Towards Trustworthy Usage of Indoor Positioning Data in Manufacturing Simulation

Zur vertrauenswürdigen Verwendung von
Innenraum-Positionsdaten in der Fertigungssimulation

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Abstract

The usage of data from Indoor Positioning Systems (IPSs) within manufacturing simulation presents both challenges and opportunities. This dissertation explores the potential applications of IPS in manufacturing and focuses on utilizing IPS data for simulation studies. The research systematically gathers and organizes use cases through a structured literature review, revealing a significant yet largely unexplored potential for IPS in manufacturing by highlighting manifold benefits beyond mere localization. Additionally, on-the-ground examination of IPS applications in a sheet-metal manufacturing environment reveals associated challenges, particularly ethical and technical dimensions, underscoring the necessity of examining the trustworthiness of IPS data usage.

A framework is developed to enrich IPS data for simulation parameterization and input modeling, tailored for the sheet metal industry. The framework addresses the absence of directly applicable standards by refining existing data models and standards, providing a structured approach transferable to similar industries and discrete production systems. A qualitative analysis demonstrates the framework's potential to enhance data quality in manufacturing simulation across various dimensions, highlighting the spatio-temporal nature of IPS data as an untapped resource.

Furthermore, an ex-ante trustworthiness assessment of the framework is conducted using the Z-Inspection® process, identifying ethical issues and tensions associated with IPS-based simulation systems in manufacturing. Recommendations for improving trustworthiness are gathered, advocating for responsible and ethical development and deployment of IPS in the simulation framework. The findings contribute to enhancing ethical considerations in manufacturing simulation, with implications for industry practice and future research.

The dissertation identifies future research directions in advancing data modeling and analysis techniques, standardizing trustworthiness assessment processes, and quantifying and ensuring the trustworthiness of IPS-based simulation systems.

Zusammenfassung

Die Nutzung von Indoor-Lokalisierungs-Daten in der Fertigungssimulation birgt sowohl Herausforderungen als auch Chancen. Diese Dissertation untersucht die potenziellen Anwendungen von Indoor-Lokalisierungs-Systemen (engl. IPSs) in der Fertigung und konzentriert sich auf die Nutzung von IPS-Daten für Simulationen. Dafür werden systematisch Anwendungsfälle durch eine strukturierte Literaturrecherche gesammelt und ein bedeutendes aber weitgehend unerforschtes Potenzial für IPS in der Fertigung aufgezeigt, indem vielfältige Vorteile, die über die reine Lokalisierung hinaus gehen, verdeutlicht werden. Darüber hinaus offenbart eine Untersuchung von IPS-Anwendungen in einer Blechfertigung praktische Herausforderungen mit sowohl ethischer als auch technischer Dimension, welche die Notwendigkeit einer Prüfung der Vertrauenswürdigkeit der IPS-Datennutzung unterstreichen.

In dieser Arbeit wird ein Konzept entwickelt, um IPS-Daten für die Parametrisierung und Eingangsmodellierung von Simulationen zu nutzen, was dann am Beispiel der Blechindustrie vorgestellt wird. Da bestehende Datenmodelle und Standards dafür nicht genutzt werden konnten, wurde ein strukturiertes Vorgehen entwickelt, um diese für den Anwendungsfall der Blechindustrie und vergleichbare diskrete Produktionssysteme anwendbar zu machen. Eine qualitative Analyse zeigt das Potenzial des Konzepts zur Verbesserung der Datenqualität in der Fertigungssimulation auf und verdeutlicht das bisher ungenutzte Potential von IPS-Daten.

Das vorgestellte Konzept wird anschließend unter Verwendung des Z-Inspection® Verfahrens einer ex-ante Vertrauenswürdigkeits-Bewertung unterzogen, bei der ethische Probleme und Spannungen identifiziert werden, die mit IPS-basierten Simulationssystemen in der Fertigung verbunden sind. Empfehlungen zur Verbesserung der Vertrauenswürdigkeit werden gesammelt, welche die Basis für die verantwortungsvolle sowie ethische Entwicklung und Anwendung von IPS im Simulationssystem dienen. Die Ergebnisse tragen zur Verbesserung der ethischen Aspekte in der Fertigungssimulation bei und haben Auswirkungen auf die industrielle Praxis und zukünftige Forschung.

Die Dissertation identifiziert zukünftige Forschungsschwerpunkte, wie die Weiterentwicklung von Datenmodellierungs- und Analysetechniken für IPS-Daten, die Standardisierung von Prozessen zur Vertrauenswürdigkeits-Bewertung sowie die Quantifizierung und Sicherstellung der Vertrauenswürdigkeit von IPS-basierten Simulationssystemen in der Praxis.

Contents

Acronyms

AAS Asset Administration Shell

ANN Artificial Neural Network

AGV Automated Guided Vehicle

AI Artificial Intelligence

APS Advanced Planning and Scheduling

ASMG Automated Simulation Model Generation

CAD Computer-Aided Design

CAM Computer-Aided Manufacturing

CMSD Core Manufacturing Simulation Data

EDD Earliest Due Date

ERP Enterprise Ressource Planning

FIFO First In First Out

GAN Generative Adversarial Network

GDPR General Data Protection Regulation

HPN Highest Priority Number

ID Identifier

IPA Institute for Production Engineering and Automation

IMU Inertial Measurement Unit

JSON JavaScript Object Notation

KPI Key Perfomance Indicator

MDA Manufacturing Data Aquisition

MES Manufacturing Execution System

ML Machine Learning

MTBF Mean Time Between Failures

MTTR Mean Time To Repair

NC Numeric Control

OPC UA Open Platform Communications Unified Architecture

PPC Production Planning and Control

PLM Product Life-Cycle Management

RFID Radio-Frequency Identification

RL Reinforcement Learning

IPS Indoor Positioning System

SMP Sheet Metal Processing

SPT Shortest Processing Time

SISO Simulation Interoperability Standards Organization

UML Unified Modeling Language

UWB Ultra-Wideband

VDI Verein Deutscher Ingenieure (engl. Association of German Engineers)

WIP Work-In-Process

XML eXtensible Markup Language

Chapter 1

Introduction

In the realm of manufacturing simulation, the integration of Indoor Positioning System (IPS) data presents both challenges and opportunities. On one hand, leveraging IPS data offers the potential to revolutionize manufacturing processes by providing real-time insights into the movements and interactions of objects and personnel within production environments (Mieth et al. 2019a; Hayward et al. 2022). This data can significantly enhance the accuracy and granularity of simulation models, enabling more precise analyses and optimizations (Mieth et al. 2019b; Tran et al. 2021). However, the effective utilization of IPS data in simulation studies also poses significant challenges (Thiede et al. 2021; Flossdorf et al. 2021). These include the efficient and seamless enrichment of IPS data with meaningful context information, ensuring the accuracy and reliability of the derived simulation inputs through the development of suitable analytical methods, and addressing ethical concerns such as user privacy, fairness, and the respect for human autonomy. Despite these challenges, the promise of IPS data in manufacturing simulation underscores the importance of exploring its potential and developing strategies to ensure trustworthiness.

1.1 Scope of this Dissertation

Indoor localization is a promising technology that has been increasingly adopted within production systems over the last few years (Pilati et al. 2022; Gerwin et al. 2022; Thiede et al. 2022). These systems are primarily developed to support the finding of objects and thus reduce non-value adding search times on the shopfloor. However, the resulting data, known as spatio-temporal trajectories of tracked objects, offer potentials that extend beyond simple locating and finding. So far, these potentials have not been sufficiently explored, prompting this dissertation to aim to provide an overview of the potentials of IPS in manufacturing. This is reflected by the first research question, which will be answered in Chapter 4 with an extensive literature review.

Research Question 1: Which are the usage potentials of IPS and their data in manufacturing?

Subsequently, attention is directed toward a specific potential: the utilization of IPS data in manufacturing simulation. This focus arises from the author's professional involvement as the leader of the smart factory simulation team at TRUMPF machine tools, providing firsthand insight into the laborious nature of data collection and input modeling for simulation projects. This observation resonates with existing literature, which consistently identifies data quality as a primary challenge in simulation studies (Bokrantz et al. 2018; Bärring et al. 2018; Reinhardt et al. 2019). Given this backdrop, the prospect of leveraging IPS data to surmount this challenge emerges as an appealing avenue for research exploration.

Research Question 2: How can IPS data be used for manufacturing simulation?

A framework will be presented in Chapter 5 which enriches IPS data with context information to allow for more detailed analyses and provide high-quality inputs for simulation model generation and parameterization. The sheet metal industry serves as the investigation environment for which an industry-specific data model is derived. This choice is due to the fact that the author commenced her dissertation in cooperation with TRUMPF machine tools, a company that develops machines for flexible sheet metal manufacturing. TRUMPF is increasingly interested in holistically optimizing shop floor operations of its clients with the help of digital technology and simulations.

While improving data quality in manufacturing simulation is an important aim of this work, there is also a focus on the trustworthy usage of IPS data. This is crucial as IPS data can provide insights into worker movements (Thiede et al. 2022) and productivity (Zhong 2019), which can be easily exploited within the power dynamics and hierarchies in production systems, especially between blue-collar and white-collar workers. This leads to the third research question:

Research Question 3: How can the trustworthiness of a framework for utilizing IPS data in manufacturing simulation be assessed and ensured?

For Artificial Intelligence (AI)-systems, the EU High-Level Expert Group on AI (European Commission and Directorate-General for Communications Networks, Content and Technology 2019) state three requirements for trustworthiness which should be fulfilled over a system's entire life cycle:

- Lawfulness: Compliance with the laws and regulations
- Ethics: Adherence to ethical principles and values
- Robustness: Avoidance of (un)intentional harm both from a technical and social perspective

This work will focus on the ethics component of trustworthiness in the assessment in Chapter 6. The framework will be examined ex-ante, i.e., before it is being implemented. Technical robustness cannot be tested prior to the start of implementation and should be the focus of another future assessment. The social aspect of robustness will be covered by the ethical assessment as issues regarding societal and environmental well-being are collected and analyzed. The lawfulness component of trustworthiness is out of scope for this work. It would have required another set of expertise of the investigators to accurately evaluate the legal aspects of the framework. Moreover, the field of regulating AI is very dynamic at the moment with ongoing discussions regarding future legislation like the European AI Act leaving uncertainty and room for interpretations that hinder a solid compliance assessment at the time when the assessment was undertaken (2022).

1.2 Outline

In the following, the structure of the work is described as shown in Figure 1.1. After this first introduction chapter, the motivation and necessity for the research are derived in the two consecutive chapters.

- In Chapter 2, the environment of Sheet Metal Processing (SMP) is introduced, highlighting its key characteristics, basic production steps and the forms of organization. Subsequently, Production Planning and Control (PPC) are elaborated upon, with a specific focus on PPC targets and processes. The chapter also discusses rule-based production control, emphasizing its prevalent use in sheet metal industry production systems and its necessity in accurately replicating the behavior of SMP systems in simulations.

- In Chapter 3, the critical role of data in simulation studies and the challenges associated with its management, particularly focusing on data quality, are explored. The limitations of traditional data sources in accurately capturing dynamic processes are highlighted. Furthermore, through a literature review, existing information models are identified, revealing a lack of a standardized solution. This necessitates the adaptation of these existing standards to accommodate specific SMP domain requirements in simulation studies.

The core contribution in the main body of this dissertation is presented in three chapters. Each of these chapters answers a research question, which is depicted on the right side next to the chapter title in Figure 1.1. Chapter 4 first contains some fundamentals on IPS before it focuses on answering the research question on the potentials of this technology.

- Chapter 4 provides an overview of IPS and their relevance in manufacturing. It begins by introducing the fundamental concepts of IPS technology and discussing the essential requirements for its effective implementation. The chapter explores various technologies, with a focus on Ultra-Wideband (UWB) technology's advantages in SMP. Furthermore, it examines how IPS not only facilitates object localization but also offers additional benefits through the data it collects. A structured literature review categorizes manufacturing use cases of IPS and identifies the need for more research and awareness regarding privacy. Lastly, the chapter discusses technical and ethical challenges related to integrating IPS into sheet-metal manufacturing processes.

- This Chapter 5 introduces a framework that utilizes an IPS as the central data harmonizer, designed to integrate production data into a manufacturing simulation from a single source of truth. A simulation data model tailored for the

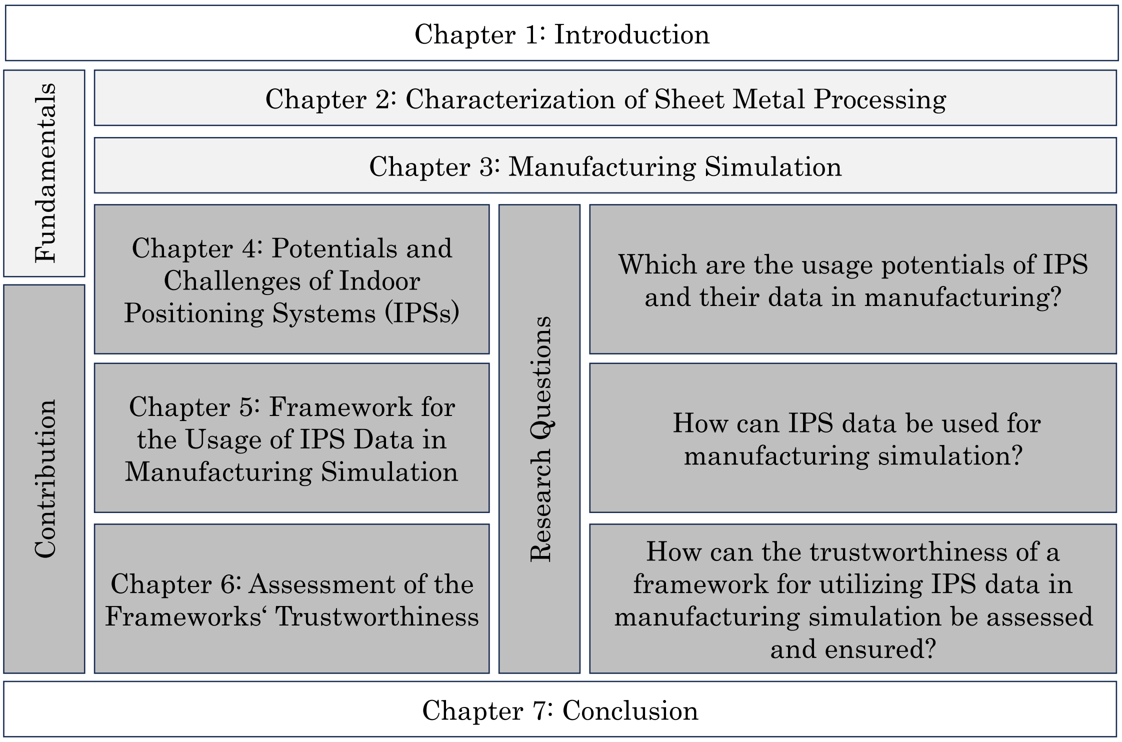

Figure 1.1: Structure of this work: Overview of the seven chapters with the corresponding research questions.

sheet metal industry is developed, forming the core of the framework. Additionally, socio-technical scenarios are introduced to describe the environment in which the framework will operate, illustrating the interaction between humans and technology within the production system. Lastly, the framework's contribution to enhancing overall data quality in manufacturing simulation using data quality dimensions is discussed.

- In Chapter 6, an ex-ante assessment for trustworthiness of the presented framework is performed, which means that the evaluation occurs before the system is developed and deployed in production, ensuring responsible use of IPS technology for improving manufacturing simulation. The assessment uses the Z-Inspection® process, which is the first process to assess trustworthy AI in practice (Zicari et al. 2021). Through expert workshops, issues and tensions are identified, grouped, and mapped to ethical principles. Recommendations are gathered to address these issues during implementation. Insights gathered on the process are provided to improve future trustworthiness assessments.

The last chapter concludes this dissertation's work. It summarizes the findings concerning the research questions and emphasizes the primary outcomes in the first section. The relevance and impact of the results for practice and research are discussed subsequently. Lastly, an outlook on future research directions is provided.

Chapter 2

Characterization of Sheet Metal Processing

This chapter explores Sheet Metal Processing (SMP), discussing its basic steps (Section 2.1), organizational forms (Section 2.2), and Production Planning and Control (PPC) principles (Section 2.3).

2.1 Fundamentals of Sheet Metal Processing

Sheet metal products are ubiquitous (Rinciog et al. 2020) and needed in many industries (Kashid and Kumar 2012) such as automotive, consumer electronics, and mechanical engineering. There are various examples of sheet metal products in the Business-to-Business market like heating and ventilation, land and construction machinery, switch and server cabinets, and industrial kitchens, but also for the Business-to-Customer market like jewelry, furniture, and lamps. A sheet metal product can be either a two- or three-dimensional object consisting of two- or three-dimensional parts manufactured from sheet metal. Examples are depicted in Figure 2.1.

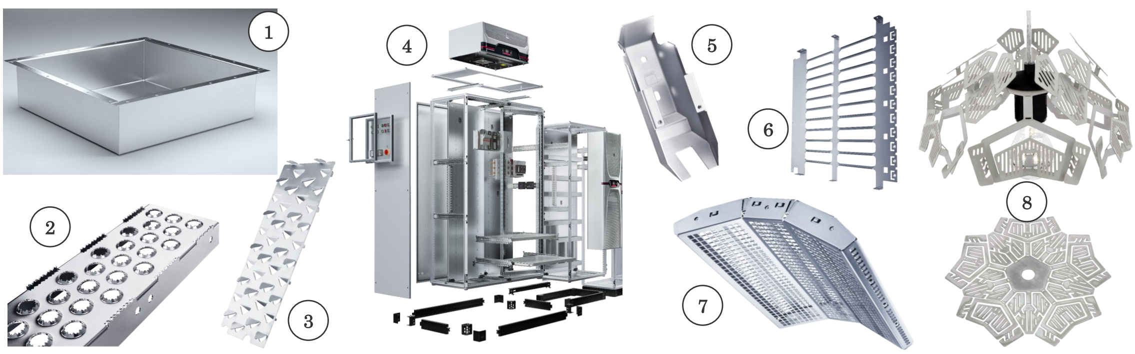

Figure 2.1: Exemplary sheet metal products from different industries: 1. Battery box for e-mobility (automotive), 2. Entry step of a tractor (land and construction machinery), 3. Air turbulator plate (heating and cooling), 4. Switch and server cabinets, 5. Cover of the clamping claws of a punching machine (mechanical engineering), 6. Hard disk storage rack (consumer electronics), 7. Filter mat support in a cooker hood (industrial kitchens), 8. Designer lampshade. Image courtesy of TRUMPF.

The production of sheet metal products can be explained along the sheet metal process chain. Each product has to pass through it, whereby quality, time, and costs are optimized (Buchfink 2005, p.30). The process chain consists of four steps: Construction, programming, production, and finishing. These are explained in the following:

Construction: The initial step involves creating a 3D part model from a product idea using Computer-Aided Design (CAD) software, followed by software checks for manufacturability. The construction process, often requiring experienced design experts, aims to produce cost-optimized parts, resulting in a 2D model with essential information for subsequent programming steps.

Programming: In the second step, the programmer configures machining strategies, tools, and machine process parameters using programming software which is generating the required Numeric Control (NC) code automatically. Various software solutions, not exclusively distributed by machine tool manufacturers, are available for this purpose.

Production: The manufacturing of each sheet metal product follows three main production steps in a fixed order: flat processing, forming, and joining. At the start, parts are separated from the material through laser cutting or punching. A straightening process becomes necessary if the laser cutting's thermal input has caused warping. The edges of parts that must be welded or meet optical standards are deburred to remove slag, punch marks, or other irregularities. Forming is the subsequent production step, encompassing bending, drilling, and thread forming. Some of these steps can be performed on a punching machine for small shapes with special tools. Drilling and thread forming are often done manually at separate workstations. Bending is usually executed at a manual press brake, but there are also automated bending solutions, including robots for material handling. The final production step, joining, involves assembling sheet metal parts through methods like mounting, stapling, or various welding techniques. The sequence required for product production is established and finalized during the construction phase, following the order depicted in Figure 2.2, with the flexibility to skip non-required steps. Once approved for production, this sequence remains unchanged.

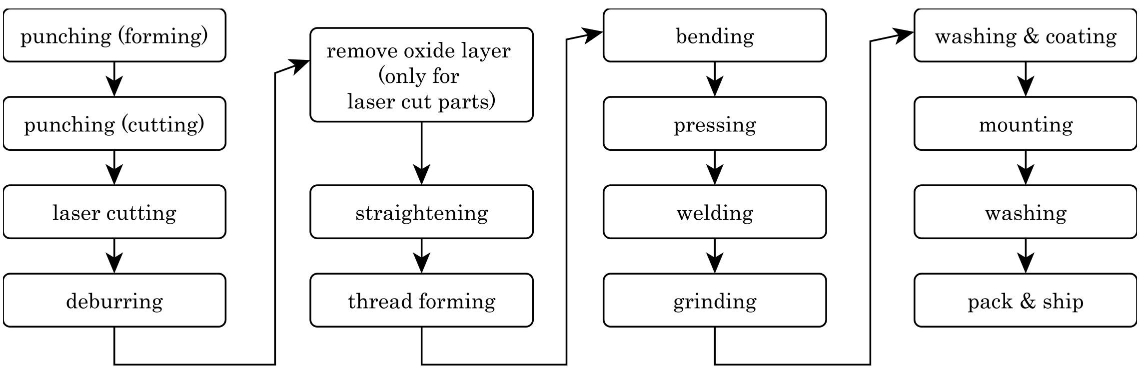

Figure 2.2: Order in which production steps are performed in SMP. If a production step is not required for the manufacture of a product, this step is simply skipped.

Finishing: This stage encompasses activities enhancing the visual appearance of the product without altering its 3D shape. Sheet metal products may exhibit scratches, visible weld seams, fingerprints, or other contaminants after production. Post-processing steps vary based on the product's requirements. For welded products, edges are often ground and rounded to eliminate weld seams. Some items undergo polishing and optional marking, while others, especially those destined for powder coating or painting, may be washed. The final step involves packaging the products for shipment, concluding their journey from SMP to the customer.

In this process chain, not all sheet metal products undergo every production and finishing step; unnecessary steps are omitted without altering the overall sequence. Each production step can be executed using different machines, with experienced production planners determining machine assignments prior to the start of production. Intralogistics in SMP are typically managed by employees, utilizing boxes for small parts or euro pallets as load carriers. About 90%[1] of sheet metal parts are transported on euro pallets, often moved on ants or forklift vehicles. When using boxes, they are either placed on euro pallets, carried by a human or maneuvered between processes on rollable trolleys. There is a growing trend in SMP towards automating intralogistics through Automated Guided Vehicles (AGVs) (Steclik et al. 2022) or by connecting machines via automation units and conveyor belts (see Figure 2.3).

2.2 Organization Principles

The production type of companies in the sheet metal industry is the variant-rich small to medium batch production with a trend towards smaller lot sizes. The vast majority of companies work according to the make-to-order principle, whereby a product is only manufactured once an order is received. Specific products for which demand can be well anticipated are produced in stock or a customer order decoupling point is introduced between cutting and bending. Before this point, orders are produced based on a sales forecast. After that, they are completed order-specific (Wiendahl 2014, p.253).

In the sheet metal industry, production organization revolves around three main principles or a combination thereof: the workshop, group, and flow principles. Wiendahl (2014, p.41) defines a manufacturing principle as determining the association of actual system components - workpiece, human, and operating resources. The workshop principle involves arranging workstations based on machining processes, offering high flexibility in product manufacturing and routing. However, it comes with extended throughput times, especially for large batches. On the other hand, the group principle decentralizes both production and planning, reducing lead times by implementing a flow-oriented machine setup. Despite increased flexibility, this method introduces complexity and higher personnel requirements. Lastly, the flow principle structures production based on the sequence of work steps, minimizing throughput times but potentially leading to uneven station utilization. Elastic linking and buffer storage help synchronize line timing, but the approach lacks flexibility in responding to product changes or demand fluctuations. Examples of these organization principles in SMP are presented in the following.

[1]According to internal investigations at TRUMPF

Examples of Sheet Metal Processing Systems

The flow principle in the sheet metal industry is implemented in automated and networked systems, illustrated here by the production line shown in Figure 2.3. The process initiates with raw sheets retrieved from the storage tower on the right side of the figure, transferred to a punch laser machine by an automation unit. Following cutting, another automation unit separates the blanks onto a conveyor belt, directing them into the bending cell. To address potential bottlenecks in the bending process, additional pallets are strategically placed for buffering. A robotic arm within the bending cell precisely positions each part for bending. Subsequently, after the forming process, a forklift transports the bent parts to a welding machine located on the left side of Figure 2.3.

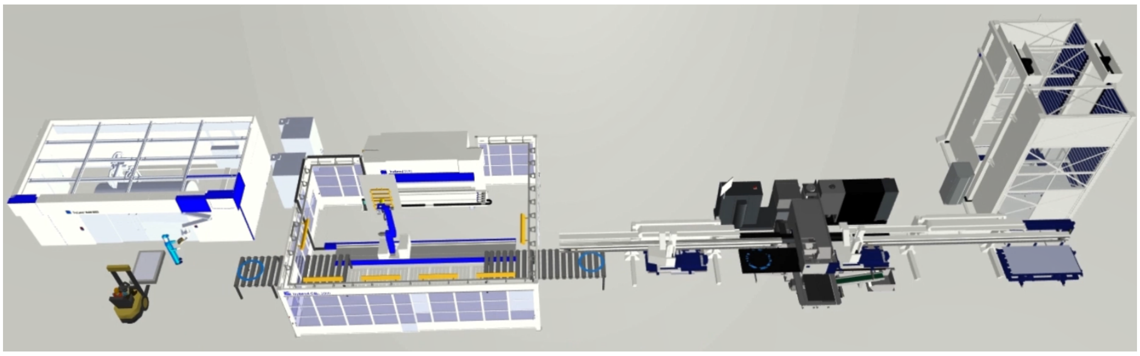

Figure 2.3: Exemplary sheet metal processing system structured according to the flow principle. Image courtesy of TRUMPF.

Figure 2.4 illustrates an instance of a production system organized according to the workshop principle. The automated storage system in the background, depicted in white, directly supplies raw material to the central punch laser machine or, alternatively, via a forklift, to the second punch laser machine situated in the lower right corner of the figure. The two machines on the left side are automated bending machines, each equipped with loading and unloading units. Forklifts enable a flexible material flow between machines.

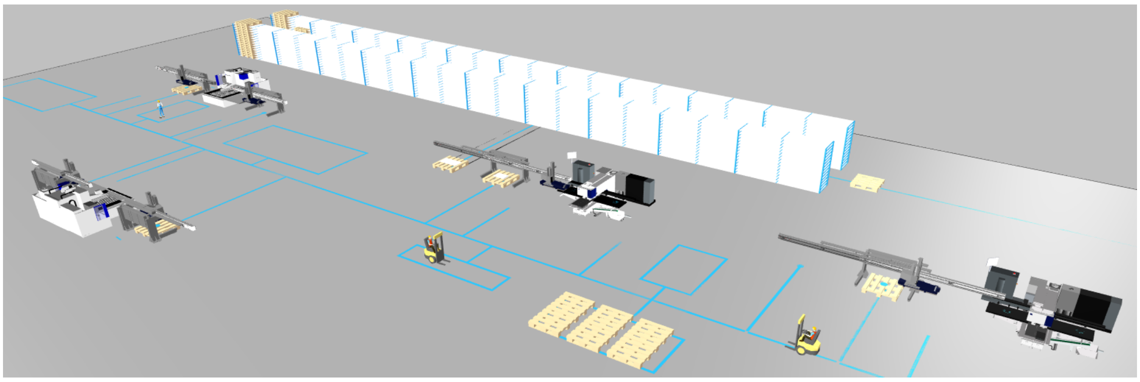

Figure 2.4: Exemplary sheet metal processing system structured according to the workshop principle. Image courtesy of TRUMPF.

Figure 2.5 presents an example of a production system organized according to the group principle. There are three distinct groups - A, B, and C - indicated by labeled rectangles. A designated mounting area (Group A) in the lower left corner of the figure focuses solely on the manufacturing of a specific product. Group C consists of machines dedicated to producing only products for one specific customer. The remaining machines are grouped to manufacture all other products (Group B). All groups receive their parts from the same area for flat sheet processing (cutting, punching, deburring), located on the right side of the shop floor. The long vertical shape on the right side of the production hall is the high-bay warehouse that is connected to two laser cutting machines and a punching machine.

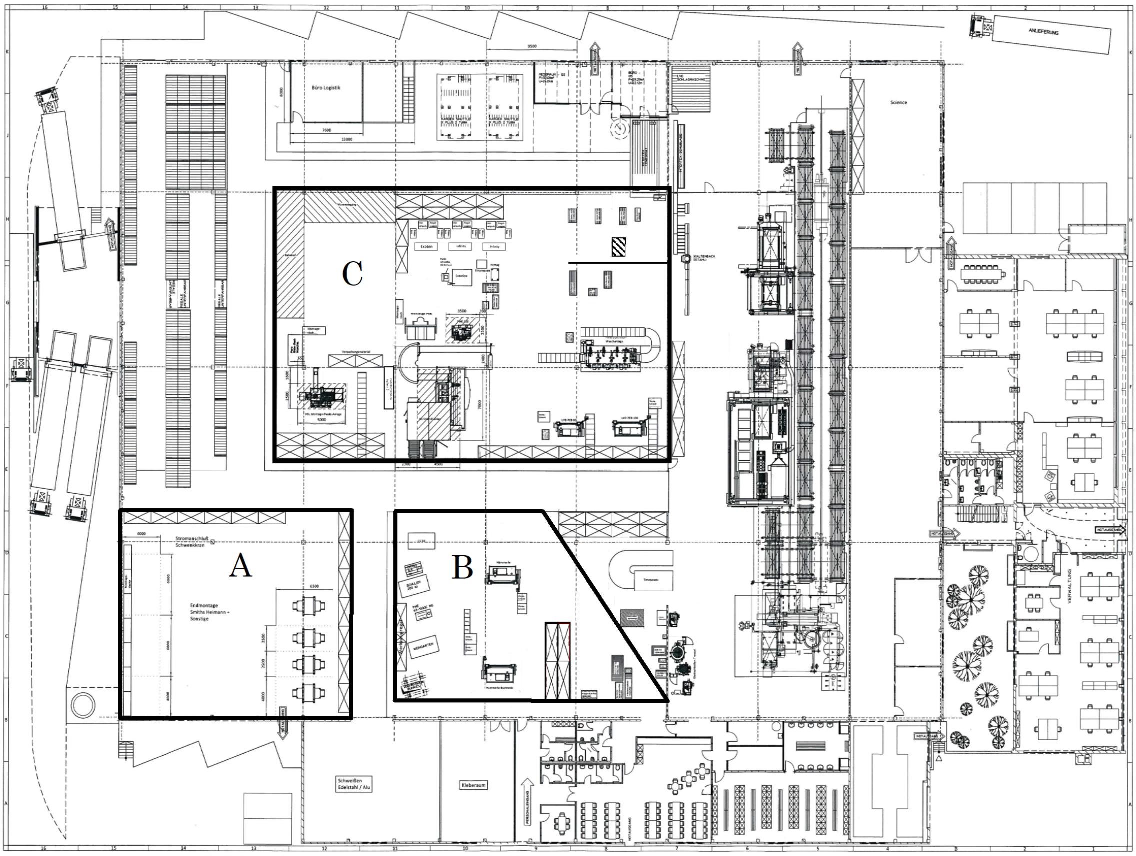

Figure 2.5: Layout plan of a sheet metal processing system structured according to the group principle. The groups correspond to: Group A: Product-specific mounting area, Group B: General production for all customers, Group C: Costumer-specific production. Image courtesy of TRUMPF.

This dissertation focuses on production systems organized according to the workshop or group principle, as they typically involve manual intralogistics that can benefit from the implementation of an Indoor Positioning System (IPS). Conversely, IPS are generally not incorporated into automated systems due to the potential disruption of automated processes. In automated systems, data on processes is readily available in the control system, making them more straightforward to simulate, and the incremental value of using an IPS is typically limited.

2.3 Production Planning and Control (PPC)

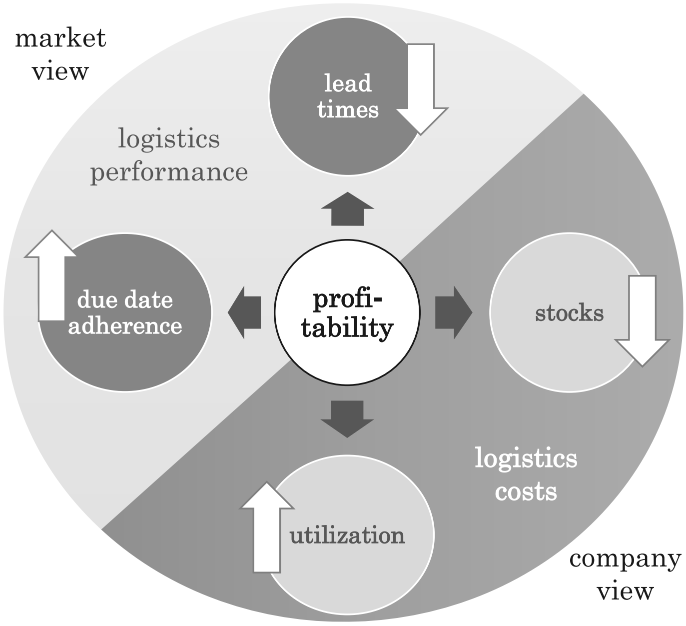

Figure 2.6: Target system of production logistics based on Wiendahl (2014, p.251).

Within the operative planning and control of production processes, PPC systems have the goal of optimally allocating resources to produce a defined quantity of products (Hausladen 2016, p.116). The underlying target system is shown in Figure 2.6. The market view in the upper left of the figure focuses on the logistics performance: Short throughput times and a high adherence to delivery dates positively impact the system's profitability. In the lower right of the figure are the logistics costs, viewed from the company's perspective. Here, profitability is achieved through low stocks (low capital commitment) and high utilization of resources. The difficulty in optimizing these targets lies in the competitive nature of the objectives, which must be balanced against each other from a business management point of view (Hausladen 2016, p.116). This conflict of targets is often referred to as the dilemma of production control (Wiendahl 2014, p.250). The pressure on PPC systems has increased significantly in the past decades due to the shift towards a buyer's market, shorter life cycles of products, smaller batch sizes, and increased requirements on delivery time (Hausladen 2016, p.116). Therefore, the importance of market-related target figures like due date adherence and short lead times increases (Wiendahl 2014, p.250).

As part of a research collaboration between TRUMPF and Fraunhofer Institute for Production Engineering and Automation (IPA), a survey involving 25 German SMP companies was conducted to assess the significance of target parameters, including quality, due date adherence, throughput times, material utilization, and resource utilization. The findings, presented in Figure 2.7, reveal that quality holds the utmost importance for 60% of the companies, followed by due date adherence at 36%. This prioritization aligns with the customer-centric nature of SMP companies, where customer satisfaction hinges on receiving high-quality components within the agreed-upon timeframe. Lower throughput times ranked third in importance, with material efficiency following closely, and resource utilization ranked the least significant. This underscores the general consensus that product quality takes precedence over logistical performance metrics.

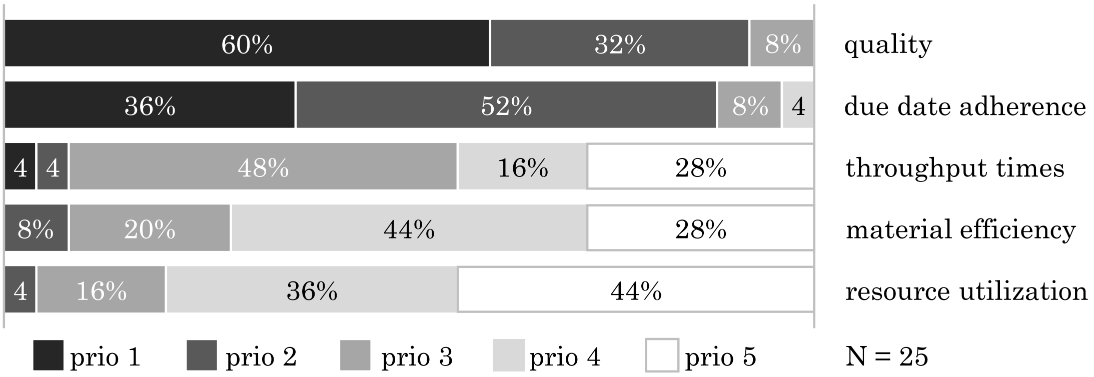

Figure 2.7: Importance of production targets in SMP rated by 25 SMP companies. Visual representation based on a 2015 survey conducted by TRUMPF and Fraunhofer IPA.

2.3.1 PPC in Sheet Metal Processing

The Production Planning and Control (PPC) process in SMP is illustrated in Figure 2.8. It initiates with a customer inquiry stored in the Enterprise Ressource Planning (ERP) system, leading to the creation and dispatch of an offer. Upon receiving the order, a preliminary production plan is generated based on rough estimations and unlimited resources. This initial plan is then refined in either the Manufacturing Execution System (MES) or Advanced Planning and Scheduling (APS) systems under consideration of machine resource limitations and process time estimates. The APS system additionally optimizes nesting and scheduling in an integrated manner (Pfitzer et al. 2018). Nesting involves solving a two-dimensional packing problem for part geometries within a specified time horizon. Once parts are assigned, sheets are allocated to different machines, determining the order of processing at the machines. The interplay between nesting and scheduling influences logistical targets and is, therefore, an integral component of PPC (Heger et al. 2015). Local search and genetic algorithms have been employed to address packing and scheduling with recent research exploring Reinforcement Learning (RL) (Rinciog et al. 2020) or quantum computing[2]. The optimization result is a detailed production plan. Subsequently, a CAD program transforms the construction drawings of all products in that production plan into three-dimensional technical drawings, incorporating essential production details such as material types, dimensions, and steps. The Computer-Aided Manufacturing (CAM) system utilizes these drawings to generate NC programs and machine setup plans, providing operators with the necessary instructions on the shop floor. Upon completion, the product is logged in the ERP and dispatched to the customer.

[2]`https://www.qutac.de/en/trumpf-optimized-production-planning-for-tomorrows-metal-processing/`, accessed March 2024

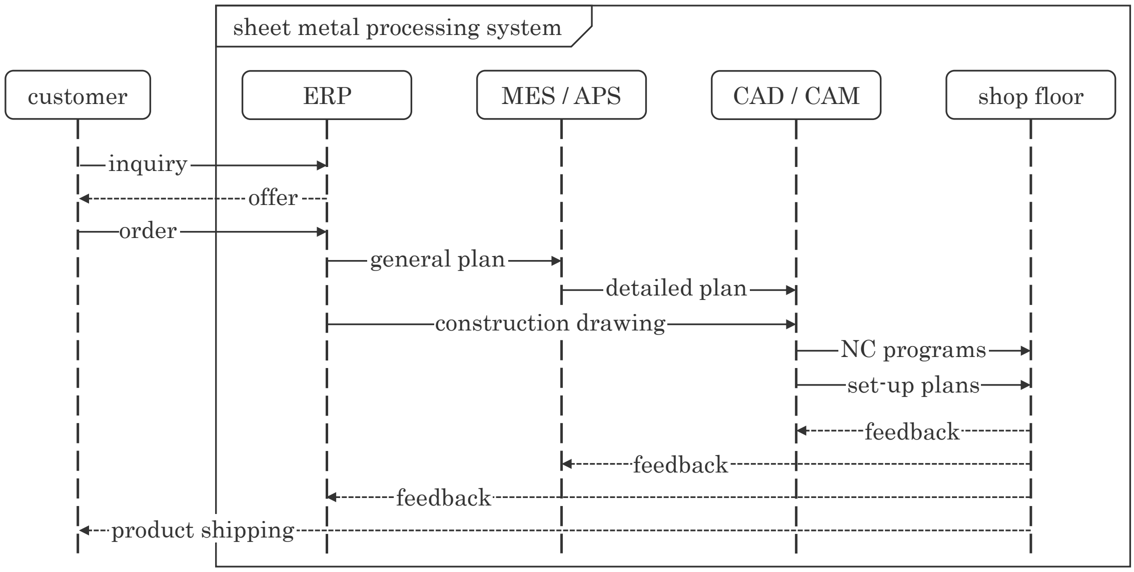

Figure 2.8: Sequence diagram of Production Planning and Control (PPC) in SMP showing the interaction between the SMP company and a customer. Own illustration, created by merging and extending figures from Pfitzer et al. (2018, Fig. 1) and Buchfink (2005, p.229).

