delivery date [6]. Parameters often conflict with each other, as these examples demonstrate. Factoring in all the individual parameters' interdependences is virtually impossible. We observed that the presentation of information influences the production planners' decision-making, a phenomenon known as presentation bias. This effect is described well in literature about cognitive biases and human decision-making and occurs frequently when several information is presented and the decision-maker has to detect the relevant ones [44]. We detected two presentation biases, the *ambiguity effect* and the *primacy/recency effect*. Sequence, font size and the presentation of parameters' dependences in production planning systems can influence planners' decisions.
Retaining all relevant information is quite a challenge to production planners since they have to consider a number of variably interdependent parameters. The presentation of supporting information supplied by advanced.

We therefore hypothesise that
H4: The more smart technologies are implemented in manufacturing systems, the more various dashboards and information displayed must be considered by production planners in their resource management decision-making and the more production planners are influenced by presentation bias leading to distorted decision-making depending on how the information is presented.

Developing a more human-centered PPC system would consequently require paying close attention to the way relevant information is presented to production planners. The amount of information ought to be reduced to a minimum and only information relevant to the most important key performance indicators ought to be displayed. Moreover, font size and colors ought to be used wisely because a bigger font size might be understood as indicative of more

important information or the color red has might be understood to imply something that elicits an action.

Option/response selection decisions and go/no-go decisions: Option/response selection decisions are mainly made during production program planning, whereas go/no go decisions are made during order monitoring. The production planners have different options for developing the production program, such as using different sequences, production lots or product options [56]. These options have to be evaluated to select the best program. The *gambler's fallacy* and *correlation bias* are two *statistical biases* come into play here since several parameters have to be evaluated based on their probability. Especially, in decision where estimations and probabilities have to be evaluated statistical biases tend to occur [47]. We observed active statistical biases during the adjustment of lead times. Although, the production planners knew that it would take four weeks before the impact of adjusted lead times materialized in improved schedule adherence, they assumed that the coincident adjustment of lead times and the improvement of schedule adherence were correlated [63]. We additionally observed that production planners tended to assume that coincident events were correlated, even when this was false. A delay in material delivery and a coincident machine breakdown induced the planners to increase the scrap rate in the system but they failed to verify the correlation of these two events. Since there was no actual correlation, the inventory level rose excessively since additionally ordered material accumulated.

We therefore hypothesise that

H5: The smarter a manufacturing system is in terms of the number of implemented digital technologies the more options the production planners have to consider in their decision leading to a strong influence of statistical biases.

Allowing for this effect in a human-centered PPC system would require not only presenting potential scenarios to production planners but also relevant statistical information, such as the probability of a specific event's occurrence or potential dependences between individual decision parameters.

DISCUSSION

Behavioral factors in operations management have been the subject of study for a number of years. Among other things, research in the field of production planning strongly focuses on behavioral estimations for the development of mathematical models that improve planning and performance [64],[65]. Behavioral factors and human decision-making in PPC have rarely been treated in the literature to date [5], [55]. We contribute to this research gap by combining PPC activities in smart manufacturing systems with typical decision types from psychology literature. [66] observe that the question of how common biases affect operating systems and processes still remains unanswered and suggest integrating behavioral factors in common operations models. This is particularly relevant for smart manufacturing systems that seek to divide labor between robots and humans is aimed. The impacts of cognitive biases, which can be reinforced by the decisions environment, must be factored into flexible and high-performance smart manufacturing systems that require rapid decisions from humans and confront production planners with a high level of complexity. This is why we formulated initial, testable hypotheses on the influence of cognitive biases on PPC decisions in smart manufacturing systems and their impact on performance, which can serve as the initial basis for integrating cognitive biases in common PPC models. Increasing digitalization accompanied by growing discussion of hybrid intelligence and the division of labor between humans and machines will make better understanding of the decision-making process and its influence on decision outcomes even more necessary in the future [67]. Intelligently connecting machines and humans is extremely important for smart manufacturing systems in particular. [68]. [69] emphasize the need to integrate human needs and human wellbeing in smart manufacturing to ensure high productivity. This necessitates understanding the different decision types and the influence of cognitive biases on human decision-making. Moreover, this would provide the basis for further research on human-centered design guidelines for decision support systems that facilitate better decision outcomes.

Contribution, Limitation and Outlook

The intention of this paper was to formulate initial hypotheses on the impact of cognitive biases on specific decision-making situations in PPC based on the observed behavior of production planners at a German case company. This is intended to provide the basis for further research on the design of decision support systems for smart manufacturing systems that factor in human needs. We therefore combined several models of different decision types from various research

fields of psychology in a new framework. We correlated these decision types with the different phases of PPC based on [38]. To our knowledge, this paper is the first to apply decision types from the field of psychology to the field of PPC. Research on cognitive biases concentrates heavily on high-risk and uncertain decision situations [8]. We have extended this research by examining different decision-making situations in PPC in smart manufacturing systems under a variety of environmental conditions. Based on this work, we formulated initial hypotheses on the impact of cognitive biases on various decision-making situations in different phases of PPC. Our hypotheses are, however, based solely on theoretical research and a single case study and have yet to be validated in wider practice. Moreover, biases cannot be classified in practice as in theory. Some cognitive biases overlap and often appear in several different situations. Further research could involve testing the hypotheses in behavioral experiments that apply the classification of different decision-making types.

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5. Paper 4: The Ignored Human Factor in Supply Chain Risk Management: Evidence for a Needed Transition from Industry 4.0 to 5.0

Authors: Melanie Kessler, Julia Arlinghaus

Status of Publication: Submitted for publication in International Journal of Productivity and Performance Management, currently under review

Contribution of Melanie Kessler to the work: Conducted the data analysis, wrote the paper, contributed to discussions on the findings.

Contribution of the co-authors: Julia Arlinghaus reviewed the paper, helped with structuring the paper and contributed to discussions on the findings.

Contribution of the paper to the PhD project: Based on Paper 1, it was found that the response of supply chain risk managers was often paradoxical regarding the identified risks and the definition of mitigation strategies. Therefore, a detailed analysis of the human behaviour and human decision-making within these digital implementation projects was conducted. Through the combination of literature streams from psychology and behavioural operations management, as well as the results from the qualitative data analysis, first testable hypotheses are derived.

Note: In the interest of uniformity, all articles have been reformatted according to the dissertation format.

The Ignored Human Factor in Supply Chain Risk Management: Evidence for a Needed Transition from Industry 4.0 to 5.0

Abstract

Purpose: The purpose of this paper is to answer the research question: "How does cognitive bias influence human decision-making in supply chain risk management (SCRM) in industry 4.0 projects?". To this end, initial hypotheses are derived.

Design/Methodology/Approach: The hypothesis development is based on a structured literature review and on 53 interviews with experts and managers from industrial companies. These interviews relate to specific Industry 4.0 use cases and research.

Findings: The analyzed use cases do show an influence of cognitive bias effects on human decision-making in supply chain risk management (SCRM) and confirm the importance of considering human needs, and therefore of a shift to a more human-centric industry 5.0.

Research limitations/implications: The derived hypotheses can be used for further practical validation and hypothesis testing.

Social implications: Our research contributes to creating an awareness of cognitive bias. The debiasing techniques proposed are initial recommendations for practitioners in order to mitigate the types of cognitive bias identified at the three stages of SCRM and to improve risk managers' overall decision-making.

Originality/value: This first attempt to combine the research streams of psychology, supply chain risk management and digitalization presents an advancement in behavioural operations management research.

Keywords: industry 5.0, human factor, supply chain risk management, human decision-making, cognitive bias, digitalization, debiasing

Paper type: Research paper

1. Introduction

Increasing digitalization and the concomitant implementation of digital technologies are transforming supply chains by making them more complex, more prevalent, and more vulnerable to disruptions (Xu *et al.*, 2018). This technological development entails several new challenges, such as technical, human and data security risks, which require appropriate risk management (Vilko *et al*., 2014). Human factors have been identified as a critical risk factor in the implementation and operation of digital applications (Kessler *et al.,* 2021). Adequate,

factoring in humans prevents system performance from diminishing (Neumann *et al.,* 2021). High-performance decision support systems (DSS) that assist human decision-making in manufacturing and logistics are essential to a new form of supply chain risk management (SCRM) that has been adapted to meet the new challenges (Holford, 2019). Contributing to human needs is thus unavoidable when considering the implementation of digital technologies and an adequate SCRM. To this end, the European Commission introduced its concept of *Industry 5.0* in early 2021 as a human-centered and resilient evolution of Industry 4.0 (European Commission, 2021). The European Commission identified human needs, behavior and decision-making as essential for maximizing the capabilities of Industry 4.0, which had been envisioned when that concept was introduced in 2011(Kagermann *et al.,* 2013). Neumann et al. (2021) defined a framework considering the human factor in the context of Industry 4.0 projects and also highlighting the still underrepresented research concerning human behavior in the context of Industry 4.0 projects.

In their seminal study, Tversky and Kahnemann (1979) demonstrated that the impact of cognitive bias on human decision-making affects corporate performance adversely. A cognitive bias effect is defined as a systematic error in individuals' thinking as they process and interpret information (Tversky, Kahneman, 1979). To our knowledge, no structured research studies on the potential impacts of biased decision-making in SCRM exist. Prospect theory, however, illustrates the negative impact of one type of cognitive bias on supply chain risk assessment.

Imagine a supply chain planner facing the following two scenarios with different probabilities of occurrence and different periods of disruption:

- *Option I:* There is a 50 % probability that the supply chain will be disrupted for 25 days.
- *Option II:* There is a 90 % probability that the supply chain will be disrupted for 10 days.

Since people are loss-averse, supply chain risk managers prefer Option I. In adverse situations, humans prefer a greater but uncertain loss to a more likely but smaller loss. They behave inconsistently when events are positive, as the following example demonstrates (Arlinghaus *et al.,* 2019):

- *Option A:* There is a 50 % probability that the risk mitigation action will reduce the disruption by 25 days.
- *Option B:* There is a 90 % probability that the risk mitigation action will reduce the disruption by 10 days.

Humans are risk-averse when events are positive. They are risk-seeking when events are negative. In other words, humans prefer lower but certain utility to higher but uncertain utility.

Supply chain risk managers therefore tend to choose Option B. These examples confirm the need for further research into the influence of these cognitive bias effects on human decision-making in SCRM.

SCRM has become an intensely researched field of supply chain management (SCM) in the past decade (Manju and Metzner, 2008). Various models for the implementation of efficient SCRM, incorporating all the relevant steps from risk identification to risk assessment and risk mitigation, have been proposed (see, for instance, Jüttner *et al*., 2005; Tummala *et al.,* 2011). However, these models neglect human factors, assuming instead that human behavior is wholly rational. As Tokar (2010) observed, this is typical of SCM models in general. The phenomenon of individuals' systematic deviation from logic in their decisions and judgments has been studied extensively in the field of psychology, though. Tversky and Kahneman (1974) were among the first to challenge the assumption of rational human behavior and dubbed systematic deviation from rationality 'cognitive bias'. Although human factors have subsequently been transferred to operations management and SCM, a specific focus on risk assessment and management is absent (see, for instance, Bendoly *et al*., 2006; Fahimnia *et al.*, 2019).

Bendul and Knollmann (2016) demonstrated that cognitive bias is the underlying cause of systematic failures to meet predefined key performance indicators in production planning and control (PPC). The authors establish that production planners tend to overreact and to deviate systematically from rationality in their decision-making whenever schedule adherence declines. In response, planners modify scheduled lead times too frequently, thus actually worsening schedule adherence. Matter and Plossl (1977) were the first to write about this negative feedback loop as the "lead time syndrome" and the "vicious cycle of PPC" but the root causes of the phenomenon up to the present day have not been identified. Several other researchers have also demonstrated that the so-called bullwhip effect is attributable to behaviour (see, for instance, Croson *et al.,* 2006, Udenio *et al.,* 2018, Häussler *et al.,* 2021).

Cognitive bias and human behaviour play a crucial role in effective digital risk management, adequate risk management being essential to the effective implementation of new digital technologies (Ivanov *et al.,* 2018). Humans are still one of the most important factors in the decision-making process and in the implementation and operation of technology in projects with a high level of digitalization (Ancarani and Di Mauro, 2011). Cimini *et al.* (2020) see the combination of digital technologies and humans with a focus on human wellbeing as one emerging trend in manufacturing and supply chain management. This makes it imperative to understand the underlying factors that influence human decision-making if efficient SCRM is

to be implemented and shows the needed transition from Industry 4.0 to a human-centric Industry 5.0.

We aim to close the research gap at the interface of behavioural research and SCRM by systematically exploring the impacts of cognitive bias and its role in supply chain risks and the management of such risks. Therefore, we conducted 53 interviews with experts and analyzed a set of digital use cases to provide practical insights into the impacts of cognitive bias on human decision-making in SCRM. Every interview constitutes a case study of an Industry 4.0 project, specifically the digitalization of a specific subprocess in the supply chain. On this basis, we have formulated initial hypotheses and guidelines that enable practitioners and researchers to include human factors in the designing of effective SCRM, and thus make digitalized supply chains more resilient.

The remainder of this paper is structured as follows: First, we combine the literature streams of SCRM and human behavior in order to identify the research gap. Second, we describe our research methodology. Third, we present our findings on the role of cognitive bias in decision-making in SCRM in several digital use cases, and we formulate initial hypotheses. Then, we develop several debiasing techniques that mitigate the impact of cognitive bias. Finally, we discuss our findings and suggest further research.

