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FACULTY OF ENGINEERING

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DOCTORAL THESIS

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Rijeka, 2026

SVEUČILIŠTE U RIJECI
TEHNIČKI FAKULTET

Elvis Krulčić

RAZVOJ METODOLOGIJE ZA INTEGRACIJU DIGITALNIH TEHNOLOGIJA U PROJEKTIRANJU PROIZVODNIH SUSTAVA

DOKTORSKI RAD

Rijeka, 2026.

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The doctoral thesis was defended on __________________ at the University of Rijeka, Faculty of Engineering, Croatia, in front of the following Evaluation Committee:

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3. Assoc. Prof. Nikola Gjeldum, PhD, University of Split, Faculty of Electrical Engineering, Mechanical Engineering and Naval Architecture

„ Any fool can know.

The point is to understand. “

Albert Einstein

Acknowledgements

I wish to express my sincere gratitude to all who contributed in any way to the completion of this doctoral thesis.

First and foremost, I thank my supervisor, Associate Professor Sandro Doboviček, PhD, for his expert guidance, valuable advice, patience, and continuous support throughout the research, preparation of this thesis, and completion of the doctoral study programme. His expertise, availability, and constructive feedback were crucial in shaping and finalising this doctoral thesis.

I extend special thanks to my co-supervisor, Associate Professor Simon Klančnik, PhD, for his insightful suggestions, critical comments, and many helpful discussions that significantly improved the quality of this work, as well as for his generous support during multiple research visits to the Faculty of Mechanical Engineering in Maribor, including organisational and professional assistance and access to the necessary research equipment during my stay and research activities at the faculty.

I am also grateful to Professor Duško Pavletić, PhD, for his support, constructive comments, and willingness to share his knowledge and experience, which further guided the course of my doctoral studies and enriched my research.

My sincere thanks go to the Faculty of Engineering, University of Rijeka, for its institutional support and stimulating research environment, as well as for the financial and organisational support without which this research would not have been possible.

I also thank the representatives and employees of the companies that participated in this research for their cooperation, time, and for providing the data necessary for the empirical part of the study. Their openness and practical insights were vital for the applicability of the results obtained.

I am grateful to my colleagues and collaborators for their support, encouraging discussions, joint work, and exchange of ideas throughout the doctoral study programme. I also thank the administrative staff for their assistance with the organisational aspects of my work and studies.

My deepest gratitude goes to my family. I thank my parents for their support, encouragement, and understanding throughout all the challenges of this journey. Above all, I wish to express my heartfelt gratitude to my wife, Sanja, for her patience, love, and unwavering support and encouragement, as well as to my sons, Luka and Aleks, for their inspiration and the additional motivation to persevere until the very end, without whose support this doctoral thesis would not have been possible.

Abstract

The dissertation develops a methodology for integrating digital technologies into manufacturing system design within the context of Industry 4.0 and Industry 5.0. It addresses the gap between high-level reference architectures and concepts and fragmented, technology-driven approaches in practice, particularly in small and medium-sized enterprises with limited digital maturity. The objective is to enable systematic optimisation of performance and key performance indicators already in the design phase, reducing the need for costly corrections after installation of the physical system. Based on an extensive literature review and the author’s industrial experience, a structured framework of thirteen manufacturing system design elements is defined, along with a 13×16 matrix linking these elements to selected digital technologies. A production system lifecycle model with seven phases is developed and connected to several perspectives and a meta-layer, while a two-layer key performance indicator framework combines core operational indicators with advanced, design-oriented indicators. Together, these contributions establish a concept of production system lifecycle management that integrates strategic thinking, digital models, performance management, and Industry 5.0 principles across the lifecycle. Empirical validation in four industrial companies uses expert questionnaires, a case study, an evidence-informed Delphi process, and a comparative analysis of design schedules for traditional and digitally based approaches. Results show that experts consider digital technologies crucial for achieving target indicators, and that advanced, design-oriented indicators are conceptually accepted but only partially embedded in existing measurement systems, indicating untapped potential. The case study and schedule comparison demonstrate that optimisation can be shifted from the operational to the virtual design phase and that systematic application of the proposed methodology can significantly shorten key design phases, with fewer iterations and physical prototypes. The dissertation thus offers an integrated conceptual and methodological framework for the use of digital technologies in manufacturing system design and demonstrates its potential to accelerate digital transformation and improve industrial performance.