Schedules can be unreliable due to factors such as poor planning times resulting from an insufficient data foundation, unpredictable events like machine breakdowns or rework tasks, human decision-making on the shop floor, and the use of simplified assumptions to reduce the computational complexity of multi-objective optimization problems (Pfitzer et al. 2018). Therefore, feedback loops exist between the production process and the planning systems. For instance, if operators encounter issues with the machine setup or the generated NC programs, they report to the CAD/CAM team. In cases where operators are unable to complete all tasks as per their schedule, they report to the planning supervisor. Time data is recorded and stored in ERP and MES/APS systems. If as-is times frequently deviate from planned times, adjustments are made to enhance future planning.

Leveraging IPS data to augment the data foundation, improving planning times, and incorporating human decision-making into the data can enhance scheduling. Understanding how individuals make decisions on the shop floor allows for consideration of their behavior in planning. Strategies can be prepared to cope with unpredictable events, and flexibility becomes advantageous for adapting to changes. Selecting reliable technology and production processes can help minimize or eliminate rework tasks. The ongoing increase in computational power, coupled with emerging quantum computing approaches, holds promise for achieving better solutions to optimization problems within shorter time frames.

2.3.2 Rule-based Production Control

The human decision-making and interference with processes on the shop floor of SMP should be understood, as they must be accurately reflected in a simulation model to generate realistic insights.

Rule-based production control, characterized by minimal computational complexity, is easily applicable by humans (Scholz-Reiter et al. 2009, pp. 1–2). These rules are usually chosen during detailed production planning (Van Brackel 2009, p.22), serving as practical alternatives to directly solving the underlying, often computationally complex mathematical optimization problems, which may not be feasible within the time constraints of production reality. Determining a suitable, well-performing priority rule for a specific production system is an empirical task, often requiring methods like simulation since a deductive proof is unattainable (Corsten and Gössinger 2012). The effectiveness of priority rules is contingent on factors such as the use case, overall complexity, and desired utilization level in the production system (Scholz-Reiter et al. 2009). No single rule universally outperforms all others (Heger et al. 2015). In Mieth et al. (2019c), rule-based organizational areas in SMP were investigated, addressing concerns such as:

- Sequencing: Prioritizing orders in queues in front of a machine or machine pool.
- Picking: Sorting parts on pallets effectively.
- Transportation: Determining who should transport which order and how.
- Dispatching: Choosing the appropriate technology and deciding on which machine (from a pool of identical ones) the job should be produced.
- Material Handling: Planning the nesting of parts on sheets over a specific time horizon and managing remaining sheets and waste.

These considerations are crucial for achieving an accurate representation of a specific system in a simulation model, and will be elaborated in the following.

Sequencing / Priority Rules

Sequencing, or priority rules, serve as a straightforward heuristic for establishing a suitable order of tasks. Typically, stations or groups of stations are assigned a backlog of orders with detailed information such as release date, work content, planned processing time, due date, and other relevant data for the current production step. This order backlog indicates the approximate number of orders that can be produced within a shift. Regardless of whether the information on the individual orders is provided digitally or traditionally printed, it is organized in a folder and managed with the help of tools such as planning boards, hanging files, or terminal devices (tablet, phone, computer) as can be seen in Figure 2.9.

First In First Out (FIFO) and Earliest Due Date (EDD) are the most common priority rules for order sequencing in SMP, followed by Shortest Processing Time (SPT) and Highest Priority Number (HPN)[3]. Interested readers are referred to Herrmann (2011, p.321), Hübl et al. (2013), and Swamidass (2000, p.482) for in-depth discussions.

- Earliest Due Date (EDD): Prioritizes jobs based on their due date, minimizing the maximum delay (Herrmann 2011, p.327–329). Suitable when the system is sensitive to due date changes and when the goal is to reduce job lateness (Swamidass 2000).

[3] TRUMPF internal study with expert interviews conducted in 2018

Figure 2.9: Example of a digital order backlog provided to the operator of a bending machine as a table on the upper monitor. Image courtesy of TRUMPF.

- Shortest Processing Time (SPT): Prioritizes jobs with the shortest processing time at the current workstation, minimizing average throughput time, average job lateness, and work-in-process inventory (Herrmann 2011, p.327–329). However, it may increase the risk of longer jobs missing their due date (Swamidass 2000).

- First In First Out (FIFO): Ensures the job that arrived first is processed first, but it is considered inferior to the SPT rule (Swamidass 2000).

- Highest Priority Number (HPN): The HPN rule ensures that the job with the highest priority number at the current workstation is processed first. Production planners specify priority numbers, which can lead to arbitrary prioritization decisions. HPN is thus not recommended, but it is still common practice in some SMP companies.

Picking Rules

Picking rules provide guidelines for workers on how to pick and sort parts for transportation, whether placing them on pallets, trolleys, or in boxes, and when to use a new transportation resource. In the absence of a comprehensive overview of picking rules for SMP or similarly organized production environments in the literature, it is beneficial to draw insights from analogous challenges. For example in warehouses, picking lists guide pickers on which products to collect and the order in which to place them onto transportation resources. Commonly, products are grouped by customer affiliation to optimize downstream processes, including sorting times (Liu 1999). In scenarios with large customer orders, the single-order picking policy proves advantageous (De Koster et al. 2007). When picking multiple customer orders simultaneously, two strategies are common: In the pick-while-sort strategy, picking and sorting activities occur concurrently, eliminating the necessity for a subsequent sorting process but diminishing the pick-rate of pickers (Jiang et al. 2018). Conversely, the pick-and-sort strategy involves sorting after the picking process, maintaining a high pick-rate for pickers but necessitating a distinct sorting process (Jiang et al. 2018). In Mieth et al. (2019c), relevant picking rules for SMP are presented. They originate from interviews with 30 SMP companies in 2015 and are since mapped into the PPC system of TRUMPF:

- Same Panel: All parts cut from the same sheet metal panel are picked together.
- Same Next Process Step: Parts with the same next process step are picked together, irrespective of customer affiliation.
- Same Customer Order: Parts from the same customer order (same product) are picked together, analogous to the single-order picking policy in warehouse logistics.
- Same Set: All parts in one set, comprising parts from the same product order (e.g., painting, mounting, or welding sets), are picked together. This rule is applied when material flows converge in the sheet metal process chain.
- Same Customer: Parts from one customer are picked together, regardless of their status as part of the same product or order.

Transportation Rules

Internal transport in SMP is typically managed by dedicated employees, aligning with lean principles to prevent machine operators from assuming logistical tasks and potentially causing disruptions and delays. Various means, such as ants, forklifts, or trolleys, are employed for transportation, with sheet metal parts carried on pallets or in boxes. However, the industry is moving towards automated solutions like AGVs for internal transport (Steclik et al. 2022). AGV operations involve defined entry and exit zones for material pick-up or deposition. Observations reveal that outgoing storage areas are usually smaller than incoming ones, reflecting the prompt transport of parts to subsequent stations following the completion of a process step. Logistics personnel typically adhere to the same shift schedules as machine operators, occasionally incorporating milk runs, while also meeting intraday deadlines for off-site transports.

Dispatching Rules

Dispatching rules are applied to assign a job to a machine. When a machine becomes idle, the job with the highest priority is taken from a backlog (Heger et al. 2015). Dispatching rules in SMP are applied during production planning to decide on which machine a product should be produced if alternative machines are available. For example, parts can be cut from sheet metal with laser cutting or punching. The technology choice is made by considering quality aspects and constraints, such as punching diameters. Another example is the assignment to bending machines. Press brakes use the same technology but come in different sizes and strengths, which necessitates the consideration of sheet thickness and the length of the longest thigh when dispatching jobs.

Material Handling Rules

The material cost, constituting approximately half of the sheet metal product price, prompts SMP to implement rules for material utilization to minimize waste and associated costs. These rules predominantly address the time horizon for nesting geometries on sheets. A short time horizon reduces production stocks but increases waste, while a longer horizon enhances material utilization. Typically, there is a rule specifying how far into the future due dates of nested parts can extend. Recurring nestings, proven to be process-safe, are approved for unoccupied night shifts, while new nestings are often cut during the day to confirm their feasibility. Some SMP practices involve partially cutting sheets and separating a residual sheet, used for reclamation orders or special jobs. Additional rules determine the acceptable size for retained residual sheets and when disposal is necessary. However, certain SMP companies choose to avoid handling residual sheets altogether.

2.4 Summary

In this chapter, Sheet Metal Processing (SMP) was characterized to introduce the reader to the studied environment and its peculiarities. First, in Section 2.1, the basic steps of SMP were presented, which include construction, programming, production, and finishing. Intralogistics was also considered an important aspect between these steps. In the subsequent Section 2.2, the forms of organization in a SMP system were considered in more detail, and concrete examples of SMP systems were given. In this dissertation, it is generalized that SMP-systems follow either the workshop or the group principle. In Section 2.3, PPC in SMP was explained with a focus on PPC targets and processes. This was followed by a more in-depth discussion of rule-based production control. These rules are still predominantly used in production systems in the sheet metal industry, and a simulation of such a system must include them to accurately reflect the system's behavior.

Chapter 3

Manufacturing Simulation

This chapter provides an overview of simulating manufacturing systems. Simulation is used to better understand complex systems through experiments conducted in risk-free virtual environments. In the context of this work, the complex system is a Sheet Metal Processing (SMP) environment. During the modeling process, the system is projected on a suitable abstraction level which is always use-case dependent.

In Section 3.1, the goals and execution of simulation projects are detailed. The subsequent Section 3.2 delves into the existing challenges associated with simulation data, particularly with regard to issues surrounding data quality. Additionally, it provides an overview of various input methodologies that have been developed within this research domain, along with the specific data sources they draw upon. In the last Section 3.3, the related work on simulation input modeling for the manufacturing domain and recent advances in input data management and modeling are presented.

3.1 Simulation Projects

This chapter starts with a definition of simulation, which originates from the guideline "Simulation of systems in materials handling, logistics and production" issued by the Association of German Engineers (VDI - Association of German Engineers 2014):

Definition 3.1.1 (Simulation) *"Representation of a system with its dynamic processes in an experimentable model to reach findings which are transferable to reality; in particular, the processes are developed over time." (VDI - Association of German Engineers 2014, p. 3)*

Further, we want to create a common understanding of the scope of a simulation project. A simulation project is the sum of all work to answer one or more hypotheses about a complex system's behavior using an experimental model. The work within such a project consists of simulation experiments which the above mentioned guideline defines as:

Definition 3.1.2 (Simulation Experiment) *"Targeted empirical investigation of a model's behaviour by a set of simulation runs with a systematic variation of parameters or structures" (VDI - Association of German Engineers 2014, p. 3).*

An essential advantage of simulation is conducting experiments in a risk-free virtual environment. In practice, testing adaptation ideas in the actual system is not feasible for several reasons: Tight production schedules prompt the production lead to prioritize meeting due dates instead of experimenting with the adaptation of routines, as missed due dates may result in penalties as per contract agreements. Moreover, the inability to foresee whether the adaptation idea yields an overall improvement of Key Perfomance Indicators (KPIs) compared to the status quo is another argument for virtual experimentation in simulations. Lastly, there is often limited time to generate insights into the system's behavior. Simulations can run faster than real-time, and different adaptation measures can be run in parallel.

Procedure Models for the Management of Simulation Projects

Different procedure models have been developed to manage the complexity of simulation projects. The most common are from Banks et al. (2005), Law and Kelton (2015), and Rabe et al. (2008). Rabe's procedure model is part of the VDI standard 3633 (VDI - Association of German Engineers 2014) making it the only officially standardized procedure model. For the rather new area of Automated Simulation Model Generation (ASMG), another methodology based on best-practice implementations of the Core Manufacturing Simulation Data (CMSD) standard (Riddick and Lee 2010) was proposed by Bergmann (2013). The CMSD standard was developed to improve the interoperability between different simulation tools and facilitates data exchange between different simulation applications (more details follow in Section 3.3.2). Another recently developed procedure model by Andreasson et al. (2019) focuses on planning production systems. The model is supposed to cope better with planning uncertainties due to limited data availability and more frequent concept revisions. So far, the newer models of Bergmann (2013) or Andreasson et al. (2019) have not been found to replace the established model of Rabe et al. (2008).

All mentioned procedure models have in common that the activities within a simulation project are divided into phases with certain assigned tasks. Despite the variety in the literature, they often contain same or similar elements which are[1]: 1. Problem definition, 2. Model building, 3. Implementation, 4. Experimentation and analysis, and 5. Execution of adaptations. The first step is the problem definition, a phase where the project's goal is specified and work hypotheses are derived. Based on the problem definition, a model is built in the second phase. Once the model is completed, it is implemented in simulation software and experiments are run. The results are evaluated to derive recommendations for action. The knowledge gained and the accompanying adjustments to the actual system are then executed in the final phase.

Data plays a decisive role in all project phases. It is collected and analyzed to support a precise problem definition, to make the right modeling decisions, to parameterize the implemented model and simulation experiments, and, lately, to derive the proper actions from the simulation results. Skoogh et al. (2012) emphasize that because of data pervasiveness in simulation projects, the data management is often challenging. Simulation data and its associated challenges will be explored in detail in the following section.

[1] TRUMPF internal master thesis by Patrick Wöhe (2020): Konzeptentwicklung zur simulationsgestützten Neu- und Anpassungsplanung in der Blechindustrie, p.45

3.2 Simulation Data

This section on simulation data starts with a definition of simulation data types and presents typical data sources. This is followed by an overview of data quality dimensions and challenges with simulation data. The data quality dimension are later used to qualitatively assess the improvements that can be realized with the developed framework in Chapter 5. This section ends with the introduction of the simulation data life-cycle.

Simulation data refers to data required by the simulation model. According to VDI - Association of German Engineers (2014)[p. 15], there are four different data types in simulation projects:

- Input data refers to static or stochastic data that the user of the model supplies before a simulation run is started.
- Experiment data consists of starting time and duration that are set for a simulation run, as well as model parameters that are updated for each simulation run within an experiment.
- Internal model data refers to all model constants set during the model implementation and all internal variables dependent on the simulation time.
- Simulation result data is generated and logged during simulation runs. Afterwards, this data is aggregated and analyzed to extract insights from the experiments.

When simulation data are mentioned in the following, only the input data, model parameters, and constants for the experiments are meant, i.e., everything that is available before starting a simulation run.

Sources for simulation data in manufacturing are diverse, because of the heterogeneous IT system landscape with many proprietary systems (Schuh et al. 2015). Primary simulation data are collected directly for the simulation project via measurements, inspections, and observations on the shop floor (Bärring et al. 2018). The secondary data sources can be divided into an external reference system, corporate business systems, and project-specific data (Bärring et al. 2018; Skoogh et al. 2012). The first two were not collected for the simulation but are available for other reasons, e.g., to ensure the operation of the production system. Secondary data need to be processed and analyzed to get valuable insights for the simulation project. Thus, one tries to extract as much information as possible from the secondary data to have as little effort as possible to collect primary data. Relevant information for simulation projects can typically be found in corporate business systems like:

- Enterprise Ressource Planning (ERP) Systems
- Advanced Planning and Scheduling (APS) Systems
- Manufacturing Execution System (MES)
- Manufacturing Data Aquisition (MDA)
- Product Life-Cycle Management (PLM) Systems including, among others, data from Computer-Aided Design (CAD)/Computer-Aided Manufacturing (CAM) Software

3.2.1 Data Quality Dimensions

Different lists of quality dimensions appear in the literature, and different authors work with different subsets. Accuracy, completeness, and consistency are the most commonly used quality dimensions in the literature. In this work, the eleven dimensions and their definition of Balci et al. (2000) and Bokrantz et al. (2018) are used, because they contain all common and relevant dimensions from the other authors, who often reference back to Balci et al. (2000). The quality dimensions of simulation data are listed alphabetically with a short definition from Balci et al. (2000):

- Accessibility: Degree to which data are available or easily and quickly retrievable
- Accuracy: Degree to which data possess sufficient transformational and representational correctness
- Clarity: Degree to which data are unambiguous and understandable
- Completeness: Degree to which all parts of the data are specified with no missing information
- Consistency: Degree to which (a) data are specified [...], and (b) any one data value does not conflict with any other
- Currency: Degree to which the age of the data is appropriate for the use of the data
- Precision: Degree to which data possess a sufficient number of significant digits in their numerical values
- Relevance: Degree to which data are applicable for use
- Reputation: Degree to which data are trusted or highly regarded in terms of their source or origin
- Resolution: Degree to which data possess a sufficient level of detail
- Traceability: Degree to which data are easily attributed to a source

3.2.2 Challenges with Simulation Data

Data is essential to every simulation project, yet challenges remain to access and understand data that is lacking clarity. Thus, data collection in simulation projects is time-consuming and often includes interviews or workshops with production employees and experts (Robertson and Perera 2002). This "best" practice has the disadvantage that a collection of quantitative values such as average process times or machine availability by interviewing people is subject to their perception (Akhavian and Behzadan 2018). Because of their experience, they can estimate an average, but neither the distribution nor the function representing the actual underlying context. This lack of accuracy and precision in the creation and parameterization of simulation models should be avoided to make more reliable statements based upon the simulation results. Nowadays, a large amount of data is already available in real-time, but the critical question is whether it is also the relevant data for the simulation use case. A fact is that the systems collecting the data have not been designed with simulation requirements in mind (Bokrantz et al. 2018; Skoogh and Johansson 2008). A lot of data is gathered by MDA systems and is stored in heterogeneous systems such as the MES or ERP. Usually, inconsistencies occur, and it cannot be decided which source of data can be trusted (Li et al. 2016). Completeness of data is another issue, as there is still a lack of high-quality data necessary for implementing and parameterizing manufacturing simulation models. For example, actual process times are usually not known in make-to-order manufacturing. Target times are commonly used if no feedback data from the shop floor is available. In this case, such data usually has a bad reputation because it is known that the deviation between actual and target times in production can be considerable. Accurate simulation results can only be achieved with accurate data input, known as the "garbage in, garbage out" theory (Robertson and Perera 2002). The traceability of data for the modeling of manual processes is another challenge in job shops. Automated processes on machines are already well monitored, whereas the indirect manual processes are not well depicted due to their stochastic behavior (Kück et al. 2016). In addition, the times for manual processes must usually be reported by the employees. Therefore, the currency and resolution of data depend primarily on work ethic and are inherently prone to errors.

3.2.3 Simulation Data Life-Cycle

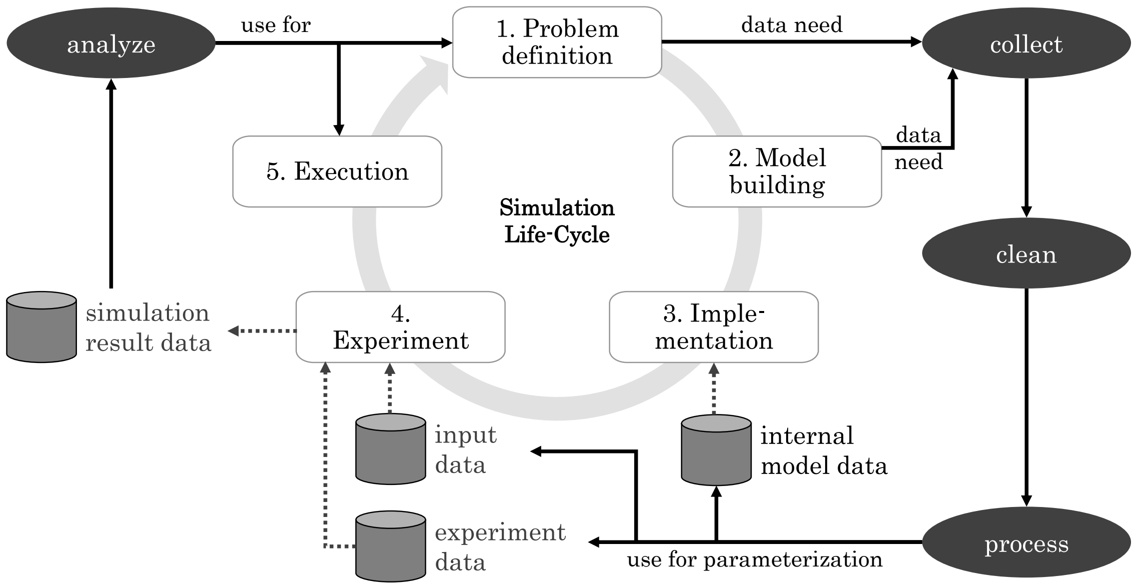

Figure 3.1: Simulation data life-cycle: The inner circle contains the five phase procedure of a simulation project introduced in Section 3.1. The outer part contains the activities that are performed with data, depicted in black. The simulation data is shown as gray cylinders for the different types presented in Section 3.2.

Simulation and data are closely intertwined and iteratively interdependent. This interaction of data and simulation is explained in Figure 3.1. The simulation life-cycle is depicted in the middle of the figure as the five phase procedure introduced earlier in Section 3.1. Remember that these five phases typically occur in each procedure model and thus, serve well the purpose of showing the relation between simulation and simulation data. Next, we add the various simulation data shown as gray cylinders, presented at the beginning of Section 3.2 and supplement the activities performed with the data, depicted in black. The data needs are identified within the first two phases, problem definition and model building. Therefore, data collection is conducted in parallel with these phases. The collected data has to be cleaned, and processed to be available in a format that can be used to parameterize the different data types in Phases 3 and 4 of the simulation life-cycle. After completion of the simulation experiments in Phase 4, the simulation result data will be analyzed, and conclusions for the execution phase will be drawn. In addition, the findings can also be used to update the problem definition, which then triggers a new iteration of the simulation and data life-cycle.

3.3 Related Work on Simulation Input Modeling

This section consists of four parts. It starts with presenting the different existing data input methodologies. Second, an overview of existing information models used within simulation projects is provided. Some are specifically developed for the simulation use case, like the CMSD standard and the Verein Deutscher Ingenieure (engl. Association of German Engineers) (VDI) 3633 standard. In contrast, others like AutomationML and the asset administration shell have a broader focus on cyber-physical systems in general. These are also presented in the spirit of completeness because they have been used at least sporadically or historically in simulation projects. Third, an outlook on the current trends toward data-driven and more automated simulation input modeling is given. Lastly, it is presented how machine learning methods are used in simulation projects.

3.3.1 Data Input Methodologies

Four different data input methodologies have emerged from the literature according to Skoogh et al. (2012). These are depicted in Figure 3.2 and range from manual to automated solutions.

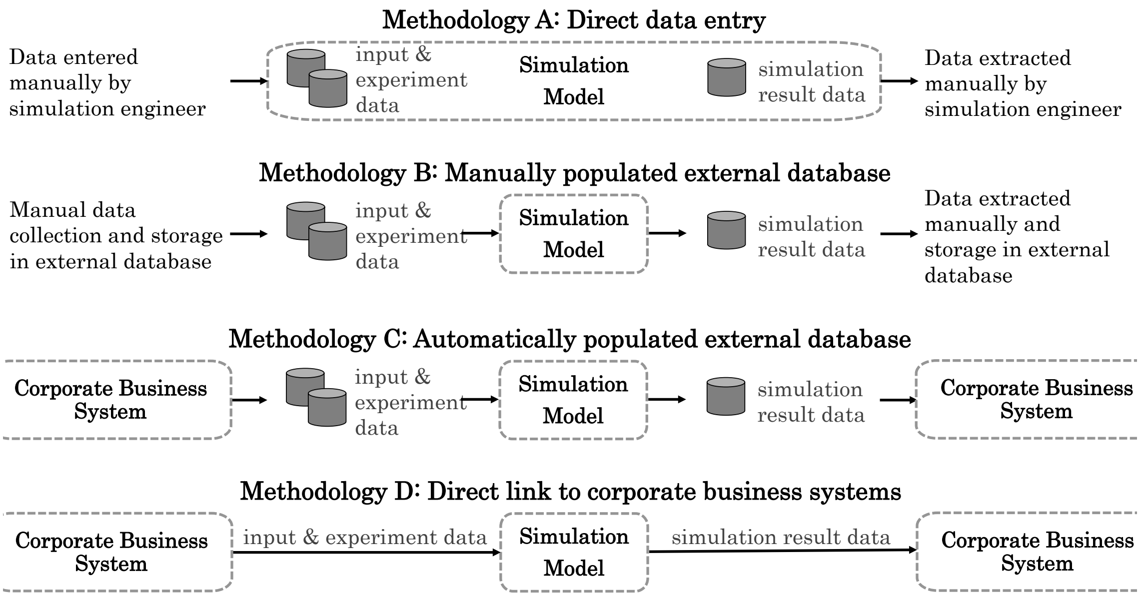

Figure 3.2: Four data input methodologies according to Skoogh et al. (2012)

The first Methodology A in Figure 3.2 is called direct data entry. It is the simplest method, especially for beginners, and was thus widely used over the last decades and is still common today. Data is manually collected (e.g., via interviews, observations on the shop floor, or from business systems), processed, and, manually entered into the model by the simulation engineer. A disadvantage is the decentralization of data in the simulation models, which makes versioning or fact-checking very tedious. Nevertheless, the modeler can still check each value for correctness before entering it. (Skoogh et al. 2012)

Methodology B, manually populated external data source, is similar to Methodology A in the aspect that data is still manually collected, processed, and entered. The difference lies in how data is stored in an external database (e.g., a spreadsheet), which is linked to the simulation. Methodology B has the advantage over Methodology A that verification and model updating become easier, since data is stored centrally. The authors argue that spreadsheets have a familiar interface, accessible also to non-simulation experts, which is probably the reason why this is the most commonly used methodology today. (Skoogh et al. 2012)

Methodology C, automatically populated external data base, extends Methodology B by linking the external data sources not only to the simulation model but also to the corporate business system. Now the data collection and processing are automatically done by the corporate business system and all relevant data are automatically stored in the external database yielding considerable time-savings for data maintenance tasks. However, the effort is now front-loaded, as setting up a data integration takes time. For each project, it must be evaluated how often the pipeline will be used and whether the effort for the integration is justified. Due to the relatively high complexity of this methodology it is not very common. (Skoogh et al. 2012)

With Methodology D, direct link to corporate business systems, no data is stored in an intermediate database. The simulation model is directly linked to the corporate business systems. Every entity in the simulation model has a reference to its ground truth data point. This has the advantage that the model is always up to date with the latest data, it reduces time spent on data management and has a lower error rate by avoiding typing errors. However, it takes a considerable effort to set up this close link between simulation and corporate business systems. Further, data quality remains a challenge, as data was usually not collected for simulation purposes (Moon and Phatak 2005). Methodology D is complex and lacks transparency on where and how data are processed. This may potentially harm the credibility of the simulation results. (Skoogh et al. 2012)

The authors Skoogh et al. (2012) recommend Methodology C due to its capability to integrate data from various sources in an external database. Especially in the common case, where not all data is available in the linked corporate business system, additional data from interviews and other databases can be easily added. However, it is also argued that Methodology D holds strong potential to eliminate the need for human assistance in simulation projects. They point out that more research is needed to move forward in this area, including from ERP vendors who could expand their software offerings in simulation.

3.3.2 Information Models for Manufacturing Simulation

It is essential in manufacturing simulations to obtain information for model creation and parameterization. However, the challenge arises from the diverse range of simulation tools, making data exchange and model reuse complex. Various initiatives have emerged to address interoperability and reusability concerns. The subsequent discussion introduces existing standards that specify information models for manufacturing simulation. The last two standardization initiatives that will be presented are not simulation-centric, but have been utilized in simulation projects and will therefore be briefly discussed for completeness.

VDI 3633 Guideline

The association of German engineers (Verein Deutscher Ingenieure - VDI) published the VDI 3633 guideline (VDI - Association of German Engineers 2014) in 2014. Its first part contains an illustration of simulation data categorized into system load data, organizational data, and technical data, which can be seen in Figure 3.3. It shows a hierarchical structure but is missing necessary details about the simulation inputs associated with different categories.

Since it is a guideline, not a standard, they do not share an information model that can be used to improve interoperability. Nevertheless, their categorization of input data is a good starting point for simulation projects to collect the required data in a structured way and is thus later used in the presented framework in Chapter 5.

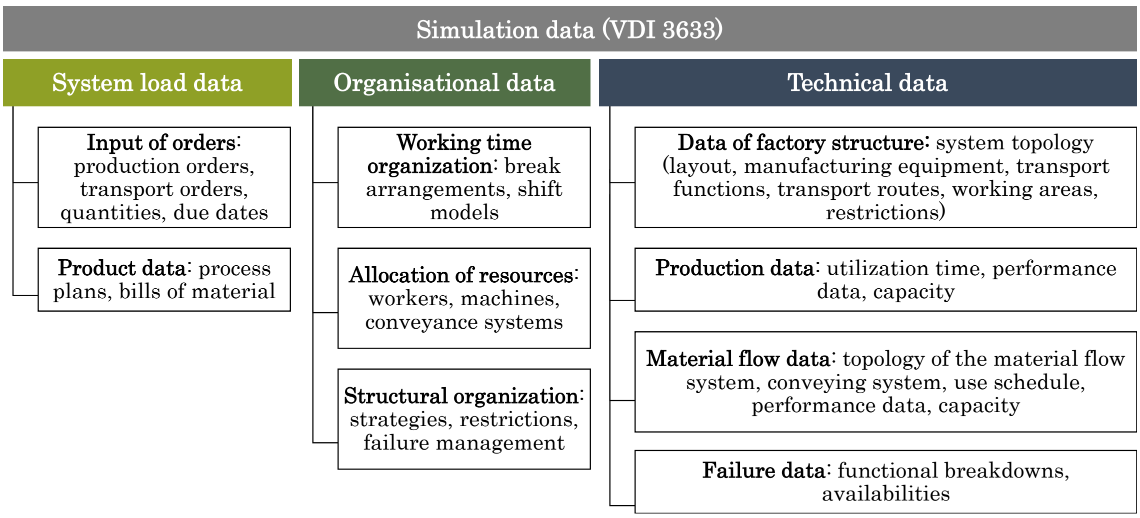

Figure 3.3: Categorization of simulation data according to VDI - Association of German Engineers (2014)[part 1, p.34]

Core Manufacturing Simulation Data Standard

The Core Manufacturing Simulation Data (CMSD) serves as a standardized representation for manufacturing simulation information, developed by the National Institute of Standards and Technology under the US Department of Commerce. It provides a neutral, computer-interpretable model defining core manufacturing entities and their relationships on the shop floor (Riddick and Lee 2010). In 2010, the

Simulation Interoperability Standards Organization (SISO) introduced the CMSD Standard – UML Model (Lee and Riddick 2010), followed by an XML representation in 2012, aiming to enhance interoperability among diverse simulation tools. This initiative addresses the need to minimize costs associated with redundant model creation and data exchange in simulation projects.

While the CMSD standard has gained recognition in research, notably utilized by scholars like Barlas et al. (2014) and Bergmann and Straßburger (2015) for automatic simulation model generation, its adoption within the industry remains limited. Simulation software providers have not actively advocated for the standard, likely to avoid facilitating transitions to competing products. Critics argue that in most simulation projects, the information model often needs extension to incorporate project-specific components. While standardization addresses general manufacturing simulation data, it lacks the depth to accommodate industry specifics. This limitation is not surprising given the diverse landscape of manufacturing companies. However, the alternative of mapping all possibilities in the standard is also impractical. This underscores the practical difficulties associated with striving for universal applicability.

AutomationML

AutomationML[2] is an open, neutral and free eXtensible Markup Language (XML)-based object-oriented data modeling language. Like CMSD, it relies on XML, which is good for representing hierarchically structured data in the format of a text file that is human- and machine-readable. AutomationML was developed to model, store and exchange engineering models across disciplines and companies as well as planning data of plants in the manufacturing and process industry. The standard is administrated, disseminated, and further developed by the AutomationML association and acknowledged internationally within IEC 62714[3], which specifies the engineering data exchange format for use in industrial automation systems engineering.

Asset Administration Shell

The development of the Asset Administration Shell (AAS)[4] was initiated by Plattform Industry 4.0, a German network backed by the federal ministry of economic affairs, education and research. Introduced in 2018, the AAS serves as the digital model for Industry 4.0 assets, providing a structured approach for companies to uniformly prepare and exchange information across partners in the value chain. The AAS consists of a technology-independent metamodel that represent asset information and functionalities for interoperability. The AAS supports serialization mappings such as XML, JavaScript Object Notation (JSON), and Open Platform Communications Unified Architecture (OPC UA) and can also work with sub-models from AutomationML. Adding domain-specific information to sub-models is facilitated via templates.

[2] `https://www.automationml.org/`, accessed February 2022

[3] `https://www.vde-verlag.de/iec-normen/225580/iec-62714-1-2018.html`, accessed February 2022

[4] `https://www.plattform-i40.de/IP/Redaktion/DE/Downloads/Publikation/AAS-ReadingGuide_202201.html`, accessed February 2022

3.3.3 Advances in Simulation Input Data Management and Modeling

The literature highlights two primary trends in simulation input data management and modeling pertinent to this dissertation. Firstly, there is a shift towards employing more sophisticated data input methodologies. Secondly, there is a growing emphasis on automatically generating simulation models from provided information. Both trends share the common goal of minimizing the effort involved in simulation projects, thereby saving time and costs, and fostering wider adoption of simulation methods in practical applications.

Trend Towards Advanced Data Input Methodologies

The trend towards more advanced data input methodologies was identified and described by Skoogh et al. 2012. They asked $N = 86$ companies worldwide which data input methodology they are using (see methodologies A, B, C, and D in Section 3.3.1). Their results are given in Table 3.1.

Methodology	A	B	C	D
surveyed in 2010	17%	63%	17%	3%
projected for 2020	3%	18%	41%	38%

Table 3.1: Dissemination of various data input methodologies in 2010 by (Skoogh et al. 2012). Their survey also asked for an expert's view on the projected numbers for 2020.

Skoogh et al. (2012) showed that only 20% of the interviewed companies use Methodology C and D. However, there is a optimistic projection that in 2020 79% will use it. They also found that 74% of data is retrieved from computer-based systems in manufacturing. As a simulation project needs a variety of data, it is not intriguing that 80% reported that they use more than one source. Most companies are also still dependent on manual data collection and interviews.

Barlas and Heavey (2016) affirmed that the principal challenge in this scientific domain lies in automating the input data process. Advanced data input methodologies and software that streamlines data input automation holds the potential to significantly enhance the broader acceptance of simulation techniques among both manufacturing companies and researchers.

Trend Towards Automated Simulation Model Generation (ASMG)

The discussion on ASMG in the simulation field stems from various advantages. ASMG streamlines simulations, making them less labor-intensive and error-prone, enabling more frequent runs. According to Vieira et al. (2018), ASMG is a catalyst for the Digital Twin concept. Digital Twins are crucial to understand inherently complex manufacturing systems. The Digital Twin concept combines the physical assets of a manufacturing system with its digital models. These are connected via an exchange of (real-time) data and the feedback of control information. ASMG can be used to keep the Digital Twin up to date without manually updating the incorporated simulation model.

The application of ASMG as illustrated by Kallat et al. (2020), automates the search for planning variants and generates feasible solutions through component-based software synthesis and constraint solving. Jain and Lechevalier (2016) emphasize that ASMG reduces the expertise required from simulation users, potentially expanding the adoption of simulation methods in manufacturing.

However, Bergmann (2013) argues that the full potential of ASMG remains untapped due to insufficient data availability, often relying on historical datasets unsuitable for modeling current system dynamics. A survey by Reinhardt et al. (2019) identifies various data sources for ASMG, including CAD data, enterprise data, knowledge bases, program code, sensor data, stochastic values, and user input. The complexity of ASMG is rooted in the diversity of data sources and retrieval methods. Moreover, the research community argues that commercial simulation software prefers interactive model building in the graphical user interface and that the implementation of ASMG is thus really challenging (Jain and Lechevalier 2016).

3.3.4 Machine Learning and Manufacturing Simulation

Machine Learning (ML) methods can be applied in simulation projects before, during, and after a simulation run, which is explained in the following.

Before the Simulation Run

The application of ML techniques in input data modeling includes unsupervised methods for identifying outliers and anomalies, clustering methods for detecting groups of similar production orders, and pattern recognition for unveiling recurring processes. Additionally, supervised methods are beneficial in scenarios where creating analytical models is either impractical or challenging. Vernickel et al. (2020) integrate a ML-based approach into the simulation to enable parameterization via model inference at runtime. Through manual feature construction, preprocessing steps, and employing XGBoost regression with hyperparameter optimization, the model outperformed other data mining methods, accurately predicting processing times based on 42 different features on a large-scale industrial dataset. Montevechi et al. (2021) investigates the application of Generative Adversarial Networks (GANs) in input data modeling, especially in cases where traditional methods fall short. The study evaluates GANs' effectiveness in generating highly accurate synthetic samples, showcasing their superior performance, particularly in the case of correlated data such as bivariate normal distributions.

Modeling human behavior for simulation poses another challenge. The literature offers examples demonstrating the efficacy of ML in improving the representation of human behavior in simulation. Li and Olafsson (2005) developed an approach to derive dispatching rules from production data by training a decision tree classifier. Reinhart and Gyger (2008) identify dynamic workflows caused by human decisions using pattern recognition methods on production data. Bergmann et al. (2015) successfully approximated decision rules with exceptionally high decision quality, even under challenging conditions like low data quality. Their study involved comparing the performance of various methods, including K-nearest neighbors, naive Bayes classifier, support vector machines, and decision trees. In a prior paper, they already showcased an approach where Artificial Neural Networks (ANNs) effectively captured scheduling strategies (Bergmann et al. 2014).

During the Simulation Run

Another trend in the literature is the use of simulation models for Reinforcement Learning (RL). Especially in agent-based simulation, this works intuitively because all objects are modeled as agents. If an agent should be improved with RL, the simulation serves as the learning environment. The focus of the various publications is almost exclusively on optimizing the operational control of factory processes. In Heger and Voss (2020), RL is used to optimize sequencing decisions. They refer to RL as "hyper-heuristic", which dynamically chooses the optimal rule from a given set depending on the state of the simulation model. Kim et al. (2020) performed experiments to analyze how machine agents can learn to improve negotiating the dispatching of jobs between machines based on priorities. Another common application of RL in manufacturing is the transportation control of Automated Guided Vehicles (AGVs). This is done, for example, in Li et al. (2019) with a deep Q-network. There is also criticism of scientific practice in RL for manufacturing simulations, as often the simulation model is not published with the rest of the code, which then makes reproducibility of the results impossible (Rinciog and Meyer 2022).

After the Simulation Run

After the simulation, the results must be evaluated. There was already the idea in the 90s to use regressions for metamodeling during evaluation (Madu 1990). They have shown that metamodels can generalize a complex simulation model within the constraints defined for the use case. This had the great advantage that sensitivity analyses could now be performed without a large number of time-consuming, and back in these days, costly simulation runs. This basic idea has been further developed over the years. Instead of metamodels, the term surrogate models is often used today. This was also the case in Sobottka et al. (2019), where a simulation-based planning method was modeled using an ANN. The ANN is then deployed in production planning to provide faster answers than the simulation. They evaluated their approach on an example from the food industry. Another use case in logistics is studied in Dunke and Nickel (2020), where the results show that the ANN can reproduce the behavior quickly and sufficiently well.