2. Theoretical Background

2.1 Supply Chain Risk Management in the Era of Digitalization

Digitalization is both changing and heightening operational risks. It is also spawning new risks (Gottlieb *et al.,* 2019). A number of researchers have analyzed the risk factors of specific Industry 4.0 technologies in depth (see, for instance, Zimmermann *et al.* 2019, Kessler *et al.* 2021). Nevertheless, particularly the human factor in Industry 4.0 projects is still underresearched (Sgarbossa *et al.,* 2020). Various models for efficient operational and supply chain risk management have been proposed (see for instance, Kleindorfer and Saad, 2005, Manju and Metzner, 2008, Rao and Goldsby, 2009; Tummala and Schoenherr, 2011). Regardless of the specifics of such frameworks, the underlying process always includes the three main steps of

(1) Risk Identification

The first step in risk management is the identification of potential risks. This step is critical, since all other risk management activities are contingent on it. The focus is on scanning the

environment for potential risks (Kern *et al.,* 2012). The range and interdependences of different activities in the supply chain tasks have to be factored in order to devise suitable risk management strategies (Chopra and Sodhi, 2004).

(2) Risk Evaluation and Assessment

The likelihood of the identified risk's occurrence and its potential impact are established in this step in order to deliver detailed information on whether and how the risk can be prevented and its likelihood of occurrence and impact can be controlled, or whether the risk has to be accepted and contingency plans need to be developed (Kern *et al.,* 2012).

(3) Risk Mitigation and Control

Adequate mitigation strategies are developed and implemented. This also involves defining potential countermeasures and subsequently evaluating the potential mitigation strategies. The capital expenditure for and the value of each mitigation action have to be determined (Kleindorfer and Saad, 2005).

2.2 Performance Metrics in SCRM

Performance and risk are interrelated in production systems and supply chains. To enhance supply chain performance, an effective SCRM contributing to these factors is required. Christopher and Peck (2004) defined supply chain resilience as the ´ability of a system to return to its original state, within an acceptable period of time, after being disturbed´. They proposed a framework for supply chain resilience based on four principles

(1) *Supply chain (re-)engineering:* Based on detailed understanding of the composite supply chain, the supply chain should be designed to build in resilience, e.g., by keeping a safety stock.

(2) *Supply chain collaboration:* Collaborative work and information sharing among supply chain partners reduce uncertainty and risks significantly.

(3) *Agility:* Visibility and velocity ought to create a high level of agility in the supply chain so that it can respond rapidly to new conditions, such as changes in demand. Visibility ought to be created through collaborative planning with all supply chain partners. Streamlined processes, short lead-times and the elimination of non-value-added activities ought to increase speed.

(4) *Creation of a supply chain risk management culture:* Risk management issues ought to be the concern of everyone in an organization and considered in every business decision.

Whereas resilience focuses more on reestablishing the baseline situation, robustness as defined by Kitano (2004) is the ´ability of the supply chain to maintain its function despite internal or external disruptions´. A robust supply chain is able to withstand risks and maintain its operation (Brandon-Jones *et al.,* 2014).

2.3 Human Decision-Making in SCRM

Human decision-making has been researched extensively in the field of psychology. The first models from the 1950s, e.g., the standard decision-making model, assume that human behavior is rational (Edwards, 1954). Researchers have subsequently determined that time constraints and psychological stress affect human decision-making. This has led to the development of the naturalistic decision-making paradigm (NDM). Dynamic and constantly changing conditions, rapid responsiveness to changes, time pressure and interconnections between individual parameters, which have immediate consequences when mistakes are made, are typical environmental decision-making features of NDM (Klein and Klinger 1991), and they all apply to the SCRM decision environment, too.

Research studies on NDM (e.g., Orasanu and Fischer *et al*., 1997) advance a seven-stage decision-making process, as presented in Table I.

Stage	***Task within decision-making***
Stage 1: Problem detection	Identifying an event that requires an action
Stage 2: Interpretation of information	Gathering sufficient data on the situation and evaluating contextual information
Stage 3: Sensemaking	Merging the available data to diagnose the current situation and to predict the system's potential future state
Stage 4: Identification of options:	Considering alternatives
Stage 5: Evaluation of conflicting goals	Considering and prioritizing potentially competing goals
Stage 6: Selection of appropriate steps	Defining the steps required to achieve the goal
Stage 7: Development of a procedure	Defining the tasks and the sequence in which they should be completed

Table I Stages of the decision-making process

Figure 1 correlates the stages of SCRM (Tummala and Schoenherr, 2011) and these stages of decision-making.

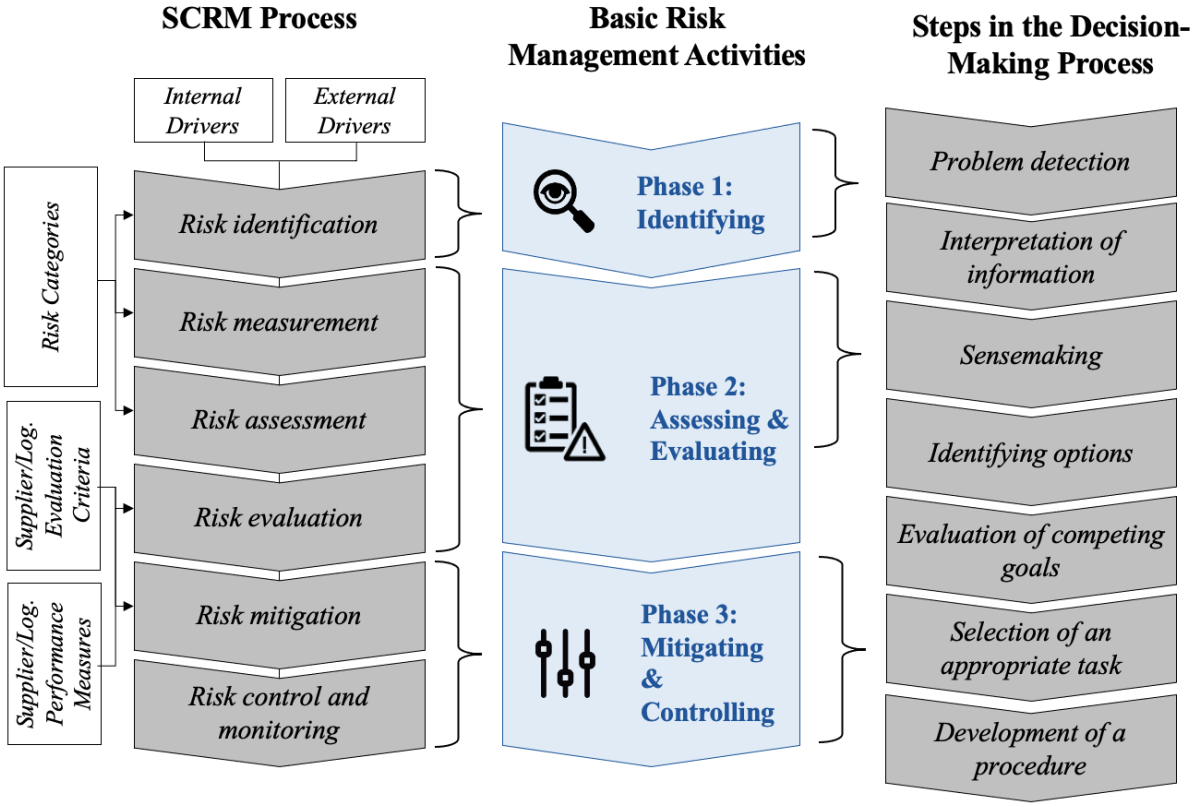


Figure 1 Decision-making in SCRM, based on Tummala and Schoenherr (2011)

2.4 Theoretical Foundation: Supply Chain Decision-Making from the Novel Perspective of Cognitive Bias

Departing from rational choice theory in human decision-making, Tversky und Kahneman (1974) were among the first to demonstrate that humans systematically deviate from theoretically optimal predictions when making decisions, and the researchers introduced the term ‘cognitive bias’. They conducted a number of experiments and described the factors underlying intuition and reasoning which heighten the impact of cognitive bias whenever individuals are confronted by complex and uncertain decision-making situations (Tversky and Kahneman, 1983). A number of authors (see, for instance, Stanovich and West, 2000; Kahneman, Frederick, 2002; Evans and Stanovich, 2013a) subsequently explored the interaction between these two systems and proposed a variety of names for the cognitive

processes. Stanovich and West (2000) called them 'System I' and 'System II' and these have become the standard designations for this dual decision-making process. These two systems comprise different decision areas in the decision-making process. System I creates spontaneous impressions, System II judgements (Kahneman, 2002). Although the two systems are treated separately, they operate and interact simultaneously in practice. Evans (2013b, p.454) succinctly described this duality as 'two minds in one brain'. Kahneman and Klein (2009) nevertheless demonstrated in further experiments that humans prefer the intuitive impressions of System I, especially when they are under time pressure to make decisions. Moreover, cognitive effort is required for System II to override an initial decision and to assume a kind of monitoring function that changes thought processes. The literature abounds with studies of cognitive bias ever since the publication of Tversky and Kahneman's (1974) seminal study, sometimes using different names for it. Various researchers have developed taxonomies of cognitive bias (see, for instance, Hogarth, 1987; Bazerman and Moore, 2013). Arnott (2006) proposed a taxonomy with six major categories, each containing a large subset of cognitive bias relevant to manufacturing and to supply chain management (Bendul 2019). The following table shows the six categories.

Cognitive bias category	**Description**
Memory bias	Influences humans' ability to remember specific information.
Statistical bias	Describes humans' tendency to misinterpret specific statistical parameters.
Confidence bias	Influences individuals' confidence in their decision-making skills.
Adjustment bias	Describes humans' tendency to adhere to easily available information or to a reference point when making decisions.
Presentation bias	Denotes the influence of the presentation of information on individuals' decision-making.
Situation bias	Describes the way individuals respond to a general decision situation.

Table II Overview of cognitive bias categories

Each of these six major categories subsumes several additional forms of bias that affect human decision-making:

Forms of memory bias: The *availability heuristic* and *imaginability bias* are two types of memory bias. The availability heuristic describes individuals' tendency to overestimate the likelihood of events on which they can readily recall information (Kahneman, 2002). The outcomes of their previous decisions consequently influence their current decision-making. Imaginability bias describes individuals' assumption that an event is more probable if they can readily imagine it (Taylor, 1982).

Forms of statistical bias: The *gambler's fallacy*, *correlation bias* and *prospect theory* are subsumed under the category of statistical bias. The gambler's fallacy describes individuals' assumption that future events are determined by past events, even if these events are unrelated (Barron and Leider, 2010). *Correlation bias* denotes individuals' perception of a correlation between two variables, even though these variables are not actually related (Kahneman, 2002). Prospect theory describes individuals' behavior towards risk based on the assessed certainty. Humans are risk-averse when events are positive. They prefer a smaller but certain utility to higher but uncertain value. In negative situations, humans prefer a greater but uncertain loss to a more probable but smaller loss (Tversky and Kahneman, 1974).

Forms of confidence bias: The *illusion of control* describes people's belief that they are in full control of a situation and able to influence the outcome of a certain event, even though it is a random occurrence (Brenner *et al.,* 1996). *Confirmation bias* describes individuals' tendency to seek more information that confirms their prior ideas and judgment and to ignore information that contradicts their own beliefs (Russo, 1996).

Forms of adjustment bias: The *anchoring effect* is the tendency to rely unduly on initial information that serves as a reference point for subsequent decisions (Tversky, Kahneman, 1974). *Conservatism bias* describes individuals' tendency to adhere to initial information and not to revise their decision when they encounter new information (Edwards, 1968).

Forms of presentation bias: The *ambiguity effect* describes individuals' preference for simplistic options and avoidance of complex options when making decisions (Ellsberg, 1961). The *primacy/recency effect* describes the influence of the sequence of a series of items on an

individual's recall of them. The first and last items in a series are recalled best, whereas items in the middle are recalled worst (Yates *et al.,* 1986).

Forms of situation bias: The *ostrich effect* describes individuals' tendency to ignore negative information (Karlsson *et al.* 2009). The *complexity effect* describes how individuals systematically make wrong decisions when they are under time pressure or overloaded with information (Ordonez and Benson, 1997). The *bandwagon effect* describes people's habit of doing something because many others are doing the same thing. This is also known as 'herd mentality' (Carter *et al.,* 2007).

2.5 Debiasing: Managing the human factor

Debiasing comprises techniques that reduce or eliminate the influence of cognitive bias in decision-making. However, the effectiveness of debiasing strategies is discussed controversly in literature. While the ones are convinced that debiasing strategies help to reduce or eliminate the negative influence of cognitive biases the other stream in literature claims that a complete elimination of the influence of cognitive biases never can be achieved (Tokar, 2010; Yang et al, 2021; Ferretti et al, 2023).
Larrick (2004) proposed three main methods of effective debiasing, specifically, motivational, cognitive and technological, and several submethods., Kaufmann and Carter (2010) recommended five debiasing strategies for SCM research: (1) decomposing/restructuring, (2) putting oneself in another person's shoes, (3) drawing attention to alternative outcomes, (4) playing devil's advocate and (5) being aware of bias in general. We combine the methods and strategies and apply them to the stages of SCRM.

Motivational methods: Incentivization and accountability are the proposed techniques in this category. Larrick (2004) suggested offering incentives to decision-makers based on the quality of their decisions in order to enhance decision quality. This strategy's real effectiveness for reducing cognitive bias is a subject of debate in the literature. The lack of replicated studies demonstrating an improvement of decision outcomes though incentives has been criticized (Camerer and Hogarth, 1999). Moreover, this strategy requires that the decision maker is qualified to apply different methods (Camerer and Hogarth, 1999). Epley (2004), however, demonstrated that incentives help to reduce the anchoring effect.