Keywords: Digital transformation, Industry 4.0, Industry 5.0, Digital maturity, Manufacturing system design, Strategic thinking, Digital technologies, Production system lifecycle management

Prošireni sažetak

Disertacija se bavi razvojem metodologije za integraciju digitalnih tehnologija u projektiranje proizvodnih sustava u kontekstu Industrije 4.0 i Industrije 5.0. Polazi se od uočenog jaza između referentnih arhitektura i koncepata ovih industrijskih paradigmi te fragmentiranih, tehnološki vođenih pristupa u praksi, osobito u malim i srednjim poduzećima s ograničenom razinom digitalne zrelosti. Cilj disertacije je razvoj metodologije koja omogućuje da se optimizacija performansi i ključnih pokazatelja uspješnosti provodi već u fazi projektiranja, čime se smanjuje potreba za skupim korekcijama nakon instalacije fizičkog sustava i ubrzava proces digitalne transformacije. Na temelju opsežnog pregleda literature o industrijskim paradigmama, digitalnoj transformaciji i modelima digitalne zrelosti te višegodišnjeg iskustva autora u automobilskoj industriji definiran je strukturirani okvir od trinaest elemenata projektiranja proizvodnih sustava. Ti elementi obuhvaćaju cijeli spektar odluka – od zahtjeva, proizvoda i procesa, preko resursa, izgleda, logistike, kvalitete, održavanja te područja zdravlja, sigurnosti i okoliša, do učinkovitosti i digitalnih tehnologija. Razvijena je matrica dimenzija 13×16 koja pojedine elemente projektiranja proizvodnih sustava povezuje s reprezentativnim skupom digitalnih tehnologija te omogućuje identifikaciju dominantnih i potpornih rješenja u pojedinim fazama projektiranja. Matrica je koncipirana kao skup preporuka i smjernica utemeljenih na rezultatima istraživanja literature i dugogodišnjem iskustvu autora, uz jasnu mogućnost prilagodbe kako nove tehnologije ulaze u praksu a postojeće se razvijaju i proširuju područje primjene. Predložen je i novi model upravljanja životnim ciklusom proizvodnog sustava u sedam faza, povezan s različitim perspektivama i meta-slojem, kojim se uvodi koncept cjeloživotnog upravljanja proizvodnim sustavom usklađen s načelima Industrije 5.0. Posebno je naglašena uloga strateškog promišljanja i dinamičkih sposobnosti, pri čemu digitalne tehnologije podupiru faze prepoznavanja prilika, njihova zahvaćanja i transformacije kroz simulaciju više scenarija u virtualnom okruženju. Empirijska validacija predložene metodologije provedena je u četiri industrijska poduzeća kombinacijom ekspertnih upitnika, studije slučaja, Delfi postupka utemeljenog na dokazima i usporedne analize terminskih planova. Usporedba je obuhvatila tradicionalne pristupe projektiranju, s ograničenom primjenom digitalnih rješenja, i napredni pristup utemeljen na strukturiranoj i sustavnoj primjeni digitalnih tehnologija. U okviru studije slučaja primijenjen je digitalni model koji je omogućio detaljnu analizu izvedivosti ostvarivanja ciljanih pokazatelja uspješnosti te identifikaciju mogućih ograničenja u ranim fazama projektiranja. Usporedna analiza terminskih planova omogućila je procjenu utjecaja različitih razina digitalne integracije na organizaciju i tijek projektiranja. Konačno, Delfi analiza poslužila je za sustavno prikupljanje i sintezu stručnih mišljenja o ulozi simulacija, virtualne i proširene stvarnosti te umjetne inteligencije u donošenju odluka i planiranju sustava, uz razmatranje faktora digitalne zrelosti i aspekta usmjerenosti čovjeku.