In instances where there is insufficient data for applying ML methods to the output data, simulation models can find utility in data farming, which is referring to a collection of tools and techniques for designing and analyzing large-scale simulation experiments (Sanchez 2018). From a ML perspective, the aim is to generate sufficiently relevant data on the input-output behavior of the simulated system so that a trained model can accurately reflect it. Another advantage of this approach is the augmentation of real-world data sets with simulated data of corner cases, rare events, and error scenarios. This augmented data set is the basis for a more robust ML solution. In Chan et al. (2022), synthetic data were generated from three different simulation models to study how the simulation time relates to the system's complexity. Their results are not surprising. It was confirmed that the more complex the simulation model is in terms of layout and the number of features, the more time it takes to generate synthetic data.

3.4 Summary

In Chapter 3, the approach to simulation studies, types of data input methodologies, and common data sources were presented. It was demonstrated that data constitutes a crucial component of any simulation, and challenges persist in its management. Specifically, data quality is recognized as a pervasive issue involving multiple dimensions, including accuracy, completeness, and consistency, among others. The discussion on data sources highlighted that information is frequently extracted from business systems that contain data that was originally collected for purposes unrelated to simulation. Moreover, the dynamic nature of processes is often inadequately reflected, necessitating the collection of data through observations and manual measurements. However, Indoor Positioning System (IPS) systems capture dynamic processes and movements that can be exploited instead and used for different applications in manufacturing, yet to be investigated.

The literature review section discussed various information models for manufacturing simulation. However, it was found that no common standard adequately caters to diverse domains (Mourtzis et al. 2014). Consequently, simulation studies often extend information model standards by incorporating user-defined properties (Bergmann and Straßburger 2015). Similarly, in addressing the domain-specific requirements of SMP, the development of a solution is imperative.

Chapter 4

Potentials and Challenges of Indoor Positioning Systems (IPSs)

In this chapter, an exploratory literature review is performed to reveal the potentials of Indoor Positioning System (IPS) usage in manufacturing. In Section 4.3, the found publications are categorized, and the identified use cases are presented. After the view on IPS from the literature, the point of view is changed to report on the current use of IPS in the investigation environment (Section 4.4) and accompanying challenges (Section 4.5) in the Sheet Metal Processing (SMP) industry.

4.1 Fundamentals on Indoor Positioning

Definition 4.1.1 (Indoor Positioning Systems (IPSs)) *IPSs determine the position of objects over time by measuring signals between reference nodes and mobile nodes and using calculations to determine the object's position within a reference system.*

An IPS consists of reference and mobile nodes. Latter represent the object's position in the reference system. Reference nodes, alternatively referred to as anchors or landmarks, are static at predetermined positions. Conversely, mobile nodes, referred to as agents, targets, or mobile users, dynamically change their positions over time. A line of sight is the connection between a reference node and an object. Estimating the position of mobile nodes, termed the tracking estimation problem (Mautz 2012), involves various methods employing different measurement and calculation techniques. This study does not focus on enhancing position tracking or IPS technology; rather, it aims to utilize position estimations from an IPS for simulation purposes. For more details on localization methods and position estimation, interested readers can consult the work of Mautz (2012) and Cheng et al. (2012).

Alternate terms for IPS in the literature include Real-Time Location/Localization System (RTLS), Real-Time Indoor Location/Localization System (RTILS), and Indoor Location/ Localization System (ILS). The term "real-time" implies that positions are instantly available, a feature already standard in the majority of contemporary systems. Henceforth in this document, the term IPS will be consistently used without explicitly specifying the real-time aspect of localization.

Market Overview and Projections for IPS IPS are experiencing a significant surge in prominence, emerging as a key technology for indoor location-based services (Mautz 2012, p.6; Dardari et al. 2015). Enhancing the capabilities of indoor positioning technologies holds the potential to unlock unprecedented business opportunities (Mautz 2012, p.7). According to data gathered in 2021 from various market research sources, including alliedmarketresearch[1], businesswire[2], marketsandmarkets[3], IndustryARC[4], and verifiedmarketresearch[5], the global market for IPS and indoor navigation witnessed a valuation ranging from $3-8 billion between 2017 and 2020. Projections anticipate a substantial growth, reaching approximately $17-24 billion by 2025, with an expected compound average growth rate of 22-42% over the forecasted period.

Exploring Challenges and Advantages of Positioning Indoors Positioning indoors has a higher degree of complexity than positioning outdoors (Dardari et al. 2015), due to the complexity of the indoor environments. Reasons for this are according to (Mautz 2012, p.7-8):

- Multi-path phenomenons from signal reflections at objects and walls
- No line-of-sight
- High attenuation and signal scattering as there are many objects indoors
- Fast temporal changes due to moving objects (people, forklifts, material)
- High demand for precision and accuracy
- Interference of signals from different sender types

For balance, however, the advantages of indoor localization must also be mentioned. According to (Mautz 2012, p.7-8) these are:

- Smaller coverage areas
- Fewer weather influences
- Geometric constraints: planar surfaces and orthogonality of walls
- Infrastructure: electricity, internet access, senders can be mounted on walls
- The speed of the moving objects is lower

Consequently, a thorough comparison of various indoor localization technologies is essential, with the selection of the most suitable solution tailored to meet the specific requirements of the sheet metal industry.

[1] https://www.alliedmarketresearch.com/indoor-positioning-and-indoor-navigation-ipin-market, accessed January 2021

[2] https://www.businesswire.com/news/home/20200615005247/en/Global-Indoor-Positioning-and-Navigation-Market-2020-to-2025---Featuring-Google-Qualcomm-Microsoft-Among-Others---ResearchAndMarkets.com, accessed January 2021

[3] https://www.marketsandmarkets.com/Market-Reports/indoor-location-market-989.html, accessed January 2021

[4] https://www.industryarc.com/Report/43/global-indoor-positioning-navigation-market.html, accessed January 2021

[5] https://www.verifiedmarketresearch.com/product/indoor-positioning-and-indoor-navigation-ipin-market/, accessed January 2021

4.2 Requirements and Considerations for IPS Selection in Manufacturing

This section provides a literature review in Table 4.1 of key user requirements essential for selecting the best IPS for the simulation use case in SMP. From the literature, twenty user requirements for evaluating IPS performance are identified, and their definitions are available in Appendix A.1. The frequency of occurrences for various user requirements is tallied within the range of $[1, 10]$. This count is then utilized to establish a metric for importance, with a rating of ten denoting the highest importance, and a rating of one indicating requirements mentioned in only one reference. In cases where a user requirement is indirectly stated, it is denoted with half of a Harvey ball and counted as 0.5.

Requirement	Liu et al. 2007	Gu et al. 2007	Ruiz-López et al. 2010	Mautz 2012	Farid et al. 2013	Mainetti et al. 2014	Liu 2014	Alarifi et al. 2016	Brena et al. 2017	Batistić and Tomic 2018	**Importance**
Accuracy	●	●	●	●	●	●	●	●	●	●	10
Costs	●	●	●	●	●	●	○	●	●	●	9
Coverage area	○	○	●	●	●	●	●	●	●	○	7
Update rate & responsiveness	○	●	●	●	●	○	●	●	○	◑	6.5
Scalability	●	○	●	●	●	○	○	●	○	○	5
Robustness & security	●	●	●	●	○	○	○	◑	○	◑	5
Precision	●	●	●	○	○	○	●	●	○	○	5
Required infrastructure	○	○	●	●	○	○	●	●	○	◑	4.5
Privacy	○	●	○	●	○	○	○	●	○	◑	3.5
Availability	○	○	●	●	○	○	○	●	○	○	3
Adaptiveness	○	◑	○	○	●	○	○	●	○	○	2.5
Market maturity	○	●	○	●	○	○	○	○	○	○	2
Intrusiveness	○	●	○	●	○	○	○	○	○	○	2
Number of users	○	○	○	●	○	○	○	○	○	◑	1.5
Output data	○	○	○	●	○	○	○	○	○	○	1
Interface	○	○	○	●	○	○	○	○	○	○	1
System integrity	○	○	○	●	○	○	○	○	○	○	1
Approval	○	○	○	●	○	○	○	○	○	○	1
Energy consumption	○	○	●	○	○	○	○	○	○	○	1

Table 4.1: Own literature review on user requirements for indoor positioning systems. The importance of a user requirement is calculated as the sum of the mentions. Legend: ● the user requirement is directly mentioned and is counted as one; ○ the user requirement is not mentioned and is counted as zero; ◑ the user requirement is indirectly mentioned and is counted as 0.5.

4.2.1 Use Case Requirements

In the process of selecting a suitable IPS technology for simulation in manufacturing, the focus is set on the most important requirements from Table 4.1. Accuracy emerged as the top priority, mentioned in every considered paper, followed by costs with nine mentions and coverage area with seven mentions. Given that obtaining cost information typically requires quotes from manufacturers, the initial focus is on finding the optimal trade-off between accuracy and coverage. A practical method is to examine an accuracy-coverage area diagram for various technologies, as illustrated in Figure 4.1. In this diagram, lines can be incorporated to represent the minimal and maximal error, as well as the minimal and maximal coverage area specific to the manufacturing simulation scenario.

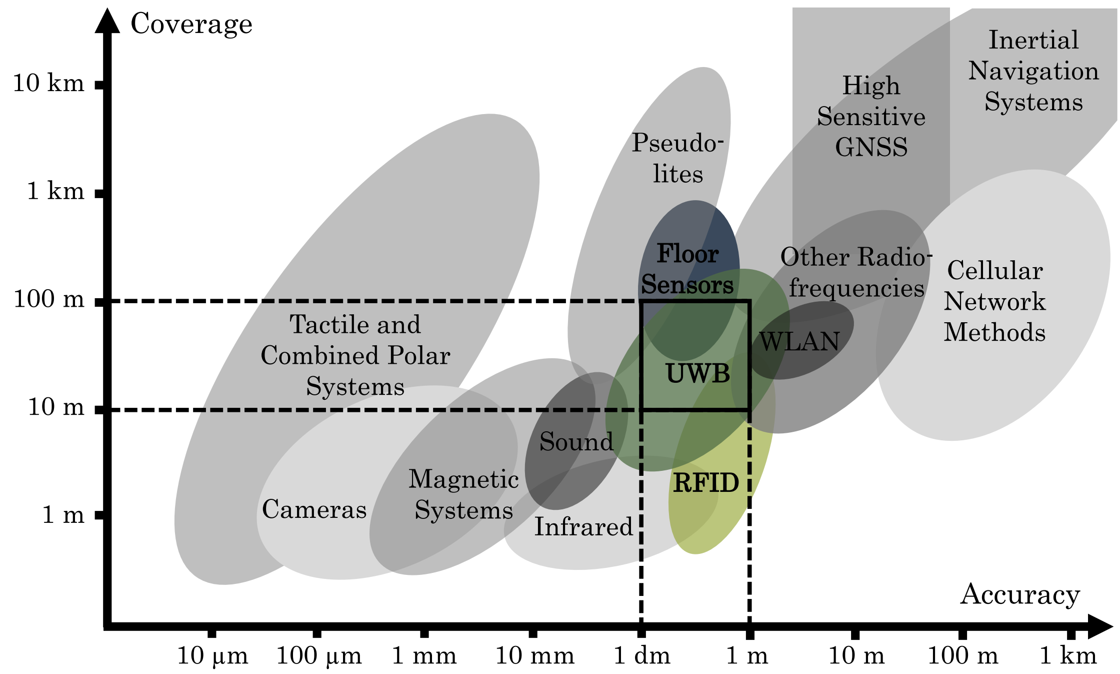

Figure 4.1: Comparison of indoor positioning technologies concerning coverage versus accuracy, adapted from Mautz (2012). Dashed lines represent use case boundaries for coverage (10-100 meters) and accuracy (0.1-1 meter error). Localization technologies relevant to the use case are within the resulting rectangle: Floor sensors (dark blue), UWB (green), and RFID (light green). Other, here irrelevant, localization technologies are depicted in grayscale.

Considerations regarding required accuracy: In this context, the focus is on distances relevant to manufacturing simulation. Accepting an one-decimeter error for the lower accuracy threshold is reasonable, as a 0.1 meter discrepancy from the correct location should not have a significant impact on simulation outcomes. However, deviations should not exceed one meter, given that approximately 90%[6] of parts in sheet metal manufacturing are transported on euro pallets. These pallets have dimensions of 1.2×0.8 meter. Ideally, the error should be less than 0.4 meter, equivalent to half the length of the smaller side of the pallet.

[6] According to internal investigations at TRUMPF

Considerations regarding required coverage: Manufacturing plants and production systems typically surpass the size of a room, ranging from greater than ten meters to several hundred meters. As an example, the Boeing Everett Factory, recognized as the largest manufacturing building globally by volume[7], has a long side of approximately 730 meters. However, in sheet metal manufacturing, production sites are comparatively smaller. Therefore, for this scenario, it can be assumed that the coverage area is limited to a few hundred meters.

4.2.2 Use Case Relevant Localization Technologies

The identified boundaries for accuracy and coverage are added as dashed lines to Figure 4.1. The resulting square includes three use case relevant technologies which will be presented in the following: Floor sensors, RFID, and UWB.

Floor Sensors Integrated into tiles, they track objects by detecting capacitance differences between tiles or using force-sensitive resistors that measure pressure beneath human feet (Mautz 2012, p.105). This technology is not suitable for the simulation scenario, as it works without mobile tags and the tracked objects are therefore not identifiable. Consequently, it only provides abstract movement patterns of unidentified entities that are not useful for modeling simulation inputs.

Radio-Frequency Identification (RFID) This technology utilizes radio waves to transfer the identity of an object or person wirelessly (Alarifi et al. 2016). Examining the designated area in Figure 4.1, it becomes evident that RFID can only partially meet the desired accuracy and coverage requirements. RFID proves effective for smaller areas, when employing proximity-based methods where the system registers the presence of a RFID tag near an antenna rather than determining precise positions (Alarifi et al. 2016). Notably, RFID-based localization faces challenges such as false-positive classifications, usually mitigated by reducing antenna power at the expense of detection rates (Hauser et al. 2015). For broader coverage, it is recommended to utilize the more expensive active RFID tags. Equipped with their own power supply, they are able to transmit radio signals over extended distances between the transmitter and receiver.

Ultra-Wideband Technology (UWB) This technology aligns best with the specified accuracy and coverage requirements. UWB exhibits superior accuracy compared to RFID, as illustrated in Figure 4.1. The accuracy discrepancy can be attributed to the prevalent use of the proximity method in RFID, where an object is localized only in the vicinity of the antenna. In contrast, UWB utilizes a broad bandwidth ($\geq$ 500 MHz) for information transmission (Ruppert and Abonyi 2020). The short pulses emitted by UWB systems are easily filterable, enabling precise differentiation between correct signals and those caused by multi-path reflections (Liu et al. 2007). The broad bandwidth minimizes interference, facilitating higher positioning accuracies and efficient data transmission with reduced energy consumption (Alarifi et al. 2016; Sahinoglu et al. 2008). Although UWB, like other radio-frequency-based technologies, encounters challenges with metallic surfaces, strategic satellite placement can effectively mitigate this issue (Liu et al. 2007).

[7] `https://en.wikipedia.org/wiki/Boeing_Everett_Factory`, accessed May 2022

Given the superior alignment of UWB-based tracking systems with the specified requirements for the simulation use case in SMP, UWB is recommended as the technology of choice for the current scenario. This recommendation aligns with findings from other authors, including Ruppert and Abonyi (2020) and Ćwikła et al. (2018). Another plausible approach could involve a hybrid solution, combining the strengths of two technologies. Specifically, RFID could be employed at workstations, leveraging the proximity-based localization, to achieve a higher resolution in tracking production steps.

For an in-depth comparison of various IPS technologies, interested readers are directed to comprehensive works such as Alarifi et al. (2016), Mautz (2012), Zafari et al. (2019), and Hayward et al. (2022). These works provide thorough evaluations of standard measurement methods, outlining the advantages and disadvantages of different technologies.

4.3 Literature Review on the Potentials of IPS in Manufacturing

This section is a comprehensive update of the literature review from the authors' paper on the potentials of IPS in manufacturing (Mieth et al. 2019a). IPS, as the name implies, are developed for indoor object localization. Besides the mere functionality of positioning objects, the gathered data can be enriched and used to create further benefits, which are referred to as secondary benefits (Mieth et al. 2019a). In the next Section 4.3.1, the approach to identify relevant literature is presented. All relevant publications are categorized in Section 4.3.2 according to the mentioned use cases' primary use, application area and maturity level. In Section 4.3.3, the use cases mentioned in the publications are categorized in the columns of the shown tables. From this, it becomes evident which use cases are more prominent than others. Lastly, in Section 4.3.5, a closer look is taken on the privacy concerns raised in these publications and how they are handled.

4.3.1 Approach to Identify Publications

The approach in this section is self-developed but rooted in exploratory literature research. Only peer-reviewed literature published in journals or conferences is considered. This literature review intends to investigate the potential of IPS in manufacturing, which also encompasses production, logistics, assembly, and warehousing applications for the manufacturing area. Publications focusing on other industries, such as healthcare, smart cities, or the construction industry, are omitted. Purely technical review publications dealing with the comparison of IPS technologies, their implementation or algorithms are not considered. However, if the abstract mentioned that they are presenting an overview of applications, these mainly technical survey publications are included.

The overview of the different search strings in chronological order and the number of identified publications can be seen in Table 4.2. For all search strings, no restriction on the publication period is made. The top 100 results from Google Scholar are screened for promising publications. The search strings are modified in each round, resulting in seven search rounds with 100 publications evaluated each time. Duplicates in the list of promising publications are directly removed. A duplicate is defined as a publication that appeared in a previous search within the top 100 highest-ranked results.

For the identified candidates, the abstract is reviewed. For publications that still appear attractive, the entire publication is examined for potential benefits of IPS in manufacturing. In rare cases, publications are excluded after a thorough reading due to a lack of relevance. From the old review paper (Mieth et al. 2019a), four publications where added to the literature corpus along with three publications that cite it. Another three publications are added, that were found in other previous search activities. Through this approach, a total of 41 publications highlighting the potential of IPS in manufacturing are identified and analyzed. These 41 publications are listed in the rows of the Tables 4.3-4.6 in this section.

	promise-ing search results	after reading abstracts	after reading full text
potentials of indoor positioning	8	4	3
potentials of indoor localization	3	2	2
potentials of indoor localization manufacturing	15	9	8
potentials of indoor positioning manufacturing	7	3	2
applications use cases indoor localization positioning manufacturing	15	9	7
manufacturing simulation input modeling indoor localization positioning	3	3	3
digital twin manufacturing indoor localization positioning	18	6	6

Table 4.2: Overview of the different search strings in chronological order and the number of publications considered in each step of the literature review.

4.3.2 Categorization of Publications

The primary use (first column in Table 4.3) of a tracking system is to locate objects. Therefore, it is always stated which objects are tracked. A distinction is made between four categories of primary use. The first one is called asset & order tracking and covers goods, products, bins, trays, and pallets. The second category is checked whenever transport vehicles are tracked. The third category is equipment & tools, which consists of predominantly expensive objects. The last category is checked whenever the publication mentions a use case where humans are tracked. With 73% (30 publications), asset & order tracking is the most mentioned category, closely followed by 25 publications (61%) mentioning the tracking of humans or equipment & tools each and 23 (56%) publications with use cases on tracking transport vehicles. The use cases are classified equally frequently in production and logistics, with 31 publications each (76%). Ten publications are included in the literature review that mention use cases for a more generic environment. Mainly survey publications fall into this category.

	primary use				area			maturity level						
	asset & order tracking	transport vehicles	equipment & tools	humans	logistics	production	generic / other	only mention	idea state	ongoing / prototype	implemented	research environment	industrial environment	privacy concerns
Zhou and Shi 2009	x	x	x				x	x						
Schmitt et al. 2010			x		x	x				x	x	x		
Stephan and Heck 2010			x	x	x	x			x	x		x		x
Mautz 2012	x	x	x	x	x	x	x	x						x
Véjar and Charpentier 2012	x				x	x		x			x	x		
Koch et al. 2014				x		x	x			x		x		
Niehues 2016	x				x	x					x	x		
Alarifi et al. 2016	x		x	x			x	x						x
Erol et al. 2016	x	x			x	x			x	x		x		
Ionescu et al. 2016	x	x	x	x	x	x				x	x		x	
Syberfeldt et al. 2016			x	x	x	x			x	x			x	x
Yassin et al. 2017			x	x			x	x						x
Brenner and Hummel 2017	x	x		x	x	x				x		x		
Uhlemann et al. 2017	x	x	x	x	x	x				x		x		
Zafari et al. 2019	x			x			x	x						x
Ćwikła et al. 2018	x	x	x	x	x	x		x	x			x		
Falkowski et al. 2018a	x	x	x	x	x	x		x	x				x	x
Falkowski et al. 2018b	x				x	x								x
Schroeer 2018	x	x	x	x	x	x		x						
Zhuang et al. 2018	x	x	x		x	x				x		x		
Maghazei and Netland 2019			x		x	x		x	x					
Mier et al. 2019	x	x	x	x			x	x						x
Deja et al. 2020			x		x	x		x	x					
Ruppert and Abonyi 2020	x					x				x			x	
Židek et al. 2020	x					x				x		x		
Flossdorf et al. 2021	x	x	x		x	x				x			x	
Gutewort et al. 2021	x	x		x	x					x			x	
Hesslein et al. 2021	x	x		x	x					x		x		
Müller and Vogelsang 2021	x	x	x	x	x	x		x	x				x	
Pitkäaho et al. 2021				x		x					x	x		
Thiede et al. 2021	x	x	x	x	x	x		x						x
Tran et al. 2021	x	x			x	x				x	x		x	x
Xianjia et al. 2021		x	x		x			x	x					
Chowdhury et al. 2022	x			x		x	x				x		x	
Farahsari et al. 2022	x	x	x	x	x	x	x	x						x
Gerwin et al. 2022	x	x	x		x	x				x	x		x	
Hayward et al. 2022	x	x	x	x	x	x	x	x						x
Pilati et al. 2022				x	x	x					x		x	x
Thiede et al. 2022	x	x	x	x	x	x			x	x	x	x		x
Wu et al. 2022	x	x	x		x					x	x		x	x
Zhan et al. 2022				x	x						x		x	
number of mentions	30	23	25	25	31	31	10	17	10	18	12	14	13	16
percentage	73	56	61	61	76	76	24	41	24	44	29	34	32	39

Table 4.3: Categorization of the 41 publications for the literature review.

To track the maturity of the mentioned use cases, it is recorded for each publication whether it only mentions use cases, whether it is in the idea stage or already in implementation, and finally, whether the implementation has been completed. In addition, a distinction is then made as to whether the implementation is within a research environment, such as a learning factory, an artificial mock setup, or a virtual experiment, or whether one had worked on an implementation in a real-world setup in the industry. Seventeen publications (41%) only mention use cases without working on them. Ten publications (24%) describe potential use cases in the idea stage. Eighteen publications (44%) present prototypes of the use case, and 29 publications (29%) have finished implementations. Please note that all the categories used so far are not mutually exclusive. However, there is a mutually exclusive differentiation made between use cases that were or are currently implemented in research environments or the industry. Both occur almost equally frequently, with 14 (34% research) and 13 (32% industry) publications, respectively. The figures show that there is still more talk about the potential than actual implementations.

4.3.3 Identified Use Cases

The literature search resulted in 51 use cases, which are classified into twelve groups. A representation in a single table on one page would lack readability. Therefore, the analysis is divided into three tables, with the rows in all three tables corresponding to the set of publications. The use cases and groups in the columns are distributed across the three Tables 4.4, 4.5 and 4.6. Due to this split, some rows in some tables have no crosses and are therefore hidden to save space. At the bottom of each table, the number of mentions per use case is given in absolute and relative terms (in relation to the 41 publications). The use cases are listed in descending order in each column group, from most frequently mentioned to least frequently mentioned. The top four use cases are monitoring & transparency (21 publications, 51%), process/movement analytics (19 publications, 46%), and sharing the third place, process optimization and navigation & wayfinding (17 publications each, 41% each). The group of use cases with the most mentions in sum is transparent management. The twelve groups with their use cases are presented in the following.

The Twelve Groups of Use Cases

The twelve groups of use cases correspond to the grouped columns in Table 4.4, 4.5, and 4.6. An overview of the first fifteen use cases in the Groups 1–4 and which of the 41 publications mention them is given in Table 4.4. The first group consists of basic use cases such as using the IPS to realize time and cost savings through less searching and faster finding. Three publications also mentioned that the flexibility and adaptability of processes should be increased with the help of indoor localization. The second group, automation of procedures, sums up different use cases that focus on automating the status data collection, which is currently done manually or not at all. An automated log-on/log-off procedure can help to gather data on the operational status, e.g., breaks, and helps with allocating humans to tasks. Eleven publications stated that the order progress can be tracked, which is used for automated documentation of flow, progress, process procedures, and cost calculations. The third group is a compilation of use cases around transparent management. A frequently mentioned use case with 21 mentions, which is about

	basic		automation of procedures				transparent management					lean management			
	time & cost savings	flexibility & adaptability	track order progress	automated logon/logoff	automated booking	automated documentation	monitoring / transparency	digitization of movements	inventory management	operation management	asset management	process optimization	quality control	reduce waste (lean)	avoid overproduction
Zhou and Shi 2009	x	x	x			x			x	x	x	x			
Stephan and Heck 2010	x		x				x					x			
Mautz 2012				x			x		x	x	x		x		
Véjar and Charpentier 2012	x						x	x	x						
Niehues 2016		x	x		x			x							
Alarifi et al. 2016										x					
Erol et al. 2016					x		x		x						
Ionescu et al. 2016			x	x			x	x	x		x	x			
Uhlemann et al. 2017								x							
Zafari et al. 2019									x	x	x				
Ćwikła et al. 2018							x	x		x		x			
Falkowski et al. 2018a				x	x		x		x	x	x	x	x		
Falkowski et al. 2018b											x	x			
Schroeer 2018		x						x			x	x			
Zhuang et al. 2018			x			x	x		x			x	x	x	
Mier et al. 2019							x			x	x		x		
Ruppert and Abonyi 2020			x				x	x				x			
Židek et al. 2020			x					x							
Flossdorf et al. 2021	x						x								
Gutewort et al. 2021	x			x	x	x	x	x	x	x		x		x	
Hesslein et al. 2021			x	x	x	x	x	x				x			
Müller 2020	x		x	x	x	x	x		x						
Thiede et al. 2021	x		x	x	x	x	x	x	x	x			x	x	
Tran et al. 2021							x		x			x	x	x	x
Chowdhury et al. 2022			x	x			x	x		x		x			
Farahsari et al. 2022							x	x				x			
Gerwin et al. 2022	x				x		x		x		x	x		x	
Hayward et al. 2022	x			x	x	x	x	x	x	x	x	x	x		
Thiede et al. 2022				x	x	x		x					x		
Wu et al. 2022	x						x					x			
number of mentions	10	3	11	10	10	8	21	15	14	11	10	17	8	5	1
percentage	24	7	27	24	24	20	51	37	34	27	24	41	20	12	2

Table 4.4: Use case overview part 1 of 3 with the first fifteen identified use cases in the Groups 1–4: Basic, automation of procedures, transparent, and lean management.

every second publication, is monitoring processes to improve transparency. This is realized by digitizing movements with the IPS. Other use cases in this group focus on managing inventory, operations, and assets. This category mainly includes use cases where transparency is achieved in a simple way, for example, only through a visual representation or rudimentary analyses. Transparency can, of course, also be achieved on the basis of more complex analyses. However, such use cases are grouped under following more specific groups. The fourth group is called lean management and shows use cases that help in classic lean tasks such as process optimization, the

	intralogistics						security			safety					descriptive analytics					
	transport optimization	robotics	AGVs	fleet management	drones	augmented reality	access monitoring	anti-lost	theft prevention	safety systems	collision avoidance	health monitoring	speed control	dangerous goods	movement analytics	process times	KPIs	area utilization	asset utilization	anomaly detection
Zhou and Shi 2009	x		x							x	x								x	
Schmitt et al. 2010		x																		
Stephan and Heck 2010															x		x			
Mautz 2012	x	x	x	x			x		x	x	x				x					
Véjar and Charpentier 2012		x		x											x	x				x
Niehues 2016															x	x				
Alarifi et al. 2016		x							x											
Ionescu et al. 2016	x						x								x	x				
Syberfeldt et al. 2016						x														
Yassin et al. 2017		x								x	x	x								
Brenner and Hummel 2017			x																	
Uhlemann et al. 2017															x	x		x		
Ćwikła et al. 2018															x					
Falkowski et al. 2018a				x			x			x					x		x			
Falkowski et al. 2018b							x								x					
Schroeer 2018		x								x										
Zhuang et al. 2018	x															x				
Maghazei and Netland 2019					x															
Mier et al. 2019		x	x				x			x										
Deja et al. 2020					x															
Ruppert and Abonyi 2020															x	x	x			
Gutewort et al. 2021	x														x					
Hesslein et al. 2021	x			x						x			x							
Müller 2020	x									x			x		x	x	x	x		x
Pitkäaho et al. 2021		x								x										
Thiede et al. 2021	x		x	x			x			x	x	x			x		x			
Tran et al. 2021	x														x	x	x			
Xianjia et al. 2021	x	x	x	x	x															
Chowdhury et al. 2022															x	x	x			
Farahsari et al. 2022	x	x						x		x		x			x					
Gerwin et al. 2022	x		x				x			x	x	x		x	x	x				
Hayward et al. 2022	x						x	x		x						x		x	x	
Pilati et al. 2022												x								
Thiede et al. 2022										x	x				x					
Wu et al. 2022															x					
Zhan et al. 2022										x										
number of mentions	13	10	7	6	3	1	8	2	2	15	6	5	2	1	19	11	7	3	2	2
percentage	32	24	17	15	7	2	20	5	5	37	15	12	5	2	46	27	17	7	5	5

Table 4.5: Use case overview part 2 of 3 with the next twenty identified use cases in the Groups 5–8: Intralogistics, security, safety and descriptive analytics.

reduction of waste, and work-in-process (WIP) monitoring. One publication even mentioned that IPS should be used to avoid overproduction. Eight publications saw the potential of IPS in quality control and mentioned that cold chains in food or pharmaceutical operations could be better monitored.

An overview of the next twenty use cases in the Groups 5–8 and which of the 41 publications mention them is given in Table 4.5. The fifth group consists of intralogistics use cases such as routing and transport optimization mentioned by roughly a third of the authors. Indoor positioning systems enable use cases with robots, Automated Guided Vehicles (AGVs), and even drones. One publication demonstrated how to use localization information in an augmented reality use case. An-

	location-based services								maintenance			predictions		advanced methods		
	navigation	location-based services	providing context info	worker assistance	map creation	proximity detection	tool setup	picking aid	maintenance optimization	fault management	remote diagnosis	delivery forecast	anomaly prediction	(real-time) production control	digital twin	simulation
Zhou and Shi 2009						x										
Stephan and Heck 2010	x	x	x	x					x							
Mautz 2012	x	x	x	x		x			x							
Véjar and Charpentier 2012	x															x
Koch et al. 2014	x		x	x					x	x	x					
Niehues 2016														x		
Alarifi et al. 2016	x	x		x												
Ionescu et al. 2016														x		
Syberfeldt et al. 2016			x													
Yassin et al. 2017	x	x	x													
Brenner and Hummel 2017		x													x	
Uhlemann et al. 2017															x	x
Zafari et al. 2019	x	x	x			x										
Ćwikła et al. 2018		x														
Falkowski et al. 2018a	x	x	x	x			x		x							
Falkowski et al. 2018b	x	x	x				x									
Schroeer 2018	x		x													
Zhuang et al. 2018														x	x	
Mier et al. 2019		x		x					x							
Ruppert and Abonyi 2020					x							x			x	x
Židek et al. 2020															x	x
Flossdorf et al. 2021				x	x					x			x	x		
Hesslein et al. 2021	x	x	x		x							x		x		
Müller 2020	x		x	x				x				x	x	x		x
Pitkäaho et al. 2021															x	
Thiede et al. 2021	x						x							x		
Farahsari et al. 2022	x	x														
Gerwin et al. 2022	x	x	x											x		
Hayward et al. 2022	x	x	x		x									x		
Thiede et al. 2022	x															
Wu et al. 2022		x													x	
number of mentions	17	15	13	8	4	3	3	1	5	2	1	3	2	9	7	5
percentage	41	37	32	20	10	7	7	2	12	5	2	7	5	22	17	12

Table 4.6: Use case overview part 3 of 3 with the last sixteen identified use cases in the Groups 9–12: Location-based services, maintenance and fault management, predictive analytics and advanced planning and control methods.

other six publications want to use IPS to manage their logistics fleet. The sixth group summarizes different use cases focusing on security. Access to certain areas can be monitored with the help of IPS. Sometimes specific areas have restricted access (e.g., for visitors or specialists), and only people with certain qualifications and access rights can enter. Two publications mention that IPS can help not to lose important objects, and two other publications supplement that it could be used to prevent theft of expensive tools and assets. The seventh group is a compilation of use cases around safety. The localization data can be fed to safety systems that send warnings to people in certain areas or can be used to find them during an evacuation scenario. When people work alone, they sometimes have to wear a lone worker device to call help in case of an emergency which could be beneficially combined with the localization capabilities of an IPS. The movement data can also be analyzed to detect a collapse through anomaly detection. IPS can help in collision avoidance and control speed limits. The proximity of objects can be tracked for health monitoring use cases, such as keeping a distance to prevent the spread of the Covid-19 disease. Many accidents in production happen due to a collision of humans with vehicles. Lastly, one publication mentioned that storing dangerous goods can be controlled. The eighth group is called descriptive analytics and presents use cases that analyze the movement data to learn more about the underlying processes. Around half of the publications mention this idea. One crucial goal of these analyses is to determine process times. Also, the calculation of Key Perfomance Indicators (KPIs) is an attractive use case that can focus, for example, on analyzing the utilization of areas and assets. Two publications want to detect anomalies in the movement data.

An overview of the last sixteen use cases in the Groups 9–12 and which of the 41 publications mention them is given in Table 4.6. The ninth group consists of location-based services, which are mentioned fifteen times. Location-based services include, for example, navigation and wayfinding as prominent use cases with seventeen mentions. Three publications suggest a location-based tool setup, and one publication sees potential using IPS for picking processes. The IPS data helps create up-to-date maps of the shop floor. In general, the IPS position data helps to provide context-related information on mobile devices and thus enables different types of worker assistance systems working with proximity measures to trigger notifications. The tenth group summarizes different use cases focusing on maintenance and fault management. IPS can play a crucial role in the optimization and support of maintenance activities and even in remote diagnosis. Two publications say that fault management procedures would benefit from doing rework within the production process enabled by IPS. The eleventh group is compiling use cases of predictive analytics, which are not that numerous yet. Only three publications mentioned that they want to use the historic IPS data to forecast delivery times or to predict anomalies. Although the own survey (Mieth et al. 2019a) mentioned predictive maintenance as a use case, it could not be found in any publication in the updated review. The last and twelfth group is called advanced planning and control methods and presents use cases where IPS data is used in (real-time) production control, digital twins, and simulations. Of the five publications that mention simulation as a use case related to IPS, three do this in combination with the digital twin concept, which inherently has a model, here the simulation model, of the system built into its definition. In the next section a closer look is taken on the publications where IPS are used for the simulation use case.

4.3.4 Publications on IPS for the Simulation Use Case

The first publication that considers IPS data for simulation is from Véjar and Charpentier (2012). They implemented a generator to produce synthetic location data streams representing product trajectories. The generated synthetic data (product ID, location, and time) was then used to create queuing network simulation models. The presented example considered only three product types on three machines. Also, it is unclear how and if at all measurement uncertainties of IPS were added to the synthetic data, as was done in own research (Volk and Mieth 2022), where a decline in the performance of algorithms determining lead times was shown when the measurement error of the IPS is increased. Moreover, their queuing networks are an easier way to model a shop floor than with a discrete event simulation model.

Uhlemann et al. (2017) is presenting a concept for a learning factory environment where position data is gathered via a radio-based localization system to track humans and a camera-based system at each workstation. The aim is to automate the static value stream mapping process with the help of a digital twin in Technomatix Plant Simulation. The publication's result is a qualitative comparison between the characteristics of a digital twin versus classic value stream mapping, showing the superiority of the digital twin concept. The last sentence in their publication states that their next step is the physical implementation of this concept.

Ruppert and Abonyi (2020) utilize real-world IPS data to parameterize a simulation model of a conveyor-based wire-harness assembly line. UWB tags are mounted to the flat wire harnesses. The simulation, developed with Siemens Technomatix Plant Simulation software, incorporates data from the IPS, Manufacturing Execution System (MES), and Enterprise Ressource Planning (ERP). Process mining is used to analyze localization data, determining the assembly time distribution for the two products. Their analysis uses data spanning a month, with updates to the model made once per shift, though no explanation is provided for this frequency difference. While they say that they have derived a shop floor layout from the data, specific details are lacking. What was interesting is that mobile and stationary tags were used to infer the running times of the machines via vibration sensing. In addition, this made it possible to link the data from mobile and stationary tags. Presumably, the stationary tags were further used as reference points to generate the hall layout in the virtual model and semantic details regarding station types at respective locations were manually annotated. The use case's complexity is notably reduced due to the system's limited product types and structured station workflow. There is no mention of how outliers were handled during the analysis or how IPS measurement errors were addressed. Furthermore, validation of trajectory analysis and simulation accuracy is not done.

Židek et al. (2020) present a digital twin implementation with a simulation model in Siemens Tecnomatix Plant Simulation. They created an experimental setup of an assembly system with a belt conveyor and a quality inspection station, which had the size of a table. One RFID reader checks the presence and identity of a part at the end position. For the quality check, a camera-based system was used. The authors show a consistent concept for a digital twin in their publication. Unfortunately, however, the part on location data analysis is very simplified and needs to come closer to the actual conditions in the industry: Analyzing localization data from one RFID reader is trivial since no exact position has to be determined, but only whether the part arrived, i.e., was close enough to the reader.

There is still no literature on methods and algorithms to derive input data for a simulation from localization data. Own publications, like Mieth (2019) and Volk and Mieth (2022) focus on process time determination, which is a complex task due to a lack of standardized processes, measurement errors, and difficulties validating developed algorithms in real-world settings because of missing ground truth data.

4.3.5 Privacy Concerns in the Literature

During the literature search, each publication was reviewed for privacy concerns. The results are shown in the last column of Table 4.3. Only 39% of the publications mentioned privacy concerns, although 61% of the publications consider use cases where humans are tracked. In most cases, the concerns were very general and always a side note. Only in rare cases were recommendations given on how to cope with data privacy issues.

A project report from the EU-funded project i-locate identified three main reasons that impede the adoption of indoor location-based services (Conti et al. 2016). Next to the need for more standardization and IT integration, privacy was of major concern. A more recent discussion initiated in Thiede et al. (2021) with representatives from the industry revealed that their mainly perceived challenges with IPS adoption lie in the areas of costs, accuracy, and data privacy. Although privacy is a valid concern from the practice, this aspect is not sufficiently addressed in research on IPS (Mautz 2012; Alarifi et al. 2016; Zafari et al. 2019; Farahsari et al. 2022; Hayward et al. 2022).

Privacy is a major concern (Zafari et al. 2019), especially when humans are tracked (Thiede et al. 2022). Syberfeldt et al. (2016) point out that the integrity of constantly monitored workers is breached. Valuable personal data is collected, possibly without the individual's knowledge (Zafari et al. 2019). Farahsari et al. (2022), and Mier et al. (2019) rightfully state that location data is sensitive data that can compromise user privacy and security and therefore a strong access control over personal data is crucial (Alarifi et al. 2016). Care must also be taken to ensure that the data is not simply used for unintended purposes or even misused (Syberfeldt et al. 2016).