Cognitive methods: Soll and Klaymann (2004) and Larrick (2004) proposed training programs and consideration of the opposite as debiasing techniques in this category. These techniques have similarities with Kaufmann and Carter's (2010) methods of creating awareness of bias and playing devil's advocate. Creating awareness of cognitive bias serves as an overall debiasing strategy and can be considered a framework for further debiasing techniques. Renner and Renner (2001) determined in their studies and experiments that debiasing training can reduce the influence of cognitive bias and increase the accuracy of judgments. Even though a general understanding of the underlying factors influencing decisions can improve the quality of judgments in decision-making, it cannot eliminate bias entirely (Kaufmann and Carter, 2010). ′Considering the opposite' – or also named 'devil´s advocate' – is *another debiasing technique in this category. The idea behind that method of considering the opposite or playing* devil's advocate *is to enhance decisional quality by examining opposing views. This forces decision-makers to broaden their horizons and explore different alternatives* (Epley and Gilovich, 2005). Mussweiler *et al.'s* (2000) strategy of drawing attention to alternative outcomes helps reduce the influence of confirmation bias by counteracting individuals' tendency to consider only arguments that are supportive to their decisions. Through this technique, they are forced to consider opposing views and alternatives that they would otherwise have ignored (Slovic and Fischhoff, 1977, Epley and Gilovich, 2005).

Technological methods: Group decision-making supplants individual decision-making. The different experiences and opinions of the individuals in a decision-making group make this a validation and error-checking system that reduces an individual's errors (Larrick, 2004). A similar method, putting oneself in another person's shoes, invites the decision maker to assume a different perspective by viewing the situation though another party's eyes. Faro and Rottenstreich (2006) determined in their experiments that predicting others' actions in a situation reduces mispredictions and enhances decision quality.

2.6 Research Gap and Objectives

The analysis of the relevant research streams revealed that the influence of cognitive biases on decision-making has a huge impact on SCRM and supply chain resilience. Although human factor have been steadily attracting interest in SCM research in recent years, little research has been done on the influence of human factor on supply chain risk analysis. SCRM literature on the influence of cognitive bias on human decision-making in the stages of risk assessment and

mitigation and the implementation of proper SCRM in digitalization projects in particular is even scarcer. Montibeller and von Winterfeldt (2015) expressed surprise at the relatively limited attention paid to the impact of human factor on decision-making in SCRM, given its significance for supply chain management and performance. They suggested further research on cognitive bias and debiasing techniques in SCRM.

Consequently, our main research question is: *How does cognitive bias influence human decision-making in SCRM?* We glean three different research objectives from our research question:

- Systematic exploration of cognitive bias and its role in the supply chain and SCRM in digitalization projects
- Development of hypotheses on the influence of cognitive bias on decision-making in SCRM
- Formulation of recommendations for managing human factor in decision-making in SCRM for practitioners and researchers

3. Research Design

Given the research objectives, we have applied a twofold research design. Since a literature review helps to advance research by providing historical data and consolidating the current state of the art (Metzner and Kahn, 1995), we have combined the literature streams of psychology, behavioural operations management and supply chain risk management to highlight the existing research gap. Then, we conducted a qualitative secondary analysis of fifty-three semi-structured interviews with professionals who are involved in risk issues relating to the introduction of digital applications. Drawing on the principles of abductive reasoning, our empirical research was guided by a systematic iteration between theory and empirical data (Ketokivi and Choi, 2014). The unit of analysis in our study was the specific projects in which a digital Industry 4.0 technology had been implemented and human-behavior-biased SCRM. To select adequate interview partners with Industry 4.0 use cases, we analyzed the platform ‘Plattform Industrie 4.0’ of the German Federal Ministry for Economic Affairs and Energy in collaboration with the Federal Ministry of Education and Research (Federal Ministry for Economic Affairs and Energy and Federal Ministry of Education and Research, 2019). This database was launched and is monitored by an official government institution, and it is ensured that only industry 4.0 use cases using digital technologies are published on the platform. A review process before publication validates that all the relevant information is provided for each category.

The interviews from the parent study were conducted in German over the phone or face to face between November 2018 and March 2019 with a duration of 25-50 minutes. Only individuals involved in past or present Industry 4.0 projects were interviewed. Personal information, such as interviewee and company names, was anonymized to preserve confidentiality. All interviews were recorded, transcribed, or extensively summarized (whenever interviewees did not agree to being recorded).

The interviewees came from a range of sectors. Nineteen were representatives of the manufacturing industry (electrical and electronic equipment manufacturing, automotive manufacturing, machinery manufacturing and automated systems manufacturing). Twelve were working in industrial consulting, providing an outside perspective on Industry 4.0 projects in various companies. Nine interviewees came from IT companies, eight from logistics companies and five were academics. The semi-structured interviews lasted between twenty-five and fifty minutes. Responding to a semi-structured questionnaire, interviewees first described an Industry 4.0 use case that they had implemented in their company. Then they described the risks identified in the technology life cycle and their risk management activities (see the Appendix for a full list of interviewees and the used questionnaire).

As part of our analysis, we reviewed all the transcripts and relistened to all the original interviews, focusing on interviewees' accounts of risks encountered during the implementation of their Industry 4.0 project and their applied risk management activities.

We identified several types of cognitive bias active in risk management. Based on the categories of cognitive bias presented in section 2.3, we identified biased human decision-making situations and correlated them with the corresponding type of cognitive bias.

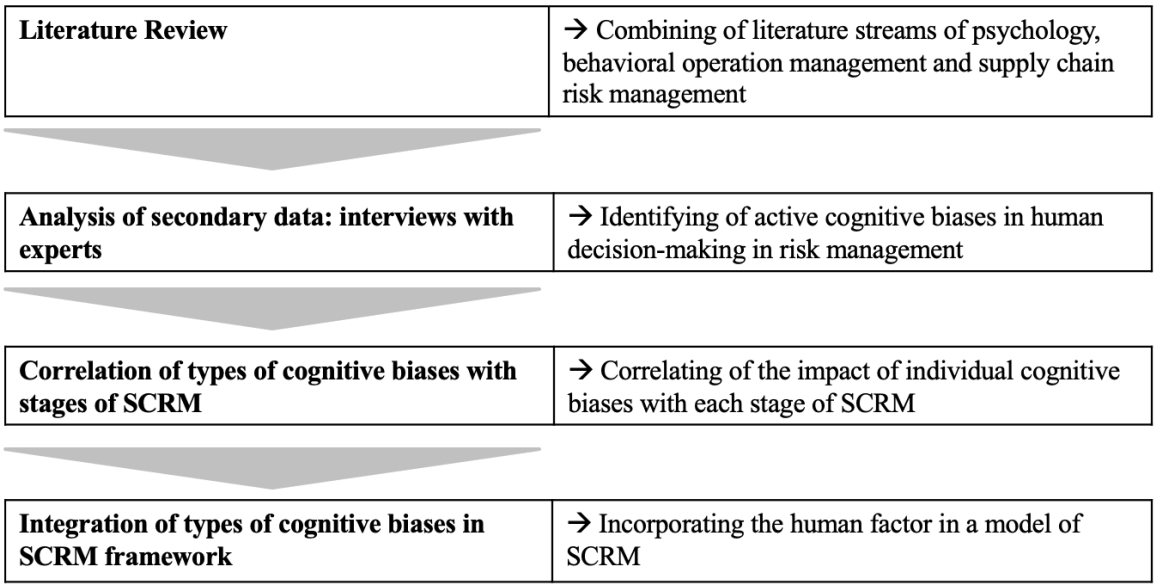


Figure 2 Research design

We employed Eisenhardt's (1989) research approach to a cross-case analysis in order to ensure research validity and reliability. This methodology combines the research objective with real-world experience (Yin, 1994). Amabile *et al.* (2001) consider a case study approach to be particularly suitable for ascertaining recommendations for management because the research method entails substantial interaction with practitioners. (Denzin und Lincoln, 2013). Our cross-check of the information from the different interviews ensured that the validity of our research was attained throughout (Denzin and Lincoln, 2013).

4. Findings: The Impact of Cognitive Bias on Decision-Making in Risk Management and on Supply Chain Performance

SCRM subsumes all relevant strategies, metrics and technologies that enhance supply chain performance, robustness and resilience (Christopher and Peck, 2004). The different types of cognitive bias that are active in the different stages of SCRM affect human decision-making. Our findings are structured on the basis of the three key activities of risk management and are correlated with the types of cognitive bias identified in the interview data. We aggregate our findings into a developed framework in order to formulate our initial hypotheses on the influence of cognitive bias on decision-making in risk management and on a supply chain performance which demonstrates the need for a paradigm shift to Industry 5.0.

Stage 1: Risk Identification

Risk identification entails scanning supply chain processes, such as the supply and demand process and the operational logistics and manufacturing processes, in detail to identify potential threats. In the Industry 4.0 technology implementation cases that we examined, practitioners analyzed the pertinent processes, e.g., logistics, manufacturing, supplier interaction etc., on the basis of the technology selected. Then, the identified potential threats, such as cyberattacks, legal restrictions, misuse and malfunctions, that could affect the implementation and operation of the technology. For instance, the implementation of a stock software solution that facilitates warehouse picking and reorders low stock falls under the category warehouse logistics and purchasing. Since any malfunction of this software would disrupt the supply chain, the environment has to be carefully scanned for all potential threats and scenarios that could cause disruptions. Errors in stock quantity, software downtime or software misuse constitute potential threats. Introducing such a new technology requires decision-making in the risk management process, as the example shows.
In our data, we identified several forms of cognitive bias that are active at the stage of risk identification and which resulted in some risks being overlooked and others being overestimated or underestimated.

Memory bias: Practitioners are often influenced by information about risk which is readily available or currently prevalent in the media. Instead of objectively evaluating technologies and their uses, practitioners tend to prefer risks that are familiar to them (Kahneman, 2002). The evaluated use cases reveal that the risk of cyberattacks was ascribed to virtually every technology regardless of the actual situation, since reports of cyberattacks are omnipresent in the media.

Statistical bias: SCR managers fell for the gambler's fallacy, assuming that a previously encountered risk was no longer a concern. They consequently refrained from implementing suitable mitigation strategies. One manager defended the decision to discount potential cyberrisks, observing that 'a recent cyberattack did not hurt the company's operations.'

Situation bias: We identified the bandwagon effect and the ostrich effect with regard to decision-making processes in risk identification. Practitioners were influenced by their basic attitudes toward digital technologies. Were they critical of digitalization and technical solutions,

they classified more risks as ‘critical’ and identified more risks, thus confirming their opinion. Conversely, an SCR manager who was open to digital solutions classified fewer potential risks as ‘critical’.

Presentation bias: The primacy/recency effect was identified when interviewees researched potential risks. They mainly recalled risks identified at the beginning or at the end of their research and were unable to name any risks encountered during the project, ultimately claiming there were no serious risks.

Situation bias: We identified the bandwagon effect and the ostrich effect with regard to decision-making on risk identification. Since it relates to trends, the bandwagon effect is frequently encountered in decision making on Industry 4.0 solutions. Since innovative and technologically sophisticated Industry 4.0 solutions are common topics of discourse in large companies, in current research and in the media, small and medium-sized businesses feel under pressure to keep pace. They often merely follow the lead of large companies without analyzing and modifying a technology for their own processes and environmental conditions. When doing so, they often overlook or fail to analyze their own company’s specific risks, since they rely on the experiences of innovators and the risks reported by them. One manager involved in the implementation of RFID technology at his company described this situation as the pressure to forge ahead with technology in order to keep pace with innovation. ‘We’re pressured into implementing innovative solutions. That’s why, when we see solutions like RFID, we ask ourselves where we could implement it in our own operations, instead of considering the problem first and asking ourselves how it could be solved before thinking about a specific technology.’

We also identified the ostrich effect in decision-making in SRCM. Since Industry 4.0 implementation cases entail high capital expenditures, the projects are often doomed to fail and the parties involved deny any risks in order to keep the project going. Failure to address the risk of unauthorized WLAN access in risk analyses was a frequent occurrence in the use cases that we analyzed. Practitioners confronted with this risk claimed that their use cases were not critical, since any stolen data ‘would be of no use’ to any hacker.

Cognitive bias category	**Cognitive bias effect**	**Quote**
Memory bias	Availability heuristic	´There was a malware attack and people were soon reading and hearing about it everywhere. The result has been that , everybody is talking about cyberrisks now.´
Statistical bias	Gambler's fallacy	´We've already had a cyberattack and nothing really bad happened, so I think we're well prepared.´
Confidence bias	Confirmation bias	´The manufacturing manager and the IT department manager had already had negative experiences with these technologies, so they were both against implementing the Industry 4.0 warehouse solution.´ ´The technology had convinced our management and they wanted its implementation regardless of whether the solutions would fit to our processes'
Presentation bias	Primacy recency effect	´We bought the data gloves from a company that we had come across at a trade show. We thought it was the only company on the market and didn't bother to look for alternatives.´ 'We stuck to much of our initial risk analysis for the smart glasses and failed to add the risks that evolved during the implementation phase´
Situation bias	Bandwagon effect	´Small and medium-sized businesses in particular are under a sort of pressure to innovate in order to keep up with the large companies.´ 'Because one of our largest competitors had published their technology implementation, our management wanted us toto implement the EDI communication too.'

Table III Quotes from the analyzed uses cases illustrating types of cognitive bias that are active in risk identification

Our first hypothesis states:

H1: *Cognitive bias in the memory, statistical, confidence, presentation and situation bias categories impact risk identification in a way that potential risks are overlooked or systematically underestimated in subsequent risk evaluation, and supply chain robustness is diminished.*

Stage 2: Risk Evaluation and Assessment:

Risk evaluation entails assessing the likelihood of occurrence and potential severity of risks identified in the preceding stage. Since Industry 4.0 use cases are often based on new technology, the absence of a substantial source of data on comparable corporate projects or experiences complicates evaluation and assessment. Moreover, specialized knowledge of a specific technology is required to estimate the likelihood of risk occurrence and the severity of identified risks. For instance, a proper risk evaluation of a warehouse robot requires several parameters and experience with the technology. Since the likelihood of a robot malfunction and the subsequent repair time have to be assessed, a sound knowledge of robot technology is essential.
In our analysis of the use cases, we also identified cognitive bias that affects decision quality in risk evaluation.