Disertacija time donosi novi, cjelovit konceptualni i metodološki okvir za korištenje digitalnih tehnologija u projektiranju proizvodnih sustava te pokazuje njegov potencijal za ubrzanje digitalne transformacije i poboljšanje performansi u industrijskoj praksi, uz jasno naznačena ograničenja istraživanja i prijedloge za buduća empirijska i longitudinalna ispitivanja.

Ključne riječi: Digitalna transformacija, Industrija 4.0, Industrija 5.0, Digitalna zrelost, Projektiranje proizvodnog sustava, Strateško promišljanje, Digitalne tehnologije, Upravljanje životnim ciklusom proizvodnog sustava

Contents

Chapter 1

1. Introduction

In today's highly dynamic and uncertain global environment, constant cost pressures from competition require business systems to adopt various approaches, methods, and technologies to improve operations and secure a stable long-term market position. Continuous changes in a dynamic market demand a shift in industrial production towards smaller volumes and more personalised products [1]. The accelerated era of electrification in the automotive industry and other transport sectors is driving rapid changes in established organisational and operational models, while global crises such as the COVID-19 pandemic and the war in Ukraine have created new conditions for business and process organisation that must be adapted, accelerated, and reshaped to meet emerging global realities. One of the most significant processual changes occurring across society, and all its domains is digital transformation, which has become essential for securing long-term benefits such as the acceleration of information flows, activities, and processes. Industrial organisations must therefore also undertake digital transformation if they wish to maintain their competitive market position, by adapting their organisation, processes, and products.

1.1. Problem statement and research subject

The Fourth Industrial Revolution and the digitalisation of all business processes through digital transition have become imperative for industrial business systems advancing towards Industry 5.0 (I5.0) [2,3]. New methods and technologies are being developed to improve business processes in line with the principles of lean processes, zero waste, automation, and the informatization of processes to support faster decision-making [4,5]. These technologies can significantly assist in predicting the behaviour of production systems and reducing the time required for implementation and ramp-up of new systems, directly contributing to cost reduction and enhanced competitiveness. At the same time, each organisation must develop its own model for selecting and applying new technologies to accelerate digital transformation without neglecting the achievements of previous efforts to attain operational excellence through initiatives such as lean production and similar process improvement methodologies.

A major limitation of such methods is their restricted ability to influence the very definition of the production system concept in industrial business systems that have not yet reached the level of Industry 4.0 (I4.0). Achieving I4.0 requires substantial financial resources, the adoption of new knowledge and technologies, as well as organisational and business model changes, all of which take time. These preconditions can become decisive constraints on the speed of digital transformation, which is increasingly emerging as a fundamental factor for the long-term sustainability of any company. This raises the question of how companies with limited resources for digitalisation can accelerate specific phases of the digitalisation process [6]. Such resource constraints are particularly pronounced in small and medium-sized manufacturing companies (SMEs), where most investment is directed towards capital equipment for core operations. Given the longstanding lack of an appropriate methodology in industrial practice for the use of digital technologies in the design of production processes, this area becomes the author’s primary research focus.

1.2. Overview of previous research

The initial phase of the research focused on acquiring knowledge in the fields of I4.0 [7,8] and I5.0 [9,10]. This phase extended existing insights into trends in the use of new digital technologies within digital transition and included a review of the available literature, with particular focus on the possibilities of applying these technologies in industrial environments. Adapting business processes to digital transition is critical throughout the value chain, from product or service development to delivery or market launch. It is well known that the relative costs of product design changes increase severalfold depending on the product lifecycle phase in which the changes are made, as illustrated in Figure 1.1. These costs rise dramatically if design changes become necessary only once the product has reached the production phase [11]. The literature review did not yield comprehensive data on the costs of changes over the lifecycle of a production process, which can be attributed to the substantial diversity of production processes and the high rate of change during their lifecycle, driven by multiple causes. Key drivers of change may include product improvement, shifts in market and customer requirements, alignment with new management, quality or environmental standards, various improvement initiatives aimed at enhancing competitiveness such as green and digital transformation, as well as missed opportunities to define an optimal production system concept at the outset. Since every production process stems from the requirements of product realisation, it can be assumed that the costs of changes in the production process follow a similar pattern, with the important caveat that changes in product design and in the production system concept exert the greatest influence on costs over the product lifecycle. In any case, there is a strong imperative to achieve an optimal production process as early as possible in the lifecycle of the production process. Although the production process is continuously changing and adapting to new requirements and optimisation during its lifecycle, it is necessary to ensure conditions that avoid or minimise major changes in the production phase. Any optimisation identified and carried out in the earliest phase of the operational life of the production system yields multiple benefits, including higher customer satisfaction, lower costs and improved market competitiveness, which are key drivers of a company's competitive position.