Low acceptance for collecting personal data is one of the main reasons hindering the adoption of localization-based services (Zafari et al. 2019; Hayward et al. 2022). Often, users of IPS understandably do not want to share their personal location data (Zafari et al. 2019) and are concerned about disclosing too much information (Mautz 2012). Mautz (2012) emphasize that consideration of privacy preferences influences user consent, and Stephan and Heck (2010) further argue that user privacy requirements must be discussed upfront to implement industrial location-based services successfully. Also, IPS architectures should comply with regulations such as General Data Protection Regulation (GDPR) and the Data Protection Act, which can only be achieved if this is already considered in the system design phase (Hayward et al. 2022). The secure processing, storage, and interaction with data are critical for IPS to be widely deployed and gain user adoption (Hayward et al. 2022). Mautz (2012) is giving some guiding questions to elaborate on user acceptance:

- How comfortable are users with their data (e.g., trajectory) being stored?
- Do users have legal concerns about their privacy?
- Can private users be motivated to provide personal data?

Stephan and Heck (2010) think that analyzing location data, especially if conclusions are drawn from it about personal movement profiles and work processes, causes rationalization fears among users and, thus, low acceptance. In Thiede et al. (2021), the analysis focuses on the operational status of the worker and thus determines their break times which is a piece of sensitive information. There are even more privacy issues when an image-based IPS system is used instead of a tag-based system because it technically allows for even further analyses and also captures visitors or external personnel (Thiede et al. 2021; Thiede et al. 2022).

Some technical challenges complicate ensuring privacy in IPS. According to Farahsari et al. (2022), these include database corruption, radio frequency interference, malicious nodes, privacy protocols of devices, and network security. Mier et al. (2019) highlight that security is crucial to protect data from intruders, theft, and misuse. This is not only important for the collected data but also during data transmission (Wu et al. 2022). Challenging are especially hardware limitations in energy and computing power, as this often hampers the application of good cryptography algorithms (Hayward et al. 2022; Farahsari et al. 2022).

The authors have also listed some specific recommendations for improving user privacy, which is now compiled here. A distinction is made between technical, organizational, and process recommendations. Suggestions for technical improvements to privacy in IPS include security mechanisms (Alarifi et al. 2016), anomaly detection algorithms (Farahsari et al. 2022), and data access restrictions (Yassin et al. 2017). The architecture of the IPS is decisive for privacy too. For example, self-localization on edge devices ensures a higher level of privacy (Yassin et al. 2017; Thiede et al. 2022). Another technical advice is to aggregate data, e.g., for a group of people, so that conclusions about individual behavior cannot be drawn anymore. This was done in Pilati et al. (2022) to provide the management of a manufacturer with data on social distancing efforts during the COVID-19 pandemic. Organizational recommendations on data privacy focus on raising awareness of the issue among the workforce and establishing policies on what data is collected and for what purpose, how it is stored and processed, how long it is retained, and who may have access to it (Syberfeldt et al. 2016). Such policies should be developed in close cooperation with worker unions or other important labor associations to increase user acceptance (Stephan and Heck 2010; Thiede et al. 2021). Approval could also be improved by having the IPS certified by a trusted authority (Mautz 2012). Last but not least, clearly explaining and communicating the personal benefits to the employee increases the acceptance of location data collection, e.g., when the data is used to implement better security measures or reduce routine work (Stephan and Heck 2010). Privacy can also be enhanced through well-thought-out processes. In Tran et al. (2021), the localization of objects only takes place in production zones. Pilati et al. (2022) use anonymous tags so that no conclusions can be drawn about individual persons. Only the person can look up their COVID-19 risk score if they are interested. Zafari et al. (2019) suggest designing IPS as a location support system, not as a tracking system, allowing users to choose to discover location-based services rather than sharing their location automatically.

Protecting the privacy of IPS users is a relevant research topic that needs to be addressed at the legislative, regulatory, policy, and implementation level (Falkowski et al. 2018a). Monitoring humans in a production environment needs further research, especially in realistic scenarios to characterize the effect of dynamic environments and human activity on the appropriate function of IPS (Hayward et al. 2022). Zafari et al. (2019) see privacy and security concerns as the major challenges facing research. Without new insights from research, the lack of trustworthiness between users and IPS providers cannot be overcome.

4.4 Today's Use of IPS in the Investigation Environment of SMP

Figure 4.2: Work accompanying documents on sheet metal parts. Image courtesy of TRUMPF.

In SMP, there is a trend toward increasingly smaller lot sizes. As batch sizes decrease, the number of accompanying documents relatively increases. There are long search times because the positions of the production orders are generally not known. Each production order can only be identified by its accompanying papers containing the necessary work steps (see Figure 4.2). This makes it more difficult to find an order. In addition, the documents are often misplaced, and after printing, they can become outdated very quickly. To enable paperless production and reduce non-value-adding search times, an IPS was developed that replaces accompanying documents with markers. The markers have an e-ink display that shows the information needed for production. At the start of production, the markers are linked to an order via a user interface on the computer. For easier handling, there are handheld scanners that can be used to scan a QR code on the marker's display and barcodes from the production papers. The setup for this task can be seen in Figure 4.3. With this initialization, a unique object ID (ID_{object}) is assigned to the unique marker ID (ID_{marker}). Each event sample from the IPS data is a state vector that is structured as follows:

$$s(t) = (x(t), y(t), z(t), \mathrm{ID}_{marker}, \mathrm{ID}_{object}) \tag{4.1}$$

where $x(t)$, $y(t)$, and $z(t)$ are the Cartesian coordinates in the reference system of the satellites. After the order has been produced, the marker is physically removed and virtually decoupled from the order. The markers are collected and taken to a charging station, where they are inductively charged and then returned to the marker supply, from which an employee can pick a marker to initiate a new order.

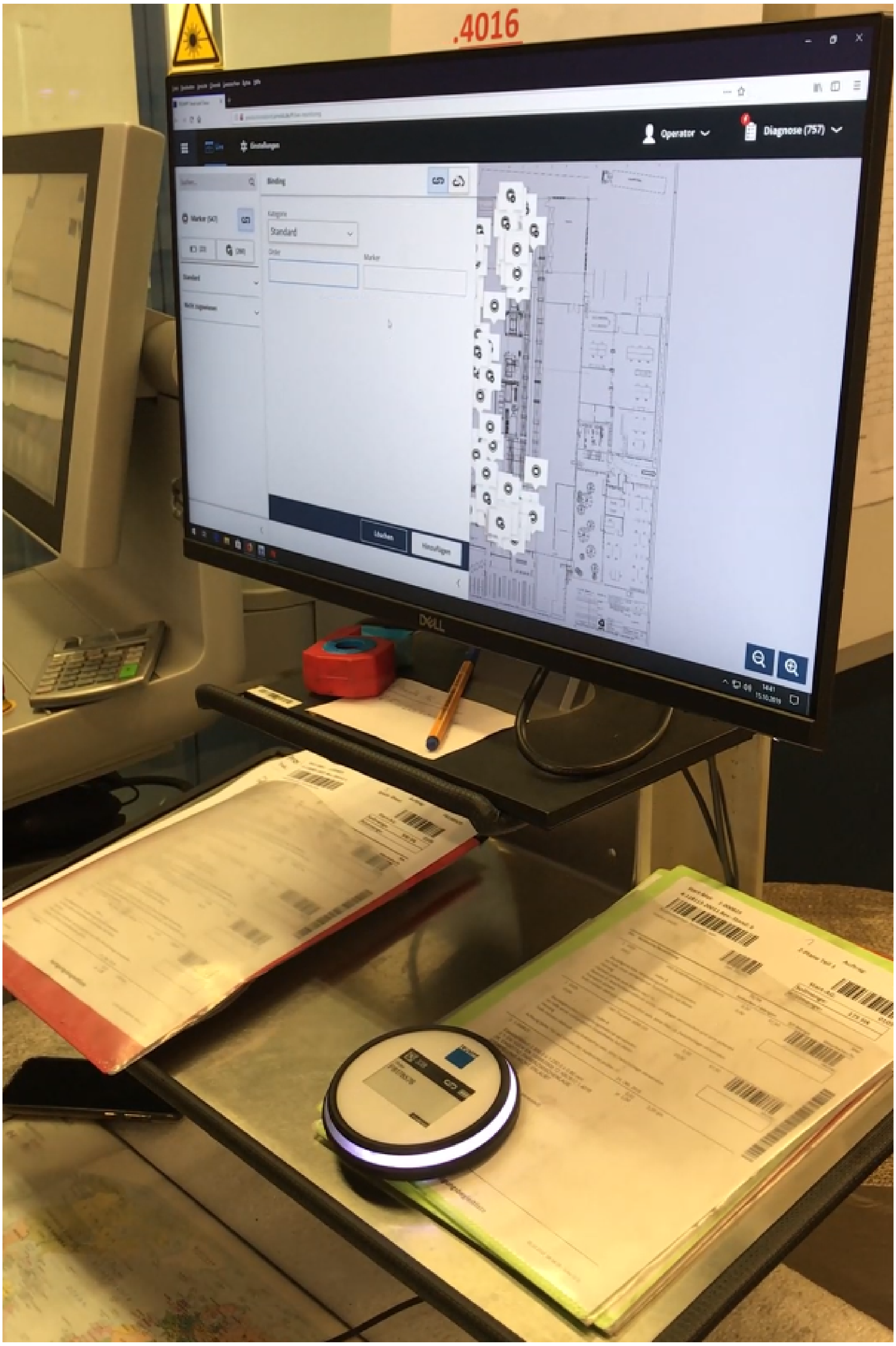

Figure 4.3: At the computer, the marker is linked with the production order within the IPS software. To accomplish this, the operator scans the code on the accompanying papers along with a QR code displayed on the marker. On the left side of the screen, an input interface allows for manual data entry. Meanwhile, on the right side, a portion of the hall layout is illustrated, indicating the locations of already linked markers with small signs. Image courtesy of TRUMPF.

4.5 Technical and Ethical Challenges of IPS Usage in Production

Through observation and data analysis projects, technical and ethical challenges associated with the use of IPS in manufacturing were identified. The observations were conducted over four consecutive days in 2019 at a single customer site where the IPS was deployed in production. For this purpose, four students and the author accompanied the production team for a full workday. Five observation tasks were assigned, with each person performing them at least twice on a rotating basis. One of these tasks involved documenting marker handling and system usage. While it is acknowledged that this specific SMP company may not be representative of the entire industry, fundamental technical and ethical issues were nevertheless discerned from the observations. Additionally, further technical and ethical challenges emerged during data analysis projects conducted by the author while working at TRUMPF.

4.5.1 Observed and Derived Technical Challenges

First, the focus was on analyzing the technical challenges of using IPS in production, and how this affects data quality. This is shown in an Ishikawa (cause-and-effect) diagram in Figure 4.4.

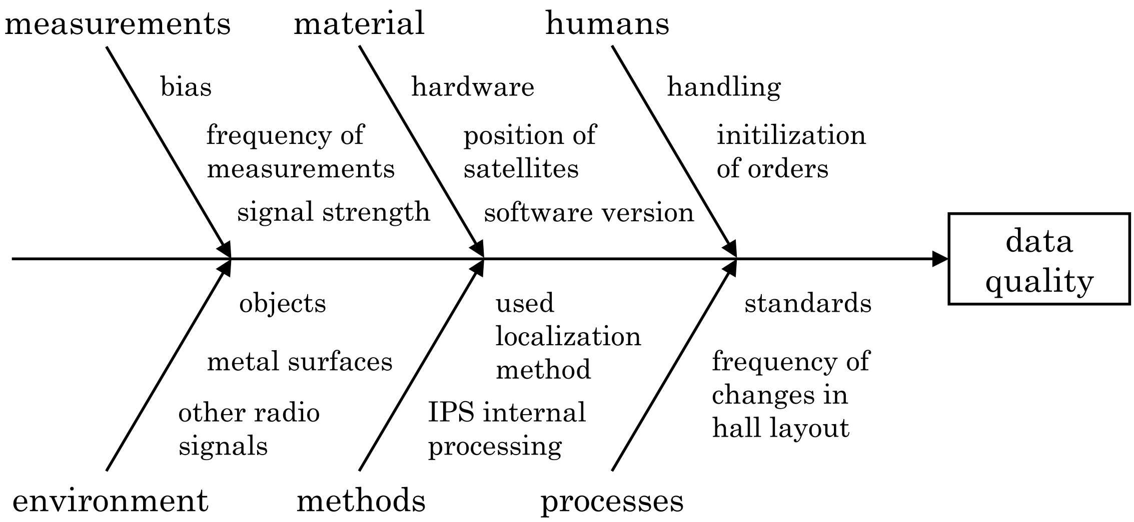

Figure 4.4: Ishikawa diagram showing technical challenges and other causes that contribute to data quality.

Data quality can be impacted by many factors. Measurements may have a systematic bias reducing position accuracy. The frequency of the measurements can be too low, affecting the system's ability to track fast objects. Weak signals decrease measurement accuracy, as distinguishing between direct and reflected signals is more difficult. Technical issues can be caused by the material used, e.g., if the hardware or software is defective or the marker battery is empty. Furthermore, proper satellite mounting on walls is crucial for optimal positioning, ensuring that all tracked areas have line-of-sight with at least three satellites.

By handling the markers, humans have a decisive influence on the data acquisition and, in the worst case, can even manipulate it. This already starts with the initialization of the markers. If this is forgotten or carried out too late, valuable data about the production process of an order is lost. During on-site observations, it was noticed that each employee performs the marker initialization at different times during the production process. Some do it before the order is started on the first machine, others only after the first production step, and others even initialize all orders in batches at the beginning of their shift. There were also some orders in production without linked markers, which shows that some employees do not use the system. At workstations, the markers are removed to process the workpiece and each worker places the marker somewhere different. Since orders must be booked at the time clock, workers walk the markers to the nearest terminal and back again. After the last production step, some employees deactivate the marker, while others bring them directly back to the loading station, collect them in boxes, or leave them in the forklift cabin and drive them around all day.

The production environment can affect the system's performance if there are large objects, such as machines or warehouse racks, in the line of sight between the satellites and markers. In the presentation of the positioning technologies, it was already mentioned that metallic surfaces reflect and scatter radio frequency signals and thus cause multi-path effects. Moreover, there can be interference with other radio signals. The localization method has an impact on the data quality as well as the proprietary internal methods (e.g., signal processing and filtering) implemented by the IPS system developer. Last but not least, processes can impact data quality. The more standardized processes are, the better they can be understood from the data. Moreover, frequent changes in manufacturing layout pose technical challenges, necessitating updates to the digital representation. The observations highlight a direct causal relationship between technical challenges and poor data quality.

4.5.2 Observed and Derived Ethical Challenges

The examination of ethical challenges related to implementing an IPS in a production system derives insights from observations made during the same period at the aforementioned customer site. The first observation pertains to the acceptance and utilization of the system. Only certain employees received training upon its introduction. Notably, those who underwent training utilized the system more frequently than those reliant on assistance. In addition, not every employee had the same access to the system. For example, each machine operator had a PC to link orders. All other workers did not have their interface to the system and, therefore, could not use it on an equal basis. Those with limited interaction with the system missed out on localization benefits, leading to higher skepticism compared to more frequent users. There were also rare cases of employees reporting that the system was not helpful when searching for orders, primarily due to measurement errors and unlinked orders. Another issue is that employees responsible for linking the markers do not typically search for orders themselves. The linking process occurs at the beginning of production, and subsequent stations retrieve the cut sheet metal parts from intermediate storages. Only at these later stages do employees have the advantage of using the IPS to locate the orders. Therefore, initially, someone must perform the additional task of linking a marker to facilitate later ease of use for others.

The next observation is that the system allows for conclusions to be drawn about the productivity of individual employees. Since specific tasks in production require specialized training, many machines have fixed employee assignments documented in shift plans. The inflow and outflow of markers at these workstations can be utilized to derive worker productivity. However, a significant issue arises from the fact that employees are often unaware of this potential monitoring, as the tracking system is linked to the order rather than the individual.

Furthermore, employees routinely carry the marker to the time clock to input the order number from the display into the terminal, allowing for the movement data to be associated with them. During data analysis, it was also observed that employees occasionally take markers with them when leaving the production hall. Although tracking ceases outside the hall, familiarity with the layout enables the determination of destinations, such as restrooms, smoking areas, or kitchens. The duration of breaks can be easily calculated by analyzing the time difference between the last measurement upon exiting the hall and the first upon re-entry.

The lack of awareness among employees regarding the potential for this analysis is concerning. In many production environments, there exists a power asymmetry wherein knowledge of individual productivity, facilitated by indirect tracking, can be exploited due to the hierarchical relationship between managers and workers.

It is crucial to note that specific details pertain to this customer, yet the underlying ethical concerns identified are fundamental and could manifest in other manufacturing companies utilizing IPS. The following observations underscore the need for a thorough assessment of the ethical aspects of IPS data usage for the identified simulation use case, which is provided in Chapter 6.

4.6 Summary

Section 4.1 introduced the basics of indoor positioning, while Section 4.2 outlined important requirements for utilizing IPS technology. A discussion on suitable technologies for SMP concluded that UWB technology offers advantages due to its accuracy and coverage properties. While IPS systems primarily serve for object localization, their collected data offer secondary benefits. Additionally, a structured literature review identified potentials of IPS usage in manufacturing, categorizing 51 use cases into twelve groups. Following this review, Sections 4.4 and 4.5 shifted focus to the current use of IPS in the investigation environment and the associated ethical and technical challenges in SMP.

Chapter 5

Framework for the Usage of IPS Data in Manufacturing Simulation

This chapter introduces a framework that uses an Indoor Positioning System (IPS) as the central data harmonizer designed to streamline production data into a single source for manufacturing simulation. It includes the development of a simulation data model for Sheet Metal Processing (SMP) (Section 5.1), which forms the core of the framework (Section 5.2). The framework's contribution to enhancing data quality in manufacturing simulation is discussed in Section 5.3. Finally, Section 5.4 explores the framework's application through socio-technical scenarios, illustrating alternative implementations and the dynamic interaction between humans and technology within the production system.

5.1 Simulation Data Model for SMP

In this section, essential inputs for simulating SMP systems are identified. Reviewing existing data models and standards (Section 3.3.2) revealed no direct applicability to SMP. Thus, this work extends existing data models to address domain-specific data requirements. When referring to the VDI or CMSD standard in this chapter, it is in reference to the following sources: (VDI - Association of German Engineers 2014; Riddick and Lee 2010; Lee and Riddick 2010).

5.1.1 Approach to Derive the Simulation Data Model

The three-step approach to derive the simulation data model for SMP is illustrated in the flowchart of Figure 5.1 and elaborated upon in the following. This approach culminates in the simulation data model depicted in Table 5.1.

STEP 1: Creation of a List of Simulation Inputs for the New Domain

In the initial step, a structured list of simulation inputs for SMP is established, utilizing the categorization from the VDI standard (see Figure 3.3), which classifies inputs into technical, organizational, and system load data. Additional inputs not covered in the VDI standard are sought from the technical documentation of the CMSD standard and incorporated into the list. This list is further augmented with domain-specific inputs for SMP. This extended list is reviewed independently by three simulation experts who are working in SMP, the simulation team of a technical consultancy, and the simulation team of a research institute. All involved experts have deep domain knowledge gathered from conducting various simulation studies in SMP. Their feedback was incorporated, resulting in a refined list of 42 simulation inputs. The origin of each input can be traced back to the standard mentioning them via the crosses in column (a) in Table 5.1. Domain-specific inputs for SMP are written in italics and will be explained in the next section.

STEP 2: Categorization of SMP Simulation Inputs

The second step is performed separately for the 42 data inputs. For each, it is stated in column (b) in Table 5.1 whether it is used during the implementation/creation of the simulation model, the parameterization of the simulation experiment, i.e., before its execution, or whether it is changed/updated during the run time of the simulation experiment.

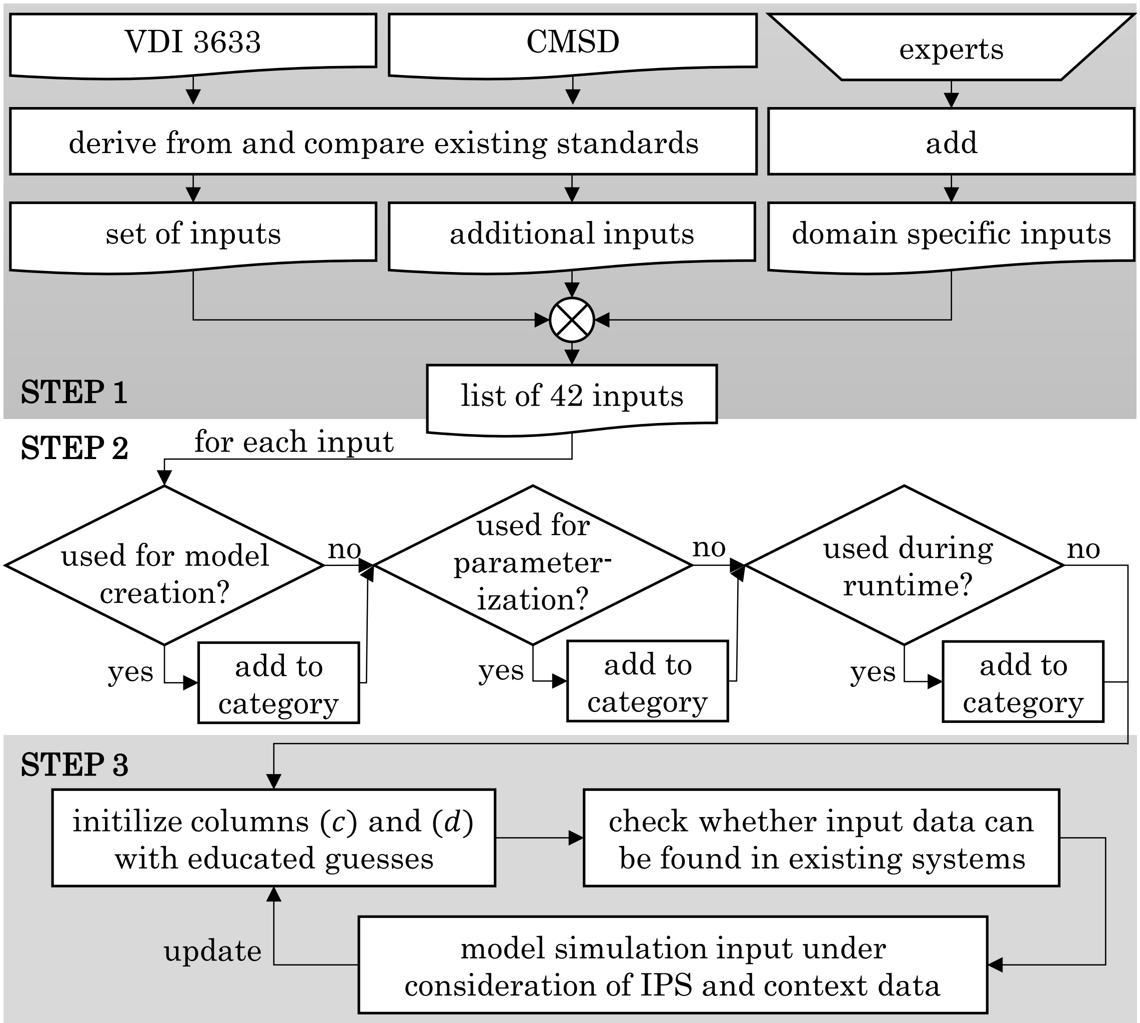

Figure 5.1: Flow chart of the approach to derive the simulation data model shown in Table 5.1. STEP 1: Creation of a list of simulation inputs for the new domain, here SMP. STEP 2: Categorization of SMP simulation inputs. STEP 3: Comparison of data supply and demand for input modeling.

STEP 3: Comparison of Data Supply and Demand for Input Modeling

Step three starts with the initialization of the data demand. An initial guess of what IPS and context data is needed to derive the particular input is given in column (c) and (d). For each simulation input, the data supply from existing systems like Enterprise Ressource Planning (ERP) and Manufacturing Execution System (MES) is checked and noted in column (e). Crosses in parentheses refer to inputs that are sometimes available in these systems, but are usually of low quality and, thus, not of use for the simulation purpose. Lastly, the simulation input has to be modeled using the IPS and context data. If the analysis yields insights on which context data has to be further enriched or else is maybe not needed, then columns (c) and (d) are updated respectively.

5.1.2 Resulting Simulation Data Model

The outcome of the described approach is the data model presented in Table 5.1. In total, 42 simulation inputs were identified, comprising 13 inputs sourced from the VDI standard and 27 from the CMSD standard, with an overlap of nine inputs. The CMSD standard encompasses a broader range of inputs compared to the VDI standard, reflecting its more detailed approach to simulation data. Additionally, 13 new domain-specific simulation inputs have been added to the list, which will be elaborated upon here. They can be identified in Table 5.1 by their italicized formatting.

- Row 4: Departure point: In the VDI standard, transport orders are mentioned without specifying required input data further. Transport resources receiving these orders must know the pickup location for materials. Departure points specified in transport orders must align with the configured material flow network (see Row 31).
- Row 5: Destination point: Similar to departure points but listed separately. While a departure point can be identified in real-time upon departure, the destination point cannot. However, both are essential specifications in transport orders.
- Row 7: Sheet metal type: A refinement of the generic material type from CMSD, specifying the type of sheet metal, including its thickness, which significantly impacts processing times in SMP.
- Row 10: Geometry: The CMSD standard provides a vague definition of part size, potentially only considering a bounding box. Accurate geometry, including cutting length and shape, is crucial in SMP for nesting, processing time calculation, and deriving required process steps.
- Row 24: Dispatching, priority, and picking rules: An extension of generic strategies from the VDI standard, covering rules for dispatching, prioritizing, and picking orders. These rules, detailed in Section 2.3.2, significantly affect system performance (Mieth et al. 2019c).
- Row 25: Warehousing and storage: In SMP, various strategies exist for warehousing and storage, such as sending parts to warehouses for made-to-stock items or storing them between process steps to balance workload.

			No.	Input	a: origin – VDI 3633	a: origin – CMSD	a: origin – domain-specific	b: usage – model creation	b: usage – parameterization	b: usage – run time	c: IPS – UWB	c: IPS – IMU	c: IPS – RFID	d: context – layout/geofences	d: context – process plan	d: context – pictures/scan	e: MES/ERP
system load data	input of orders	production orders with unique ID	1	order release		X			X	O	RT						X
			2	order due date	X	X			X								X
			3	quantities	X	X		X	X		H						X
		transport orders	4	*departure point*			X	X	X	X	RT			O			(X)
			5	*destination point*			X	X	X	X	H			O	X		(X)
	product data	per order ID	6	bill of materials	X	X			X								X
			7	material / *sheet metal type*		X	X		X							X	X
			8	position		X			O	X	RT	O	O				
			9	last finished process step		X				X	RT		O	X	X		(X)
			10	part size / *geometry*		X	X		X							X	(X)
			11	sequential process plan	X	X			X		H			X			X
		per process step number	12	type of process step		X			X	O	RT		O	X			X
			13	actual process time		X			X	X	RT	O	O	X	X		(X)
			14	job assignment / lot		X			X	X	RT						(X)
organizational data	working time organization	breaks	15	list with break times	X	X		X	X		H			X			(X)
			16	maintenance schedule		X		X	X		H			X			(X)
		shift model	17	for workers and machines	X	X		X	X		H			X			(X)
	allocation of resources	workers	18	list of workers	X	X		X	X		H					O	(X)
			19	worker–process–allocation		X			X	O	RT		O	X	X		(X)
		machines	20	machine–process–allocation		X		X	X		H			X	X		(X)
			21	sequence-related setup times		X			X		H	O	X	X	X		
		conveyor system	22	list of transportation resources		X		X	X		H					X	(X)
			23	transport system–part–allocation		X			X	X	RT						
	structural organization	strategies	24	*dispatching–, priority–, picking rules*			X	X	X		H			X	X		
			25	*warehousing and storage*			X	X	X		H			X	X		
			26	express order handling		X		X	X		H				O		(X)
		restrictions	27	*access permissions, quality assurance*			X	X	X		H			X			
		failure management	28	*troubleshooting and rework rules*			X	X	X		H		O	X	X		
technical data	factory structure	system topology	29	hall layout	X	X		X			H				X	X	
			30	manufacturing equipment	X	X		X			H				X	X	
			31	transport functions	X			X			H				X		
	production data	utilization time	32	for each resource	X				O		H			X			(X)
		performance data for each resource	33	*target material utilization*			X		O		H					O	X
			34	*scrap and rework rates*			X		O		H			X	X		(X)
		capacity	35	for each worker and machine	X				X		H						(X)
	material flow data	topology material flow system	36	*transported resources to routes*			X		X	X	RT			X			
		performance data	37	velocity		X			X	X	RT	RT					
			38	*battery life of transportation resource*			X		X		H	H		X			
		capacity	39	*for each transportation resource*			X		X		H						
	failure data	functional failures	40	frequency of faults (MTBF)		X			X		H			X			
			41	duration of faults (MTTR)		X			X		H			X			
		availability	42	for each resource	X				X		H			X			

Table 5.1: Required simulation inputs for manufacturing simulation in SMP. Columns represent: (a) input origin; (b) input use; (c) input derivable using IPS data; (d) necessary context information to derive input; (e) input available in existing systems. Symbols in rows: X = found/required; (X) = input usually of low data quality; RT = input derivable in real-time; H = input derivable using historical data; O = optional input.

- Row 27: Access permissions and quality assurance: This input further elaborates on the subcategory restrictions outlined in the VDI standard for structural organization. It encompasses access permissions for specific areas or machines on the shop floor and permissions related to parts designated for processing, ensuring adherence to safety and quality standards.
- Row 28: Troubleshooting and rework rules: Incorporates failure management into the simulation, including troubleshooting and rework rules. It considers skilled labor requirements for problem resolution and specifies whether faulty parts are repaired at a rework station or disposed of and reproduced.
- Row 33: Target material utilization: Needed during production planning and job-to-sheet allocation to minimize material waste in the cutting process.
- Row 34: Scrap and rework rates: The percentage of scrap and rework may vary based on quality concepts and demands of the SMP company. Scraped parts require new orders to be released into production, sometimes as express orders. Low-quality parts might undergo repair at a rework station. These rates parameterize the implemented rules mentioned in Row 28.
- Row 36: Transported resources to routes: Essential for determining the material flow system's topology, indicating which transport resource follows which route, and detailing the source-sink relationship (Row 31).
- Row 38: Battery life of transportation resource: Added due to the growing importance of Automated Guided Vehicles (AGVs) in modern production systems. Considering AGVs in simulations requires accounting for their charging behavior.
- Row 39: Capacity for each transportation resource: Critical for determining how frequently a transport resource needs to travel between departure and destination points. Capacity is specified by maximum weight and dimensions.

5.1.3 Insights

A notable finding of this approach is that the majority of extensions to the standards have been concentrated in the area of input data, traditionally gathered through interviews, site visits, and work samplings. Specifically, four inputs have been added in the realm of organizational data concerning structural organization (Rows 24, 25, 27, 28). Additionally, three inputs have been supplemented in the technical data category concerning material flows (Rows 36, 38, 39). Furthermore, departure and destination points have been incorporated as features of transport orders within the system load data category (Rows 4 & 5). The remaining four inputs provided (Rows 7, 10, 33, 34) are closely linked to the unique characteristics of SMP.

The majority of inputs (34–38) are essential for parameterizing the model, while only 14 inputs are required for the initial implementation. Additionally, 10–12 inputs can be dynamically updated during runtime, depending on the simulation study's objectives. For instance, the destination point of a transportation order can be adjusted based on queue conditions at stations capable of executing the next process step. The majority of these inputs (36) can be derived from historical IPS data, with 11 of them also available in real-time.

Context information is necessary for determining many of the inputs. For 22 inputs, layout information with geofences is needed, and in 13–14 cases, knowledge about the production process in the form of a process sequence is required. Only eight inputs could be found reliably in MES or ERP systems. However, due to manual input of values or difficulties in determining them, 17 are usually of poor quality. The lack of simulation data in ERP systems is already known and discussed, for example, in (Moon and Phatak 2005).

There are many simulation inputs for which the consideration of IPS data shows great potential, especially when no information is available. In general, the inputs can be derived more easily if the variable being searched for is position-related, e.g., the departure and destination points of transport orders (Rows 4 & 5). If there is no position reference, this does not imply that the inputs cannot be derived. For example, the quantities (Row 3) can be determined by counting trajectories with identical order IDs. The inputs classified as not derivable from the IPS must be queried via interfaces or considering context data or information from additional sensors. For example, the unique order ID cannot be derived and must therefore be assigned to the respective marker ID via an interface at the beginning of production.

During the preparation of the table, recursions were noticed, e.g., in the determination of process plans and geofences. The process plan can be derived from historical trajectories of the Ultra-Wideband (UWB) data using geofences, whereas the geofences can be approximated if the process plan is known. To resolve this recursion, geofences should be defined so that a specific allocation of processes to positions is possible. This will be especially important to identify strategies and dispatching rules (Rows 25–28). Today, the definition of geofences is done manually by experts drawing in the layout plan of the manufacturing system. However, in the future, geofences could result from advanced analyses of the IPS data.

There are some further remarks, which are given in the following list:

- Table 5.1 was reviewed and published in a previous version for the CIRP Conference on Manufacturing Systems (Mieth et al. 2019b).
- Only some simulation models need exactly all 42 inputs. Selecting the required inputs depends on the objectives of the respective simulation project.
- Availability A can be calculated with Mean Time To Repair (MTTR) and Mean Time Between Failures (MTBF) according to

  $$A = \frac{\text{MTBF}}{\text{MTBF} + \text{MTTR}}. \tag{5.1}$$

  All three inputs are included in Table 5.1 to leave it open, which two values are used.
- Weight is not listed as simulation input because it can be calculated with knowledge of the material (Row 7) and part size (Row 10).
- The data model is specifically tailored for SMP. However, for similar industries and domains, the list can be easily adapted using the presented approach.

To conclude, the derived list of required simulation inputs from this section shows that 38 of 42 inputs (90%) benefit from considering IPS data during simulation input modeling. Thus, this work puts IPS in the center of the analysis and proposes an IPS framework which is presented in the next section.

5.2 Framework

The framework is designed to enhance manufacturing simulation through the utilization of IPS data for input modeling and parameterization. To accomplish this, emphasis is placed on ensuring that simulation data is stored in a single source of truth, harmonized with the IPS. This harmonization enables advanced analytics and facilitates straightforward control of data quality. Additionally, the framework is tailored to accommodate real-world applications, which often involve heterogeneous machine parks, a common scenario in production systems.

The realized framework for IPS-based manufacturing simulation is shown in Figure 5.2. In the core of the framework is an indoor positioning system which acts as data harmonizer between corporate business systems, other data sources and the simulation model. The framework consists of three parts, which will be described in detail in the following sections.

1. Semantic enrichment (Section 5.2.1; gray box in Figure 5.2)
2. Data harmonization with IPS (Section 5.2.2; blue box in Figure 5.2)
3. Digital twin (Section 5.2.3; green box in Figure 5.2)

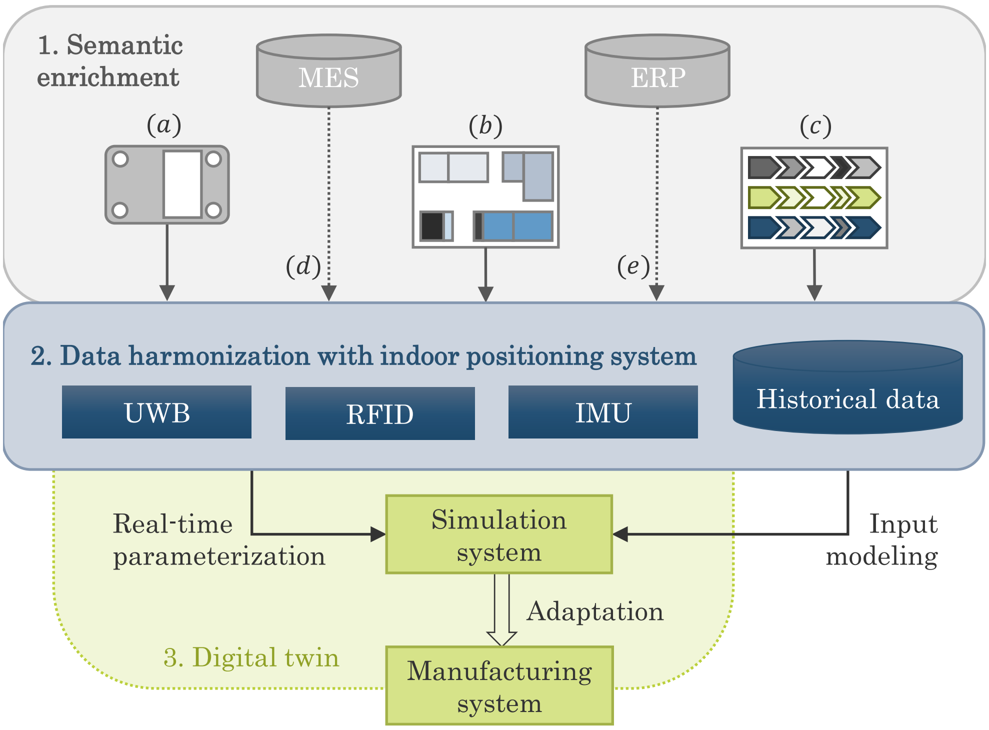

Figure 5.2: IPS framework for a manufacturing simulation based on an indoor positioning system. The IPS acts as main data harmonizer (blue part). A semantic enrichment process augments the localization data (gray part), which can then be used in the digital twin of the manufacturing system (green part). The pieces of context information depicted in the picture are (a) the geometry of parts, (b) the manufacturing layout, (c) process/production plans, (d) MES data, and (e) ERP data.

5.2.1 Semantic Enrichment

The upper part of the framework in Figure 5.2 shows the semantic enrichment which refers to the process of attaching context information from heterogeneous sources to a main type of data, in this case, the IPS data. Examples of relevant context data in manufacturing are e.g., the part's geometry (a), the layout of the production shop floor with geofences (b), process/production plans (c) that contain the sequence of process steps, and different data storage and acquisition systems like MES (d) and ERP (e) systems.

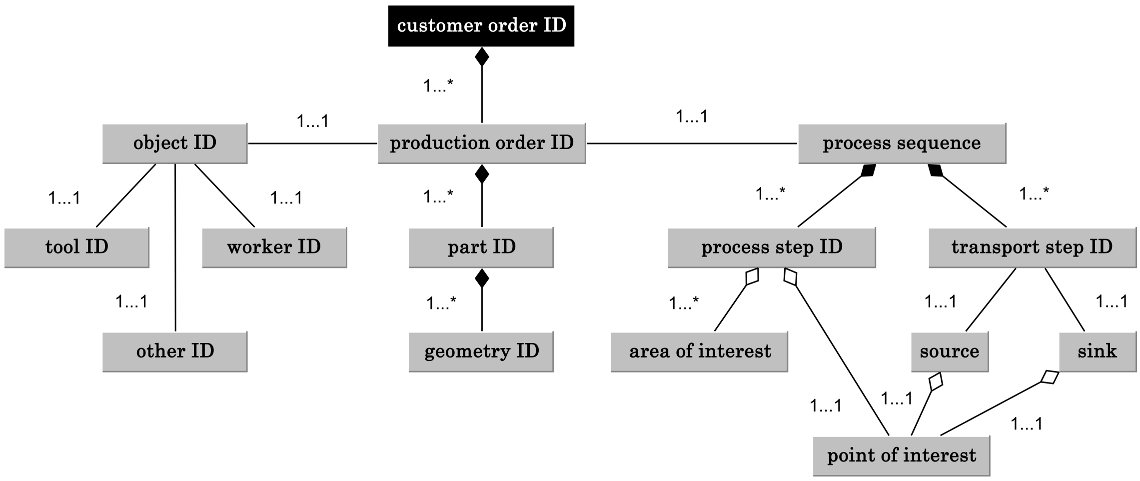

Figure 5.3: UML class diagram describing the relations between IDs used for the data enrichment.