Memory bias: Imaginability bias was evident in the assessment stage. Practitioners rated the likelihood of occurrence of familiar and easily imaginable risks as high. Since they often lack experience with digital technologies, they tend to classify common risks, such as human failure and supplier error, as probable and to underestimate new risk factors, such as legal issues and technology risks. One interviewed manager introduced a software with a remote maintenance function in manufacturing but underestimated the data security risk, since he was unfamiliar with the new technology. He stated, ˝We didn't realize that we were allowing outside access to employee data by using the remote maintenance function˝.

Adjustment bias: We identified conservatism bias in the estimates of the likelihood of occurrence of several risks at the stage of risk evaluation. Despite technological progress, which has an impact on risk probability, practitioners often adhere to the results of their initial assessment, consequently over-and underestimating potential risks. Should technological progress elevate security, e.g., through better security standards, retaining the initial risk assessment would become a costly undertaking. Technological progress also spawns new risks. Adherence to an initial assessment can result in underestimating the threats that impair supply chain operations.
The anchoring effect also biased managers' risk evaluations, The cases analyzed revealed that managers let themselves be influenced by data on the likelihood of occurrence, which they had

learned of during their initial research or during their initial discussion with management. As a result, they did not revise their initial estimates to match current developments.

Cognitive bias category	**Cognitive bias effect**	**Quote**
Memory bias	Imaginability bias	´We weren't able to use the robot for automated machining because we had underestimated the lighting risk in this process. The lighting was good enough for the human eye but it was too dark for a camera.´ 'We were surprised about the low acquisition rate of the RFID technology. We simply didn't consider that the workers in the warehouse did not use the RFID gate in case they needed the material very quick.`
Adjustment bias	Conservatism bias	´Rationally, it's actually better to use a large provider's cloud infrastructure. But most companies stick to their original decision to host the system themselves, and that decision harbours a greater risk of cyberattacks.´

Table IV Quotes from the analyzed use cases illustrating types of cognitive bias that are active in risk evaluation

Our second hypothesis states:

H2: *Cognitive bias in the memory and adjustment bias categories impact the risk evaluation in the way that the likelihood and severity of occurrence are misestimated and supply chain robustness is diminished.*

Stage 3: Risk Mitigation and Control:

Risk mitigation strategies have to be defined at the final stage of SCRM. Supply chain risk managers have to consider capital expenditures and resources. This stage illustrates the difficulties arising from the lack of comparable projects with industry 4.0 technologies. Our use cases have demonstrated that practitioners often face cost pressure and pressure to succeed. These decision conditions and uncertainty foster the various types of cognitive bias that we identified in the use cases

Statistical bias: We identified correlation bias in risk evaluation. Since SCR managers not only associated process problems but also process optimization with the introduction of a new digital

technology, they implemented more risk mitigation strategies focused solely on the digital technology instead of analyzing the processes too. They implemented fewer risk mitigation strategies whenever they felt that the technology optimized the process.
Prospect theory could be applied to SCR managers' decisions on risk mitigation strategies too. The necessary risk mitigation strategies cost money, whereas the actual likelihood and severity of losses potentially caused by risks is uncertain. As a result, practitioners prefer to accept uncertain future costs arising from risks rather than accept certain immediate costs for suitable actions.
Most practitioners avoid modifying their existing corporate IT security after digital tools – such as VR glasses or robots – have been integrated into specific operations over the company's WLAN because they are aware of the expense, time and labour required. The related risk of a cyberattack or loss of data remains a mere possibility with an uncertain but assumed low likelihood and indeterminate severity.

Confidence bias: The illusion of control plays an outsized role in risk management. SCR managers tend to implement risk mitigation strategies too little and too late because they assume that they have any risks fully under control. The implementation of digital applications is often part of a corporate strategy that is desired by management and is under a tight schedule. This puts decision-makers under pressure to succeed and to deliver good news to the management. Believing in their own ability to manage risks, they usually try to solve problems by themselves and do not communicate with higher ups. By the time they realize that a risk exceeds their own knowledge and ability, it is often too late for proactive risk mitigation strategies, and reactive and costly counteractions become the only option.

Presentation bias: The cases we analyzed corroborated that the ambiguity effect induces SCR managers to select the simplest option rather than to analyze all factors and options when formulating their risk mitigation strategies. SCR managers prefer stand-alone solutions – which require much more work in order to manage risk – over more complex integrated solutions.

Situation bias: The complexity effect has an impact on decision-makers who have to manage digital risks spontaneously and promptly. The decision environment is complex, since digital applications integrated in the infrastructure and the process landscape create extensive interdependences. Since risks in supply chain networks can easily affect the entire supply chain

and cause costly disruptions, practitioners must make decisions under time pressure. Complex digital technologies often overtax decision-makers, who are normally not IT experts.

Cognitive bias category	**Cognitive bias effect**	**Quote**
Statistical bias	Correlation bias	´It's an investment in an unfamiliar technology. But we can't afford to fail, because management wants the investment to pay off.´
Confidence bias	Illusion of control	´The people in charge didn't report the exoskeleton's problems immediately and we then lost time fixing them.´ 'We thought we could solve the issue ourselves and could avoid informing too many people in our company. Then we realized that our knowledge of the software was insufficient for coping with the issue.`
Presentation bias	Ambiguity effect	´We preferred a stand-alone solution because integrating a solution into our IT landscape just seemed too complex.´
Situation bias	Complexity effect	´It was a totally new technology and nobody knew how to deal with the error´. 'There were so many intrarelationships between the individual parameters of the remote function that we failed to consider the legal aspects'.

Table V Quotes from the analyzed use cases illustrating types of cognitive bias that are active in risk mitigation

Our third hypothesis states:

H3: *Cognitive bias in the statistical, confidence, presentation and situation bias categories affects the selection of mitigation strategies adversely and diminishes supply chain robustness.*

4.1 Debiasing: Human Factor in Digital Risk Management

Based on our findings, we have formulated initial recommendations for practitioners and hypotheses for researchers, which would enable them to include human factor in SCRM. We have correlated the debiasing techniques with the three stages of SCRM in order to formulate recommendations for researchers and practitioners about which of these techniques are best.

Awareness of bias serves as an overall debiasing strategy that ought to be implemented at every stage of SCRM. This can be done with special training courses or online tutorials on cognitive bias for supply chain risk managers in order to create an awareness of behavioural mechanisms in decision-making. Debiasing techniques for the three stages of SCRM are presented below.

Risk identification: As a motivational strategy, risk managers could be offered incentives based on the quality of their decision outcomes (Eply, 2004). SCRM decision-makers could be given a stake in risk management by their being rewarded for hours of trouble-free operation or being penalized for problems caused by risks that they overlooked at the identification stage. In addition, a standard checklist template could be used to ensure structured analysis of all relevant risk factors and parameters and to prevent the omission of risks. This would help decision-makers to stay focused on the relevant information in situations where they are overloaded with information and required to make decisions fast. These techniques encourage risk managers to consider more factors and not to adhere to certain information or one parameter too heavily, thus countering the anchoring effect and the availability heuristic.

Our fourth hypothesis states:
H4: *Motivational strategies boost the quality of the risk identification and diminish the impact of the anchoring effect and the availability heuristic*.

Risk evaluation and assessment: The methods of considering the opposite, playing devil's advocate and putting oneself in another person's shoes can be applied to risk evaluation and assessment (Larrick, 2004). They force risk managers to consider other options and alternative outcomes, compelling them to explain and justify their estimates of likelihoods and severities so that they cannot hide behind numbers or scores. These methods can be applied in group meetings to arrive at a diverse set of assumptions on potential risks and their likelihood of occurrence (Soll and Klaymann, 2004).

Our fifth hypothesis states:
H5: *Cognitive and technological debiasing techniques reduce cognitive bias in risk evaluation.*

Risk mitigation and control: Group decision-making is a good method for reducing the influence of cognitive bias in mitigation and control (Larrick, 2004). Instead of one person

being responsible for each specific risk area, a group bears responsibility for several risk areas, such as technology or logistics risks. Different experiences and opinions introduce new perspectives, which can be useful in the evaluation of different risk mitigation strategies. Since the group also acts as an error checking system, this method is also useful for controlling the effectiveness of the risk mitigation strategy selected. It also keeps individuals from overestimating their own problem-solving ability or from searching for arguments that reinforce their own beliefs. This method can be made more effective by rotating responsibility for specific risk areas or presenting selected risk mitigation strategies to a group normally responsible for another risk area. This keeps decision-makers from 'growing blind' to potential risks and from applying avoidance strategies in the risk area with which they are familiar (Faro and Rottenstreich, 2006).

Our sixth hypothesis states:
H6: *Group decision-making diminishes the impact of the illusion of control bias and confirmation bias for risk mitigation decisions.*

4.2 Detailed Framework

Based on our analysis of the use cases, we have developed a framework (see Figure 3) that subsumes our findings and hypotheses. Cognitive bias has an impact on every stage of risk management and therefore directly affects supply chain performance. The framework includes six categories of cognitive bias that influence human decision-making in risk management.
Decision-making in risk identification, mitigation and control entails a high level of uncertainty and high time pressure. The impact of cognitive bias is most evident at this stage. Current Industry 4.0 and digitalization trends amplify uncertainty in many decision-making situations. Decision-makers often lack the knowledge of IT and technology required to grasp the full implications of a decision. This decision environment reinforces cognitive bias that affects supply chain resilience and robustness adversely.
We have formulated initial recommendations for debiasing methods to manage human factor. Different debiasing techniques and strategies are suitable for different types of bias and stages of SCRM. These strategies can also serve as design guidelines for decision support systems in SCRM.

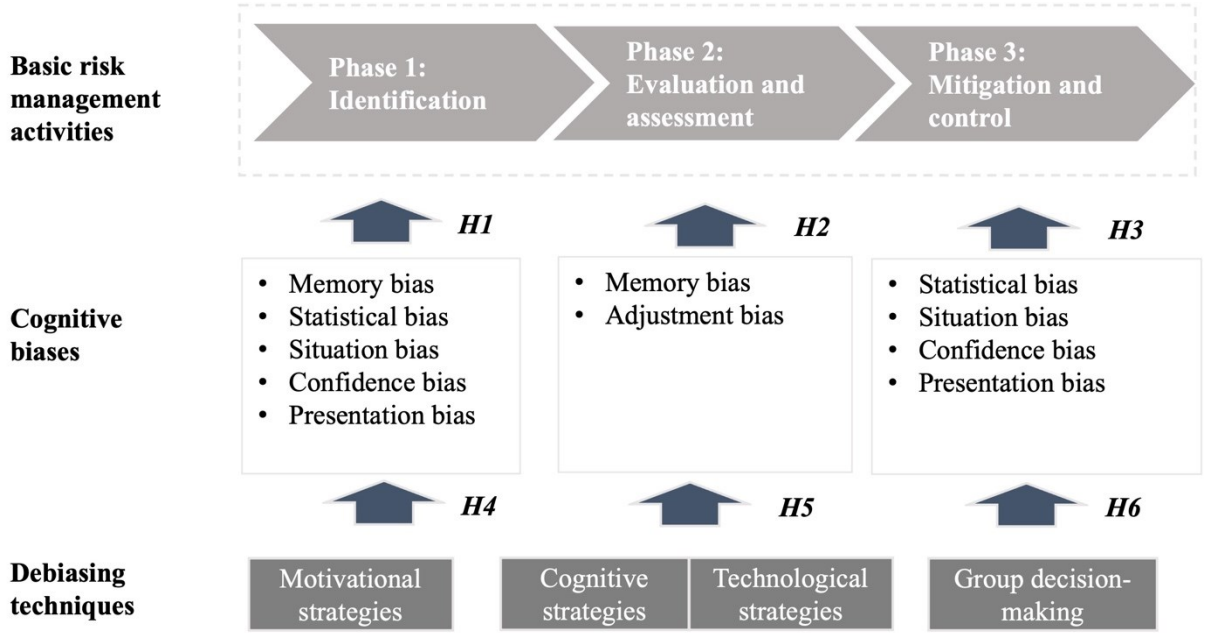


Figure 3 Detailed framework of cognitive biases and debiasing techniques in SCRM

5. Discussion and Conclusion

This paper is intended to formulate initial hypotheses on the impact of cognitive bias on specific decision-making situations in SCRM as well as providing initial recommendations for debiasing techniques for researchers and practitioners who work with digital supply chain applications, and thus highlighting need for a more human-centric industry vision.

Based on the combined psychology and SCM literature streams, we argue that cognitive bias in decision-making in SRCM have adverse impacts on supply chain resilience and robustness. New risks from new technologies and concomitant increases in uncertainty heighten these impacts. Our detailed framework subsumes our findings and hypotheses.

Theoretical contribution

Although behavioural SCM has gained momentum in recent years (see, for instance, Bendoly *et al.* 2006, Tokar, 2010, Fahimnia *et al*. 2019), Schorsch *et al.* (2017) demonstrated that the thirty-six publications on behavioural SCM per year merely constitute a niche in the SCM literature and the authors have encouraged researchers to publish more studies in this field. The importance of effective SCRM has been recognized in the literature and in practice (Sodhi *et al.* 2011). Our findings demonstrate the need for a shift towards a more human-centric supply chain risk management and show the high importance of considering human needs, which is in

line with the findings of Sgarbossa *et al.* (2020) and Neumann *et al.* (2021), who recommend a human-focused industry.

The growing connectivity of supply chain activities particularly makes adequate SCRM that enhances supply chain resilience vital. Increasing digitalization that spawns new risks is rendering the need for such SCRM all the more acute (Ivanov *et al.,* 2018).

Ghadge *et. al* (2012) observed that unbiased decision-making techniques in SCRM are an unexplored field of research. This implies that it is important to understand behavioural and other factors that have an impact on cognitive bias in human decision-making (see, for instance, Crater *et al.,* 2007; Gino and Pisano, 2008). We contribute to this research by analyzing the impact of cognitive bias on human decision-making in SCRM and risk management in Industry 4.0 use cases. The debiasing techniques that we recommend for reducing cognitive bias in human decision-making are just that, i.e. recommendations. We add to Jüttner *et al.* (2005), Manju and Metzner (2008) and Tummala and Schoenherr's (2011) work by integrating human factor in SCRM. The underlying idea is consonant with the work of Bendoly *et al.* (2006), Tokar (2010) and Fahimnia *et al.* (2019), who transferred human factor to operations management and SCM.