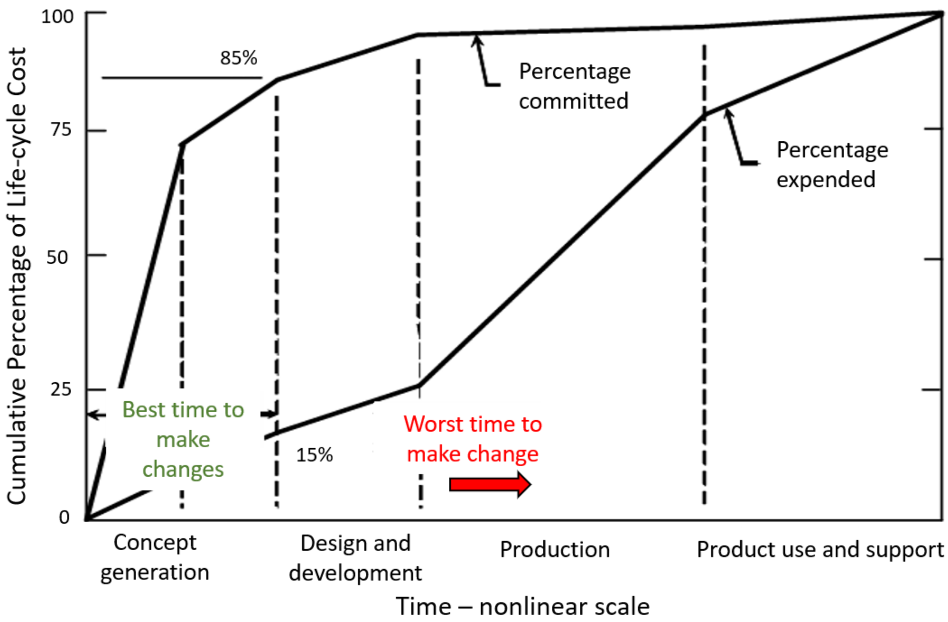


Figure 1.1: Cumulative lifecycle costs in phases of product realisation [11]

The subsequent direction of the research was shaped by the lack of suitable methods for determining the most appropriate configuration of the production system in terms of efficiency, reliability, and quality within digital transformation, using all available digital technologies. Existing studies highlight the absence of a comprehensive framework, set of guidelines, or methodology for integrating digital technologies into the design of production systems. Most research focuses on analysing individual technologies or their combinations, primarily in the production execution phase, while the application of digital technologies is mainly examined from a product perspective rather than from the perspective of the production process itself. Timely definition of the optimal production system concept before the start of production can prevent unnecessary subsequent costs related to changes arising from factors such as productivity, quality, availability, and economic efficiency [12]. The starting point of the proposed research is based on the author's many years of experience in the metal processing industry and an analysis of the possibilities for applying digital technologies in production systems. These insights confirm the need to define a methodology for the use of digital technologies in the design of production systems. This thesis therefore investigates the possibilities of integrating digital tools in the development phase of the production process, aiming to reduce the need for later adaptations during its lifecycle.