Assigning context data during enrichment is realized with IDs. In Figure 5.3, the relations between the used IDs are presented in an Unified Modeling Language (UML) class diagram. It can be seen that a customer order consists of one-to-many production orders and the latter of one-to-many parts. Each part has an associated geometry. The object ID depends on the object being tracked and can either be a production order, a worker ID, or a tool ID. Some of these unique object IDs have to be specified when setting up the system, and others can later be created when adding new objects in the software on the IPS computer. During production planning, each production order is split into a sequence of process and transport steps that have to be performed in manufacturing. Each process step can happen at one or more points of interest or areas of interest. A point of interest refers to a position x, y, z on the shop floor that has a semantic meaning, e.g., a machine or a workplace. An area of interest, sometimes also called geofence, refers to an arbitrarily shaped area on the shop floor that has a semantic meaning, e.g., the work area around a machine or storage. Each transport step has a source and a sink, defined as point of interest. The enrichment of the context data for the five sources depicted in Figure 5.2 is described below:

(a) Enriching information on part geometry relies on the utilization of unique CAD file IDs. These IDs are utilized for part management within CAD-/CAM systems, which are usually integrated with order management systems like ERP-/MES systems. This integration facilitates associating geometry ID with production order IDs, which are utilized as link to the object ID.

(b) Enriching information on the manufacturing layout involves integrating two-dimensional hall layouts with position data, which initially requires aligning the coordinate systems of the hall layout and the positioning system. Typically, this alignment occurs during the installation of the IPS, where the layout is incorporated into a dashboard. However, to analyze enriched positioning data effectively, additional context information on specific points and areas of interest is necessary. This entails assigning specific coordinates or areas on the hall layout to the process steps associated with executing production orders.

(c) Enrichment of information on process sequence requires access to production plans typically available in the MES. The process sequence (see Figure 2.2) is defined during production planning and linked to a production order ID.

(d/e) Enrichment of context information from MES/ERP systems with IPS data is accomplished through the production order ID, which is linked as an object ID to the marker ID at the start of production, or via the object IDs associated with workers, tools, etc.

5.2.2 Data Harmonization with IPS

The fundamental concept of the framework is to elevate IPS from being just one of many disparate data sources in production systems to a central role as the primary data harmonizer. Data is now centralized using the simulation data model introduced in Section 5.1. With this, real-time manufacturing simulation can be conducted, ensuring that all input data is available and harmonized.

The IPS is depicted in blue at the center of the framework in Figure 5.2. The framework is technology-agnostic, gathering position data via UWB, Radio-Frequency Identification (RFID), and Inertial Measurement Unit (IMU) data, depending on the IPS system employed. RFID and IMU are represented in a lighter shade of blue because not every UWB-based IPS includes these technologies. As discussed in Section 4.2.2, UWB is considered the most suitable technology for the presented simulation use case. Additionally, while the IPS is centrally displayed in the image and position data is stored in a central database, its satellites are distributed throughout the production system, and markers are attached to tracked objects. It is important to note that the decision whether the data is managed locally or in the cloud is intentionally left open to maintain flexibility in later implementations, considering data compliance, regulations, and the preferences of SMP companies.

Data harmonization within the IPS is achieved through the initialization of each marker upon release to production, wherein a unique identifier ID_{object} is assigned to the object being tracked and linked to the unique marker identifier ID_{marker}. Each event sample from the IPS data is represented as a state vector $s(t)$ (as shown in Equation 4.1), enriched with context information $\mathbf{C}$:

$$s_{\text{enriched}}(t) = (s(t), \mathbf{C}) = (x(t), y(t), z(t), \mathrm{ID}_{marker}, \mathrm{ID}_{object}, \mathbf{C}) \tag{5.2}$$

To enrich the data, the context information must reference either the position $x(t), y(t), z(t)$, the marker identifier ID_{marker}, or the object identifier ID_{object}. It is important to note that the marker ID is unique for each piece of marker hardware.

5.2.3 Digital Twin

The digital twin part of the framework is depicted in the green box in the lower part of Figure 5.2. A digital twin of a manufacturing system is a combination of latter with its simulation model through bidirectional real-time data parameterization and control (Nikolakis et al. 2018). With the help of a digital twin, it is possible to simulate and forecast production plans and processes (Tao et al. 2018). Digital twins serve as a decision support system which decision-makers can use to play through adaptation measures. The digital twin can use historical data from the IPS for input modeling and real-time data for parameterization. The simulation can be enhanced with Artificial Intelligence (AI), e.g., if machine learning methods are used to model the behavior of complex system components (see also Section 3.3.4). The insights from simulation experiments with the digital twin are used to improve manufacturing operations by comparing different adaptation measures and applying the most suitable one in the manufacturing system. Digital twins are thus very useful in continuous improvement loops: Implemented adaptation measures will influence the newly collected data, which is then used as input for another simulation experiment from which new adaptation measures are derived and so on.

5.3 Contribution to Data Quality Improvement

The framework's development was driven by the need to enhance data quality in manufacturing simulation. This section represents an initial qualitative analysis of the framework's improvement on data quality, utilizing the eleven dimensions outlined by Bokrantz et al. (2018) and defined by Balci et al. (2000) (see also Section 3.2.1). This analysis was also part of the initial paper that presented the framework (Mieth et al. 2019b).

- Accuracy and Precision: Enhancements in accuracy and precision are achieved through the utilization of UWB-based IPS data, instead of inferior localization technologies (as discussed in Section 4.2) or relying solely on non-localization data.

- Accessibility: All data necessary for the simulation is digitally accessible, structured in the simulation data model for SMP and stored in a central database. Access management is solely required for this repository, which may reside on an on-site server or with a cloud provider. This marks a notable progression from the distributed and non-harmonized data sources typically employed in simulation projects.

- Currency: Real-time data from the IPS, complemented by the latest updates from connected systems, accurately depict the current state of the production system, ensuring the highest level of timeliness. However, when historical data is employed for analysis, precautions must be taken to verify that no hall layout changes have occurred, which could potentially skew the results.

- Completeness: The existing context data undergoes harmonization through integration with location data, resulting in a comprehensive database tailored for simulation purposes. Moreover, it was observed that most of the newly introduced domain-specific inputs focus on input data traditionally obtained through interviews, site visits, and work samplings, which were only collected when simulation data was initially incomplete.

- Relevance: The position data captures the dynamic behavior of the production system, making it crucial for simulation purposes and enabling more sophisticated analyses.
- Resolution: Objects in manufacturing move very infrequently and rarely because the average duration of processes is very long. All industrial IPS acquire data in a sufficient resolution to detect the movement of objects.
- Clarity: Visualizing IPS data on the shop floor layout facilitates trajectory filtering and enables dynamic animation over time. Additionally, overlaying trajectories with contextual information adds further depth and insight to the analysis.
- Traceability: The data origin can be traced via the unique IDs used for data enrichment (see Figure 5.3).
- Reputation: IPS data is automatically collected and harmonized, which makes the simulation results based on this data more trustworthy.
- Consistency: The specification of the SMP data model is a key element of the IPS framework that ensures data consistency.

5.4 Socio-Technical Scenarios for the Application of the Framework

This section will explain how the framework can be applied in different socio-technical scenarios. Socio-technical scenarios are structured narratives of plausible future implementation that integrate social, political, and technological elements. They are vital tools for engaging stakeholders in discussions, ensuring they are socially acceptable, politically viable, and desirable. They assist in innovation management by fostering knowledge integration, assessment, and strategy building among experts and stakeholders. They differ from traditional approaches like quantitative modeling by including socio-political developments and contextual descriptions. (Magnusson et al. 2020)

Overview on Socio-Technical Scenarios

With the help of socio-technical scenarios, different implementation possibilities of the framework will be described that illustrate how humans and technology interact in the production system, commonly working towards a common goal like the improvement of profitability (see target system in Figure 2.6). The scenarios are summarized in Table 5.2. For simplicity, categories (columns of the table) have been introduced to show the main differences between the scenarios: tracking, data analysis, simulation, and decision-making. Of course, the list of categories could be further detailed and is thus neither exhaustive nor complete.

scenario	tracking	data analysis	simulation	decision-making
baseline scenario	orders	predominantly manual	predominantly manual	human
	⋮	⋮	⋮	⋮
future scenario	all objects and workers	automated	automated	automated

Table 5.2: Continuum of socio-technical scenarios.

In this work, the focus is on the baseline scenario, which reflects the current use of location systems in SMP, and the future scenario, which outlines the full implementation of the framework. Between these scenarios, there is a continuum of possible framework implementations. The idea is to span a solution space from the status quo to the maximum possible.

Baseline Scenario

The baseline scenario describes how the localization system is used in SMP today. A marker is linked to the order upon production start and is disconnected before shipping. Data scientists analyze the data recorded during this process. The preprocessing is already automated, but the specific analyses are still being developed. The results of the data analyses are made available to the simulation experts for the parameterization of the simulation model. The simulation model is created manually based on the factory layout and a library of simulation building blocks. The simulation results are interpreted by the simulation experts and presented to the production managers or, depending on the simulation use case, to other decision-makers.

Future Scenario

The future scenario is the target vision of the framework developed in this dissertation, introduced in the previous Section 5.2. Not only orders are being tracked here, but also workers during their shifts and mobile objects of interest, such as order papers, workpieces, pallets, hand trucks, forklifts, and tools. The data collection and analysis is automated and enables Automated Simulation Model Generation (ASMG), model parameterization and the deployment of Machine Learning (ML) models. For this, ML pipelines are in place to monitor and update trained models. In this scenario, ML models are used within the simulation to model the behavior of entities, such as the input/output behavior of simulation modules, human behavior, or control decisions. In addition to the classical application fields in factory and production planning, the simulation model is also used to (a) learn policies via Reinforcement Learning (RL) that improve planning and control and (b) train supervised models on the input/output behavior of the simulation with the help of data farming. This surrogate model can provide answers faster than the simulation (computation time advantages). Automated decisions are made based on the simulation results.

Intermediate Scenarios

There are several intermediate scenarios between the baseline and the future scenario. Assuming that only two states exist for each category (columns) in Table 5.2, this already results in 14 intermediate scenarios. In reality, however, each category consists not only of two levels but of partly discrete gradations. For example, in the decision-making category, the decision can be proposed automatically and released by a human. It quickly becomes apparent that evaluating each scenario individually is very complex and a time-intensive task. The assessment in the next chapter will focus on the future scenario, since it presents the most challenges. With the findings from the analysis of this scenario, conclusions can be drawn in the further course of this dissertation about possibly necessary gradations within the categories.

5.5 Summary

In Section 5.1, a data model tailored for simulation projects in SMP was meticulously developed based on established industry standards. The presented approach exhibits versatility, with the potential to stimulate further utilization of IPS data in simulation projects across diverse industries and domains. The presented data model forms the core of the framework introduced in Section 5.2, wherein IPS assumes the pivotal role as the central data harmonizer, seamlessly channeling production data into a manufacturing simulation.

Modeling simulation inputs with the help of IPS data opens up a new and broad field of research opportunities. In parallel research endeavors, the author directed attention towards the critical task of determining process times, recognizing their foundational importance in deriving other inputs. A first publication outlined the enrichment of localization data (Mieth 2019). Collaborative efforts with student Maximilian Volk further advanced lead time determination from IPS data. Comparative analyses, conducted with a range of optimization approaches and heuristics on synthetic data, yielded promising results in achieving precise lead time estimates (Volk and Mieth 2022). Regrettably, the reliance on synthetic data was necessitated by the absence of actual times in real-world datasets.

The framework's development was driven by the need to enhance data quality in manufacturing simulation. The comprehensive analysis in Section 5.3 demonstrated improvements across all eleven considered dimensions of data quality. This encouraging outcome lays a solid foundation for future research that can explore the full potential of IPS data in simulating and optimizing production systems.

Lastly, Section 5.4 illustrated how the framework could be implemented in different socio-technical scenarios. The description of interactions of humans and technology in the scenarios is fundamental for assessing the framework's trustworthiness. The presented future scenario will be examined thoroughly in the forthcoming chapter.

Chapter 6

Assessment of the Frameworks' Trustworthiness

In this chapter, an ex-ante assessment for trustworthiness of the presented framework from Chapter 5 is performed, i.e., the evaluation takes place before the system is developed and deployed in production. This should ensure that the IPS technology is used in a responsible manner for improving manufacturing simulation.

6.1 On the Assessment of Trustworthiness

Trustworthiness has gained increasing prominence, propelled by the proliferation of autonomous systems and Artificial Intelligence (AI) in everyday life. This surge encompasses various domains, including social media algorithms, the spread of fake news, the emergence of deep fakes, social scoring mechanisms, targeted marketing practices, advancements in ChatGPT, the development of self-driving cars, and numerous other facets of modern technology.

Trust has been studied across disciplines such as social psychology, human factors, and industrial organization, with the aim to understand human relationships and interactions with machines (Lewis et al. 2018). There is a general consensus that trust is a complex psychological attitude encompassing beliefs and expectations regarding the trustworthiness of a trustee, influenced by experiences in situations involving uncertainty and risk (Jones and George 1998). Trustworthiness is a characteristic of an agent (or organization) that inspires trust for that agent in another agent (Devitt 2018).

The notion of Trustworthy AI is intricately intertwined with the principles of Responsible or Ethical AI, often used interchangeably due to their shared emphasis on a common set of requirements for systems. These principles collectively contribute to the development of systems that not only exhibit technical reliability but also adhere to ethical considerations and societal values.

On April 21, 2021, the European Commission published a proposal for the regulation and harmonization of rules for AI[1]. The resulting legislation is now known as the European Union's Artificial Intelligence Act (AI Act). The European approach to trustworthy AI involves a risk-based framework, categorizing AI systems into minimal, high-risk, and unacceptable risks. Minimal-risk applications, like AI-enabled

[1] `https://digital-strategy.ec.europa.eu/en/library/proposal-regulation-laying-down-harmonised-rules-artificial-intelligence`, publication 21 April 2021

recommender systems, enjoy exemptions, while high-risk AI systems face stringent requirements such as risk mitigation, robust data sets, and human oversight. Unacceptable risk AI, posing threats to fundamental rights, will be prohibited, and fines will be imposed for non-compliance. The AI Act introduces rules for general purpose AI, and governance will involve national authorities and a new European AI Office. The political agreement awaits approval, with the AI Act becoming applicable in two years, featuring a transitional period and the launch of an AI Pact for early implementation. The EU will also engage internationally to promote trustworthy AI standards.[2]

6.1.1 Overview on Existing Guidelines, Principles and Rules

In recent years, the ethical and societal implications of deploying AI systems have raised widespread concerns, leading to the emergence of numerous ethical guidelines. Jobin et al. (2019) identified 84 distinct guidelines for ethical AI, a number that has increased since then due to the growing trend of companies, research associations, and other organizations publishing their own sets of guidelines. AlgorithmWatch has addressed this proliferation by initiating the AI Ethics Guidelines Global Inventory[3], a database project aimed at collecting various AI ethics frameworks. The database, last updated in April 2020, encompasses a comprehensive list of 167 guidelines, reflecting the expanding landscape of ethical considerations in AI development and deployment. To facilitate further exploration, a curated excerpt of guidelines is presented, offering readers a comprehensive yet not exhaustive overview of principles, rules, and guidelines for Responsible, Ethical, and Trustworthy AI.

Major technology corporations, including Google[4], Microsoft[5], SAP[6], IBM[7], and OpenAI[8], have individually released their ethical principles as a commitment to fostering the development of responsible AI.

Different research associations have published own guidelines, e.g, the IEEE Global Initiative on Ethics of Autonomous and Intelligent Systems[9], the Association for Computing Machinery[10], Fraunhofer [11], and, the German Informatics Society [12].

The statement of the European Group on Ethics in Science and New Technologies on AI, Robotics, and Autonomous Systems[13] presents fundamental ethical princi-

[2] `https://ec.europa.eu/commission/presscorner/detail/en/ip_23_6473`, press release, 9 December 2023

[3] `https://inventory.algorithmwatch.org/`, accessed February 2022

[4] `https://ai.google/responsibility/responsible-ai-practices/`, accessed February 2022

[5] `https://www.microsoft.com/en-us/ai/responsible-ai`, accessed February 2022

[6] `https://www.sap.com/documents/2018/09/940c6047-1c7d-0010-87a3-c30de2ffd8ff.html`, as of October 2021

[7] `https://www.ibm.com/policy/trust-transparency-new/`, accessed February 2022

[8] `https://openai.com/charter`, published April 9, 2018

[9] `https://standards.ieee.org/wp-content/uploads/import/documents/other/ead_v2.pdf`, released 2019

[10] `https://www.acm.org/binaries/content/assets/public-policy/2017_usacm_statement_algorithms.pdf`, published January 2017

[11] `https://www.iais.fraunhofer.de/content/dam/iais/fb/Kuenstliche_intelligenz/ki-pruefkatalog/Fraunhofer_IAIS_AI_ASSESSMENT_Catalog_Web.pdf`, published July 2021

[12] `https://gi.de/ethicalguidelines`, published June 29, 2018

[13] `https://lefis.unizar.es/wp-content/uploads/EGE_Artificial-Intelligence_Statement_2018.pdf`

ples and democratic prerequisites like human dignity and autonomy, responsibility, justice, equity, and solidarity, democracy, rule of law and accountability, security, safety, data protection and privacy, and, sustainability. These principles are taken up and further developed in the EU Guidelines on AI and data protection[14].

Although the guidelines can provide valuable guidance during the design of AI systems, they were not designed to provide a structured process to assess the trustworthiness of an AI system or be used in algorithmic or AI audits. Having identified the lack of a structured process, Zicari et al. (2021) propose Z-Inspection®, a process based on applied ethics that addresses the described downside of existing guidelines. To the best of their knowledge, Z-Inspection® is the first process to assess trustworthy AI in practice (Zicari et al. 2021). Therefore, the assessment in this chapter is based on the Z-Inspection® process. Their approach will be presented in the following section and then applied in the Sections 6.2–6.4.

6.1.2 Introduction to the Z-Inspection® Process

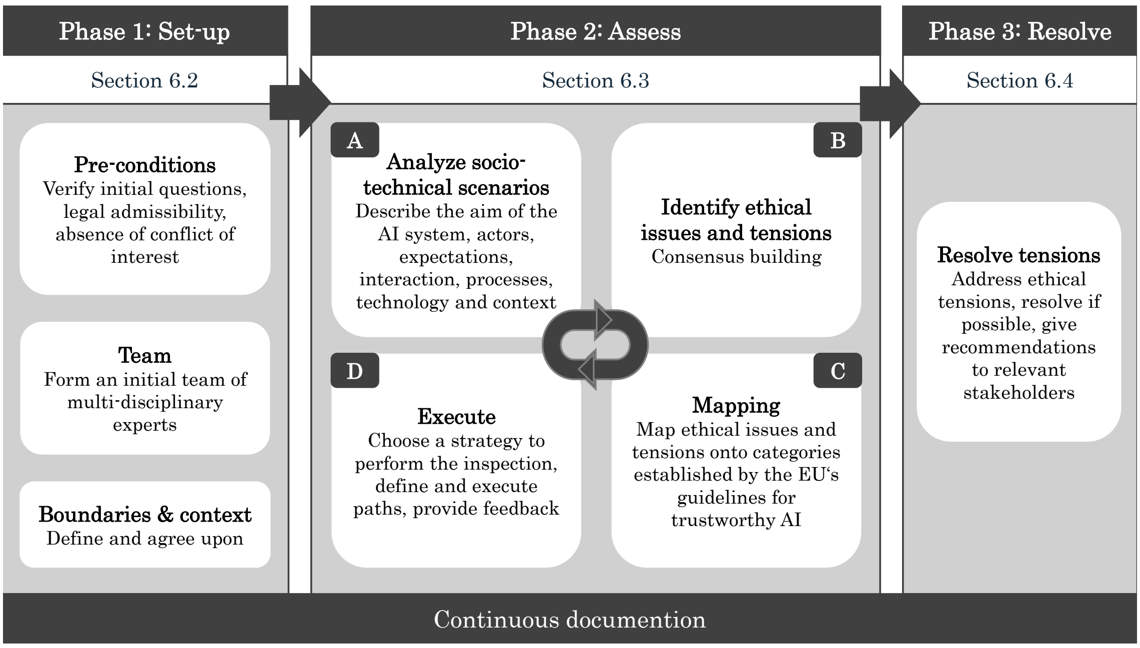

Figure 6.1: Overview on the Z-Inspection® based on Zicari et al. (2021, Fig.1).

The Z-Inspection® process comprises three consecutive phases, illustrated in Figure 6.1. Each phase involves a documentation process, wherein a protocol is meticulously crafted to record the outcomes. The framework developed in this dissertation undergoes the execution of the three phases. The documentation for each phase is presented in one of the subsequent Sections 6.2, 6.3, and 6.4. The phases will be explained in the following based on the publication by Zicari et al. (2021).

In the first phase, the project is set up, encompassing a thorough examination of its preconditions to guarantee the absence of conflicts of interest and legal admis-

[14] `https://rm.coe.int/2018-lignes-directrices-sur-l-intelligence-artificielle-et-la-protecti/168098e1b7`, adopted by the Committee of the Convention for the Protection of Individuals with regards to Processing of Personal Data (Convention 108) on 25 January 2019

sibility. To achieve this, a predefined set of initial questions is rigorously assessed with a team comprising experts from diverse disciplines. The team should be clear about the boundaries and context of the project, which requires clear definitions and agreements to be made before the evaluation begins. Additionally, the team engages in discussions to determine the intellectual property owner and reaches a consensus on the time frame for conducting the assessment.

The second phase, known as the assessment phase, encompasses four iterative steps, denoted with the letters A to D in Figure 6.1. Initially, a socio-technical analysis is conducted, focusing on the usage scenarios of the AI system. This entails describing the system's objective, the expected behavior it should exhibit, the involved actors, their interactions through processes, the technology employed, and the deployment context. The second step involves the identification of ethical, technical, and legal issues, highlighting any inherent tensions. Subsequently, the third step maps the identified issues to the ethical principles (human autonomy, prevention of harm, fairness, explainability) and requirements of trustworthy AI (see list below). In the last step of the assessment phase, a strategy to perform the inspection is chosen and executed. The Z-Inspection® process suggests utilizing the established requirements set by the independent High-Level Expert Group on AI, as instantiated by the European Commission. While not exhaustive, these requirements encompass systemic, individual, and societal aspects (European Commission and Directorate-General for Communications Networks, Content and Technology 2019, p. 14):

- Human agency and oversight (including fundamental rights)
- Technical robustness and safety (including resilience to attack and security, fallback plan and general safety, accuracy, reliability, and reproducibility)
- Privacy and data governance (including respect for privacy, quality and integrity of data, and access to data)
- Transparency (including traceability, explainability, and communication)
- Diversity, nondiscrimination, and fairness (including the avoidance of unfair bias, accessibility, universal design, and stakeholder participation)
- Societal and environmental well-being (including sustainability and environmental friendliness, social impact, society, and democracy)
- Accountability (including auditability, minimization, and reporting of negative impact, trade-offs, and redress)

The final and third phase in the Z-Inspection® process focuses on resolving ethical tensions, where feasible. A wide array of potential ethical tensions exists, arising from the opposition between two ethical values. Moreover, feedback to the relevant stakeholders is provided to improve the AI system. As emphasized earlier, the entire process, along with its outcomes and recommendations, is meticulously documented. The following three sections serve as a protocol for the evaluation of the framework presented in this dissertation and are named according to the three phases of the Z-Inspection® process.

6.1.3 Deviations from the Z-inspection® Process

In specific instances, it was imperative to diverge from the proposed implementation of the Z-Inspection® process outlined in Allahabadi et al. (2022) and Zicari et al. (2021) to tailor the process for the specific context of this dissertation. Consequently, the author independently executed Phase 1, given that the preconditions, boundaries, and context are inherently predefined within the scope of this dissertation. The author also assembled the team in this step. The results from the set-up phase including the developed socio-technical scenario was then communicated to the investigators through a concise four-page workshop manual. Subsequently, the experts conducted steps two and three of the evaluation phase in three identical two-hour workshops, all of which were moderated and prepared by the author. After each workshop, a dedicated brainstorming session was held to explore potential solutions for the identified ethical issues. The author meticulously collected and organized ideas from these three workshops and carried out the remaining steps of the process. The following three sections provide a detailed presentation of the steps taken, with any deviations from the standard procedure thoroughly described.

6.2 Phase 1: Set-Up Phase

This section explains the set-up of the project, covering the steps of the first phase of the Z-Inspection® process (see Figure 6.1). Each aspect of the set-up phase is subsequently detailed. In Section 6.2.1, the project's prerequisites are thoroughly examined using a provided catalog of questions. Section 6.2.2 introduces the team of investigators. The last Section 6.2.3 delimits the project's scope, providing explicit definitions for its boundaries and context.

6.2.1 Clarification of Preconditions

To elucidate the project's preconditions, the provided catalog of questions from (Zicari et al. 2021) is utilized. The questions, verbatim excerpts from the source, are presented in the following, accompanied by their respective answers from the author below.

Who requested the inspection? The inspection was not formally requested; rather, it originates from the author's intrinsic commitment to develop a framework characterized by trustworthiness. Motivated by the pursuit of excellence and ethical standards in system development, the author initiated the inspection to proactively ensure the framework's integrity and alignment with ethical guidelines.

Why carry out an inspection? The author acknowledged the need for a thorough inspection of her framework against ethical guidelines, motivated by the aim of fostering a resilient and dependable solution. This strategic evaluation aims to pinpoint potential ethical considerations, refine the framework's design, and lay the groundwork for responsible development. By systematically scrutinizing the framework, the author aims to enhance its ethical integrity, and contribute to the broader discourse on ethical development practices.

For whom is the inspection relevant? The inspection holds relevance for various stakeholders:

- TRUMPF Machine Tools: The results can be utilized by TRUMPF Machine Tools to enhance their Indoor Positioning System (IPS) product and services based on the insights gained.

- Scientific Community: The inspection provides an additional use case, contributing to the improvement of processes in the domains of trustworthiness assessments and production optimization.

- The Author: The inspection is crucial for the author to evaluate her framework's trustworthiness and derive potential avenues for future improvements.

Is it recommended or required (mandatory inspection)? The inspection is neither recommended nor mandatory; it is conducted voluntarily. The author undertakes this process driven by a personal commitment to ensuring the highest standards of trustworthiness in the framework, exceeding any formal obligations.

What are sufficient versus necessary conditions that need to be analyzed? This evaluation revolves around the comprehensive assessment of trustworthiness of the framework proposed in this dissertation. It explicitly does not assume the system's development and focuses on an ex-ante assessment. However, it is assumed that an IPS will be employed, equipped with a comprehensive set of analysis functions capable of providing all derivable simulation inputs.

How are the inspection results to be used? The inspection results hold significance for two primary purposes: first, to validate the proposed framework concerning its design; and second, to derive recommendations for the future development of IPSs, specifically those utilized for simulation input modeling.

Will the results be shared (public) or kept private? In the latter case, the key question is why it is kept private. The assessment results will be meticulously documented in this chapter, ensuring their open availability after the publication of this dissertation. This transparency aligns with the commitment to disseminate findings openly and contributes to the collective knowledge in the field of trustworthy system development.

6.2.2 Set-up Team of Investigators

The author set up the team of investigators in May 2022, as detailed in Table 6.1. She contacted 14 individuals from her LinkedIn network, comprising seven experts in AI ethics and seven experts in manufacturing and digitization. The selection process involved considering three criteria outlined in Zicari et al. (2021):

- Multi-disciplinary experts: For the AI ethics inspection of the IPS based simulation system used in manufacturing, experts from all involved disciplines are required, such as computer science, mechanical and electrical engineering, production management, ethics, simulation engineering and similar.

- Required skills: In the initial selection phase, the author prioritized individuals with expertise in AI ethics and manufacturing, the intended domain of the system. Additionally, consideration was given to candidates with proficiency in machine learning, simulation, IPS, innovation management, and psychology.
- Interest to build knowledge in a new domain: All individuals approached exhibit a high level of openness and curiosity. Many possess backgrounds in research or consulting, professions that demand rapid adaptation to new topics, involvement in innovative projects, and continuous self-education.

Investigator	manufacturing expert	digitization expert	ML Expert	ML systems developer	AI ethics expert	consultant	researcher	simulation expert	IPS expert	innovation manager	psychologist	workshop number
Tom	●	●	○	○	○	●	○	◕	◑	◔	○	1
Sabeth	●	●	◕	◔	○	◑	◔	○	○	◑	○	1
Johannes	○	●	◑	◔	●	●	◔	○	○	◑	○	1
Anna	○	○	◑	○	●	●	◑	○	○	○	○	1
Yahel	◑	●	○	○	○	◑	◔	○	●	●	○	2
Sandra	○	◑	◕	◑	●	●	○	○	○	◔	◔	2
Veronika	◕	◕	○	○	○	○	●	○	○	◑	●	2
Thorsten	◑	◑	◕	◕	○	○	◑	●	○	○	○	2
Flemming	●	◕	◔	○	○	◔	○	◑	●	○	○	3
Lynn	●	●	◔	○	◔	◕	●	○	○	◕	○	3
Charleen	○	◔	●	◑	●	●	●	○	○	○	○	3
Ute	○	◑	●	●	●	●	●	◕	○	○	○	3

Table 6.1: Overview of investigators and their knowledge in different fields relevant to the interdisciplinary workshops. The names of the investigators were anonymized while their gender was retained. The ratings are derived from the mean values of both self-assessment and assessments by the author. Within each category, the options included no knowledge (○), medium knowledge (◑), and advanced knowledge (●). For a detailed breakdown of all assessments, please refer to Appendix A.3.

Each investigator was informed that their participation in the Z-Inspection® process meant a voluntary commitment to a two-hour online workshop in July 2022, plus an additional hour of preparation reading a workshop manual that was provided to them in advance. Of 14 experts approached, 13 agreed to participate in the workshops. These 13 people voted on possible dates for the online workshop. Their availability was limited, so there had to be three workshop dates. Shortly before the workshops, one person had to withdraw, leaving the author with 12 experts who participated in three identical workshops with four participants each. The author wanted to do more extensive workshops with more people first. However, in retrospect, the group size of four proved to be an excellent number for the online workshop setting since four people can cover the different professional backgrounds needed while at the same time leaving enough time for discussion and contribution of each expert. When assigning participants to workshops, the author ensured each workshop had at least one person with expertise in simulation and IPS. She also ensured that half of the participants were AI ethics experts and the other half were manufacturing experts.

Check for Conflicts of Interest

Zicari et al. (2021) underscore the substantial ethical implications of expert selection, specifically in defining the skills, background, and roles involved in the investigation. To address potential conflicts of interest, they have integrated a checklist into the ethical verification of the team. This checklist, as outlined by Zicari et al. (2021), was used by the author after setting up the group of experts:

- No conflict of interest exists between the investigators and the entity or organization to be examined: When selecting the team, care was taken to ensure that none of the investigators selected were currently employed by TRUMPF or had a previous history with TRUMPF. One investigator had already conducted podcast interviews with TRUMPF employees in the past. However, the risk of a conflict of interest is considered to be low as these interviews have already taken place and no further collaboration is planned at the time of the workshops.

- No conflict of interests exists between the investigators and vendors of tools, tool kits, frameworks, data platforms to be used in the inspection: TRUMPF's indoor localization system or any competitor products are not utilized by any of the selected individuals, nor do they have plans to integrate them in the future. One person currently holds a position in a large company that provides real-time indoor localization systems and had previously worked in the product development of the IPS. At the time of the workshop, there was no ongoing collaboration with the individual's previous department. The person's extensive expertise in localization systems is considered an advantage, outweighing any unlikely negative impact from their past position on the workshop's conduct.

- Any potential bias of the team of investigators is assessed: A person is actively involved in the research and development of the Z-Inspection® process. Consequently, there is a possibility that the person may exhibit less critical judgment if issues arise during the execution of the process according to the scheme. However, the prevailing advantage lies in the person's expertise in the field and their prior application of the process in other projects, which enhances the overall value of their involvement.

All three areas were thoroughly reviewed. The three named individuals in the conflict of interest analysis above are three different individuals. Importantly, it was taken care of, that only one of these individuals was present at each workshop, ensuring that there was never a majority in voting. In summary, the thorough analysis of the investigators has identified no conflict of interest. Consequently, nothing impedes the successful execution of the Z-Inspection® process with the selected experts.

Overview Investigators

Table 6.1 was created to provide a better overview of the experts involved. It lists the twelve investigators and groups them according to their workshops number (see the last column). The names have been anonymized, but the gender is correctly reflected. Four men and eight women participated in the workshops. The rating shown in Table 6.1 is the mean of the investigators' self-assessment and the author's assessment. She made her assessment before she knew the investigators' self-assessment in order to avoid any influence. The investigators were not shown their external rating for the same reason. For the assessment of the expertise, it was possible to choose between no knowledge ○, medium knowledge ◑, and advanced knowledge ●. The categories are listed as columns in Table 6.1 and include expertise in manufacturing, AI ethics, and the other skills that were considered important. Since many investigators have a background in consulting or research, this was also included as a category. In Table 6.1, one also sees quarter or three-quarter Harvey Balls, which can be attributed to the averaging between the assessments. For the sake of transparency, the self-assessment of the investigators and the authors' assessment are attached in Appendix A.3.

6.2.3 Definition of Boundaries and Context

In the final step of Phase I, it is essential to define the boundaries and context of the assessment. Additionally, considerations regarding intellectual property and the investigation's time frame need to be clarified.

The Z-Inspection® process can be used to assess a system ex-ante and ex-post (Allahabadi et al. 2022, p.4). The system in question is evaluated ex-ante, i.e., the evaluation takes place before it is developed. This offers the advantage of directly adhering to the principles of trustworthiness during implementation, potentially avoiding costs associated with revisions. However, a drawback of the ex-ante approach is the lack of detailed system specifications, potentially leading to varied interpretations among investigators regarding the system's final appearance and functionality. Furthermore, a comprehensive review of the code and the database is not feasible, so that such investigations must be carried out during the implementation of the system. In this ex-ante assessment, the primary focus will be on identifying ethical issues rather than technical or legal ones. Technical and legal aspects, while crucial, demand distinct expertise not central to the scope of this dissertation. Nevertheless, acknowledging their importance, these aspects should be addressed in future work and during the actual implementation of such a system.

The investigation period aligns with the time frame for preparing this chapter in 2022. Investigator involvement is confined to the execution of Phase II in July 2022, necessitating their familiarity with socio-technical scenarios through a workshop manual and their subsequent participation in a workshop. The investigators remain available for any ensuing queries. The investigators were explicitly informed, both in writing and verbally, that their consent was required for the intellectual property developed during the process to be used by the author for the purpose of publishing the results in this dissertation. The investigators participated voluntarily and thus had the option to withdraw their participation at any time if they did not agree. In addition, the examiners were obliged to treat the contents and results of the workshop confidentially until the official publication of the dissertation.

6.3 Phase 2: Assess Phase

This section outlines the assessment of the system using the four steps from Phase II of the Z-Inspection® process depicted in Figure 6.1. In contrast to the original process, Step D, involving the planning of the execution strategy, is addressed first in Section 6.3.1, reflecting the actual sequence of how the assessment phase was conducted. This adjustment was made when it became evident that planning the execution strategy was a prerequisite for the subsequent steps. Section 6.3.2 details Step A, covering the description and analysis of socio-technical scenarios. Section 6.3.3 combines the presentation of Step B, identifying ethical issues and tensions, with Step C, mapping them onto ethical values and requirements, showcasing results from workshops with the team of investigators. After completing steps A-C, and before initiating the next iteration, the execution strategy can be revised, and feedback can be incorporated to enhance efficiency in subsequent iterations. In this dissertation, only one iteration of the assessment phase was undertaken. Based on the results, initiating another iteration is plausible, particularly if the socio-technical scenario has been revised based on findings from the initial iteration. Subsequently, investigators would need to conduct another assessment for the updated system.

6.3.1 Step D: Planning and Execution

The content of this section unfolds in three parts. Initially, the execution approach from the literature is introduced. This is succeeded by a discussion of the necessity to adapt it to the boundaries of this assessment. Lastly, the tailored execution approach is presented.

Execution Approach from the Literature

Previous assessments conducted using the Z-Inspection® process were examined for planning the conduct of the study, focusing on the recent publication by the developers and advocates of this process. Allahabadi et al. (2022) assessed a deep learning system predicting a multi-regional score for the degree of lung compromise in COVID-19 patients. Their approach employed is summarized in Table 6.2, outlining the roles responsible for specific actions in each step, the methodologies employed, and the outcomes derived.

For Step A, an interdisciplinary team engaged with stakeholders, defined as actors with direct ownership of the AI system's development and deployment (Allahabadi et al. 2022). They collaboratively developed socio-technical scenarios in multiple online workshop meetings. The number of participants in these meetings remains unclear.

For Step B, the interdisciplinary team splintered into eight intradisciplinary working groups, with varying sizes from two to 21 experts. These groups assessed the system based on their expertise during online workshops and generated preliminary reports, which were shared among the groups to gather feedback and refine them. Step two concluded with a final report listing identified risks and issues.

In Step C, the intradisciplinary working groups reconvened in multiple online workshops to map the identified issues onto the four ethical principles and seven requirements outlined by the High-Level Expert Group of AI. Each working group employed different mapping strategies. An example of such a mapping strategy described by Allahabadi et al. (2022) involved creating a list of key issues identified in the initial meeting, distributing responsibilities for issue descriptions among group members, and iteratively mapping these issues to ethical pillars and requirements through discussions across multiple meetings. To consolidate the mappings from each working group, an interdisciplinary team was formed, comprising one expert from each working group. Discrepancies between the mappings of the working groups were identified and attributed to the different backgrounds of the investigators, and were resolved through group consensus. (Allahabadi et al. 2022)

	WHO	HOW	WHAT
Step A	**inter**disciplinary teams + stakeholders	several online workshop meetings	socio-technical scenarios
Step B	**intra**disciplinary working groups	several online workshop meetings	each working group prepared preliminary report
		each working group reviewed the reports of the other working groups	feedback on preliminary reports for each working group
		each working group updates the reports with the feedback from other working groups	final reports with a list of identified risks & issues
Step C	**intra**disciplinary working groups	several online workshop meetings	mapping of issues on four ethical principles and seven requirements for each working group
	interdisciplinary team	several online workshop meetings	consolidated mapping of issues
			list of recommendations

Table 6.2: Z-Inspection® execution approach from Allahabadi et al. (2022).

Need for Adaptation

The execution approach presented in Allahabadi et al. (2022) reflects a singular assessment phase, while the process diagram from the underlying process by Zicari et al. (2021) (see Figure 6.1) suggests an iterative nature. Given the impracticality of involving 58 investigators like Allahabadi et al. (2022) for every project, especially in real-world industry applications, a streamlined execution approach is essential for broader adoption. In this dissertation, with limited resources and voluntary investigators, a new execution approach for the Z-Inspection® process is derived. This streamlined version aims to balance thorough assessment within time constraints, facilitating practical applicability and encouraging assessments even with limited resources.

Execution Approach in this Dissertation

The author tailored an own execution approach, depicted in Figure 6.3, inspired by the methodology outlined by Allahabadi et al. (2022), but customized to suit the project's constraints. This approach streamlined investigator efforts by emphasizing the identification and evaluation of ethical issues and the proposal of improvement recommendations. The primary emphasis in this ex-ante assessment is on identifying ethical issues rather than technical or legal ones, as the latter require specialized expertise beyond the scope of this dissertation. The workshops were conducted online to enhance accessibility for the experts, which was the same reason as in Allahabadi et al. (2022).

Before the online workshop, the socio-technical scenarios were incorporated into a workshop manual, serving as an introductory document outlining the workshop's objectives, the system to be assessed, and the assessment context. Distributed to investigators beforehand, the manual aimed to familiarize them with the framework, set expectations for the workshop, and act as an educational resource on less familiar topics. AI ethics experts gained insights into the indoor-localization system, while manufacturing experts delved into the ethical principles and trustworthy AI key requirements relevant to the workshop. The manual also directed interested readers to relevant literature. Feedback from investigators, sought on the scenarios and for clarification questions, contributed to continuous improvement of the manual after each workshop, with subsequent teams receiving an updated version.

Each of the three identical online workshop commenced with a 20-minute introduction featuring participant introductions and a self-assessment of expertise. The moderator (the author) presented the workshop agenda, emphasizing the recording and use of results in the author's dissertation. A recap covered the workshop goal, framework, socio-technical scenarios, actors, and decision points. Despite repetition from the workshop manual, feedback indicated that refreshing the content enhanced understanding. Following this introduction, participants had an opportunity for questions and additions, particularly regarding the mind map of actors.