Practical Contributions

Our findings demonstrate the impact of cognitive bias on human decision-making in SRCM and confirm the need for a paradigm shift from Industry 4.0 to Industry 5.0 that incorporates human factor (European Commission, 2021). Our research contributes to creating awareness of cognitive bias, a debiasing technique in and of itself. What is more, the debiasing techniques proposed here are initial recommendations to practitioners for mitigating the types of cognitive bias identified at the three stages of SCRM and improving risk managers' overall decision-making. The techniques could also be used as basic design guidelines for the development of decision-support systems in SCRM.

Limitations and Further Research

The limitations of our study suggest further avenues of research. Interviews with experts are influenced by personal experience. Moreover, the types of bias are not classified as rigorously in practice as they are in this paper. Since types of cognitive bias can overlap, some of our observations may need readjustment, while others may need honing. Furthermore, we have employed a general risk management approach, which may not apply to all digital applications.

Further research in this field might identify more types of cognitive biases at the three stages of SCRM. Moreover, our hypotheses still need to be tested in behavioural experiments to validate the effectiveness of the debiasing techniques that we present**.** This could also contribute to the controverse discussion in literature about the effectiveness of debiasing strategies.

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Appendix: Overview of Interview Partners

Interview Partner No.	Sector	Implemented Digital Technology Use Case
1	Automotive	RFID for warehouse processes
2	Machine manufacturing	Automated Guided Vehicle (AGV) in production
3	Electronic equipment manufacturing	Mobile maintenance
4	Automated systems manufacturing	Data analysis of machine data through sensor technology
5	Electronical manufacturing	EDI interface for supplier communication
6	Automotive	Predictive maintenance
7	Automotive	Smart Kanban system
8	Electronical manufacturing	Cloud computing for warehouse processes
9	Machine manufacturing	Exoskeleton for assembly process
10	Manufacturing	Digital factory layout design via software simulation
11	Electronic equipment manufacturing	Remote maintenance of elevators
12	Machine manufacturing	Predictive maintenance
13	Manufacturing	Human-machine interface for digital worker assistance
14	Automotive	Data gloves for picking process
15	Electronical manufacturing	Data glasses
16	Automotive	Digital shopfloor solution
17	Automotive	Automated Guided Vehicle (AGV) in production
18	Electronic equipment manufacturing	Smart spare part management
19	Automotive	Robot for assembly process
20	Logistics	Drone for inventory counting
21	Logistics	Automated Guided Vehicle (AGV) for warehouse processes
22	Logistics	Data gloves for picking process
23	Logistics	Geofencing
24	Logistics	Automated Guided Vehicle (AGV) for warehouse processes
25	Logistics	Smart transportation process
26	Logistics	Actuators (mobile loading and transportation)
27	Logistics	Data gloves for picking process
28	Academics	-
29	Academics	-
30	Academics	-
31	Academics	-

32	Academics	-
33	Consulting	-
34	Consulting	-
35	Consulting	-
36	Consulting	-
37	Consulting	-
38	Consulting	-
39	Consulting	-
40	Consulting	-
41	Consulting	-
42	Consulting	-
43	Consulting	-
44	Consulting	-
45	IT	-
46	IT	-
47	IT	-
48	IT	-
49	IT	-
50	IT	-
51	IT	-
52	IT	-
53	IT	-

6. Paper 5: Toward Human-Centered Smart Production Systems: Evidence from Behavioral Experiments

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Contribution of Melanie Kessler to the work: Developed the design of the behavioural experiments, wrote the paper, contributed to the analysis of the results as well as to their selection and interpretation

Contribution of the co-authors: Julia Arlinghaus conceptualised the research, gave feedback on the design of the experiments and helped with the setup of the behavioural experiments. She reviewed the paper and gave feedback. Doreen Neubert contributed to the statistical analysis.

Contribution of the paper to the PhD project: This paper validates the hypotheses derived in Paper 3 based on behavioural experiments. Especially the involvement of PPC practitioners in the experiments, which is new to this research area, contributes to the confirmation of the derived hypotheses and gives them a high practical relevance.
The findings of this paper confirm the influence of cognitive biases in various typical PPC decision-making situations and show that even experts are not spared from biased decision-making, leading to a systematically deviation from a rational optimum. The paper contributes to all three sub-research questions as well as to the main research goal.

Note: In the interest of uniformity, all articles have been reformatted according to the dissertation format.

Toward Human-Centered Smart Production Systems: Evidence from Behavioral Experiments

Abstract

Purpose: This study is intended to fill the research gap by exploring the impact of cognitive biases on human-decision making in production planning and control. To this end, initial hypotheses are derived.

Design/Methodology/Approach: The hypothesis development is based on human behavioural experiments with 99 participants including 75 PPC practitioners.

Findings: Our findings clearly demonstrate that the cognitive biases active in various decision-making situations cause both experts and non-experts to deviate systematically from the rational optimum in their decision-making.

Research limitations/implications: The derived hypotheses can be used for further practical validation and hypothesis testing.

Social implications: Our research contributes to creating an awareness of cognitive bias in operations management. This serves as a basis for decision support systems developer to consider the human factor in the design.

Originality/value: This study is one of the first based on empirical evidence from human behavioral experiments.

Keywords: Human experiments, human decision-making, smart factory, production planning and control

Paper type: Research paper

1. Introduction

The concept of Industry 4.0, a vision of future industrial manufacturing enabled by autonomous and self-learning digital technologies, was introduced as the fourth industrial revolution in 2011 [1]. More than ten years later, huge potential remains untapped [2]. Research has identified one reason for this. The substantial lack of study and understanding of non-rational decision-making is one factor behind inefficient outcomes in supply chains, such as supply bottlenecks, disruptions or high storage costs [3]. Several studies have demonstrated the criticality of the human factor to the implementation and operation of digital technologies in smart production systems featuring autonomous, digitalized and connected production processes [4], [5].

The European Commission introduced the concept of *Industry 5.0* in 2021. Based on Industry 4.0 (fully autonomous, connected and self-controlling industrial production), *Industry 5.0* promises more human-centered, resilient and sustainable industrial manufacturing that fully harnesses to the capabilities of digitalization.

Several extensively studied dynamic phenomena in production systems, such as the lead time syndrome and the bullwhip effect, are attributable to biased human decision-making[6], for instance, show in their research on LTS how biased human production planning causes a negative feedback loop of diminishing schedule adherence in production systems. [7] demonstrated that biased decision-making causes order variability to increase as it progresses through a supply chain.

[8] introduced the concept of bounded rationality in human decision-making, in the early 1950s, especially in production planning and control (PPC) most models still assume a human behavior is rational and based on the *Homo oeconomicus* who is interested in maximizing personal profit and make fully rational decisions [9].

Although psychology research findings have been transferred to many areas of operations management, behavioral operations management is still in its incipiency [10]. The influence of human behavior has been studied in various operations, such as product development, inventory management, supplier selection, supply chain management and production management [10]. Human behavioral experiments in the field of PPC in particular are fairly new, though [11]. Behavioral experiments with practitioners and corresponding analysis of different parameters, such as level of experience, gender and age, rarely appear in current literature [12], [13].

[14] were some of the first to demonstrate the influence of cognitive biases on human decision-making, resulting in a systematic deviation from a rational optimum, with their research.

Through our research, we intend to answer the research question *How do cognitive biases influence human decision-making in typical production planning and control decision*

situations and does the level of experience make a difference? We additionally contribute to remedying the dearth of human behavioral experiments by conducting one with 99 subjects including 75 PPC practitioners. To our knowledge, this is the first study to apply human behavioral experiments with PPC practitioners. The remainder of this article is structured as follows. Section two provides a brief overview of the fundamental research on cognitive biases. Section three presents our experiment design in detail. Section four presents our findings and is followed by discussion and a conclusion in sections five and six.

2. Theoretical foundations and hypothesis development

Cognitive biases arise from mental shortcuts that are based on incomplete processing of available information and result in a systematic deviation from a rational optimum [15]. Building upon [8], [14] were some of the first to study humans' bounded rationality during the decision-making process and introduced the term "cognitive biases". Situations characterized by an uncertain decision environment and time pressure are particularly assumed to increase the effect of cognitive biases [16]. The underlying reason is the involvement of different regions of the human brain during decision-making. [17] described the two regions as System I and System II. System I is fast, automatic, emotional and effortless, while System II is slow, conscious, controlled and rational. Which of these two systems is involved in the decision-making process depends on the type of decision, the time horizon available and the familiarity with the decision being made [18]. Decisions which require fast thinking especially involve system I and are also known as "gut feelings". Such decision speed has its price. Active cognitive biases increase, resulting in bounded rationality [19].

According to Tversky and Kahneman cognitive biases mainly results from three heuristics which are representativeness, availability and adjustment and anchoring.

According to the representativeness heuristic people tend to assess the likelihood of an event according to their memory availability. The availability heuristics describes the human behavior of favor options where information can be restored easily. The adjustment and anchoring heuristics describe the human tendency to make a decision based on an initial set value.

Based on these initial categories, researchers identified further general heuristics such as the affect heuristic [20]. According to the affect heuristic people associate memories and events with their feeling and emotion. The affect heuristic is especially present in judgment decisions [21]. Over the years, researchers have examined over 100 different cognitive biases and developed several classifications [15], [22], [23].

Based on established PPC decision-making models such as the Aachener PPC model [24] or the PPC model of [25] researchers have identified several active cognitive biases in the human decision-making process during PPC decisions (see for instance, [26]). Based on the PPC decision-making situation such as decisions about production sequence, order release etc. as well as the decisional framework conditions such as familiarity with the decision-making situation, time availability etc. different cognitive bias effects occur [4].

The table below presents the most familiar, researched and relevant cognitive biases in PPC decision making with the respective underlaying heuristic [6], [27], [28].

Heuristic category	**Bias effect**	**Description**	**Reference**
Affect	Bandwagon effect	People' tendency to do something because many other people do the same	Carter et al., 2007; Bindra, 2022
Availability	Ambiguity effect	People's tendency to favor seemingly simple options and avoid seemingly complicated options	Ellsberg, 1961; Bendoly et al., 2006
Representativeness	Gambler's fallacy	People's tendency to assume that future events are determined by past events	Ayton, 2004; Barron and Leidner, 2010
Representativeness	Primacy-recency effect	People's tendency to recall the first and last items in a series best and items in the middle worst	Yates et al., 1986; Arnott, 2006
Adjustment & Anchoring	Anchoring effect	People's tendency to rely too heavily on the first piece of information - this affects other actions	Tversky and Kahneman, 1974; Eply and Gilovich, 2005
Affect	Confirmation bias	People's tendency to seek information that confirms their own opinions and to ignore information that contradicts their own beliefs	Tversky and Kahneman, 1979; Heath, 1996; Russo, 1996
Adjustment & Anchoring	Correlation bias	People's tendency to overestimate the probability of two events occurring	Bar-Hillel, 1993; Kahneman, 2003

		together if this has happened in the past	
Availability	Availability heuristic	People's tendency to overestimate the likelihood of the occurrence of events about which they can readily recall information	Tversky and Kahneman, 1979; Edland and Svenson, 1993; Stanovich and West, 2000
Affect	Illusion of control	People's tendency to overestimate their ability to solve difficult problems	Brenner et al. 1996; Hastie and Dawes, 2001
Affect	Prospect theory	People's tendency to assess gains and losses differently, preferring perceived gains over perceived losses.	Tversky and Kahneman, 1979; Fox et al., 2006

Table 1: Cognitive biases relevant to PPC decisions

Although, interest in the influence of the human factor in PPC has grown in behavioral operations management research [9], empirical evidence from behavioral experiments remains sparse [12]. [29] particularly criticize the focus on student experiments and the lack of practitioners involved in behavioral studies. Behavioral experiments make it possible to study the human factor and infer recommendations for real-life situations [30]. Further, experiments offer the possibility to identify causal connections and examining the effect of human behavior [11].

To our knowledge, our study is one of the first to contribute to closing this gap in the literature since the experiments we conducted with ninety-nine subjects included practitioners from PPC. Building upon the aforementioned cognitive biases identified in literature review we developed the following hypotheses as the basis for our experiments:

H1: The representativeness heuristic influences human decisions in PPC leading to a systematic deviation from a rational optimum based on the ability how information can be restored.

H2: The availability heuristic influences human decision-making process in PPC decisions in that way that people tend to stick to easily available information.

H3: Adjustment and Anchoring heuristics influence humans during PPC decisions leading to the fact that people stick closely to an initial given value.

H4: Humans during PPC decisions are influenced by their feelings and emotions leading to a systematic deviation from a rational optimum.

The influence of cognitive biases in conjunction with decision-making by practitioners and experts is the subject of controversy in the literature. Whereas some researchers claim that experts are immune to cognitive biases [31], [32], others have detected biases in decision-making among experts [33]. Research in medical and forensic literature particularly confirms that experts are also susceptible to biases in decision-making, albeit they require less effort to arrive at a decision because they can draw on a wealth of experience and are more experienced in the decision-making [34].
Therefore we hypothesis that:

H5: Regardless the level of experience humans in PPC decisions are influenced by cognitive biases.

3. Experimental Design

Behavioral experiments are well suited for testing and refining existing theory and transferring analytical models to real world problems [35]. [36] define four basic elements that ensure rigorous experimental design: (1) random selection of subjects; (2) random assignment of subjects to the different experimental conditions; (3) experimenter manipulation of the treatments and (4) experimenter control over the conduct of the experiment. We contribute to this topic with our experiment with ninety-nine volunteer subjects without regard to age, gender or level of experience. All subjects participated voluntarily in the same online experiment with an identical set of questions. We defined and manipulated the decision-making situations to test the specific hypotheses (biases). By possible selection of responses and automatic timeout the full control over the experiment was given. A high internal validity was achieved due to the laboratory-controlled setting. The high number of involved practitioners enable a practical transfer to the daily PPC business and develops several managerial implications [35].