The main workshop comprised three parts. The first part, lasting 60-80 minutes, focused on identifying ethical issues for the socio-technical scenario. For this purpose, a table with four columns was prepared on the virtual whiteboard, each representing one of the four ethical principles, but named oppositely: Disregard for human autonomy, causing harm (psychological and physical damage to people), treating people unfairly, and lacking explainability. Participants brainstormed on

	WHO	HOW	WHAT
before online workshops	Carina Mieth	writing based on the author's research	socio-technical scenarios workshop manual
	investigators	read workshop manual	feedback on scenarios and clarification questions
for each of the three identical online workshops, using three virtual whiteboards	Carina Mieth	introduction: recap, answering questions, moderation, session recording	recorded session (audio & screen recording)
	interdisciplinary team	brainstorming and clustering ethical issues	list of identified issues assigned to the four ethical principles
	each investigator	silent work: mapping issues onto Trustworthy AI key requirements	list of issues with four different assignment sets
	interdisciplinary team	discussing outliers and find a consensus for the mapping	mapping of ethical issues on 4 ethical principles and 7 requirements
	each investigator	silent work: brainstorming on system improvements	list of recommendations
after online workshops	Carina Mieth	merge and consolidate lists from different workshops	consolidated list of ethical issues mapped on 4 ethical principles and 7 requirements consolidated list of recommendations
	each investigator	written communication	optional feedback

Table 6.3: Tailored execution approach derived by adapting the execution approach from Allahabadi et al. (2022).

violations of these principles and recorded ideas on post-its. This was followed by a group discussion, consolidation, categorization into the four ethical principles, and addition of ethical tensions to the post-its. Clear categorization was recommended to avoid overly abstract issues, with encouragement to split abstract issues for better differentiation.

In the second part of the workshop, lasting between 30 and 45 minutes, the identified issues were mapped to the seven requirements for operationalization (see list in Section 6.1.2). The post-its with the issues were copied into a new table, in which the columns were correctly named with the four ethical principles. The seven requirements were placed next to the table on the digital whiteboard and numbered. Each investigator silently evaluated each issue, attaching a post-it with the numbers of the key requirements, with a soft constraint of assigning a maximum of three requirements. While the investigators evaluated, the moderator compared assignments, marking numbers red that were assigned by only one investigator. In the following consolidation performed as group discussion, the sole assigners had to justify their assignment and try to convince others. Requirements were sometimes accepted in the discussion and added to the set, otherwise deleted. The result at the end of this part was a set of mapped issues on post-its.

In the third and final part of the workshop, investigators gathered their ideas for system improvements on the digital whiteboard to eliminate or reduce ethical issues. Due to tight time constraints, only about 10-20 minutes were available for this part. Initially, the author intended to discuss the recommendations, but, unfortunately, this part had to be skipped.

At the conclusion of each workshop, feedback on the process was gathered. The feedback from the first two workshops was valuable for making minor improvements to subsequent workshops. The initially planned two-hour duration for the workshop proved overly optimistic, as each workshop extended beyond that time frame. It would be advisable to allocate a half-day for the workshop if resources allow. Despite the time constraints, the execution was successful, as investigators were able to document and map every identified issue.

After the online workshops, the author consolidated and merged the three lists of ethical issues from the different workshops as well as the recommendations. The evaluation can be found in Section 6.3.3. Based on these, a next iteration can be started if implementing the improvement suggestions caused significant changes to the system behavior and the socio-technical scenario. It is also conceivable to conduct the next iteration with other experts to obtain a new and unbiased view of the system's weak points. An exciting approach is to focus no longer on ethical issues in the next iteration but on legal or technical issues.

6.3.2 Step A: Socio-Technical Scenario

Step A of the Assess phase, as shown in Figure 6.1, presents the socio-technical scenario, which consist of a sociological and a technical aspect. The sociological aspect encompasses the presentation of various actors and their interactions within the system. On the technical side, the focus is on the system's decision points and the data and information used in these processes.

As presented in Section 5.4, multiple scenarios, ranging from a base scenario to a future scenario, exist, but evaluating each individually with the Z-Inspection® process is impractical due to time and workload constraints. Consequently, the assessment zeroes in on the future scenario, where advanced technological integration is expected to present the most ethical challenges. By evaluating the future scenario, insights can be leveraged to fine tune the scenario for implementation. Addressing ethical concerns may entail adjusting the degree of automation or limiting tracking (see categories in Table 5.2) to enhance the trustworthiness of the system. The workshop manual and the introductory segment of the workshop provided investigators with information on the baseline and future scenario, emphasizing that their assessment should exclusively focus on the future scenario.

Actors and their Relations

The implementation of the framework and the resulting consequences from design decisions have a broad impact on various stakeholders. To comprehensively understand the stakeholders involved, a stakeholder map was developed using a mind map. The initial map created by the author served as a brainstorming tool during the workshops, allowing investigators to contribute and identify any missing stakeholders on the shared virtual whiteboard. The stakeholder map that resulted from the workshops can be found in Appendix A. The author organized the stakeholders into distinct groups, presented in Figure 6.2 and detailed here:

- Manufacturing company that deploys system (gray box in Figure 6.2):
  - People with more power: Individuals higher up in the hierarchy, such as forepersons, team leaders, and managers, who primarily use the system's results for evaluating others with less power. They typically have greater access to the system's outputs and information.
  - People with less power: Individuals at the lower end of the hierarchy, subject to evaluation based on the system's outputs. They often have limited decision-making power and may hold precarious job positions, including workforce in plants, temporary workers, and external workers in the supply chain.
  - Other internal stakeholders: Divided into those involved in system implementation (e.g., IT department, IT security, legal department for General Data Protection Regulation (GDPR) compliance, and purchasing department) and those protecting the rights of individuals with less power (e.g., works council and social responsibility team).
- Public, media, and politics: Refers to individuals and entities in the outer sphere not directly affected by the system. Their opinions on the current system may influence future use. Examples include local communities, newspapers, influencers, courts, and governments.
- Customers: Individuals from the customers of the manufacturing company deploying the system.
- Company developing the system: Individuals from the company that develops the system, including management, project leads, and developers.
- External auditors: Individuals or entities assessing the company developing the system and the manufacturing company deploying the system. Examples include certification authorities and third-party investigators.

The numbered arrows in Figure 6.2 delineate specific interactions among actors within the socio-technical system. The first arrow (1) signifies hierarchical relationships within the manufacturing company, representing the evaluation of employee performance by higher-ups. The second arrow (2) denotes interactions essential for system implementation and operation, often initiated by management, with the purchasing department seeking offers from system-developing companies (6). Criteria such as data protection and IT security, crucial for consultation with the developing company, factor into the selection process (6). The works council, ensuring workforce

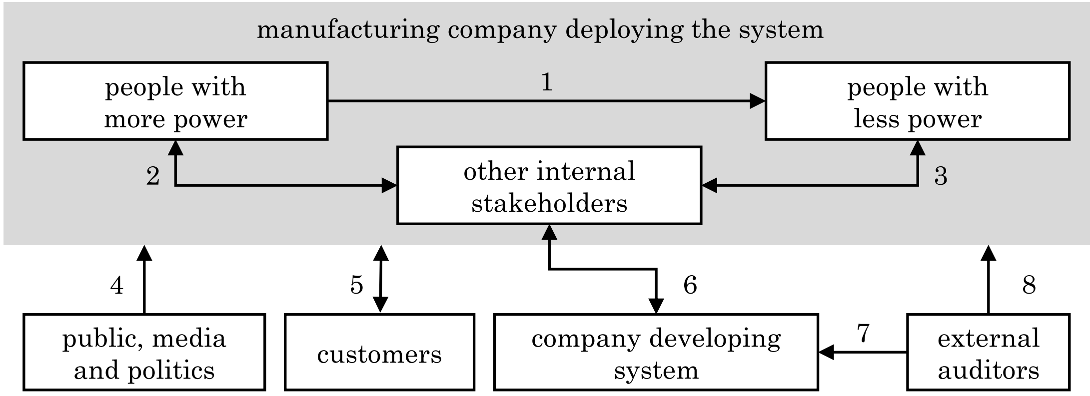

Figure 6.2: Stakeholder map providing an overview of affected actors in the ecosystem. The numbering of the arrows is used in the text to specify the interactions.

interests, participates in the roll out and gathers concerns of individuals with less power (3). External audits by a third party may be conducted on both the manufacturing company deploying the system and the company developing the system (7,8). Corporate social responsibility standards imposed by the manufacturing company's customers can influence system use (5). Conversely, customers receiving products produced with the system are impacted by the system's decisions regarding order fulfillment. Finally, an outer sphere of stakeholders, including the general public, media, and politics, indirectly influences system use (4). Notably, this overview is applicable to all scenarios.

Decision-making

Following the description of actors in the socio-technical system, the focus shifts to decision-making. The decision points within the evaluated system are the gray starting points of the dashed arrows in Figure 6.3. All instances where decisions are made automatically by or with the assistance of the system will be considered in the assessment. As depicted in Figure 6.3, decisions can be based on:

- Processed and harmonized data
- Methods from descriptive statistics: measures of central tendency (e.g., mean, mode, median), measures of variability (e.g., range, variance, dispersion), etc.
- Machine learning methods: unsupervised techniques (clustering, association, anomaly detection), supervised techniques (linear/logistic regression, decision trees, neural networks, Reinforcement Learning (RL)), etc.
- Simulation experiments and respective analyses for determining Key Perfomance Indicators (KPIs).

Note that statistical methods or machine learning may be used for data harmonization, e.g., as presented by Nessa et al. (2020). The rectangle representing data harmonization corresponds to the blue IPS layer in the framework from Figure 5.2.

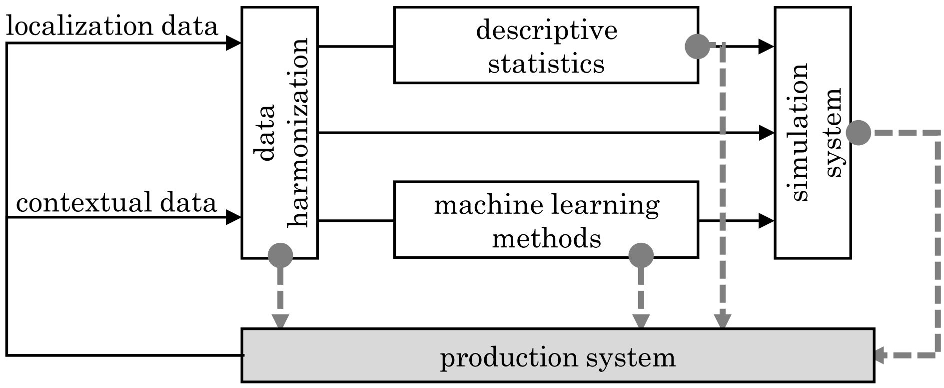

Figure 6.3: Overview of decision points (gray) within the evaluated system. Dashed arrows represent decisions closing the data-information loops, while black arrows illustrate the flow of data.

6.3.3 Step B and C: Identification of Ethical Issues and Mapping

In Steps B and C of the Asess phase (see Figure 6.1), ethical issues were examined within three identical workshops, focusing exclusively on ethical concerns and omitting legal and technical considerations. A total of 40 ethical issues were identified and categorized into four ethical principles, mapped subsequently to the seven requirements for trustworthy AI. The breakdown per workshop and ethical principle is detailed in Table 6.4.

Ethical principle	I	II	III	IV	Double assigned	Sum
Workshop 1	4	6	3	4	3	14
Workshop 2	4	4	3	3	4	10
Workshop 3	4	7	7	4	6	16
Issues	12	17	13	11	-	40
Issue cluster	3	5	4	3	-	15

Table 6.4: Analysis of ethical issues across workshops: identification and mapping on ethical principles: Respect for human autonomy (I), Prevention of harm (II), Fairness (III), Explainability (IV). Ethical issues were double-assigned 13 times. Ethical issues from the workshops were consolidated by the author into 15 clusters.

The original issue descriptions from the workshops with the assigned tension, ethical principle, and trustworthy AI key requirements can be found in Appendix B. To enhance traceability, the person voting for an AI key requirement is indicated in parentheses after the mapped requirements. The issues are categorized by ethical principles, and if an issue is assigned to two ethical principles, it is listed under the one deemed most relevant by the author to prevent duplication. A comprehensive overview of ethical tensions, which arise when two ethical principles conflict, can be found with examples in Whittlestone et al. (2019, p.20).

Clusters were created based on similar issues to present them more coherently in the following. While different workshops identified similar issues, they often emphasized different nuances. Clustering on a digital whiteboard was performed by the author using a copy of the post-its from the workshops. Each cluster includes information on the assigned issues, ethical principles, dominant tensions, and primary trustworthy AI key requirements. The dominant tension and trustworthy AI key requirements are usually the most frequently named ones from the individual issues. Occasionally, deviations are noted, particularly when a clear consensus is lacking between workshops. A total of 40 ethical issues from the workshops were consolidated by the author into 15 clusters. These clusters will be presented in the following four sections, each corresponding to one of the four ethical principles.

Issue clusters regarding ethical principle respect for human autonomy

For the ethical principle *respect for human autonomy*, the investigators identified 12 issues in the workshops, and three clusters were created by the author.

Cluster 1 - Limitation of decision making - addresses shared concerns from all three workshops regarding the complete automation of decisions by the system, devoid of human involvement. Decision-making constraints were criticized for limiting employees' options and potentially causing issues, especially in emergencies. The system's takeover of decision-making authority from previous decision-makers, particularly in middle management, raised concerns regarding processes. Criticisms also extended to the limited decision-making of workers on the shop floor, impacting their autonomy and ability to independently structure their work. This limitation, coupled with the potential lack of comprehensibility of the system's decisions, could make employees feel patronized, affecting their self-efficacy.

Ethical Issue Cluster 1: Limitation of decision making
Ethical Issues: 1, 2, 3, 8, 11
Ethical Principle: Respect for human autonomy
Dominant Tensions: Autonomy vs. efficiency
Dominant Trustworthy AI Key Requirements: Human agency and oversight; Accountability;

Cluster 2 - Against the will, self-assessment or personal preference - highlights concerns about automated, data-driven decisions by the system restricting individuals' options and potentially conflicting with their preferred courses of action. Strict system constraints limit the autonomy of individuals to plan their work independently, sometimes leading to tasks being assigned against their will. This restriction can impact work performance, especially when disliked tasks are performed reluctantly. There is also a risk of assigning tasks that individuals may not be physically able to perform, leading to psychological or physical stress (ergonomics problems), detailed in Cluster 6. The common thread in this issue cluster is the deprivation of employee autonomy in making independent decisions about their activities. The efficiency of system decisions takes precedence over individual autonomy, particularly problematic in the system or simulation, where modeling simplifies reality and omits personal preferences and characteristics of individuals. The tension satisfaction of preferences versus equality was added to this cluster by the author.

Ethical Issue Cluster 2: Against the will, self-assessment, or personal preference
Ethical Issues: 4, 9, 10
Ethical Principle: Respect for human autonomy
Dominant Tensions: Autonomy vs. efficiency, Satisfaction of preferences vs. equality
Dominant Trustworthy AI Key Requirements: Human agency and oversight;

Cluster 3 - Transparent employee - centers around critical considerations of the compromise of employee privacy to enhance system functionality. The investigators express concerns about the system's perpetual tracking of individuals, leaving no room for employees to conceal their movements. The resulting transparency of all employee activities and behaviors is viewed as a potential avenue for close control, with individuals having insight into data evaluation possibly tempted to enforce punitive measures for perceived misconduct. Additionally, the cluster highlights the identified issue of "datafication of human performance," (see Issue 7) emphasizing continuous employee tracking as the foundation for efficiency monitoring, comparisons, and the establishment of ambitious, and at times, unrealistic performance targets. This cluster sheds light on the delicate balance between system optimization and the preservation of individual privacy, raising ethical considerations surrounding constant surveillance in the workplace.

Ethical Issue Cluster 3: Transparent employee
Ethical Issues: 5, 6(i), 7
Ethical Principle: Respect for human autonomy
Dominant Tensions: Privacy vs. quality of service
Dominant Trustworthy AI Key Requirements: Privacy and data governance; Human agency and oversight;

Issue clusters regarding ethical principle prevention of harm

Under the ethical principle of *prevention of harm*, the investigators identified 17 issues, leading to the formation of five clusters. Notably, two of them, Cluster 7 - Technophobia, and Cluster 8 - Risk of cyber attacks, each contain only one issue.

Cluster 4 - Harm caused by surveillance - consists of two ethical issues, emphasizing the potential detrimental effects of continuous employee surveillance. The dominant tension identified in both issues revolves around the delicate balance between privacy and efficiency, reflecting the ethical dilemma of leveraging surveillance for operational optimization while safeguarding individual privacy. The key requirement central to this cluster is *societal and environmental well-being*, underscoring the broader impact of surveillance practices on both individuals and the overall social fabric. The investigators express concerns about the potential psychological and emotional toll on employees subjected to constant monitoring, highlighting concerns about stress, pressure, mental well-being, and the risk of reduced cognitive abilities leading to accidents over time.

Ethical Issue Cluster 4: Harm caused by surveillance
Ethical Issues: 13, 17 (i)
Ethical Principle: Prevention of harm
Dominant Tensions: Privacy vs. efficiency
Dominant Trustworthy AI Key Requirements: Societal and environmental well-being; Privacy and data governance;

Cluster 5 - Pressure to perform - delves into the psychological impact of sustained performance pressure on individuals within the system. The automated decisions and targets derived from the simulation maintain a high pace of work to ensure efficiency in the production system. Individuals are constantly challenged to meet these targets, engaging in an ongoing competition with their own past performance metrics, and those of their colleagues. Over time, the sustained stress and performance pressure may lead to burnout or depression, as highlighted by investigators in Workshop 3. The perception of the "algorithm as a ruler" or self-reinforcing effects in the system can further intensify the pace of work, contributing to workers' discomfort.

Ethical Issue Cluster 5: Pressure to perform
Ethical Issues: 14, 16, 18
Ethical Principle: Prevention of harm
Dominant Tensions: Efficiency vs. Safety & Health
Dominant Trustworthy AI Key Requirements: Societal and environmental well-being; Human agency and oversight;

Cluster 6 - *Damage due to excessive or wrong demands* - comprises three issues, all featuring the tension between safety and efficiency. The key requirements across all three issues are *human agency and oversight* and *societal and environmental well-being*. Additionally, *diversity, non-discrimination, and fairness* is listed by the author, particularly relevant in considering individual differences to prevent overstrain. Moreover, frequent changes in work content by the system for optimization purposes may overwhelm individuals, leading to potential mistakes due to inattentiveness. Prolonged excessive demands create pressure that can result in burnout, depression, or even physical accidents caused by lapses in attention. There is also the risk of individuals not using the system as intended (e.g., removing a tracking device), heightening the potential for accidents and personal injuries.

Ethical Issue Cluster 6: Damage due to excessive or wrong demands
Ethical Issues: 15, 17 (ii), 19
Ethical Principle: Prevention of harm
Dominant Tensions: Safety vs. efficiency
Dominant Trustworthy AI Key Requirements: Human agency and oversight; Societal and environmental well-being; Diversity, non-discrimination and fairness;

Cluster 7 - Technophobia - is a pseudo-cluster, as it consists of only one issue that did not fit well enough with any other cluster. It directly inherits the tension efficiency versus health named in the issue and the dominant requirement *societal and environmental well-being*. The investigators consider the fears people may have of technology, specifically the radiation from the IPS. In the vast majority of global markets, IPS are only approved if they comply with strict radiation limits that are below the level that could be harmful to humans. The damage that could be caused to people is only psychological, namely if there is an anxiety disorder against radiation or technophobia.

Ethical Issue Cluster 7: Technophobia
Ethical Issues: 12
Ethical Principle: Prevention of harm
Dominant Tensions: Efficiency vs. health
Dominant Trustworthy AI Key Requirements: Societal and environmental well-being;

Cluster 8 - Risk of cyber attacks - is another pseudo-cluster. It directly inherits the tension efficiency versus safety named in the issue, as well as the two requirements *technical robustness and safety* and *privacy and data governance* that all investigators agreed upon. At first glance, this is a technical, not an ethical, issue. However, the investigators see an existing risk that sensitive information about the employees could be stolen during a cyber attack, which could cause them anything from discomfort to psychological damage. If the attackers gain access to systems and machines, this could cause personal injuries if the equipment becomes a safety risk.

Ethical Issue Cluster 8: Risk of cyber attacks
Ethical Issues: 20
Ethical Principle: Prevention of harm
Dominant Tensions: Efficiency vs. safety
Dominant Trustworthy AI Key Requirements: Technical robustness and safety; Privacy and data governance;

Issue clusters regarding ethical principle fairness

For the ethical principle *fairness*, the investigators identified 13 issues in the workshops, and four clusters were created by the author.

Within Cluster 9 - Discrimination based on performance - investigators express concern regarding the need to appropriately address the individuality of actors in the system. As highlighted in Issue 26, this could involve differences in individual skill levels, health, physical limitations, or language. Models abstract reality and may not fully capture employees in all their facets, leading to a work process design that disproportionately favors the majority (Issue 27). This implies that the system favors individual workers based on certain criteria, such as quality, age, or speed, thereby disadvantaging other workers (Issue 29). Investigators also perceive a problem with the potential misuse of the system to measure performance, such as by collecting individual KPIs on productivity (Issues 22 and 27). In the discussion of Issue 22, Anna asserted that there is no tension because it is fundamentally wrong to use such systems to monitor human performance, especially in cases of power asymmetry. Her statement resonated with other investigators from that group.

Ethical Issue Cluster 9: Discrimination based on performance
Ethical Issues: 21, 22, 26, 27, 29
Ethical Principle: Fairness
Dominant Tensions: Personalisation vs. solidarity, Efficiency vs. equality
Dominant Trustworthy AI Key Requirements: Diversity, non-discrimination and fairness; Human agency and oversight; Transparency; Societal and environmental well-being;

In this Cluster 10 - Fairness in decision-making, the tension between accuracy and fairness arises as the system may produce precise decisions that systematically disadvantage certain individuals. Another crucial tension emerges between individuality and equality, prompting the system to navigate between addressing individual needs and ensuring equal treatment. Investigators illustrate this dilemma through considerations of workload distribution, which may not always be equitable. For instance, one might argue that older individuals should not be assigned physically demanding tasks or that younger individuals should not handle complex assembly tasks. Such decisions may reflect an unequal allocation of work that accounts for individual characteristics. Additionally, the issue of bias in data poses a significant concern. Investigators highlight that unbalanced data can introduce biases into decision-making processes, underscoring the importance of identifying and rectifying such issues within the system.

Ethical Issue Cluster 10: Fairness in decision-making
Ethical Issues: 23, 28
Ethical Principle: Fairness
Dominant Tensions: Accuracy vs. fairness; Individuality vs. equality
Dominant Trustworthy AI Key Requirements: Societal and environmental well-being; Diversity, non-discrimination and fairness; Human agency and oversight; Technical robustness and safety;

Cluster 11 delves into the delicate balance between safety and human autonomy within the system. While prioritizing workplace safety, the system often imposes limitations on personal autonomy. Additionally, the cluster introduces the tension of accuracy versus fairness, noting that heightened monitoring accuracy may inadvertently expose workers to unfair judgments or reprisals in case of errors. Investigators emphasize a significant concern regarding situations where an employee's account contradicts the data's portrayal. They underscore the importance of ensuring that data-supported allegations of misconduct do not automatically lead to punitive measures, especially when doubts persist regarding data accuracy.

Ethical Issue Cluster 11: Fairness in case of mistakes
Ethical Issues: 24, 6(ii)
Ethical Principle: Fairness
Dominant Tensions: Safety vs. human autonomy; accuracy vs. fairness
Dominant Trustworthy AI Key Requirements: Human agency and oversight; Privacy and data governance; Diversity, non-discrimination and fairness;

The final cluster under the ethical principle of fairness, Cluster 12, explores the equitable treatment of different groups within the system. This cluster addresses scenarios where disparities between groups may arise, leading to mistreatment or advantages for one group over another. Investigators cite instances across various contexts, including on the shop floor (Issue 25), among customers (Issue 30), and within different hierarchical levels of the company (Issue 31). For example, they highlight cases where unfair actions are instigated by certain groups, such as manipulating the system to allocate more favorable work conditions to one shift over another. Additionally, the system's bias towards specific customers or groups may result in preferential treatment, sometimes unintentionally and without transparency. Lastly, differential access to data among individuals in the system could exacerbate power imbalances, potentially reinforcing the authority of those with greater access.

Ethical Issue Cluster 12: Fairness of different groups among each other
Ethical Issues: 25, 30, 31
Ethical Principle: Fairness
Dominant Tensions: Efficiency vs. solidarity
Dominant Trustworthy AI Key Requirements: Accountability; Transparency; Diversity, non-discrimination and fairness;

Issue clusters regarding ethical principle explainability

For the ethical principle *explainability*, the investigators identified 11 issues in the workshops, and three clusters were created by the author.

Cluster 13 - Lack of acceptance - consists of four ethical issues. Three issues originated from Workshop 1, in which the investigators distinguished between lack of acceptance due to lack of transparency at the system level (Issue 33), about how decisions are made (Issue 34), and about what data are collected (Issue 35). During Workshop 2, investigators emphasized that a lack of transparency in decisions, especially in task assignments and procedural guidelines, could result in diminished system adoption rates. They stressed the importance of regularly sharing analysis results of worker data with employees to ensure informational justice (Issue 38). The identified tensions in this context revolve around transparency versus privacy and accuracy versus explainability. Enhancing transparency may require a deeper exploration of data to comprehend decision-making, but this raises privacy concerns for individuals whose data is scrutinized. The second tension highlights the challenge that more accurate algorithms may sacrifice transparency in decision-making. Notably, RL, a component mentioned to be used in the overall system, operates as a black box, lacking the capacity for comprehensive explanations.

Ethical Issue Cluster 13: Lack of acceptance
Ethical Issues: 33, 34, 35, 38
Ethical Principle: Explainability
Dominant Tensions: Transparency vs. privacy; accuracy vs. explainability;
Dominant Trustworthy AI Key Requirements: Transparency; Privacy and data governance;

In Cluster 14 - Poor comprehensibility - three ethical issues are addressed. The prevailing tension across all three issues is accuracy versus explainability. As systems and algorithms grow in complexity, explaining and understanding their decisions becomes increasingly challenging. Investigators underscore the necessity of accountability (Issue 32), highlighting the dilemma of individuals bearing responsibility for decisions they cannot make or understand themselves. Particularly in the case of complex simulations and if RL is used, decision-making processes lack transparency to humans, a point of critique raised by the investigators. They emphasize the difficulty of identifying causes in cases of deviations from standard processes or errors.

Ethical Issue Cluster 14: Poor comprehensibility
Ethical Issues: 32, 37, 39
Ethical Principle: Explainability
Dominant Tensions: Accuracy vs. explainability
Dominant Trustworthy AI Key Requirements: Transparency; Accountability;

Cluster 15 - Hidden Behavior Manipulation encompasses two issues highlighting the imperative of preventing errors in the system and ensuring adequate data for model training to avoid undesirable system behavior that lacks explanation. For instance, workers aware of monitoring may purposefully reduce their work pace to influence the system into assigning them less work.

Ethical Issue Cluster 15: Unnatural behavior change or manipulation difficult to detect
Ethical Issues: 36, 40
Ethical Principle: Explainability
Dominant Tensions: Accuracy vs. explainability.
Dominant Trustworthy AI Key Requirements: Technical robustness and safety;

In this section, we have presented 15 issue clusters derived from the identified ethical issues in the three workshops and their corresponding mappings (see Appendix B for complete list). With the assessment phase concluded, the next step is the resolve phase.

6.4 Phase 3: Resolve Phase

This section presents the Resolve phase of the project, wherein the steps outlined in Phase III in Figure 6.1 of the Z-Inspection® process are performed. It includes an analysis of ethical tensions (Section 6.4.1), approaches to resolve them (Section 6.4.2), and recommendations for improvement (Section 6.4.3).

6.4.1 Analyze Ethical Tensions

The aim of this section is to furnish an overview of the identified ethical tensions to be able to mitigate them during the system's development. Figure 6.4 depicts all tensions delineated in the workshops. Following the guidance from (Zicari et al. 2021), the instruction in the workshops was that a tension may occur, emphasizing that it is not obligatory. In the graph, nodes represent ethical values, while edges illustrate tensions. The number of mentions is indicated on the edges, with varying thicknesses denoting frequency. Nodes are shaded according to the degree of incoming edges, aiding in visual comprehension. The graph reveals three dominant ethical tensions, discernible by the thickest edges. These dominant tensions will be discussed in the following.

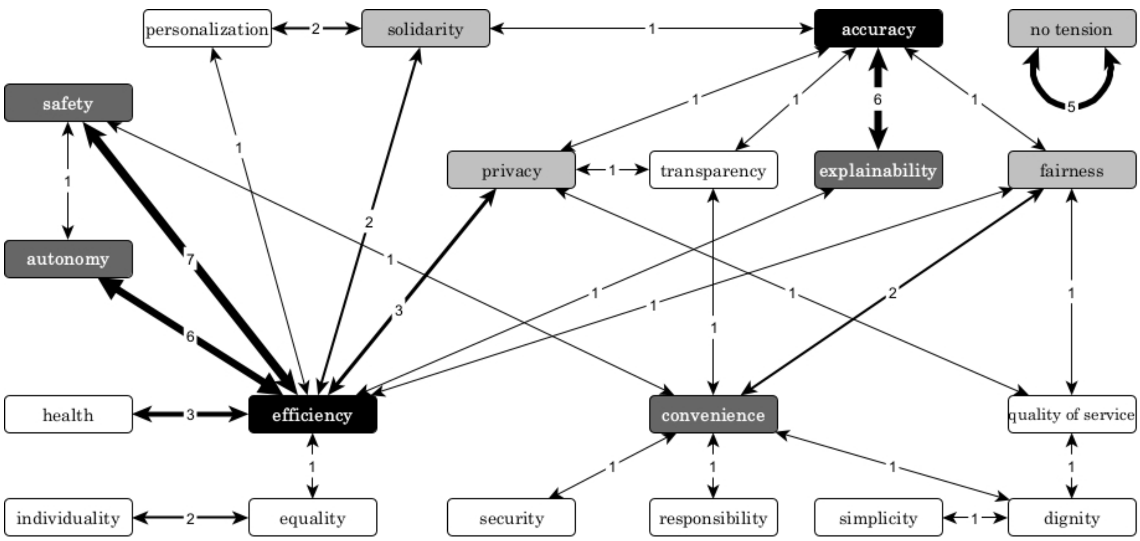

Figure 6.4: Overview of the identified tensions. The thickness of the edges corresponds to the frequency of mention. The shade of the node was set based on the number of incoming edge weights (white ≤ 3, light gray $4-6$, dark gray $7-9$, black ≥ 10).

Efficiency versus safety emerges prominently, occurring seven times across various issues (Issues 15–17, 19–21, and 25). Six of these issues were attributed to the ethical principle of prevention of harm. This underscores the frequent observation by investigators regarding the potential conflict between production efficiency and employee safety. It underscores the importance of prioritizing technical robustness and safety as a key requirement in system development to safeguard employees. Consequently, five of the issues involving the tension between efficiency and safety were also associated with this requirement. During system development, all decisions should be contextualized within a safety framework, with critical decisions receiving heightened human oversight. Moreover, the tracking process must not pose any hazards, ensuring compliance with all relevant safety standards, such as those pertaining to radiation levels. Consideration should also be given to psychological integrity to mitigate potential safety risks.

Efficiency versus autonomy was mentioned in six issues (Issues 1, 3, 4, 8, 9, and 21), all aligned with the ethical principle of respect for human autonomy. The system described in the socio-technical scenario assumes full control over decision-making, significantly restricting individual autonomy primarily for efficiency gains. During system implementation, it is crucial to assess the impact of curtailing human autonomy on efficiency. While the assumption of increased efficiency with more automated decisions is not absolute, empirical studies and data analysis are imperative to quantify efficiency gains against autonomy restrictions. Transparent communication of these findings fosters understanding among stakeholders. Where human decision-making proves superior, autonomy should be retained, unless otherwise preferred by the individual. Balancing this tension during implementation poses challenges, necessitating further investigation, such as interviews with stakeholders, to delineate areas where autonomy transfer to the system is perceived negatively or positively. Unsurprisingly, human agency and oversight were identified as key requirements across all six issues.

Accuracy versus explainability emerged as a dominant tension in six issues (Issues 31, 32, and 37–40), which align with the ethical principle of explainability, with transparency identified as a key requirement. The adoption of advanced techniques like simulation and RL enhances system accuracy but complicates understanding and traceability of automated decisions due to increased complexity. To address the lack of explainability, it is crucial during implementation to ensure transparency and design the system in a manner that elucidates decision-making processes. Clear definition of responsibilities is also paramount, reflected in the emphasis on accountability. Comparing methods based on accuracy and transparency aids in resolving this tension. Development efforts should prioritize achieving a balance between complexity and accuracy requirements, ensuring compliance with legally mandated traceability standards for automated decisions. Stakeholder involvement is essential to discern which decisions necessitate understanding, guiding the allocation of resources towards enhancing explainability without compromising accuracy.

The three dominant tensions identified can be attributed to the ethical principles of prevention of harm, human autonomy, and explainability. However, there is no dominant tension associated with the ethical principle of fairness, which is inherently multi-dimensional and requires consideration from various perspectives during system implementation. A total of five issues were not assigned any tension. This occurred, for instance, with Issue 22 because the investigators collectively deemed the identified issue as fundamentally wrong. For Issue 2, the tension of efficiency versus autonomy could have been chosen, given its prominence as one of the top three tensions in the system. Similarly, transparency versus accuracy seems appropriate for Issue 34, as decisions require high accuracy, leading to a more intricate system that may compromise transparency. Despite the absence of tensions for Issue 33 and Issue 24, they still require attention in the system's development.Particular emphasis should be placed on ethical values frequently mentioned, depicted in black and dark gray in Figure 6.4.

6.4.2 Address Ethical Tensions

The previous analysis provides initial insights into which ethical tensions should be addressed while updating the socio-technical scenario outlined in Table 5.2. To mitigate tensions such as efficiency versus autonomy and efficiency versus privacy, adjustments to the tracking approach are necessary, limiting tracking to what is essential and legally permissible.

Concerning the data analysis category from Table 5.2, prioritizing the automation of deriving simulation inputs and generating simulation models is feasible. However, it is crucial to ensure fairness in algorithmic decisions and address any biases in the data to prevent discrimination during the development of analytical methods. Involving affected individuals in the development process can enhance acceptance and understanding. Additionally, emphasizing transparency and traceability in simulation development helps alleviate tensions between accuracy and explainability.

The tension between efficiency versus autonomy can be positively influenced via the decision-making category of the socio-technical scenarios, by transitioning from fully automated decisions to human-involved decision support. Stakeholder involvement during the implementation is key to determining which decisions are suitable for system automation (e.g., tedious routine tasks) and which should remain under human control (e.g., safety-critical tasks). Providing users with control over their autonomy level within the system through customization can also enhance acceptance and self-efficacy. This approach may involve sacrificing efficiency to uphold human autonomy. Demonstrating the impact of user preferences on safety can help balance the tensions of efficiency versus safety.

Lastly, deliberate decision-making to address ethical tensions and comprehensive documentation of trade-offs are essential for improving transparency and accountability throughout the development and implementation process. Next, the workshop's recommendations for further resolving ethical tensions will be examined, providing a more comprehensive overview of the required adjustments.

6.4.3 Recommendations from the Workshops

At the end of each workshop, the investigators were asked for suggestions for improvement of the framework in the assessed future socio-technical scenario. They were allowed to attach these to the digital whiteboard. There was also the possibility of adding further ideas and recommendations after the workshop. The questioning of the improvement suggestions took place without giving a predefined structure.

In the first workshop, there were 21 suggestions for improvement; in the second workshop, 17; and in the third workshop, eight. Later, all 46 suggestions for improvement were put onto a digital whiteboard, and the author started grouping them. This yielded 19 groups. While grouping, it was noticed that it comes naturally to structure the groups along the trustworthy AI key requirements, which also became the structure of this section. The included recommendations are linked for each group and can be found in their original version in Appendix C. Whenever the author added a personal recommendation to a group, this is indicated with a (C).

Recommendations for Human Agency and Oversight

There are two groups of recommendations for human agency and oversight which are Group 1 - Human in the loop, and Group 2 - Develop a decision support system. These two groups contain seven out of 46 recommendations (15,2 %) which is close to one-seventh (14.3 %).

Group of Recommendations 1 (Human in the loop)**:** Humans should have the ability to rate, ignore, and overrule decisions made by the system (C). This functionality enables workers to report errors to the system (R1) and provide feedback for system adaptation and optimization (R22 and R23). The inclusion of an override option (R3) is crucial, allowing humans to deliberately ignore the system's decision.
Included Recommendations: 1, 3, 22, 23

Group of Recommendations 2 (Develop a decision support system)**:** The proposed solution involves transitioning from the current automated decision system, which heavily restricts human decision-making, to the development of a decision support system (R41). In this new system, decision-making authority should remain with humans (R40), even in critical scenarios (R41). The system will provide decision-makers with recommendations, upon which they will base their decisions (R39).
Included Recommendations: 39, 40, 41

Recommendations for Technical Robustness and Safety

There are two groups of recommendations for technical robustness and safety which are Group 3 - Ensure robustness of simulation, and Group 4 - Risk assessment. These contain three out of 46 recommendations which are only 6,5 % of the overall recommendations.

Group of Recommendations 3 (Ensure robustness of simulation)**:** It is essential to implement technical measures to prevent simulations from merely confirming existing assumptions (R30). Additionally, having fallback solutions in place for special situations where the system might respond incorrectly is necessary (R27).
Included Recommendations: 27, 30

Group of Recommendations 4 (Risk assessment)**:** Components of the system that impact safety-related aspects need to undergo thorough risk assessments to evaluate the potential for causing harm. Anticipating future legislative requirements, such as mandatory risk assessments for products incorporating AI for security purposes, is essential (R46).
Included Recommendations: 46

Recommendations for Privacy and Data Governance

There are four groups of recommendations for privacy and data governance which are Group 5 - Involve a data trustee, Group 6 - Privacy by preference, Group 7 - Data governance, and Group 8 - Handling of sensitive data. These contain eight out of 46 recommendations (17,4 %) which is still close to one-seventh (14.3 %).

Group of Recommendations 5 (Involve a data trustee)**:** Partner with a data trustee (R20, R42) to safeguard personal data (R42), potentially serving as a catalyst for revising the underlying business model (R42).
Included Recommendations: 20, 42

Group of Recommendations 6 (Privacy by preference)**:** Implement a feature in the localization system trackers that enables individuals to toggle localization on and off (R32). Allow employees to personalize their data privacy settings, such as when generating personal work instructions (R34). Monitor the utilization of privacy preference features to gauge system acceptance (R32).
Included Recommendations: 32, 34

Group of Recommendations 7 (Data governance)**:** Develop data governance frameworks that adhere to legal standards such as the GDPR and industry best practices (C). This involves clearly delineating roles and permissions for system interaction (R35). Define data handling and processing procedures comprehensively, ensuring all employees are well-informed (R17).
Included Recommendations: 17, 35

Group of Recommendations 8 (Handling of sensitive data)**:** Yahel raised the question of whether any personal data should be collected at all (R33). Article 6 of the GDPR stipulates that the processing of personal data is typically prohibited unless expressly permitted by law or with the consent of the data subject[15]. When consent is given, it is essential to implement technical and organizational measures to prevent unauthorized access to the data (C). Furthermore, the possibility of anonymizing the data should be explored (R19).
Included Recommendations: 19, 33

Recommendations for Transparency

There are five groups of recommendations for transparency which are Group 9 - Data transparency, Group 10 - Ensure explainablity of the AI system, Group 11 - Ensure explainability of the simulation, Group 12 - Ensure explainability of automated decisions, and Group 13 - Transparent communication. These contain twelve out of 46 recommendations (26,1 %), the biggest share amongst all key requirements. It was important to the investigators that the system is transparent and explainable. Latter refers to the ability to understand and articulate the reasoning behind decisions or behaviors in a clear and comprehensible manner, reflected in Group 10 and 11.

[15] `https://gdpr-info.eu/issues/consent/`

Group of Recommendations 9 (Data transparency)**:** The system must ensure transparency regarding the collected data and how it is stored and processed. It should tailor the presentation of data to the specific needs of the target audience (R38), such as providing tracked individuals with access to and understanding of their data (R18). The data foundation for a particular decision must be easily accessible (R36). Accessibility serves as a prerequisite for decision explainability, which is further elaborated in the following Groups 10, 11, and 12.
Included Recommendations: 18, 36, 38

Group of Recommendations 10 (Ensure explainability of the AI system)**:** Decisions made by the systems should be explainable to ensure understanding and foster trust in the system (R37). It is important that the influencing factors contributing to these decisions are known and communicated transparently (R12).
Included Recommendations: 12, 37

Group of Recommendations 11 (Ensure explainability of the simulation)**:** Ensuring accessibility of the simulation model for various groups of people is essential (R13), and employing visualization techniques can facilitate this accessibility (R14).
Included Recommendations: 13, 14

Group of Recommendations 12 (Ensure explainability of automated decisions)**:** Charleen highlights the right to explanation enshrined in the GDPR, which guarantees individuals the right to receive an explanation when automated decisions are made about them (R44). Additionally, automated decisions made by the system necessitate a data protection impact assessment to identify and evaluate all risks associated with data processing (R45).
Included Recommendations: 44, 45

Group of Recommendations 13 (Transparent communication)**:** Anna suggests initiating a project blog to facilitate communication about the project (R21). Furthermore, it is recommended to transparently present the benefits of the system (R16) and communicate the associated financial efficiency gains (R15).
Included Recommendations: 15, 16, 21

Recommendations for Diversity, Non-Discrimination, and Fairness

There are three groups of recommendations for diversity, non-discrimination and fairness which are Group 14 - Work interdisciplinary, Group 15 - Create trustworthy organizational structures, and Group 16 - Actively involve affected people. These recommendations constitute nine out of 46 recommendations (19.6%), which is higher than the expected distribution if recommendations were evenly distributed (one-seventh, or 14.3%). This suggests that the investigators place significant importance on ensuring that the system meets this key requirement.

Group of Recommendations 14 (Work interdisciplinary)**:** The development of the system should involve an interdisciplinary team (R28), comprising experts in ethics, technology, law, and other relevant fields (R43). Collaboration with workers is essential, as jointly developed solutions (co-creation) are likely to be more widely accepted (R29). The development team should not work in isolation but actively engage with the workers (R29, R43).
Included Recommendations: 28, 29, 43

Group of Recommendations 15 (Create trustworthy organizational structures)**:** An employee representative body, such as a works council, should be actively involved in the integration and use of the system and granted the necessary rights (R9). This body serves as a point of contact for employees who have concerns about the system or need to report issues (R24). Particularly during the system's introduction, trusted individuals should be designated in the affected areas to facilitate easy communication and discussion (R10).
Included Recommendations: 9, 10, 24

Group of Recommendations 16 (Actively involve affected people)**:** Employees should be actively involved in the development, implementation, and operation of the system (C). This can be achieved through information events, the appointment of contact persons, and clear communication emphasizing the importance of their concerns and ensuring that their worries are taken seriously (R11). Additionally, processes should be established to allow employees to provide suggestions for improvement, feedback, and concerns anonymously (R8). Establishing a stakeholder association based on the principle of "nothing about us without us" (Anna) is another effective measure for involving affected employees (R7).
Included Recommendations: 7, 8, 11

Recommendations for Societal and Environmental Well-being

There are three groups of recommendations for societal and environmental well-being which are Group 17 - Ethics by design, Group 18 - Keeping an eye on people's well-being, and Group 19 - Limit the speed of change. These contain seven out of 46 recommendations (15,2 %) which is close to one-seventh (14.3 %).

Group of Recommendations 17 (Ethics by design)**:** Ethical principles should be integrated into the system's development process from the outset (R31). Before deploying the system, a deliberate assessment should be conducted, weighing the potential negative aspects like autonomy restrictions, residual risks of harm, unequal treatment of employees, and lack of transparency in complex systems, against the positive aspects such as enhancing competitiveness and job security through more efficient processes (R31).
Included Recommendations: 6, 31

Group of Recommendations 18 (Keeping an eye on people's well-being)**:** Implementing a learning phase that familiarizes new employees with the system through diverse everyday scenarios can prevent overwhelming them (R2). Additionally, considering the workforce's well-being by monitoring employees' health with the system can be instrumental in long-term target planning (R5).
Included Recommendations: 2, 5

Group of Recommendations 19 (Limit the speed of change)**:** Establishing guidelines for the maximum rate of change that the system can introduce in processes is essential, particularly in areas like work instructions that directly affect humans (R25 and R26). Additionally, the RL policy should consider human adaptability limits (R4).
Included Recommendations: 4, 25, 26

Recommendations for Accountability

The investigators did not propose any improvement suggestions directly addressing the ethical principle of accountability. While Recommendation Group 2 does touch upon aspects related to decision-making, it primarily focuses on the allocation of decision-making authority rather than on accountability itself. However, critical questions arise regarding accountability in the event of erroneous system outputs. Should a human be held responsible for decisions based on incorrect system outputs? Is the system manufacturer liable for inaccurate predictions, or does the responsibility lie with the company utilizing the system? These questions underscore the importance of establishing accountability frameworks proactively, particularly in anticipation of potential mishaps. Veronika's Recommendation 35, which suggests specifying user group interactions, could be expanded to incorporate accountability considerations. Clear communication of accountability roles is crucial for ensuring transparency and responsibility in decision-making processes.

Legal uncertainties regarding liability for unforeseeable damage caused by AI systems make it challenging to discuss accountability for the companies developing them. Erdélyi and Erdélyi (2020) note that the unpredictable nature of court rulings in such cases often hinders the use of AI systems and stifles innovation. To tackle this issue, Erdélyi and Erdélyi (2020) suggest implementing measures from financial regulation, such as deposit guarantees, insurance guarantees, and investor compensation schemes, for AI systems. This proposal, termed a system of AI guarantee schemes, could provide a framework for addressing liability concerns. It is essential to consider these legal aspects in further assessments of the system.

6.5 Analysis of Issues, Issue Clusters and Recommendations

The data for the analysis in this section can be found in Appendix A.4 and was analyzed with Microsoft Excel. The most frequently cited requirement was human agency and oversight, mentioned 24 times, while the least cited was technical ro-

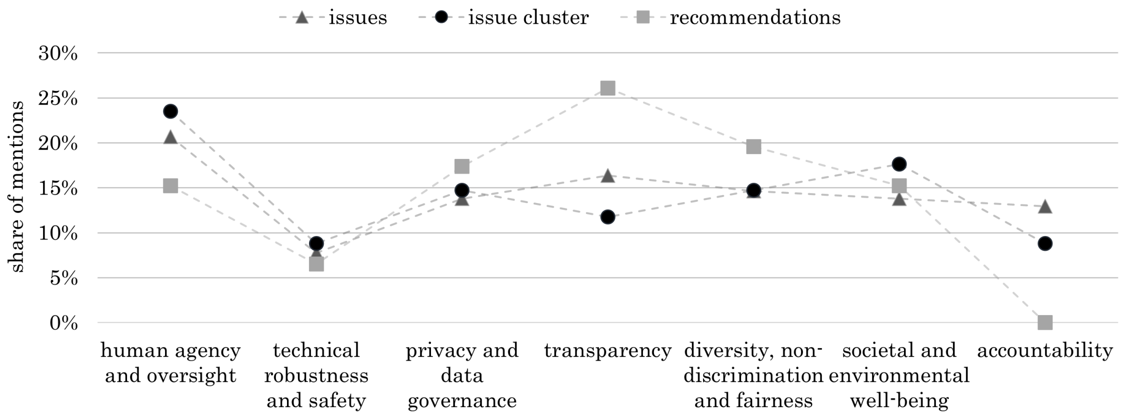

Figure 6.5: Comparison of the relative frequency of key requirements mentioned in issues, issue clusters, and recommendations. Dashed lines are included solely to facilitate the identification of deviations. Data can be found in Appendix A.4.

bustness and safety, mentioned 9 times. All other requirements were mentioned with quite similar frequency (15–19 times) as listed in Table A.4. The frequency of mentioned requirements broken down by the four ethical principles is depicted for issue clusters in Table A.5 and for recommendations in Table A.6.

Figure 6.5 illustrates the comparison of relative frequency of key requirement mentions in issues, issue clusters, and recommendations. It is crucial to note that issues and issue clusters may be associated with multiple key requirements, unlike recommendations assigned to groups, which are linked to only one key requirement. On average, there were 2.9 requirements mentioned per issue and 2.26 requirements per issue cluster. The frequency of requirement mentions for issues, and issue clusters has been normalized in the figure to enable comparison with the frequency distribution of recommendations.

The Pearson correlation coefficient (Pearson 1895) was used to analyze correlations between the frequency distributions because it is a measure of linear correlation between two data sets[16]. The special case of the Steigers Z-test[17] (Steiger 1980) was used with the hypothesis $H_0 : \rho = 0$ (no correlation) vs. $H - 1 : \rho \neq 0$, where the test statistic is t-distributed with $n-2$ degrees of freedom (ρ is the correlation coefficient of the underlying distribution). The t-score[17], in this case, can be calculated by

$$t = \frac{r\sqrt{n-2}}{\sqrt{1-r^2}}, \tag{6.1}$$

where r is the correlation coefficient for the sample of size n. A prerequisite for using this test is that the underlying data are normally distributed. For this purpose, the Jarque-Bera test[18] for normal distribution was used (Jarque and Bera 1980). The results are in Table A.7. Since the p-value was never less than 0.05, we do not reject the null hypothesis (H_0: The data are normally distributed.) Thus, there is no evidence that the data are not normally distributed.

[16] https://en.wikipedia.org/wiki/Pearson_correlation_coefficient

[17] https://de.wikipedia.org/wiki/Korrelationskoeffizient_nach_Bravais-Pearson#Test_des_Korrelationskoeffizienten_/_Steigers_Z-Test

[18] https://de.wikipedia.org/wiki/Jarque-Bera-Test

The analysis shown in Table A.8 reveals a robust positive correlation (Pearson correlation coefficient $r = 0.784$) between the frequency of requirements across all issues and their occurrence as the dominant tension within the issue clusters. This correlation proves statistically significant with a p-value of 0.037, leading to the rejection of the null hypothesis ($H_0 : \rho = 0$). Consequently, it can be inferred that clustering the issues does not distort the underlying distribution of the named requirements. This finding aligns with the fact that the frequency of mentions was taken into account during the selection of dominant requirements. The outcome also underscores the effectiveness of the author's approach to issue clustering as a suitable method for synthesizing the inputs from the various workshops.

Furthermore, an examination was conducted to assess whether there exists a relationship between the average number of votes and the relative variance in the frequency of mentions per issue cluster compared to all issues. The hypothesis posited that higher average agreement (i.e., more investigators voting for a requirement on an issue) would result in a smaller deviation between the relative frequency of mentions for all issues versus issue clusters. However, despite a small negative correlation (Pearson correlation coefficient $r = -0.26$), this relationship was not statistically significant (p-value = 0.57). Similarly, there was no correlation between the average voting and the overall frequency of mention in the issues ($r = 0.43$ and p-value = 0.34). Referring to Figure 6.5, it was anticipated that there would not be a statistically significant correlation between issues and recommendations ($r = 0.5$ and p-value = 0.25), as well as issue clusters and recommendations ($r = 0.39$ and p-value = 0.38).

Notably, transparency was recommended almost twice as often in the recommendations (26%) compared to its average appearance in the issues or issue clusters ($(16,4\%+11,8\%)/2 = 14,1\%$), suggesting its significant importance to the investigators. Another notable discrepancy was observed in the case of accountability, which was mentioned 3 times in the issue clusters and on average $10,9\%$ ($(12.9\%+8.8\%)/2$), yet no recommendations were made regarding it. This discrepancy prompts speculation as to why investigators did not provide recommendations in this area. It is plausible that accountability closely relates to legal matters that may be beyond the expertise of the investigators. Moreover, legal ambiguities may have hindered clear recommendations in this domain, even among experts.

6.6 Feedback on the Z-Inspection® Process

During the execution of the process, several noteworthy aspects emerged, both positively and negatively. These are discussed in the following.

Flexibility and versatility: Focusing solely on ethical issues proved to be efficient, although it was observed that some issues encompassed not only ethical but also legal or technical dimensions. This overlap is beneficial as it provides insights for future iterations of the Z-Inspection® process focusing on legal or technical aspects. Moreover, different expert groups can be convened based on the specific focus of each run. The versatility of the Z-Inspection® process, capable of both ex-ante and ex-post assessments, offers significant advantages for product development. For instance, in the conceptual phase, an ex-ante assessment can focus on ethical issues.

Later during the product implementation, emphasis can be shifted towards addressing legal and technical concerns. Identifying issues early in the product life cycle can mitigate subsequent costs. Employing the Z-Inspection® process thus serves as a proactive measure, reducing downstream expenses.

Involvement of affected groups: The Z-Inspection® process exhibits a notable limitation by not involving the affected groups, leading to discussions that speculate about individuals who are not present. Furthermore, no main tension was identified regarding fairness. To address this gap, involving stakeholders through interviews or workshops could be instrumental. This approach facilitates the integration of their perspectives on fairness into the development process, making it more robust and inclusive. In contrast to the scenario depicted by Allahabadi et al. (2022), which discusses the impact of an AI system on patients, the production context examined in this thesis may be less relatable to many participants. While everyone has experienced being a patient, not everyone has firsthand experience working in production. Individual investigators may possess manufacturing experience, but often at managerial or consulting levels, creating challenges in empathizing with manufacturing workers.

Victim narrative versus empowerment: Moreover, it is crucial to avoid framing individuals affected by AI systems as victims. Discussions often revolve around how these systems diminish autonomy, cause harm, and treat people unfairly. However, this overlooks the possibility that affected individuals may perceive certain aspects of the system positively. People may willingly sacrifice autonomy or accept less decision transparency if they perceive benefits. This trade-off is frequently made subconsciously in everyday interactions with digital services. Empowering affected individuals through participation in assessments is essential to address these concerns effectively.

Alignment with AI ethics principles: Another advantage of the Z-Inspection® process is its alignment with the results of the High-Level Expert Group on AI, using the four ethical principles and seven ethical requirements for trustworthy AI. During the workshops, it became apparent that navigating through each principle to identify relevant issues was straightforward. All ethical issues raised during the three workshops could be attributed to one or two of the four ethical principles, suggesting comprehensive coverage of relevant aspects. The same level of clarity applies to the key requirements. While investigators without a background in AI ethics initially found interpreting the abstract requirements challenging, they quickly grasped their significance during the mapping process.

Prioritizing ethical issues: The Z-Inspection® process has identified 40 ethical issues in this study. The system design must now undergo a thorough review. However, with this multitude of issues, practitioners face the challenge of determining where to begin. Which issue holds the highest priority and should be addressed first? Conversely, which issues are merely theoretical constructs that can be temporarily set aside? One limitation of the Z-Inspection® process is its lack of provision for weighting the identified issues. In practical application, experts could reassess the issues based on severity and likelihood of occurrence. High-severity issues with a high probability of occurrence should be addressed as a priority, while those with weaker implications and lower probabilities can be deferred. Additionally, some issues may be interdependent, meaning that resolving one could also address others. Further exploration and experience are necessary to refine this approach.

Execution approach: There is no template for an execution approach. During the Z-Inspection® process, it became apparent that planning the execution approach is crucial at the outset of the assessment phase. However, in the official process, the Execute step typically marks the final stage of the Assess phase, which, in the author's opinion, is too late to choose an execution strategy. The remaining tasks, such as providing feedback, are more suited for a later stage when the system has been implemented. In this ex-ante investigation, feedback on the implemented system could not be collected. In a real development project, this stage could provide an opportunity to involve potential users of the system, refining the system through interviews and workshops.

Involving investigators: From the publication Allahabadi et al. (2022), it was laboriously worked out who cooperated in which phase and how (see Table 6.2). The number of people involved in the assessment in Allahabadi et al. (2022) was 58 versus 12 investigators in this study. An evaluation process should also be able to get by with fewer people since, in practice, it is impossible to involve so many resources in every assessment project. The execution with 12 experts worked out very well. While the different groups formulated different issues and recommendations in the three workshops, the last workshops rarely identified fundamentally new issues but rather nuances of them. This is why it was possible to summarize them so well later.

Socio-technical scenarios: Maintaining the focus on a single socio-technical scenario during the assessment proved useful. Analyzing multiple scenarios concurrently could lead to confusion about which scenario is being referred to at any given time. Starting with a scenario that encompasses all technical possibilities and gradually narrowing down to scenarios with fewer issues proves to be efficient.

Consolidation of results: Employing majority voting within interdisciplinary teams proved effective in streamlining workshops and discussions. This method was utilized in the workshop for mapping issues and identifying dominant tensions and requirements. By analyzing the frequency of mentions of various tensions and requirements, the need for additional consolidation workshops was circumvented.

Issue Clusters: Establishing issue clusters, where different thematic issues are grouped, proves to be a meaningful step. Brusseau (2020) and Allahabadi et al. (2022) highlight that consolidating issues requires considerable effort and discussion to reach a consensus and merge issues from different working groups. The presented approach of using issue clusters, involving either a single person or four individuals (one per principle), could significantly expedite the consolidation process. As demonstrated in Section 6.5, issue clusters can be formed without compromising the underlying frequency of mentions of respective trustworthy AI key requirements.

Establish best practices: More comprehensive guidance and best practices would facilitate the adoption of ethics assessments using the Z-Inspection® process. It is crucial to tailor these practices to fit the specific resources available in each project. The author has often grappled with questions about documenting essential aspects, such as defining boundaries and context in Phase I or describing socio-technical scenarios. Clear guidelines, checklists and templates on what aspects to include in the documentation would be beneficial. In Phase 3, there was a lack of examples demonstrating how ethical tensions can and should be resolved. While it is acknowledged that some tensions may be unsolvable, it is essential to engage in discussions to balance these tensions. Clear recommendations or findings from practice regarding the frequency and timing of the process are still lacking. Zicari et al. (2021, p.90) propose the concept of ethical maintenance to ensure ongoing adherence to ethical principles during product use. Further research is necessary to effectively integrate this concept into existing practices.

6.7 Summary

In this chapter, the framework proposed for trustworthy usage of IPS data in simulation input modeling underwent assessment using the Z-Inspection® process. All three phases of the process (Set-up, Assess, and Resolve) were executed. Through three workshops, a total of 40 ethical issues were identified and subsequently grouped into 15 clusters. These issues and clusters were mapped to the four ethical principles (human autonomy, prevention of harm, fairness, and explainability). Analysis of the ethical tensions revealed key conflicts, including efficiency vs. safety, efficiency vs. autonomy, and accuracy vs. explainability. Recommendations were gathered and consolidated to address the identified ethical issues, resulting in 46 recommendations categorized into 19 groups.

The analysis demonstrated that clustering ethical issues did not alter the underlying frequency of mentions, effectively facilitating consolidation across the expert workshops. Interestingly, recommendations to enhance transparency outweighed the frequency of issues in this domain, suggesting a perceived importance of transparency as a solution. Conversely, accountability received fewer recommendations despite being mentioned in discussions, possibly due to uncertainties in legal responsibilities within such systems and the lack of legal expertise.

Overall, the chapter and its findings validate the effectiveness of the Z-Inspection® process for assessing the framework. Moreover, insights and recommendations were gathered to improve the development of the process and promote wider adoption of trustworthiness assessments in AI and simulation system design and development.

Chapter 7

Conclusion

This chapter concludes this dissertation's work. It summarizes the findings concerning the research questions and emphasizes the primary outcomes in the first Section 7.1. The relevance and impact of the results for practice and research are discussed in Section 7.2. Last but not least, an outlook on future research direction is provided in Section 7.3.

7.1 Summary of Research Findings

In this dissertation, the following three research questions were examined and a summary on the research findings is provided here.

Research Question 1: Which are the usage potentials of Indoor Positioning System (IPS) and their data in manufacturing? (Chapter 4)

This research underscores the extensive yet largely unexplored potential applications of IPS in manufacturing, a gap addressed by systematically gathering and organizing use cases to facilitate their practical implementation in industry. The initial step involved a structured literature review, aimed at revealing the diverse potentials of IPS in manufacturing settings.

The literature review categorized identified papers based on the primary focus of IPS usage, such as logistics, production, or other domains, and assessed the maturity level of each implementation. This analysis yielded 51 distinct use cases, subsequently classified into twelve thematic groups, ranging from basic applications to advanced methods.

In addition to the literature review, this research conducted an on-the-ground examination of an IPS application within a Sheet Metal Processing (SMP) environment, identifying associated challenges through shop-floor observations. These challenges encompassed both ethical and technical dimensions, and motivated the trustworthiness assessment of IPS data usage in this dissertation.

Building upon these observations, the already identified literature on IPS use cases was reviewed for ethical challenges associated with IPS. The analysis revealed privacy concerns as the primary ethical issue raised, mentioned by only 39% of the examined papers. This underscores the critical need for more comprehensive exploration and consideration of ethical issues and privacy implications in the deployment of IPS technologies.

The overall findings of this dissertation underscore the significant value of IPS data across manifold use cases in manufacturing. Beyond mere localization, the analysis of movement data offers secondary benefits that greatly enhance operational excellence, decision-making processes, and manufacturing simulation.

Research Question 2: How can IPS data be used for manufacturing simulation? (Chapter 5)

The dissertation findings demonstrate the utilization of IPS data for real-time parameterization and simulation input modeling within the developed framework. A tailored data model for the sheet metal industry was developed to address the absence of directly applicable standards in the domain. The developed approach focused on extending existing data models to meet industry specific data demands and was methodically codified to ensure applicability and transferability to other industries and domains.

The developed data model offers a comprehensive overview of required inputs for simulating SMP systems. Each of the 42 simulation inputs underwent meticulous analysis to determine the incorporation of IPS data and specify necessary contextual data. Notably, in 38 cases, historical or real-time IPS data proved beneficial for manufacturing simulation, particularly in discerning organizational and technical inputs.

A qualitative analysis presents how the framework enhances overall data quality in manufacturing simulation across eleven different dimensions. Due to the absence of relevant data sets, the analysis remained qualitative. The research findings underscored that classical data sources (such as ERP, MES, etc.) lack crucial information for the simulation use case compared to IPS, as latter provide information on material flows and as-is process sequences and times. The spatio-temporal nature of IPS data presents untapped potential for improving data quality in manufacturing simulation. Future research opportunities lie in quantitative analysis to delve deeper into how IPS data enhances data quality in simulation projects.

Research Question 3: How can the trustworthiness of a framework for utilizing IPS data in manufacturing simulation be assessed and ensured? (Chapter 6)

The proposed framework for utilizing IPS data in simulation input modeling underwent evaluation using the Z-Inspection® process. Since the framework was not yet implemented, the assessment was conducted ex-ante. However, the Z-Inspection® process can also be employed later in development and during the life-cycle to ensure trustworthiness.

An execution approach tailored to the scope of this research project was developed and used in the process' execution. The efforts invested, including time and personnel, were reasonable (three 2-hour online workshops with 12 involved investigators) and aimed at achieving practicality for industrial trustworthiness assessments. All three phases of the process (Set-up, Assess, and Resolve) were executed. A total of 40 individual issues emerged from the workshops, subsequently grouped into 15 issue clusters in Section 6.3.3. These issues and clusters were mapped to the four ethical principles, with slightly more issues identified for the principle of prevention of harm (17) than for respect for human autonomy (12), fairness (13), and explainability (11). An overview of all forty issues is provided in Appendix B.

Ethical challenges were identified where tensions arose between different values. These tensions were pinpointed for each issue during the expert workshops and subsequently analyzed to determine the predominant ethical tensions for this framework: efficiency vs. safety, efficiency vs. autonomy, and accuracy vs. explainability.

The analysis of issues and tensions in the ex-ante assessment forms the foundation for updating the socio-technical scenario to minimize potential negative impacts and enhance the framework's trustworthiness. Ideas for addressing identified ethical issues and recommendations for improving the framework were gathered from investigators at the end of each workshop and subsequently consolidated by the author. In total, 46 recommendations emerged from the workshops, categorized into 19 groups and presented in Section 6.4.3. There is an overview of all recommendations in Appendix C. The recommendations advocate for responsible and ethical development and deployment of the presented simulation framework through various measures summarized below:

- Ensure human oversight (Rec. Group 1)
- Transition to a decision support system (Rec. Group 2)
- Ensure robustness of simulation (Rec. Group 3)
- Conduct risk assessment (Rec. Group 4)
- Implement data governance (Rec. Group 7)
- Ensure privacy and transparency (Rec. Groups 5–9, 13)
- Provide explainability (Rec. Groups 10–12)
- Foster interdisciplinary collaboration in the development (Rec. Groups 14–16)
- Integrate ethical principles (Rec. Groups 17–19)

7.2 Discussion of Impact and Relevance

The results of this work can be divided into three major contributions:

1. A comprehensive overview and categorization of the potential benefits and **use cases of localization systems** in production systems.

2. Development of a **codified procedure** for the **domain-specific** creation of a **data model**, demonstrated for SMP, and integrated into a **simulation framework** utilizing localization data for parameterization and input data modeling.

3. **Ethical assessment of the trustworthiness** of the framework utilizing the Z-Inspection® process, including the introduction of a new execution approach tailored for industry applicability.

The first contribution represents an overview and comprehensive categorization of the potential benefits and use cases of localization systems in manufacturing, production, and logistics, as detailed in Chapter 4. Through a thorough literature review and the meticulous categorization of 41 papers based on application area, use case, maturity level, and tracked object, this work provides researchers and practitioners with unparalleled insight into implemented ideas and ongoing research in this domain. Furthermore, Section 4.2 underscores the significance of different requirements for selecting an IPS. This analysis holds practical relevance as it significantly aids in the procurement process, empowering decision-makers to select the most suitable IPS for their specific use case.

The second contribution is the development of a simulation framework that leverages localization data for parameterization and input data modeling. By refining existing data models and standards, this work determined the data requirements for simulating SMP, providing a structured approach that can be transferred to similar discrete industries and production systems (e.g., process optimization in logistics and healthcare simulations). The developed data model provides a comprehensive understanding of the input data essential for simulating factory operations within SMP. Each of the 42 identified input variables was assessed for its role in parameterization and input modeling of the simulation. The innovative contribution of enriching localization data with contextual information for input modeling in factory simulations, as presented in this work, was previously published by the author in Mieth et al. (2019b). The key advantage of this enrichment lies in enabling more advanced analyses. Contextual information enhances the understanding of spatio-temporal trajectories and aids in precise determination of input data. Prior studies, such as Mieth (2019) and Volk and Mieth (2022), have demonstrated the effectiveness of utilizing target processes from ERP data to accurately segment trajectories. Section 5.3 underscores the positive impact of integrating IPS data on data quality in simulation projects through a qualitative analysis. This research lays the groundwork for further quantitative studies aimed at improving manufacturing simulation methodologies.

The third scientific contribution involves an ex-ante trustworthiness assessment of the presented framework. Expert workshops were employed to identify ethical issues and tensions associated with using an IPS-based simulation system in manufacturing, facilitating preemptive addressing during implementation. Despite utilizing the existing Z-Inspection® process, a customized execution approach was developed, requiring less time and expert availability, thereby enhancing its practicality for industry application. Suggestions for improving the Z-Inspection® process were gathered during the assessment, aiming to provide feedback to its developers and encourage broader adoption. The results from using the process enable a more conscientious use of simulation data in future simulation projects.

Other research from the author, not directly related to the focus of this dissertation, include IPS data analysis (Mieth 2019; Volk and Mieth 2022), automated simulation model generation (Kallat et al. 2020; Mages et al. 2022), production control and optimization (Rinciog et al. 2020; Mieth et al. 2019c; Pfitzer et al. 2018), quantification of flexibility potentials (Müller et al. 2018), and simulation model validation (Tjaden and Mieth 2021).

7.3 Future Work

Based on this work, several areas for further research emerge. The different ideas are categorized and presented below.

Further Use Case Exploration

Research on IPS is ongoing, particularly with the increasing adoption of IPS in production. As this trend persists, novel use cases will arise, and existing ones will mature. Advancements in camera-based and hybrid systems show promise for enabling sophisticated applications like scene analysis. It is crucial to consider these advancements while developing a technology-agnostic framework, allowing for the integration of diverse IPS tailored to specific simulation use cases. Further research could explore additional industries like healthcare, retail, and smart cities to demonstrate the benefits of IPS for simulations and investigate the transferability of the presented approach to derive the underlying data model.

Implement and Optimize Simulation Framework

Conducting real-world experiments and case studies to assess the effectiveness of the simulation framework would provide valuable insights into its practical applicability, performance, scalability, usability and further optimization potentials. Additionally, performing a quantitative analysis of the quality improvements derived from utilizing IPS data in simulation, would offer a more comprehensive understanding of the benefits and limitations of integrating IPS data into simulation frameworks.

Further research is warranted to explore novel approaches for the verification and validation of simulation models that incorporate IPS data. Investigating how real-time data streams from IPS can be integrated into simulation frameworks for dynamic parameterization and adaptation would also be beneficial in enhancing the accuracy and responsiveness of simulations to real-world conditions.

Advanced techniques for automated simulation model generation can be researched and developed, leveraging domain-specific knowledge to streamline the modeling process for the framework. The integration of ML methods for generating and optimizing simulation models with IPS data can be further explored.

Advancing Data Modeling and Analysis Techniques

Further research is required to develop data analytics methods for deriving simulation inputs from IPS data. This work identified forty-two essential inputs for simulation in SMP, necessitating analytical methods to calculate these inputs accurately. Initial investigations into process and lead time estimation have been undertaken in Mieth (2019) and Volk and Mieth (2022). However, these studies highlight the non-trivial nature of the analyses due to the complexity of the production environment and compromised positional accuracy.

Furthermore, it is crucial to investigate the hierarchical relationships among simulation inputs. Previous efforts in deriving input data have revealed interconnected dependencies between variables. For instance, analyzing the battery life of a transport system requires knowledge of its speed and traveled distances, which in turn relies on departure and destination locations. These dependencies exist across all input variables and should be made transparent, potentially by visualization as a hierarchical graph to enhance understanding and facilitate modeling.

Another research task involves pattern recognition in spatio-temporal production data to derive workflows and underlying rules. It is hypothesized that standardized processes are more easily identifiable from the data. However, an essential question is how effectively data analysis can handle non-standardized processes. Investigating the capacity of analysis methods to accommodate varying degrees of process deviations is paramount for understanding the robustness and limitations of pattern recognition approaches in real-world production environments.

Exploring the integration of contextual information with IPS data warrants further research on methods for effectively merging both and on quantifying the impact of contextual data on simulation outcomes and decision-making processes within diverse production environments.

Standardize Trustworthiness Assessment

The feedback on the Z-Inspection® process suggests promising research directions, including refining and standardizing execution approaches for deployment in industrial settings. Investigating how different execution approaches impact the results of the process, such as the quantity and quality of identified issues, is crucial. Research could also delve into prioritizing ethical issues and enhancing stakeholder involvement to foster fairness and inclusivity. Additionally, overcoming barriers and increasing the dissemination of ethical assessment practices is important.

Exploration is also needed to determine the extent to which data privacy challenges can be addressed with technological solutions. Processes should be designed to ensure that data analysis does not allow conclusions to be drawn about the performance of specific workers. For instance, measures could be implemented to automatically cease storing movement data once the IPS marker is detected to be worn by a human instead of being attached to material.

Additionally, during the development of IPS data analyses for simulation purposes, compliance with the General Data Protection Regulation (GDPR) and relevant legislation is essential. The purpose of data analysis must be transparently communicated, and only necessary data for simulation input analysis should be tracked to adhere to the principle of data minimization. The system must also provide an option to object to the processing of personal data to comply with GDPR requirements.

Quantify and Ensure Trustworthiness

The determination of precisely when a system is trustworthy is complex. Trustworthiness might be achieved when all issues are resolved or when a trustworthiness assessment is completed. Ethical tensions may remain unresolved, complicating the matter. A classification method akin to the risk levels outlined in the European AI Act might be one approach to quantify trustworthiness. Future research should focus on practical approaches to continuously ensure and monitor trustworthiness in the systems' life cycles.

Further workshops with law experts, utilizing the Z-Inspection® process, should be conducted to assess the framework and its simulation system during development, addressing legal issues and upcoming regulations such as the European AI Act.

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Appendix A

Tables and Figures

A.1 User Requirements for Indoor Positioning System (IPS) Selection

The literature reveals twenty user requirements essential for the comparison and evaluation of IPSs. These requirements, as defined in Mautz (2012) and Alarifi et al. (2016), are given below:

- The **accuracy** of an IPS is the degree of correspondence of measured to the actual position and is usually expressed as absolute deviation referred to as measurement uncertainty or error.

- The **cost** of an IPS accumulate in different phases, e.g., system installation, operation, expansion, and maintenance for hardware, software, and services, and can be measured in money, time, space and energy, according to Alarifi et al. (2016). Mautz (2012) distinguishes between unique system set-up costs, per-user device costs, per-room costs, and maintenance costs.

- The **coverage area** of an IPS includes the space in which an asset can be located by the system. It also indicates whether there are restrictions to a specific area, like single rooms, buildings, or cities or if it has global coverage.

- The **update rate** of an IPS, sometimes also referred to as responsiveness, describes when the position of the located objects is updated. This update can be triggered by an event, on request, or periodically on a specified frequency.

- The **scalability** of an IPS includes the ability to expand the localization space and increase the number of trackable objects. When scaling a system, consideration should be given to whether the system is scalable with an area-proportional number of reference nodes and whether this involves a loss of accuracy.

- The **robustness and security** of an IPS is given when the system is not vulnerable to physical damage and theft on the hardware side and not susceptible to malfunction caused by jamming or unauthorized access on the software side.

- The **precision** of an IPS refers to the degree of consistency or reproducibility of measurements, indicating how close repeated measurements are to each other, opposed to accuracy, which is the closeness of a measurement to the true value, representing how well the measurement reflects reality.

- The **required infrastructure** of an IPS is a requirement that looks mainly into the hardware side of things: Is new infrastructure needed, or can existing infrastructure be reused? For example, the open localization standard OMLOX[1] is working towards a more open localization ecosystem where new devices can be located with already existing infrastructure from another system provider (Gerwin et al. 2022). Under this requirement also falls the decision of whether the system should use active or passive markers.

- The **privacy** of an IPS depends on the extent to which access to the data is secured, how well (personal) data is protected, and how the further use and analysis of data are transparently regulated.

- The **availability** of an IPS denotes the duration the system is operational, normalized over the observation period. Prospective installers of an IPS find this metric crucial as it reveals the likelihood and maximum duration of system outages.

- The **adaptiveness** of an IPS describes how well the IPS can be deployed in different environments with their typical interference factors.

- The **market maturity** of an IPS indicates the product's position in its life cycle, whether it is still in development or an established product.

- The **intrusiveness** of an IPS describes how seamlessly the system can be integrated into the target environment. User acceptance also plays a role in this requirement because the system should not hinder users from performing their activities.

- The **number of users** of an IPS is important for sizing the system to the intended use case.

- The **output data** of an IPS becomes a relevant requirement when users engage in data analysis for their use cases. While all IPS inherently provide data on tracked device positions over time, the specifics can vary significantly. Systems may offer two-dimensional or three-dimensional coordinates, and the position may be relative or absolute, with potential symbolic representations. Dynamic parameters, such as object speed, heading direction, and measurement uncertainties, can also be of interest in certain cases.

- The **interface** of an IPS can take on different forms known from other human-machine interfaces. It can be text-based or graphical on display. It can include audio and voice interfaces and digital interfaces for data exchange and communication, either wire- or hardware-based, or wireless.

- The **system integrity** of an IPS denotes the functionality according to the technical specifications. Some systems monitor integrity in operation and report when there is a failure.

[1] `https://omlox.com/`

- The **approval** of an IPS refers to the legal permission to run the IPS system in the considered environment. In some applications and countries, the system must be certified by authorities.
- The **energy consumption** of an IPS is a selection criterion to be considered if the system's energy efficiency is important in the application. For example, some systems are powered by batteries and should be used over a specific time horizon without recharging. On the other hand, some users are interested in low overall energy consumption to meet their sustainability goals.

A.2 Stakeholder Map

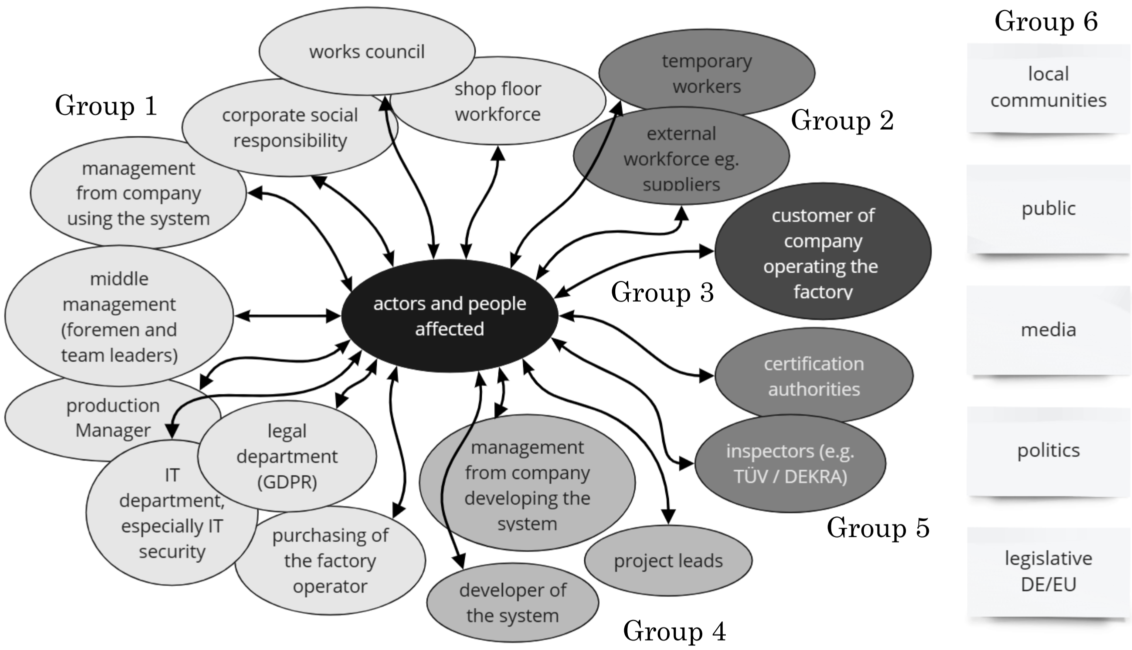

Figure A.1: Stakeholder map providing an overview of actors in the ecosystem around the assessed system, which could presumably be affected.