3.1. Experimental Setting

We used Otree software to design an online experiment to test our hypotheses. We presented fourteen typical PPC decision situations with sixteen pertinent questions to the subjects. The entire set of questions with the corresponding production planning dashboard can be found in Appendix A.

At the beginning of the experiment, we asked four generic questions about age, gender, level of experience with PPC and industry sector for actively working subjects. We provided three categories level of experience for subjects to classify themselves: no experience with PPC, basic experience (less experienced PPC practitioners including undergraduate knowledge) and advanced experience (production planning practitioners). An introductory screen explained the specific items on the production planning dashboard before the experiment started. The overall experimental situation for each question was a production planning dashboard displaying typical data relevant to production, such as schedule adherence, resource utilization, machine malfunction, etc. and presented to the subjects with a typical PPC situation requiring a decision on their part. The following question is one example: *Your production planning system dashboard displays an overview of the current key production data. Since high delivery reliability is essential to high customer satisfaction, your company's management has focused on high delivery reliability. Delivery reliability has dropped continuously in the past two weeks, though. As a production planner, you must select one of the following possible actions to improve delivery reliability quickly. What will you do?*

The production dashboard evolved during the experiment and was different for each situation. One and a half minutes was allotted for each question. A timer displayed on each screen counted down time and turned red and popped up when the final thirty seconds began. This was intended to create time pressure and imitate a typical PPC decision-making situation, which normally requires quick decisions.

3.2. Production Planning and Control Dashboard Design

We analyzed and discussed different production dashboards in use with several practitioners to design the production planning and control dashboard presented to the participants during the experiment. We were interested in the information provided on the dashboard, the interface, e.g. font size, color, etc., and the relevant key performance indicators displayed. Our analysis revealed that the dashboards in use are highly customized and that different key performance indicators are relevant for each company, depending on their production process and products.

We consolidated the information gathered and designed a dashboard that includes all the relevant indicators and parameters we identified on the dashboards.

3.3. Design Pretest

During the initial design phase, we tested the experimental design with ten subjects, who did not participate in the final experiments later, to validate usability, understandability and the conditions. The subject were five women and five men aged twenty-two to forty-six with different levels of experience. Based on results of the test, we modified time and interface color. Since the subjects indicated that the original response time of thirty seconds for each question was not enough to even read the questions, we changed the time to one and a half minutes. We also changed the colors used for different information on the dashboard. For instance, the number of machines in operation and production orders had been displayed in red, creating the impression of a problem or warning. We therefore changed them to blue since they are solely information. Aside from that, wording was revised slightly to make it more understandable.

3.4. Subjects and Procedure

This study finally sampled ninety-nine subjects of different ages, genders and levels of experience with PPC. Due to the mix of the relevant parameters of age, gender and level of experience the data set of 99 is sufficient to validate our developed hypotheses. The table below presents precise information about the subjects.

		Age								
		<30 (n=47) Women: (n=13) Men: (n=34)			30-40: (n=34) Women: (n=14) Men: (n=20)			>40 (n=18) Women: (n=3) Men: (n=15)		
		Level of experience			Level of experience			Level of experience		
		None	Medium	High	None	Medium	High	None	Medium	High
Gender	Male (n=69)	8	24	2	3	12	5	4	7	4
	Female (n=30)	5	7	1	3	8	3	1	0	2

Table 2: Overview of subjects

We contacted individuals directly through social media but did not inform subjects about the actual aim of the study. We told them they were participating in an experiment to develop design guidelines for future production dashboards without mentioning our interest in their behavior and the influence of cognitive biases. This method was chosen to avoid any changes in the behavior of the participants. We collected data between November 2020 and June 2021. We excluded responses received from twelve of the 111 respondents from further analysis since they only answered the initial general questions about age, gender and level of experience. The final data set comprised ninety-nine subjects.

3.5. Experimental Situations

We created a PPC decision situation for each as cognitive bias identified as relevant, which we intended to study. The detailed experimental situation relating to the cognitive bias tested is described below.

Bandwagon effect: In this situation, the PPC planner was confronted with diminishing schedule adherence. Since schedule adherence is one of the key performance indicators in which

executives are most interested, the PPC planner is in charge of devising an appropriated strategy to improve schedule adherence. Four different options for improving schedule adherence were presented to the subjects. A small bar chart displayed next to the responses showed subjects other PPC planners' decisions in the same situation. We were interested in whether subjects were influenced by others' decisions.

Ambiguity bias: Here the production planner was confronted a production stop caused by insufficient material in the manufacturing line and had to decide what steps to take next. We presented two option. One seemingly simple option of just one sentence in length and a more detailed solution, which normally is more appropriate in this situation. The aim was to ascertain whether humans tend to choose the seemingly simple option or analyze the situation rationally and choose the more appropriate option.

Gambler's fallacy: We explained that two scenarios of a production disruption occur with the same likelihood, a machine breakdown (B) and a material delay (D). We asked subjects whether they considered sequence 1 DDDBDDDB, sequence 2 BDDBDDBB or neither of the sequences more likely. Since we made clear in the description of the situation that both events occur with the same likelihood, the correct answer would have been option three. We were interested in whether individuals based their decision on coin-tossing, as it were, i.e., assume past outcomes determine future outcomes.

Primacy-recency effect: We showed the participants three different dashboards, each of which represents one day in the work week. Afterward, we asked the subjects questions about the information displayed, such as the number of machine breakdowns or the schedule adherence on one specific day, to ascertain which information was recalled best.

Anchoring effect: We created several anchors in some PPC decision-making situations to investigate whether humans are influenced by predefined values. We described a situation with diminishing schedule adherence and asked the subjects whether they wanted to change the predefined values for throughput time. We designed four different decision-making situations with different numbers serving as anchors. The first question asked whether the subjects wanted to change scheduled lead-times or not and, if yes, by what percent? In a second question we manipulated the dashboard by having the of the number twenty pop up in various areas of the dashboard. Then, we asked the subjects again whether they wanted to change scheduled lead

times and, if yes, by what percent. We employed a different method of manipulation for the subsequent two questions. We manipulated a wheel of fortune on the right side of the current production planning dashboard to stop at the number ten for the first question and at the number forty for the next one. Afterward, we asked the subjects again whether they wanted to change planned lead times and, if yes, by what percent. We were interested in whether predefined set values influence human decision-making and whether the magnitude of the number plays a role.

Confirmation bias: We confronted the subjects with an excess of production material in production and a low level of incoming orders. Then, we asked if the subjects wanted to adhere to or change the inventory level they had originally selected.

Correlation bias: In this situation, we told subjects that they have two types of machines in their production unit, a new machine and an older one. The production line with the new machine has recently experienced problems. One of the main suppliers delivered severely defective raw material and the new machine broke down immediately afterward. We asked the subjects which monitoring strategy they wanted to apply, i.e., whether the wanted to monitor the line with the old machine or the line with the new machine in which quality issues are also a problem. We were interested in whether subjects assume there is a correlation between the delivery of defective materials and the breakdown of the machine, even though these events happened independently from each other and we had not mention any correlation between these two events in our description of the decision-making situation.

Availability heuristic: We again confronted the subjects with diminishing schedule adherence below the value required on the dashboard. We asked whether the subjects wanted to change scheduled lead times or not. We wanted to study whether subjects assume that diminishing schedule adherence could be resolved easily by modifying scheduled lead times, even though many more factors have an influence in reality and it takes a while for a change of the throughput time to take effect in production.

Illusion of control: In this decision-making situation, the subjects were still confronted with diminishing schedule adherence and fluctuating utilization of production capacity in the coming weeks. There will be fewer production orders than available production resources in the next week and production resources will be used to full capacity in the week after that. We again

asked the subjects whether they wanted to change scheduled lead times or not. Here too, we were interested in whether the subjects assume their own procedures are best.

Prospect theory: We created two decision-making situations about a supply chain disruption and a mitigation strategy to ascertain whether the subjects assess gain and loss differently in production planning situations. In each of the situations, they had to choose one of two options. For the supply chain disruption we gave them an option with a higher degree of uncertainty but a longer disruption and another option with a more secure but shorter disruption. To test the behavior regarding the mitigation strategy we presented an option with a more unsecure but a higher gain regarding the save of the disruption days and another option with a higher probability but also shorter time of reduction of the disruption.

4. Results

4.1. General Data Analysis

We employed a chi-squared test and analysis of variance (ANOVA), including a post hoc test to determine whether the group composition differs in terms of gender, age or level of experience [37]. We found that older subjects rated themselves as experts significantly more often than younger subjects *($p= 0.012; df=2; F=4.601$).* This is not surprising since a professional career including several years of college and practical experience needed to acquire expertise takes some time. We found no evidence that the composition of our sample affects our results.

4.2. Biased PPC Decision-Making

Since we were primarily interested in whether people making PPC decisions are influenced by cognitive biases, we analyzed our dataset without factoring in additional parameters such as age, gender or level of experience. We applied several binomial distribution and chi-squared tests and found evidence of virtually all the cognitive biases analyzed in our data. except for the ambiguity effect, the illusion of control and prospect theory, which we were unable to confirm based on our data. We selected a significance level of α=5%. The table below presents the findings for each cognitive bias.

	Sig a,b	**df**	**Test result**
Bandwagon effect	.001	3	H4: Biased decision-making confirmed
Ambiguity bias	.315	3	H2: Biased decision-making not confirmed
Gambler's fallacy	.013	2	H1: Biased decision-making confirmed
Confirmation bias	.001	3	H4: Biased decision-making confirmed
Availability heuristic	.000	3	H2: Biased decision-making confirmed
Correlation bias	.005	3	H3: Biased decision-making confirmed
Illusion of control	1.000	3	H4: Biased decision-making not confirmed
Prospect theory question I	.000	3	H4: Biased decision-making confirmed
Prospect theory question II	.051	3	H4: Biased decision-making not confirmed
Primacy-recency question I	.000	3	H1: Biased decision-making confirmed
Primacy-recency question II	.004	3	H1: Biased decision-making confirmed

Table 3: Findings for cognitive biases

We applied a different statistical method to analyze the anchoring effect since we had created two different manipulated situations. We were only interested in whether preset numbers themselves rather than the signs the decrease or increase throughput times influence human decision-making. We exponentiated the values and took the square root to obtain the value. We only analyzed the dataset for which we had responses to both questions, resulting in n=64 for the first anchoring situation. We employed an ANOVA with repeated measurement for the analysis since we tested the same subjects for both anchoring situations.

We performed Mauchly's sphericity test since sphericity is one of the most important requirements of an ANOVA analysis. Since the result of the Mauchly's sphericity test was not significant, the degrees of freedom did not have to be corrected downward. The analysis ultimately reveals a significant anchoring effect *(F=4.477, df=1, p=0.033)* since the average level of adjustment increases when the anchor is set at 20 (compared to *[M=6.7344;*

SD=6,92188; df=1] when no anchor is set and *[M=8.7344; SD=8.38790; df=1]* when the anchor is set at 20).

We also performed a repeated measure ANOVA for the manipulated situation with the wheel of fortune stopping at ten and forty. Here too we only analyzed data with a complete set of responses, resulting in n=54.

Here too the average level of adjustment increases significantly when the anchor is set (*[M=7,1481; SD=7,29282; df=2]* when no anchor is set, *[M=8,6111; SD=8,57248; df=2]* when the anchor is set at 10 and *[M=27,0185; SD=13,63471; df=2]* when the anchor is set at 40). Since Mauchly's sphericity test became significant (.000), the Greenhouse-Geisser correction was used to correct for violations of sphericity. The Bonferroni-adjusted post-hoc analysis yielded significant differences ($p<.001$) for the groups without an anchor and with the anchor set at forty. We additionally analyzed the effect size by using eta-squared for multivariate tests. [38] holds that the effect is discernible with .624.

Our research confirms that people are strongly influenced by the representativeness, availability, adjustment and anchoring as well as of the affect heuristics during their decision-making process in PPC decisions.

4.3. Is Level of Experience a Factor Influencing Cognitive Biases?

Controverse discussions in the literature about whether experts are immune to biases in decision-making induced us to analyze the data for the influence of level of experience.

First, we analyzed whether any correlations exist between age and level of experience. Since subjects rated their experience as none, medium or high, we analyzed whether more older subjects rate their level of experience higher. The descriptive statistical analysis based on an ANOVA analysis indicated a significance *(p=0.353; df=2).* An additional post hoc analysis based on Hochberg's method was performed. The results confirmed the correlation between age and level of experience, meaning older subjects rated their level of experience as high more often.

We were also interested in whether the level of experience influences the occurrence of cognitive biases, i.e., whether experts are immune to cognitive biases and whether individuals with no or basic expertise are susceptible to biases in PPC decision-making.

We therefore performed Pearson's chi-squared test since we had an expected frequency of less than five for zero cells of our contingency tables. Given the level of significance, the null hypothesis had to be discarded because the level of experience was not found to have any influence on the presence of cognitive biases.

We were unable to perform any other statistical analyses for the anchoring effect because the groups with complete sets of responses grew too small. As each question was closed after the given set of time the underlaying reason for the incomplete response set was that the participant run out of time and did not answer the question. However, the creation of time pressure was needed to create a real-life situation of PPC decisions.

	Value	**Asymptotic significance**	**Df**	**Nominal dimension Phi**
Bandwagon effect	0.521	.771	2	.073
Ambiguity bias	3.269	.195	2	.182
Gambler's fallacy	4.294	.368	4	.209
Confirmation bias	3.149	.207	2	.192
Availability imaginability bias	0.075	.963	2	.030
Correlation bias	0.233	.890	2	.052
Illusion of control	1.554	.460	2	.135
Prospect theory question I	9.003	.011	2	.325
Prospect theory question II	0.685	.710	2	.090
Primacy-recency question I	1.817	.403	1	.157
Primacy-recency question II	0.292	.864	1	.065

Table 4: Findings for level of experience

The findings confirm H5 that cognitive biases affect human-decision making in PPC regardless of level of experience.

5. Discussion

Our research demonstrates that cognitive biases heavily influence human decision-making in PPC.

This underscores the need to pay attention to the human factor in the design of smart factories. The growing use of decision support systems in various domains of industrial manufacturing makes consideration of the influence of cognitive biases essential [39]. Awareness and understanding of cognitive biases are the basis for the development of debiasing strategies, i.e., actions that reduce biases in decision-making [40].

The findings of our study indicate that level of experience has little influence on susceptibility to bias, thus corroborating [14]'s early study but conflicting with the findings of [31], [32] who assume that experts are less susceptible to cognitive biases than inexperienced individuals. Especially the anchoring effect has been confirmed in various fields of research and explicitly in various fields of operations management such as purchasing decisions, valuations, and inventory decisions [41]. In particular, the level of the anchor influences the degree of the bounded decision-making. [14], suggested that the higher the anchor the higher is also the proneness to biased decision-making. Our results of the anchoring effect also confirms this research as the medium average increases with the higher anchoring level.

5.1. Theoretical contributions

Our study makes several important contributions. First, we demonstrated that several cognitive biases influence human decision-making in PPC, we contributing much-needed experiments in the field of behavioral operations management in general (see for instance [12]). [42] criticize that less than 50% of the paper on behavioral operations management published include behavioral experiments and call for more. Experiments involving practitioners are rare [12], [9]. Our study responds to this problem by explicitly involving PPC practitioners, thus ensuring internal and external validity and reliability. Further our data set includes a mix of gender, age and level of experience which also reflects practical reality and contributing to high external validity. We demonstrate that cognitive biases influence the PPC decision-making situations described and thus operational key performance indicators, such as throughput time, schedule adherence and inventory level. Our results additionally demonstrate that even PPC practitioners are susceptible to biases in decision-making, thus underscoring the need to employ debiasing techniques when designing PPC decision support systems.

5.2. Practical contribution

Our research confirms that production planners' decision making is routinely influenced by various cognitive biases. Our study facilitates awareness creation, which is always the first step toward developing countermeasures. Better understanding of cognitive biases' active influence opens new opportunities to develop debiasing strategies. This is also relevant to programmers of decision support systems, who need design guidelines that factor in human needs. This is highly relevant for industrial practice as interest in the use of such decision support systems in the smart factories grows. Further this contributes also to the ongoing discussion in practice which decisions should be made by machines and which by humans.

5.3. Limitations and future research

This study has some limitations. Given the limited number of ninety-nine valid data sets overall and sixty-four and fifty-four for the anchoring effect, future research ought to focus on expanding the data set including the variables of gender, age and level of experience. Moreover, since cognitive biases often occur simultaneously and their effects sometimes overlap in practice rather than in isolation as described in literature, our findings might include several other cognitive biases we were actively analyzing, i.e., they may well be present in PPC decisions. Future research therefore ought to examine a more extensive set of cognitive biases and a larger population. Research on cultural factors in behavioral PPC experiments expanded to include international subjects would also be interesting. In the discussion about growing diversity in teams also the understanding of gender differences concerning the proneness to cognitive biases is important. In psychology and medicine the effect of gender on human decision-making has been investigated since a while. Exemplarily, [43] found in their research concerning the overconfidence bias that men are more influenced by this bias effect than woman. Also, [44] observed a lower risk aversion for men in decision-making than woman. Therefore, further research in the context of gender would be interesting.

6. Conclusion

Cognitive biases influence human decision-making in PPC, resulting in systematic deviations from a rational optimum. These deviations in decision-making also influence logistic performance, including schedule adherence and inventory level. The findings of our experiments indicate that even experts are susceptible to biases in decision-making. In the growing discussions about Industry 5.0 considering the human needs this research indicates how the human factor influences decisions in PPC and also affects operational performance.

Additional research on strategies to reduce the influence of these cognitive biases and decision-support systems for PPC planners would be helpful for practical recommendations as well as for design guidelines for these decision support systems.

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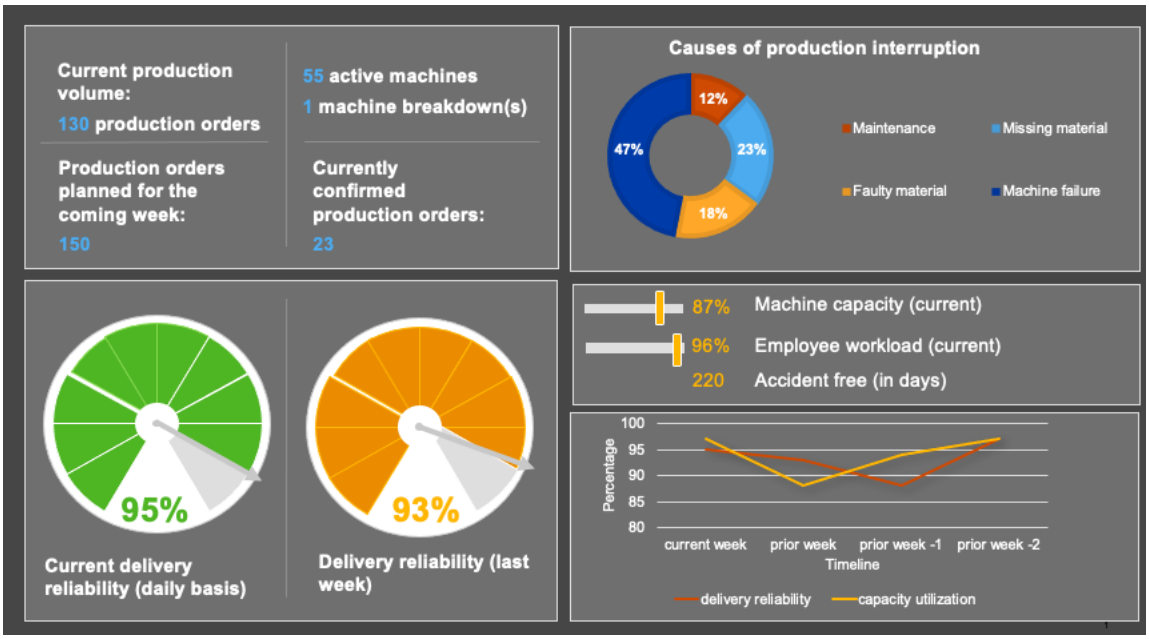
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Appendix A:

Sample dashboard for one question (translated from the German)



Overview of questions in the behavioral experiments (translated from the German)

1. General information

1.0 Email

_____

1.1 Gender

A) Male
B) Female

1.2 Age

_____

1.3 Do you have knowledge of production planning?

A) No
B) Yes – basic knowledge

C) Yes – advanced knowledge

1.4 Select your company's industry sector

A) Machinery and equipment manufacturing
B) Electrical and electronics manufacturing
C) Automotive manufacturing
D) Chemical industry
E) Pharmaceutical industry
F) Manufacturing/supply industry
G) Other

2. Specific production planning and control situations

2.1 Your production planning system dashboard displays an overview of your current key production figures in. Your company's management has focused on high delivery reliability since it is essential to high customer satisfaction. Delivery reliability has dropped over the last two weeks, though. You, the production planner, must select one of the following potential actions to improve delivery reliability quickly. What will you do?

A) Adjusting production lead times is an appropriate action in the short-term. The lead times will therefore by adjusted by 2%. New schedules for customers will only be confirmed with a later delivery date and production has more time to manufacture.
B) Nothing at all first. Since diminishing delivery reliability can have numerous causes, I will wait at first to see whether the situation improves on its own in the coming days before take further action.
C) Since adjusting production lead times is an appropriate action in the short term, lead times will be adjusted by 15%. New schedules for customers will consequently only be confirmed later and production will have more time to manufacture.
D) I will first start a detailed analysis of potential causes of declining delivery reliability.

2.2 Your production will stop in 2 hours because of a material shortage. What will you do?

A) I will order material from the warehouse for production as quickly as possible and take care of further analysis afterward
B) Since a material shortage can have many causes, a detailed analysis is necessary. Frequent causes in the past were late delivery of ordered material by the supplier. Further analysis also

revealed errors among the material expediters. The delivery date was not adjusted even though the supplier's notification of the buyer, and you, the production planner, were consequently unable to adjust the production order to the date of material availability. Increased reject rates have also caused shortages of material planned for the required output. Another cause, as in this case too, was quality defects of the required material delivered by the supplier. I will therefore have all the material in production and the warehouse inspected first and only acceptable material sent to production. At the same time, incoming goods will be analyzed.

2.3 Your dashboard displays the current status of your production. Production disruptions are one of the main parameters of efficient throughput times. The causes of production disruptions or even temporary stops are diverse. Machine failures (B) and delayed material deliveries (D) are some of the main causes with the same probability of occurrence. Employee absences due to illness or quality defects can also disrupt production. Indicate which sequence of events that causes production disruptions is more probable so that you can take appropriate countermeasures. Which option will you choose?

A) DDDBDDDB
B) BDDBDDBB
C) None of the sequences

2.4 (Different dashboards from three days are shown to subjects in succession)
Plan the current production based on yesterday's delivery reliability: How high was delivery reliability (in %) two days ago?

_____

2.5 (Different dashboards from three days are shown to subjects in succession) You have to report machine malfunctions to maintenance: How many machine malfunctions did you have yesterday?

_____

2.6 (Subjects are confronted with diminishing schedule adherence) You decide to adjust the lead times of the production orders. What percentage do you choose to change the lead times?

_____

2.7 (Subjects are confronted with diminishing schedule adherence, value of 20 is shown in different areas of PPC dashboard) You decide to adjust the lead times of the production orders. By what percentage will you change the lead times?

_____

2.8 (Subjects are confronted with diminishing schedule adherence; the wheel of fortune is manipulated and stops at 10 every time) You decide to adjust the lead times of the production orders. By what percentage more or less than the wheel of fortune will you change the lead times?

_____

2.9 (Subjects are confronted with diminishing schedule adherence; the wheel of fortune is manipulated and stops at 40 every time) You decide to adjust the lead times of the production orders. By what percentage more or less than the wheel of fortune will you change the lead times?

_____

2.10 Your dashboard displays the current status of your production. Based on your previous experience and the current planning figures, you ordered material for 200 products for manufacturing. Eighty customer orders have been received when production starts. Your material expediter now wants to know from you how to schedule the material.

A) You change your initial calculation and order exactly 80 to avoid high inventory.
B) You retain your original calculation of 200 to be able to handle short-notice customer orders as well.

2.11 Your dashboard displays the current status of your production. Your manufacturing unit has different production lines. Some of the production lines produce standard products and obtains its materials mainly from the adjacent storage area. Another production line produces custom products with a wide range of options, the supplier delivers materials directly to the line. Two months ago, supplier L delivered material with substantial quality defects to the line. Shortly after, the type 101 machine, which was just one year old, broke down and production was stopped for five days with serious consequences for delivery reliability. The ten-year-old type 102 machine in the standard line is being used for manufacturing. There have not been any incidents on this line so far. Your company was unable to deliver numerous customer orders on time because of the production disruption, resulting in a substantial loss of revenues because of cancelled orders

and penalties. Your company's management is demanding a measure for rigorous monitoring. What will you do?

A) The type 102 machine might experience a disruption in the near future since it is already ten years old and has experienced one to date. A monitoring system will be installed specifically for this machine
B) Since supplier L, one of the main suppliers, delivers material to the custom production line on a daily basis, rigorous monitoring must be introduced to prevent another breakdown of the type 101 machine.

2.12 Your dashboard displays the current status of your production. Management board designated delivery reliability the most important control indicator. You have taken various actions to improve it. Delivery reliability is nevertheless currently still below the value (> 93%) demanded by management. What will you do?

A) I will adjust the lead time.
B) I will retain the originally calculated lead times.

2.12.1 By what percentage will you adjust the lead time?

_____

2.13 Your dashboard displays the current status of your production. For days, you have been struggling with declining delivery reliability in production. Fewer orders are currently entered for the coming week. The following week is already filled to capacity with production orders, though. What will you do?

A) I will adjust the lead time.
B) I will retain the originally calculated lead times.

2.13.1 By what percentage will you adjust the lead time?

_____

2.14 Your dashboard displays the current status of your production. Production disruptions are a major confounding variable in efficient production operations and directly affect lead time. If you had a choice, which option would you choose?

A) Production will be disrupted for ten days with a probability of 20 %.
B) production will be disrupted for five days with a probability of 90%.

2.15 Your dashboard displays the current status of your production. Production disruptions are a major confounding variable in efficient production operations and directly affect lead time. If you had a choice, which option would you choose?

A) The selected countermeasure will reduce the production disruption by ten days with a probability of 20%.
B) The selected countermeasure will reduce the production disruption by 5 days with a probability of 90%.

7. Discussion and Contribution

This thesis intends to investigate how cognitive biases influence human decision-making and its results on operational performance in the two core areas of operations management, namely PPC and SCRM. The three related sub-research questions as well as the overarching research question are addressed in detail by the different research papers. The following sections discusses the contribution and show which research paper contributes to which specific research questions.

7.1 Theoretical Contribution

This thesis makes several important theoretical contributions regarding the predefined research questions.

(1) *Which decision types in PPC and SCRM are affected by cognitive biases with respect to operational performance?*

Although behavioural operations management has gained increasing interest among researchers and there are an increasing number of publications in this research field (see, for instance, Bendoly et al. 2006, Tokar, 2010, Fahimnia et al. 2019), some questions regarding human decision-making are an open research avenue.

In Papers 3 and 4, the literature streams of psychology and operations management are combined to derive the relevant decision types for each sub-area of operations management as well as the relevant cognitive bias effects.