The stakeholder map in Figure A.1 reflects the status after the third workshop in the assessment phase of the Z-Inspection® process and was further refined, yielding Figure 6.2. The different colors represent the different stakeholder groups:

- Group 1: people employed at manufacturing company that deploys system
- Group 2: people working in the supply chain for the company that deploys the system
- Group 3: customers of the manufacturing company
- Group 4: people from the company that develops the system
- Group 5: external auditors
- Group 6: social, medial, and political spheres

A.3 Assessment of Investigators

Investigator	manufacturing expert	digitization expert	ML Expert	ML systems developer	AI ethics expert	consultant	researcher	simulation expert	IPS expert	innovation manager	psychologist	workshop number
Tom	●	●	○	○	○	●	○	◑	◑	◑	○	1
Tom (C)	●	●	○	○	○	●	○	●	◑	○	○	1
Tom (Average)	●	●	○	○	○	●	○	◕	◑	◔	○	1
Sabeth	●	●	●	◑	○	●	◑	○	○	●	○	1
Sabeth (C)	●	●	◑	○	○	○	○	○	○	○	○	1
Sabeth (Average)	●	●	◕	◔	○	◑	◔	○	○	◑	○	1
Johannes	○	●	◑	○	●	●	◑	○	○	◑	○	1
Johannes (C)	○	●	◑	◑	●	●	○	○	○	◑	○	1
Johannes (Average)	○	●	◑	◔	●	●	◔	○	○	◑	○	1
Anna	○	○	◑	○	●	●	◑	○	○	○	○	1
Anna (C)	○	○	◑	○	●	●	◑	○	○	○	○	1
Anna (Average)	○	○	◑	○	●	●	◑	○	○	○	○	1

Table A.1: Assessment of the investigators from Workshop 3, which took place on July 14, 2022. The first row shows the self-assessment of the investigators. The second line (C) shows the author's assessment. The last line is the average of self-assessment and third-party assessment.

Investigator	manufacturing expert	digitization expert	ML Expert	ML systems developer	AI ethics expert	consultant	researcher	simulation expert	IPS expert	innovation manager	psychologist	workshop number
Yahel	◑	●	○	○	○	●	◑	○	●	●	○	2
Yahel (C)	◑	●	○	○	○	○	○	○	●	●	○	2
Yahel (Average)	◑	●	○	○	○	◑	◔	○	●	●	○	2
Sandra	○	◑	◑	○	●	●	○	○	○	◑	◑	2
Sandra (C)	○	◑	●	●	●	●	○	○	○	○	○	2
Sandra (Average)	○	◑	◕	◑	●	●	○	○	○	◔	◔	2
Veronika	◑	◑	○	○	○	○	●	○	○	◑	●	2
Veronika (C)	●	●	○	○	○	○	●	○	○	◑	●	2
Veronika (Average)	◕	◕	○	○	○	○	●	○	○	◑	●	2
Thorsten	○	○	◑	◑	○	○	●	●	○	○	○	2
Thorsten (C)	●	●	●	●	○	○	○	●	○	○	○	2
Thorsten (Average)	◑	◑	◕	◕	○	○	◑	●	○	○	○	2

Table A.2: Assessment of the investigators from Workshop 2, which took place on July 19, 2022. The first row shows the self-assessment of the investigators. The second line (C) shows the author's external assessment. The last line is the average of self-assessment and third-party assessment.

Investigator	manufacturing expert	digitization expert	ML Expert	ML systems developer	AI ethics expert	consultant	researcher	simulation expert	IPS expert	innovation manager	psychologist	workshop number
Flemming (C)	●	●	○	○	○	○	○	◑	●	○	○	3
Flemming	●	◑	◑	○	○	◑	○	◑	●	○	○	3
Flemming (Average)	●	◕	◔	○	○	◔	○	◑	●	○	○	3
Lynn (C)	●	●	◑	○	○	◑	●	○	○	◑	○	3
Lynn	●	●	○	○	◑	●	●	○	○	●	○	3
Lynn (Average)	●	●	◔	○	◔	◕	●	○	○	◕	○	3
Charleen (C)	○	○	●	◑	●	●	●	○	○	○	○	3
Charleen	○	◑	●	◑	●	●	●	○	○	○	○	3
Charleen (Average)	○	◔	●	◑	●	●	●	○	○	○	○	3
Ute (C)	○	◑	●	●	●	●	●	◑	○	○	○	3
Ute	○	◑	●	●	●	●	●	●	○	○	○	3
Ute (Average)	○	◑	●	●	●	●	●	◕	○	○	○	3

Table A.3: Assessment of the investigators from Workshop 3, which took place on July 22, 2022. The first row shows the self-assessment of the investigators. The second line (C) shows the author's assessment. The last line is the average of self-assessment and third-party assessment.

A.4 Data on the Analysis of Issues, Issue Clusters, and Recommendations

	in ethical principle					issues
	I	II	III	IV	count	40
human agency and oversight	10	7	6	1	24	60,0%
technical robustness and safety	1	3	3	2	9	22,5%
privacy and data governance	4	4	4	4	16	40,0%
transparency	2	2	7	8	19	47,5%
diversity, non-discrimination and fairness	3	3	10	1	17	42,5%
societal and environmental well-being	2	8	6	0	16	40,0%
accountability	3	3	6	3	15	37,5%
	25	30	42	19	116	
	21,6%	25,9%	36,2%	16,4%		

Table A.4: Frequency of key requirements mentioned in issues broken down by the four ethical principles.

	in ethical principle					clusters
	I	II	III	IV	count	40
human agency and oversight	3	2	3	0	8	53,3%
technical robustness and safety	0	1	1	1	3	20,0%
privacy and data governance	1	2	1	1	5	33,3%
transparency	0	0	2	2	4	26,7%
diversity, non-discrimination and fairness	0	1	4	0	5	33,3%
societal and environmental well-being	0	4	2	0	6	40,0%
accountability	1	0	1	1	3	20,0%
	5	10	14	5	34	
	14,7%	29,4%	41,2%	14,7%		

Table A.5: Frequency of key requirements mentioned in issue clusters broken down by the four ethical principles.

	recommendations	
human agency and oversight	7	15,2%
technical robustness and safety	3	6,5%
privacy and data governance	8	17,4%
transparency	12	26,1%
diversity, non-discrimination and fairness	9	19,6%
societal and environmental well-being	7	15,2%
accountability	0	0,0%
	46	

Table A.6: Frequency of key requirements mentioned in recommendations.

	issues	issue clusters	recommendations
sample skewness	-0,037	0,800	-0,574
sample kurtosis	1,827	0,440	0,214
Jarque-Bera test statistic	0,975	0,803	0,398
p-value	0,614	0,670	0,819

Table A.7: Results of the Jarque-Bera test for normal distribution. The number of observations for each test is seven because of the seven key requirements. Since this p-value is not less than 0.05, the null hypothesis is not rejected. There is not sufficient evidence to suggest that the dataset is not normally distributed. (H_0: The data are normally distributed. H_A: The data are not normally distributed.)

	Pearson correlation	t-score	p-value
average vote to deviation	-0.261	-0.605	0.572
issues to issue clusters	0.784	2.826	0.037
issues to recommendations	0.503	1.301	0.250
issue clusters to recommendations	0.394	0.959	0.382
issues to average voting	0.428	1.058	0.339

Table A.8: Analysis of Pearson correlation coefficients, Z-Steiger t-scores (see Equation 6.1), and p-values. Only the correlation between the frequency of mentions of issues and issue clusters is statistically significant (p-value of $0.037 < 0.05$).

Appendix B

Ethical Issues

This chapter presents the ethical issues as identified during the workshops. The description of the issues was only linguistically revised and then translated from German into English. For each issue, it is indicated in which workshop it was identified, to which ethical principles it was categorized, and whether a tension was named. For the trustworthy AI key requirements, the person who voted for the mapped requirement is indicated in parentheses. The issues are listed according to ethical principles. If an issue was assigned to two ethical principles, it is only listed under the ethical principle deemed more appropriate to avoid duplication.

B.1 Respect for Human Autonomy

Ethical Issue 1: Employees have their decisions taken by the system
Identified in: Workshop 1
Issue Cluster: Limitation of decision making - Cluster 1
Ethical Principles: Respect for human autonomy
Tension: Autonomy vs. efficiency
Trustworthy AI Key Requirements: Human agency and oversight (all four)

Ethical Issue 2: No more operational decision-making authority in middle management (foremen, team leaders). This means no emergency action can be taken (e.g., if the system makes the wrong decision).
Identified in: Workshop 1
Issue Cluster: Limitation of decision making - Cluster 1
Ethical Principles: Respect for human autonomy
Tension: -
Trustworthy AI Key Requirements: Human agency and oversight (all four); technical robustness and safety (Tom & Anna)

Ethical Issue 3: The simulation model can limit options for action.
Identified in: Workshop 1
Issue Cluster: Limitation of decision making - Cluster 1
Ethical Principles: Respect for human autonomy
Tension: Autonomy vs. efficiency
Trustworthy AI Key Requirements: Human agency and oversight (all four); accountability (Sabeth & Anna)

Ethical Issue 4: Strict system specifications with no possibility of human influence: Orders may be assigned, or decisions may be made against the will of the person performing the work. A data-driven work instruction may contradict the predefined procedure, and one cannot independently schedule one's s work. The system dictates movement.
Identified in: Workshop 2
Issue Cluster: Against the will, self-assessment or personal preference - Cluster 2
Ethical Principles: Respect for human autonomy
Tension: Autonomy vs. efficiency
Trustworthy AI Key Requirements: Human agency and oversight (all four); transparency (Yahel & Thorsten, after discussion all four)

Ethical Issue 5: Transparent employee: "Observation" of every movement. Activities can only take place if they are located on the shop floor. Only some movements are relevant to the functioning of the system. What happens to the remaining recorded movements? The restriction of the movement radius makes a person feel unfree[1].
Identified in: Workshop 2
Issue Cluster: Transparent employee - Cluster 3
Ethical Principles: Respect for human autonomy
Tension: Privacy vs. quality of service
Trustworthy AI Key Requirements: Privacy and data governance (all four); transparency (Tom & Yahel)

Ethical Issue 6: (i) Worker data reveals too many conclusions about their behavior and enables too close control. (ii) The data also allows conclusions to be drawn about incorrect behavior by persons involved (e.g., speeding forklifts).
Identified in: Workshop 3
Issue Cluster: Transparent employee - Cluster 3; Fairness in case of mistakes - Cluster 11
Ethical Principles: Respect for human autonomy, Fairness
Tension: Safety vs. autonomy
Trustworthy AI Key Requirements: Human agency and oversight (all four), privacy and data governance (all four)

Ethical Issue 7: Datafication of human performance: worker data allows conclusions to be drawn about the worker's efficiency. How good was the factory planner's planning variant compared to the proposal from the system?
Identified in: Workshop 3
Issue Cluster: Transparent employee - Cluster 3
Ethical Principles: Respect for human autonomy
Tension: Quality of service vs. dignity; accuracy vs. fairness
Trustworthy AI Key Requirements: Human agency and oversight (all four); privacy and data governance (Lynn, Ute); diversity, non-discrimination, and fairness (Lynn, Ute, Flemming), Societal and environmental well-being (Flemming, Ute)

[1]Note: Investigators think that the observation will restrict the movement radius because people do not dare to deviate from the prescribed tasks and thus locations.

Ethical Issue 8: The system restricts the decision-making authority of the previous decision-makers, such as managers, suppliers, and external partners. Examples: (1) Production controller is overridden by simulation decision or cannot comprehend it. (2) Worker receives real-time instructions via an interface. Now, the system patronizes him.
Identified in: Workshop 3
Issue Cluster: Limitation of decision making - Cluster 1
Ethical Principles: Respect for human autonomy, Explainability
Tension: Autonomy vs. efficiency
Trustworthy AI Key Requirements: Human agency and oversight (all four); diversity, non-discrimination and fairness (all four); accountability (all four)

Ethical Issue 9: Assignment to a work and break schedule: instead of human decision, there is only limited job rotation based on performance metrics or by system restrictions. (Variety pleases the employees). The system enforces optimal break times, e.g., when the employee can go to the bathroom.
Identified in: Workshop 1
Issue Cluster: Against the will, self-assessment or personal preference - Cluster 2
Ethical Principles: Respect for human autonomy, Prevention of harm
Tension: Autonomy vs. efficiency, efficiency vs. health
Trustworthy AI Key Requirements: Human Agency and oversight (Johannes & Tom), societal and environmental well-being (Sabeth & Johannes)

Ethical Issue 10: The employee is deprived of autonomy to assess their abilities and needs: When modeling people in simulation, all individual abilities and needs can never be considered. Automated decision-making will, therefore, not be able to consider these individual abilities and needs. An example is that people work slower in heat or due to disabilities. Nevertheless, the simulation predicts more productivity, and such deviation can lead to anger. Also, assigning a task to somebody unable to perform it physically or only with difficulty leads to psychological and physical stress. Performance-based assignments of employees without consideration of ergonomic aspects can cause harm.
Identified in: Workshop 2
Issue Cluster: Against the will, self-assessment or personal preference - Cluster 2
Ethical Principles: Respect for human autonomy, Prevention of harm
Tension: Privacy vs. accuracy
Trustworthy AI Key Requirements: Human agency and oversight (Veronika, Thorsten, Yahel); Diversity, non-discrimination, and fairness (Sandra, accepted in discussion)

Ethical Issue 11: Little influence on direct decision-making (self-efficacy). Example: Continuous improvement processes: How can a person influence that a better decision is made next time?
Identified in: Workshop 2
Issue Cluster: Limitation of decision making - Cluster 1
Ethical Principles: Respect for human autonomy, Fairness
Tension: Simplicity vs. dignity
Trustworthy AI Key Requirements: Human agency and oversight (all four); privacy and data governance (Sandra, Veronika); Accountability (Yahel, Thorsten, Veronika)

B.2 Prevention of Harm

Ethical Issue 12: Fear of radiation: if technically everything is okay, then no physical damage is to be expected, but purely psychological.
Identified in: Workshop 1
Issue Cluster: Technophobia - Cluster 7
Ethical Principles: Prevention of harm (psychological)
Tension: Efficiency vs. health
Trustworthy AI Key Requirements: Societal and environmental well-being (all four)

Ethical Issue 13: Emotional stress / over time mental illness due to monitoring
Identified in: Workshop 1
Issue Cluster: Harm caused by surveillance - Cluster 4
Ethical Principles: Prevention of harm (psychological)
Tension: Privacy vs. efficiency
Trustworthy AI Key Requirements: Societal and environmental well-being (all four)

Ethical Issue 14: Self-amplifying effects (e.g., in the RL policy) steadily increase the work rate.
Identified in: Workshop 1
Issue Cluster: Pressure to perform - Cluster 5
Ethical Principles: Prevention of harm (psychological)
Tension: Efficiency vs. health
Trustworthy AI Key Requirements: Societal and environmental well-being (all four), human agency and oversight (Sabeth, Anna, Johannes)

Ethical Issue 15: Frequent changes in work instruction or workflow: Is new AI-generated work instruction feasible for the worker, or does it overwhelm him/her? Error-proneness increases if new things have to be done frequently. The short-term change increases stress levels and may reduce the time for compensation.
Identified in: Workshop 2
Issue Cluster: Damage due to excessive or wrong demands - Cluster 6
Ethical Principles: Prevention of harm (physical & psychological)
Tension: Efficiency vs. safety
Trustworthy AI Key Requirements: Human Agency and oversight (all four); technical robustness and safety (Sandra & Thorsten); diversity, non-discrimination, and fairness (Veronika & Sandra); Societal and environmental well-being (Veronika, Sandra, Yahel)

Ethical Issue 16: Psychological pressure to do more to "improve the algorithm." For planners: Constant competition with the system (optimum) can lead to psychological stress (e.g., burnout, depression, etc.).
Identified in: Workshop 3
Issue Cluster: Pressure to perform - Cluster 5;
Ethical Principles: Prevention of harm (psychological)
Tension: Accuracy vs. solidarity; privacy vs. efficiency; efficiency vs. safety;
Trustworthy AI Key Requirements: Human agency and oversight (all four); Privacy and Data Governance (Lynn, Ute); Transparency (Charleen, Flemming); societal and environmental well-being (all four); accountability (Charleen, Lynn)

Ethical Issue 17: (i)[2]For workers: Tracking workers can create psychological pressure that can lead to accidents, for example. (ii)[2] Increased efficiency of machines does not necessarily lead to more efficient behavior of people. It may lead to burnout, depression, and an increased risk of accidents.
Identified in: Workshop 3
Issue Cluster: (i) Harm caused by surveillance - Cluster 4; (ii) Damage due to excessive or wrong demands - Cluster 6
Ethical Principles: Prevention of harm (psychological & physical)
Tension: Privacy vs. efficiency; efficiency vs. safety;
Trustworthy AI Key Requirements: Human agency and oversight (Lynn, Charleen, Flemming); Privacy and Data Governance (Ute, accepted in discussion); diversity, non-discrimination, and fairness (Ute, accepted in discussion); societal and environmental well-being (Lynn, Ute); accountability (Lynn, Charleen, Flemming)

Ethical Issue 18: The permanent knowledge that the simulation makes decisions can lead to psychological stress for all persons. The psychological pressure of automated decisions - the algorithm as the "ruler."
Identified in: Workshop 3
Issue Cluster: Pressure to perform - Cluster 5;
Ethical Principles: Prevention of harm (psychological)
Tension: convenience vs. dignity
Trustworthy AI Key Requirements: Human agency and oversight (Lynn, Charleen); Privacy and Data Governance (Ute, Flemming, Charleen); transparency (Charleen, Lynn); diversity, non-discrimination, and fairness (Ute, Lynn, Flemming); societal and environmental well-being (Lynn, Ute, Flemming); accountability (Lynn, Charleen)

Ethical Issue 19: Autonomous faulty control of machines or Automated Guided Vehicles (AGVs) can lead to physical accidents, e.g., if safety circuits are bypassed or because the tracking device is put down on a day or the battery is empty.
Identified in: Workshop 3
Issue Cluster: Damage due to excessive or wrong demands - Cluster 6;
Ethical Principles: Prevention of harm (physical)
Tension: Efficiency vs. safety
Trustworthy AI Key Requirements: Human agency and oversight (all four); technical robustness and safety (all four); societal and environmental well-being (Lynn, accepted after discussion)

Ethical Issue 20: Fear of cyber-attack or actual cyber-attack due to weak cybersecurity.
Identified in: Workshop 3
Issue Cluster: Risk of cyber attacks - Cluster 8
Ethical Principles: Prevention of harm (physical & psychological)
Tension: Efficiency vs. safety
Trustworthy AI Key Requirements: Human agency and oversight (Ute, Flemming, Lynn); technical robustness and safety (all four); privacy and data governance (all four)

[2]Issue was split into two parts (i) and (ii), one for each cluster it was assigned to.

B.3 Fairness

Ethical Issue 21: Trained models generalize performance: particularly "strong" or "weak" employees are not modeled appropriately and have to live with the consequences of poor modeling. The machine learning system cannot be adapted fast enough to unexpected dynamics/fluctuating performance levels.
Identified in: Workshop 3
Issue Cluster: Discrimination based on performance - Cluster 9
Ethical Principles: Respect for human autonomy, Fairness
Tension: Convenience vs. fairness; safety vs. efficiency; autonomy vs. efficiency
Trustworthy AI Key Requirements: Human agency and oversight (all four); Technical robustness and safety (Charleen, Ute, Flemming); Transparency (Lynn, accepted after discussion); diversity, non-discrimination, and fairness (Ute, accepted after discussion)

Ethical Issue 22: The system is misused for performance measurement (power asymmetry).
Identified in: Workshop 1
Issue Cluster: Discrimination based on performance - Cluster 9
Ethical Principles: Prevention of harm (psychological), Fairness
Tension: none, because it is "fundamentally wrong" (Anna)
Trustworthy AI Key Requirements: privacy and data governance (Johannes, Tom), transparency (Johannes, Sabeth), diversity, non-discrimination and fairness (Sabeth, Johannes), accountability (Anna, Sabeth, Tom)

Ethical Issue 23: The load of activities is unevenly distributed in the workforce.
Identified in: Workshop 1
Issue Cluster: Fairness in decision-making - Cluster 10
Ethical Principles: Prevention of harm (physical), Fairness
Tension: Individuality vs. equality
Trustworthy AI Key Requirements: Diversity non-discrimination and fairness (all four), societal and environmental well-being (all four)

Ethical Issue 24: "Testimony against testimony": the credibility of people may be questioned in case of different representations of reality by measured data. Example: Errors in tracking may be mistaken for errors made by employees.
Identified in: Workshop 2
Issue Cluster: Fairness in case of mistakes - Cluster 11
Ethical Principles: Prevention of harm (physical), Fairness
Tension: -
Trustworthy AI Key Requirements: Transparency (Veronika, Thorsten); diversity non-discrimination and fairness (Yahel, accepted after discussion); accountability (Veronika, Yahel, Sandra)

Ethical Issue 25: Hijacking the algorithm: Weaknesses of the ML system are exploited to gain advantages at the expense of colleagues (my efficiency score gets better, and one of the colleagues gets worse). All subsequent shifts must work faster based on the top performer's time.
Identified in: Workshop 3
Issue Cluster: Fairness of different groups among each other - Cluster 12
Ethical Principles: Prevention of harm, Fairness
Tension: Efficiency vs. safety; solidarity vs. efficiency
Trustworthy AI Key Requirements: technical robustness and safety (all four); privacy and data governance (Ute, Charleen, Flemming); accountability (Lynn, accepted after discussion)

Ethical Issue 26: The individuality of the employee is not taken into account (e.g., skill level / health / physical limitation / language)
Identified in: Workshop 1
Issue Cluster: Discrimination based on performance - Cluster 9
Ethical Principles: Fairness
Tension: Individuality vs. equality
Trustworthy AI Key Requirements: Human agency and oversight (Sabeth, Anna), Diversity, non-discrimination and fairness (all four), societal and environmental well-being (Anna, Sabeth, Johannes)

Ethical Issue 27: Calculation of individual productivity: for example, the processing speed of people is compared: Disadvantages of less "efficient" people (physically, mentally). Work processes are designed in favor of the "majority ."A worker's performance is measured over time, leading to performance expectations in specific contexts. Example: Using data to customize pay (Where is one's sphere of influence? What can be positively influenced by employees?)
Identified in: Workshop 2
Issue Cluster: Discrimination based on performance - Cluster 9
Ethical Principles: Fairness
Tension: Efficiency vs. equality, personalization vs. solidarity
Trustworthy AI Key Requirements: Human agency and oversight (Veronika, Yahel); privacy and data governance (Thorsten, Veronika); diversity non-discrimination and fairness (Yahel, Sandra), societal and environmental well-being (Veronika, Yahel)

Ethical Issue 28: Error-proneness of machine learning leads to unpredictable consequences. Example: unbalanced data leads to bias in the system. The model learns something that it should not represent.
Identified in: Workshop 3
Issue Cluster: Fairness in decision-making - Cluster 10
Ethical Principles: Prevention of harm (psychological), Fairness
Tension: Convenience vs. safety; convenience vs. security; convenience vs. fairness
Trustworthy AI Key Requirements: Human agency and oversight (all four); technical robustness and safety (all four); privacy and data governance (Charleen, Flemming, Lynn); Transparency (Ute, Lynn); diversity, non-discrimination, and fairness (Ute, Lynn); societal and environmental well-being (Lynn, accepted after discussion)

Ethical Issue 29: The system favors individual workers according to certain criteria, e.g., quality, age, speed, etc., and thus disadvantages other workers.
Identified in: Workshop 3
Issue Cluster: Discrimination based on performance - Cluster 9
Ethical Principles: Fairness
Tension: Efficiency vs. personalisation vs. solidarity
Trustworthy AI Key Requirements: Human agency and oversight (all four); Transparency (all four); diversity, non-discrimination, and fairness (Ute, accepted after discussion); societal and environmental well-being (all four); accountability (Charleen, Lynn)

Ethical Issue 30: Execute the production order from one customer faster than another (simulation prefers customer A over B).
Identified in: Workshop 3
Issue Cluster: Fairness of different groups among each other - Cluster 12
Ethical Principles: Fairness
Tension: Fairness vs. efficiency; quality of service vs. fairness
Trustworthy AI Key Requirements: Human agency and oversight (Charleen, Lynn); Transparency (Charleen, Ute, Lynn); diversity, non-discrimination, and fairness (Ute, Flemming); societal and environmental well-being (Charleen, Flemming, Lynn); accountability (all four)

Ethical Issue 31: The system's complexity (factory example) only allows one actor to understand some of the conditions for the decisions being made. More information could be available at a higher level or for privileged groups of people than at a lower level or for a less privileged group. The transparency of what data is collected and where is not the same for everyone.
Identified in: Workshop 3
Issue Cluster: Fairness of different groups among each other - Cluster 12
Ethical Principles: Fairness, Explainability
Tension: Accuracy vs. explainability
Trustworthy AI Key Requirements: Transparency (all four); diversity, non-discrimination and fairness (Ute, Flemming); accountability (Charleen, Lynn)

B.4 Explainability

Ethical Issue 32: Bearing responsibility without assessing the decision's impact (if the decision is not comprehensible). The production manager does not understand AI advice but must instruct people to follow it and assumes responsibility. How are questions of guilt clarified? Especially if someone is harmed.
Identified in: Workshop 2
Issue Cluster: Poor comprehensibility - Cluster 14
Ethical Principles: Prevention of harm, Explainability
Tension: accuracy vs. explainability; convenience vs. responsibility
Trustworthy AI Key Requirements: Transparency (Sandra, Veronika); Accountability (Sandra, Veronika, Thorsten)

Ethical Issue 33: System Transparency: Lack of acceptance by workers due to lack of information about what happens to the collected data (feedback on the result is missing)
Identified in: Workshop 1
Issue Cluster: Lack of acceptance - Cluster 13
Ethical Principles: Explainability
Tension: -
Trustworthy AI Key Requirements: privacy and data governance (Sabeth, Anna, Johannes), Transparency (all four)

Ethical Issue 34: Decision transparency: Lack of acceptability for decisions. System acceptance becomes difficult, especially for long-term employees, and thus the knowledge transfer into the system.
Identified in: Workshop 1
Issue Cluster: Lack of acceptance - Cluster 13
Ethical Principles: Explainability
Tension: -
Trustworthy AI Key Requirements: privacy and data governance (Sabeth, Anna, Johannes), Transparency (all four)

Ethical Issue 35: Data transparency: lack of acceptance of what data has been collected.
Identified in: Workshop 1
Issue Cluster: Lack of acceptance - Cluster 13
Ethical Principles: Explainability
Tension: Transparency vs. Privacy
Trustworthy AI Key Requirements: privacy and data governance (Sabeth, Anna, Tom), Transparency (all four)

Ethical Issue 36: Information about monitoring leads to conscious slowing down of the work pace.
Identified in: Workshop 1
Issue Cluster: Behaviour change and manipulation - Cluster 15
Ethical Principles: Explainability
Tension: Transparency vs. accuracy
Trustworthy AI Key Requirements: technical robustness and safety (Sabeth, Anna)

Ethical Issue 37: The development of simulations based on data is not necessarily comprehensible for humans (deviations from the happy path: approximately 5% of my processes are, e.g., not explainable)
Identified in: Workshop 2
Issue Cluster: Poor comprehensibility - Cluster 14
Ethical Principles: Explainability
Tension: Accuracy vs. explainability
Trustworthy AI Key Requirements: Transparency (all four)

Ethical Issue 38: Automated decisions without traceability are unlikely to be accepted without appropriate guidance. Changed work instructions without justification, which represents why it comes to this change and why an adjustment of the proceeding is meaningful. (informational justice relevant in change processes). Following the new instructions is questioned: Evaluation of measured data would need to be shared with all staff regularly if it results in adjustments to planning and processes.
Identified in: Workshop 2
Issue Cluster: Lack of acceptance - Cluster 13
Ethical Principles: Explainability
Tension: Efficiency & accuracy vs. explainability
Trustworthy AI Key Requirements: Transparency (all four)

Ethical Issue 39: Reinforcement Learning (RL) policies allow little transparency in explaining individual decisions in practice. The ML system is very complex. Due to the lack of explainability, errors cannot be easily detected.
Identified in: Workshop 3
Issue Cluster: Poor comprehensibility - Cluster 14
Ethical Principles: Explainability
Tension: Convenience vs. transparency; accuracy vs. explainability
Trustworthy AI Key Requirements: Transparency (all four); accountability (all four)

Ethical Issue 40: Errors in the application or data, which are then used for training the models, cannot be easily controlled. The explainability of the resulting model suffers from this. Example: Marker is forgotten or even manipulated, etc.
Identified in: Workshop 3
Issue Cluster: Behaviour change and manipulation - Cluster 15
Ethical Principles: Explainability
Tension: Accuracy vs. explainability
Trustworthy AI Key Requirements: Human agency and oversight (all four); technical robustness and safety (all four); privacy and data governance (Charleen, Lynn); Transparency (all four); diversity, non-discrimination, and fairness (Ute, Lynn, Charleen); accountability (all four)

Appendix C

Recommendations from the Workshops

In this chapter, the recommendations are presented as formulated by the investigators. Since the recommendations were given in German, the author has translated them as directly as possible into English, making only minor improvements in expression and grammar to facilitate better understanding. The recommendations are listed here in sections corresponding to the three workshops. For each recommendation, it is indicated who identified it, to which recommendation group it is assigned in Chapter 6, and which key requirement it supports. In some cases, the author has added notes under the recommendation if she felt that the recommendation could not be clearly understood without them.

C.1 Recommendations from Workshop 1

Recommendation 1: Possibility of feedback for potential wrong decisions of the Artificial Intelligence (AI).
Identified by: Tom
Recommendation Group: Human in the loop - Group 1
Trustworthy AI key requirement: Human agency and oversight

Recommendation 2: AI learning phase for new employees/new products/processes in defined scenarios.[1]
Identified by: Tom
Recommendation Group: Keeping an eye on people's well-being - Group 18
Trustworthy AI key requirement: Societal and environmental well-being

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Recommendation 3: Offer override option.[2]
Identified by: Anna
Recommendation Group: Human in the loop - Group 1
Trustworthy AI key requirement: Human agency and oversight

[1] Author's note: In the learning phase, the employee familiarizes themselves with the tasks performed by the system/AI and how to interact with it. This involves engaging with various scenarios to understand how to communicate feedback to the system/AI, such as expressing dissatisfaction with its decisions.

[2] Author's note: Humans should have the option to disregard the AI's decision.

Recommendation 4: Insert human limits in Reinforcement Learning (RL) policy.[3]
Identified by: Anna
Recommendation Group: Limit the speed of change - Group 19
Trustworthy AI key requirement: Societal and environmental well-being

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Recommendation 5: Health monitoring of employees. Use as a target variable in decision making.
Identified by: Tom
Recommendation Group: Keeping an eye on people's well-being - Group 18
Trustworthy AI key requirement: Societal and environmental well-being

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Recommendation 6: Strengthening the competitive position means job preservation (more efficiency, better prices...), weighing up with negative system aspects, and making a holistically optimized system design decision.
Identified by: Johannes
Recommendation Group: Ethics by design - Group 17
Trustworthy AI key requirement: Societal and environmental well-being

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Recommendation 7: Involve the affected persons' advisory board ("nothing about us without us").
Identified by: Anna
Recommendation Group: Actively involve affected people - Group 16
Trustworthy AI key requirement: Diversity, non-discrimination and fairness

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Recommendation 8: Establish continuous improvement processes where employees can anonymously share their feedback, concerns, etc.
Identified by: Sabeth
Recommendation Group: Actively involve affected people - Group 16
Trustworthy AI key requirement: Diversity, non-discrimination and fairness

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Recommendation 9: Involvement and rights for works council or other kinds of employee representation.
Identified by: Tom
Recommendation Group: Create trustworthy organizational structures-Group 15
Trustworthy AI key requirement: Diversity, non-discrimination and fairness

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Recommendation 10: Involve persons of trust per area in the roll-out of the system (employees, works council, coach).
Identified by: Sabeth
Recommendation Group: Create trustworthy organizational structures-Group 15
Trustworthy AI key requirement: Diversity, non-discrimination and fairness

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Recommendation 11: Involve employees in system development and implementation: inform, name contact persons, show interest in concerns and take them seriously.
Identified by: Johannes
Recommendation Group: Actively involve affected people - Group 16
Trustworthy AI key requirement: Diversity, non-discrimination and fairness

[3] Author's note: Otherwise, the algorithm may continue optimizing to the extent that humans reach their physical and mental limits, resulting in overwhelming situations.

Recommendation 12: Communicate as transparently as possible about decision-making factors for AI.
Identified by: Sabeth
Recommendation Group: Ensure explainability of the AI system - Group 10
Trustworthy AI key requirement: Transparency

Recommendation 13: How accessible is or can the digital twin be made for different user groups? (transparency)
Identified by: Johannes
Recommendation Group: Ensure explainability of the simulation - Group 11
Trustworthy AI key requirement: Transparency

Recommendation 14: Visualization of the simulation model to support transparency.
Identified by: Tom
Recommendation Group: Ensure explainability of the simulation - Group 11
Trustworthy AI key requirement: Transparency

Recommendation 15: Clarify what gains in efficiency mean financially.
Identified by: Johannes
Recommendation Group: Transparent communication - Group 13
Trustworthy AI key requirement: Transparency

Recommendation 16: Transparent presentation of system benefits.
Identified by: Tom
Recommendation Group: Transparent communication - Group 13
Trustworthy AI key requirement: Transparency

Recommendation 17: Define clear rules when which data is deleted. Where data is no longer needed or required, it should be deleted as soon as possible. Employees need to be educated about this. Don't store all routes and tracked trajectories forever.
Identified by: Johannes
Recommendation Group: Data governance - Group 7
Trustworthy AI key requirement: Privacy and data governance

Recommendation 18: Transparent presentation of anonymized tracking data ("Look, this is how the data is stored!").
Identified by: Tom
Recommendation Group: Data transparency - Group 9
Trustworthy AI key requirement: Transparency

Recommendation 19: Maximum anonymization of data to prevent misuse.
Identified by: Tom
Recommendation Group: Handling of sensitive data - Group 8
Trustworthy AI key requirement: Privacy and data governance

Recommendation 20: Possibly work with the data trustee?
Identified by: Anna
Recommendation Group: Involve a data trustee - Group 5
Trustworthy AI key requirement: Privacy and data governance

Recommendation 21: Project blog as a source of information.
Identified by: Anna
Recommendation Group: Transparent communication - Group 13
Trustworthy AI key requirement: Transparency

C.2 Recommendations from Workshop 2

Recommendation 22: Feedback mechanisms (for any situation).
Identified by: Sandra
Recommendation Group: Human in the loop - Group 1
Trustworthy AI key requirement: Human agency and oversight

Recommendation 23: Integrate feedback loops and feedback options for employees (if necessary, suggest options for the integration of further variables).
Identified by: Veronika
Recommendation Group: Human in the loop - Group 1
Trustworthy AI key requirement: Human agency and oversight

Recommendation 24: Create organizational structures where employees can go for issues or unethical observations/concerns.
Identified by: Sandra
Recommendation Group: Create trustworthy organizational structures-Group 15
Trustworthy AI key requirement: Diversity, non-discrimination and fairness

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Recommendation 25: Define change cycles, e.g., how often/quickly a system-driven adjustment to the work instruction occurs.
Identified by: Veronika
Recommendation Group: Limit the speed of change - Group 19
Trustworthy AI key requirement: Societal and environmental well-being

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Recommendation 26: A maximum number of changes to the process (to be determined) must not be exceeded.
Identified by: Yahel
Recommendation Group: Limit the speed of change - Group 19
Trustworthy AI key requirement: Societal and environmental well-being

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Recommendation 27: Fallback solutions for extreme situations.
Identified by: Thorsten
Recommendation Group: Ensure robustness of simulation - Group 3
Trustworthy AI key requirement: Technical robustness and safety

Recommendation 28: Co-creation of AI solutions instead of leaving the field to data scientists. This helps employee adoption.
Identified by: Sandra
Recommendation Group: Work interdisciplinary - Group 14
Trustworthy AI key requirement: Diversity, non-discrimination and fairness

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Recommendation 29: Interdisciplinary Teams.
Identified by: Sandra
Recommendation Group: Work interdisciplinary - Group 14
Trustworthy AI key requirement: Diversity, non-discrimination and fairness

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Recommendation 30: Self-affirmation of simulation feared at low autonomy level (self-fulfilling prophecy). A technical consideration is necessary.
Identified by: Sandra
newline **Recommendation Group:** Ensure robustness of simulation - Group 3
Trustworthy AI key requirement: Technical robustness and safety

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Recommendation 31: Ethics by Design (consider ethical aspects already in the design process).
Identified by: Sandra
Recommendation Group: Ethics by design - Group 17
Trustworthy AI key requirement: Societal and environmental well-being

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Recommendation 32: The on/off button on the marker explicitly allow employees to work without tracking at certain times. The data[4] could also be evaluated as an acceptance indicator (how willing employees are to use the marker because they see the added value).
Identified by: Sandra
Recommendation Group: Privacy by preference - Group 6
Trustworthy AI key requirement: Privacy and data governance

Recommendation 33: Is personal data allowed to exist at all?[5]
Identified by: Yahel
Recommendation Group: Handling of sensitive data - Group 8
Trustworthy AI key requirement: Privacy and data governance

Recommendation 34: Deliberate disclosure of information in order to receive personally tailored work instructions that are more compatible with one's preferences.
Identified by: Veronika
Recommendation Group: Privacy by preference - Group 6
Trustworthy AI key requirement: Privacy and data governance

[4]Author's note: Data refers to data on the use of the on/off button
[5]Author's note: This question is intended to explicitly address the question of what data may actually be collected.

Recommendation 35: Interaction possibilities between AI systems and user groups, e.g., shop floor, management, and others, should be detailed. Different levels: Who can have which influence on the system?
Identified by: Veronika
Recommendation Group: Data governance - Group 7
Trustworthy AI key requirement: Privacy and data governance

Recommendation 36: The data basis for changes must be visible to everyone.[6](data transparency law?)
Identified by: Yahel
Recommendation Group: Data transparency - Group 9
Trustworthy AI key requirement: Transparency

Recommendation 37: Explanation of decisions.
Identified by: Sandra
Recommendation Group: Ensure explainability of the AI system - Group 10
Trustworthy AI key requirement: Transparency

Recommendation 38: Data preparation: How can the data/information be prepared and presented by the AI system in a target group-specific way?
Identified by: Veronika
Recommendation Group: Data transparency - Group 9
Trustworthy AI key requirement: Transparency

C.3 Recommendations from Workshop 3

Recommendation 39: Instead of automatic decisions, the decision-makers (production planners and controllers, factory managers) are given recommendations from which to choose.
Identified by: Flemming
Recommendation Group: Develop a decision support system - Group2
Trustworthy AI key requirement: Human agency and oversight

Recommendation 40: The system should be a decision support system that supports people. The decision-making authority still lies with each person him or herself.
Identified by: Lynn
Recommendation Group: Develop a decision support system - Group2
Trustworthy AI key requirement: Human agency and oversight

Recommendation 41: Do not develop a system with purely automated decision-making; instead, develop a decision support system for people. Human oversight, especially in critical situations.
Identified by: Ute
Recommendation Group: Develop a decision support system - Group2
Trustworthy AI key requirement: Human agency and oversight

[6]Author's note: The data basis on which decisions are made that lead to changes.

Recommendation 42: Use of data trustees to protect personal data. This could also result in a new business model.
Identified by: Lynn
Recommendation Group: Involve a data trustee - Group 5
Trustworthy AI key requirement: Privacy and data governance

Recommendation 43: Develop a system with ethics and tech experts, lawyers, and best, together with workers.
Identified by: Ute
Recommendation Group: Work interdisciplinary - Group 14
Trustworthy AI key requirement: Diversity, non-discrimination and fairness

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Recommendation 44: There is a "right to explainability" in the General Data Protection Regulation (GDPR), which states that any data subject can obtain an "explanation" (whatever that means) when an automated decision is made about him/her.
Identified by: Charleen
Recommendation Group: Ensure explainability of automated decisions - Group 12
Trustworthy AI key requirement: Transparency

Recommendation 45: In the GDPR, there is also an obligation to conduct a data protection impact assessment for automated decisions, identifying and assessing all data processing risks. Performance evaluation and modeling would be such a case.
Identified by: Charleen
Recommendation Group: Ensure explainability of automated decisions - Group 12
Trustworthy AI key requirement: Transparency

Recommendation 46: The AI Act (not yet passed but in the works) would classify a product with AI used as a "security component" as high-risk and impose some requirements (risk assessment, etc.).
Identified by: Charleen
Recommendation Group: Risk assessment - Group 4
Trustworthy AI key requirement: Technical robustness and safety