In psychology, the research on human decisions-making and bounded rationality has a long history and is quite well researched. Several researchers have investigated the environmental conditions, such as time frame, involved parties or familiarity with the decision situation to develop several types of decisions depending on these factors (see, for instance, Simon et al, 1987; Klein, 1991; Wickens et al., 2013). Although the general idea of biased decision-making has been adapted to the field of operations management, the specific distinction depending on the decision type has been omitted (Bendoly et al., 2010). The conducted combination of the literature streams of psychology and operations management as well as the developed framework contribute to this issue. Based on the specific and typical decision-making situations in supply chain and supply chain risk management as well as in production planning and control, the most important and most influencing cognitive bias effects were determined. Over

the years, several classification models have been developed to structure the plenty of investigated cognitive bias effects (see, for instance, Arnott, 2006, Benson, 2016). However, the existing literature often focuses on one single effect without considering interrelationships with other effects. Nevertheless, in practice these effects never occur as concretely as described in the literature. Rather, they overlap or occur together with other effects (Tversky and Kahneman, 1979). Therefore, this thesis contributes to this issue by considering various cognitive bias effects of all relevant categories and also several effects of one cognitive bias category within one research step.

This understanding is especially relevant for the future development of decision support systems with a focus on the increasing integration and collaboration of human and machine work. Resulting from the increasing level of digitalisation, which also evokes new risks, an adequate supply chain risk management that addresses these new risks is vital (Ivanov et al., 2018). However, current SCRM models lack the influence of biased human-decision making on risk management activities (Ghadge et al., 2012). The developed hypotheses in Papers 2 and 4, based on the structured literature review and the case study analysis, enhance these models by integrating a human-centered perspective.

(2) How do cognitive biases affect different decision-making types and situations in operations management with respect to operational performance?

In Paper 3, a systematic mapping of decision types, decision-making situations and relevant cognitive biases, especially in the PPC environment, is developed. This also forms the basis for the development of the concrete decision-making situations for conducting the behavioural experiments which are described in detail in Paper 5.

Thereby, it was important to have different decision types and typical decision-making situations from practice in order to generate a high external validity and strong generalisability. In Papers 3 and 4 also testable hypotheses based on this aggregation and on the combination with existing literature are derived.

Therefore, existing PPC (Wiendahl et al., 2005, Schuh and Stich, 2012) and SCRM models (Manju and Metzner, 2008; Tummala and Schoenherr, 2011) are extended with the mapping of relevant decision-making situations depending on the specific PPC and SCRM tasks based on classification models of decision types of psychology (Orsanu and Fischer, 1997, Wickens et al., 2013). The mapping is completed with the addition of the relevant cognitive bias effects. The in depth-case analysis of a German steel manufacturer in the context of PPC (Paper 3) as

well as the multiple cases analysis of digitalisation projects with regard to applied risk management activities (Papers 2 and 4) show how biased decisions influence operational performance. As a result, in PPC this often leads to higher WIP levels and decreasing due date reliability. This thesis thereby confirms the results of research on the LTS (Häussler, et al., 2021, Bendul and Knollmann, 2016, Selçuk, B., et al., 2006) and offers a more detailed perspective of the underlying factors of human behaviour that lead to a decreasing operational performance.

In risk management as a consequence of biased decision-making, risks are missed or completely ignored, their likelihood of occurrence is misinterpreted, and inadequate mitigation strategies are applied. The case study analysis and the expert interviews which were the focus of research in Papers 1, 2 and 4 confirm this operational performance impact. The analysed cases and the developed framework (Papers 1, 2 and 4) therefore extend the research on human behaviour in risk management (see for instance Brocal et al., 2019, Sarafan et al., 2019) and allow the definition of more nuanced risk management activities.

(3) How can debiasing techniques be reflected in decision-support systems in operations management in order to improve operational performance?

The results of the behavioural experiments confirm a strong influence of cognitive biases on human decision-making in operations management, even for practitioners. These profound results, as well as the trend towards an increasing collaboration of machines and the human worker, make the definition of adequate debiasing techniques absolutely inevitable. Philips-Wren (2020) criticizes the focus on computational architecture issues in the context of the design of decision support systems and the lacking human perspective. However, especially with the increasing collaboration level between humans and machines, a human-centered design of decision support systems is becoming more and more vital (Neumann et al., 2021). This thesis contributes to this issue by adding a human-centered perspective to the proposed design frameworks in existing literature (see, for instance, Arnott et al. 2006; Arnott et al., 2019; Mora et al., 2005; Philips-Wren, 2020). Based on a more general view of the influence of cognitive biases on human decision making in operations management research so far, also the proposed debiasing techniques are of a more general nature (Bhandari et al., 2008). Due to the developed specific mapping to typical PPC and SCRM situations, the proposed debiasing techniques in this thesis are specific, depending on the decision type, and offer a more detailed perspective of the single effects. The proposed frameworks and debiasing techniques are first

recommendations for decision support system researchers on how to reflect these techniques in the design of such systems.

Summarizing the results of the three sub-research questions to the main research question: *How do cognitive biases influence human-decision making in operations management with regard to operational performance?* several important contributions can be derived.
First, the results from the structured literature review as well as the case study analysis indicate a strong influence of cognitive biases on human-decision making in operations management that leads to a deterioration of operational performance. The proposed frameworks, integrating the human perspective for PPC and SCRM, extend current existing models and contribute to the criticism by researchers that the benefits of Industry 4.0 are completely detached from a human perspective (Neumann et al., 2021). The conducted experiments with 99 participants, including 75 practitioners, confirm that the influence of cognitive biases on human decision-making leads to a systematic deviation from a rational optimum. In this context, the influence of cognitive biases on experts is discussed controversely in the literature. The results of the experiments in this thesis confirm that also experts are prone to biased decision-making. This finding contributes to the findings of (Montibeller and von Winterfeld, 2015 and van den Eeden at al., 2018) and emphasises how important the consideration of the human perspective in operations management models is in order to improve operational performance.

7.2. Practical Contribution and Managerial Implications

Despite Industry 4.0's huge potential, the vision of what it can offer has so far remained unfulfilled. Industrial practice strives to unlock these possibilities in order to achieve the expected productivity and efficiency gains. An adequate risk management which addresses these new risks is therefore essential. The proposed framework of Paper 1 is intended to support managers to understand the different risks which occur during a technology implementation project. Thereby, the presented risks are differentiated in the implementation and operation phase to enable a nuanced development of risk mitigation actions. Further, the presented risks help managers to develop a deeper understanding of the Industry 4.0 technologies and their associated risks. The special focus on the new Industry 4.0 technology-related risk profiles, such as cyber risks, support managers in the defining of adequate mitigation strategies addressing these new risks. Thereby, also first practical recommendations are proposed in order to support this process. As Industry 4.0 also triggers changing conditions at supply chain and organizational level through a higher interconnectivity, it is also necessary that risk

management addresses these arising risks. Therefore, also first practical recommendations are presented. In Research Paper 2, these recommendations are extended with further details as well as the specific focus on the level of human-machine interaction. The findings show how biased human behaviour even leads to a reinforcement of risks and gives first practical recommendations for consideration of this aspect in the definition of risk mitigation activities. In the field of risk management, the findings and the various practical examples give managers implications for their risk management activities. Particularly for the different phases of risk management, the relevant cognitive bias effects and the consequences are presented in detail. These implications and recommendations for each phase of the risk management activities can be used for implementing an adequate supply chain risk management. Particularly, the special focus on digitalisation projects gives recommendations for dealing with risk factors and special biases occurring in relation with new technologies, which helps managers to address these new risks in an adequate manner.

Further, the proposed debiasing techniques can be used to integrate these into the organisational context as well as design guidelines which can be used in the programming for decision support systems. Neumann et al. (2021) criticizes the lack of human perspective in current operations systems and claims that this is a major stumbling block towards using the full digitalisation potential. As an underlying factor they named the fact that due to the lack of attention given to human needs, digitalisation remains for most workers a black box, with the result that they do not participate in the development. The European Commission (2021) has begun to promote the concept of Industry 5.0 with a focus on human-centered design that will lead to a more sustainable and more resilient industry. Indeed, the findings within this thesis confirm this needed shift towards the Industry 5.0 concept with attention being given to human behaviour.

Also, in PPC practice, Bendoly et al. (2010) claim that some theoretical models still fail in practical use due to the lacking human perspective in these models. The framework proposed inf research paper 3 contributes to this criticism and shows how human behavioural aspects can be integrated into PPC. Research so far has strongly concentrated on the impact of cognitive biases in the context of high risk and uncertain decision-making situations. This thesis extends this research to include a wide set of typical decision-making situations in PPC with different environmental situations. Further, the impact of cognitive biases on operational performance is shown. Especially, the conducted behavioural experiments with 99 participants, including 75 PPC practitioners, show in detail the impact of biased decision-making within PPC and confirm that even experts are not immune to biased decision-making.

7.3 Limitations and further research

Even though this thesis makes several important contributions, it has its limitations and reveals an avenue for further research in the field of operations management.

The case study analysis based on expert interviews, which is applied in Papers 1, 2 and 4, is strongly influenced by the personal experiences of the interviewees. Further, the database "Industrie 4.0 Plattform", which was the basis for the case study and for the selection of experts for the interviews, is biased towards successful cases. Even though a wide variety of companies are represented by cases on the platform, there is a huge majority of small and medium sized enterprises, as these companies represent the majority of companies in the German economy and offer most workplaces for the German industry.

Further research in this field should therefore be extended by Delphi studies, surveys, or other databases to validate the data set and test the hypotheses. As the database is limited to German companies and experts, the research should also be extended to other major industry nations. Platforms similar to the "Industrie 4.0 Plattform" also exist in France and Japan. Their existence could be used as a first starting point for further research activities in an intercultural context. Thereby, the economic structure with regard to the company sizes as well as the cultural behaviour towards risk management activities and digital applications can be addressed.

Concerning the digital applications, we chose a general risk management approach, which might not apply to all available digital technologies. Some specific Industry 4.0 technologies might have different risk profiles (Pereira and Romero, 2017). The research here can be extended by a dynamic feedback loop between human, technology and emerging risks. Further, our research and the proposed hypotheses could be used as a basis and be further validated by analysing a wide range of digital applications. In the context of the managerial responses to risk management, our study is limited to the impressions of the managers. It would be interesting in further research to extend this from a triadic view-point: employee-digital technology-manager.

As our research activities in the context of supply chain risk management are limited to German cases, also here the extension to further countries would be interesting. Especially, due to the fact that Germany has a relatively high uncertainty avoidance, it would be interesting to extend the research to cultures with a low uncertainty avoidance.

One point which applies to the whole research process and therefore to all papers is that cognitive bias effects in practice never occur as concretely as described in the literature. Rather, they overlap or influence each other, or one situation can involve the influence of several effects. Therefore, some of the findings might need a readjustment or further validation.

Particularly for those effects where no evidence could be provided based on the available data set, this does not mean that there are no existing cognitive biases in practice.
The data set of 99 participants with the involvement of 75 PPC practitioners in the behavioural PPC experiments is also limited and should be extended in further research with a larger data set. For some analyses therefore the distinction in gender, age and level of experience could not be statistically validated in our research, as the groups became too small. In further research this data set should be enlarged and the focus on the three parameters should be included in further analysis. The findings on the cognitive bias effects as well as the proposed recommendations and debiasing techniques serve as a starting point for further research in the area of the design of PPC systems. Due to increasing digitalisation, especially the design and user experience of digital application are becoming more and more important. In particular for those tasks with a close collaboration between the human and machine, a human-centric design and user-friendly interaction is imperative for a high acceptance rate by humans. Therefore, the results of our research could be especially interesting for user experience designers.
Further, our results are limited to the areas of PPC and SCRM, which are only two areas of operations management. As in various other areas, such as supplier selection, logistics, inventory management, quality management, etc., several human decisions have to be made, it would be interesting to extend this research to other fields. In some of these (e.g.,in supplier selection, see, for instance, Carter et al., 2007; Kaufmann et al., 2010) first indications of a strong human behavioural influence on the decision results have been investigated. The proposed experimental setting could here serve as a basis and could be adapted to the specific decisions in the respective operations management area for further research.
The experimental design, especially the creation of the PPC dashboard, could also be used as a basis for testing different debiasing techniques. Thereby, possible debiasing techniques could easily be integrated into the experimental setting. As the experimental setting was static, it would also be interesting to extend this research to a dynamic simulation study. Thereby, the feedback loops could be integrated to show the effects on operational performance in more detail. Also, the practical recommendations regarding the debiasing techniques could be integrated into this simulation study.

In 2021 Daniel Kahneman, Oliver Sibony and Cass Sunstein published in their book “Noise” their latest research results on further influencing factors of human decision-making. Thus, they opened up a new research field for which the results of this thesis could also serve as a basis.

Based on the previous research work of the influencing factors of cognitive bias by Amos Tversky and Daniel Kahneman, the latter intensified his research with his two co-authors in the area of distorting factors in human decision-making.

Whereas cognitive biases lead to a systematic deviation from a rational optimum, the authors found that the so-called "noise" factors also distorted decisional results but in an unpredictable way. A variety of random factors, such as daytime, the current mood, the results of a favourite football team, etc., which belong to the personal preferences of the decision-maker, influence the decisional results. They started gathering first practical evidence in the insurance industry, in medicine and among judges in the adjudication process. Extending the research results of this thesis with the aspect of "noise" would be interesting, especially the transferring of these results to the context of SCRM and PPC. The designed behavioural experiment setting in the context of PPC could therefore serve as a basis which can be extended by further situations referring to the factors of noise. Further, based on the proposed decisional types which occur in operations management, it would also be interesting to investigate the interrelationship between noise and cognitive bias effects. As Kahneman et al. (2021) also recommend in their book the introducing of a standardised process for decision-making within organizations, the extension of this thesis with regard to noise could also be an interesting research field for decision support systems designers to integrate into the architecture of the systems.

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