1.3. Research goals and hypotheses

Decisions that determine the final definition of the product and the manufacturing system used for its realisation directly affect product competitiveness. This research provides an overview of previous scientific studies on manufacturing system design (MSD) using digital technologies. The main research goal is to establish the preconditions for defining an optimal concept at the earliest possible stage of the production process lifecycle, forming the basis for the research objective. Due to the absence of a clearly defined methodology for the integrated use of digital technologies in MSD, a methodological gap exists between high-level reference architectures and fragmented, technology-centric implementations. To address this gap, the present research proposes the methodology and production system lifecycle management (PSLM) framework as a coherent, lifecycle-oriented approach for the use of digital technologies in MSD and related management processes within the context of I4.0 and I5.0.

The primary aim of the research is to develop a methodology for integrating digital technologies into MSD for I4.0 and I5.0, regardless of the initial industrial maturity level, as part of the digital transformation process. Based on the research conducted so far, the following scientific hypotheses for this doctoral thesis have been formulated:

H1 (Main research hypothesis): Applying the methodology for the integration of digital technologies (MIDIT) in the MSD process significantly accelerates digital transformation towards I5.0, resulting in improved measurable business performance.

H1a (Auxiliary hypothesis): By applying digital models, key performance indicators (KPIs) of the production system can be predicted already in the MSD phase.

H1b (Auxiliary hypothesis): The use of simulation modelling and Virtual/Augmented Reality (VR/AR) directly affects the speed and quality of MSD.

H1c (Auxiliary hypothesis): Integrating Artificial Intelligence (AI) into selected parts of MIDIT methodology accelerates analysis and supports the proposal of better-justified solutions.

In the following chapters, these hypotheses are examined using both perception-based and measurement-based evidence. While H1c refers to “optimal solutions” at the conceptual level, the empirical analyses focus primarily on better-justified and more transparently justified decisions, rather than strictly mathematically optimal outcomes. Similarly, the examination of H1b distinguishes between effects on decision quality and effects on speed, acknowledging that time improvements depend on organisational and data-related conditions.

1.4. Research methodology

The research methodology is designed to systematically develop, structure, and empirically examine the MIDIT methodology and to test the associated research hypotheses. It is organised into a sequence of phases progressing from conceptual grounding, through methodological development, to empirical examination of the main and auxiliary hypotheses.

In the first phase, a comprehensive review of relevant scientific and professional literature is conducted to establish the theoretical and methodological foundations of the research. This phase identifies the state of the art in I4.0 and I5.0 technologies, existing approaches to MSD, and current gaps related to the integrated use of digital technologies in this context. The insights obtained are used to formulate the overall research problem, refine the research questions, and define the main and auxiliary hypotheses that guide the remainder of the study.

In the second phase, a conceptual framework for the methodology is developed. Based on literature findings and prior industrial experience, the MSD/PSLM perspective on the manufacturing system lifecycle is combined with a structured view of the MSD process to define a set of core MSD steps and corresponding decision points. For each step, the potential roles of selected digital technologies are conceptually mapped, resulting in a preliminary framework and an associated matrix structure linking MSD steps and digital technologies. At this stage, the emphasis is on defining the logical structure and scope of the methodology rather than its full operational detail.

The third phase focuses on formalising the MIDIT methodology as an operational decision-support approach. Building on the conceptual framework, this phase specifies the sequence of MSD steps, their inputs and outputs, and the associated digital tools and models to be used in each step. In addition, the methodology is extended to incorporate a strategic dimension, the assessment of digital maturity, and a multi-criteria decision-making logic that connects strategic priorities with the selection and configuration of digital technologies. The outcome of this phase is a structured methodological concept that can be implemented and subjected to empirical examination.

In the following phases, the methodology is examined with respect to the hypotheses defined in the introductory part of the thesis. For this purpose, appropriate empirical and analytical procedures are designed, including the use of modelling and simulation, case-based applications in industrial settings, and the exploration of advanced digital technologies such as VR/AR and AI where relevant. These procedures are planned and structured to generate evidence related to different aspects of validity: the conceptual soundness of the methodology, its operational applicability in realistic industrial contexts, and its potential causal impact on key performance indicators of the manufacturing system. The detailed design and execution of these empirical procedures, as well as their linkage to the main and auxiliary hypotheses, are presented in Chapter 5.

During the research, the existing equipment and software packages available in the CIM laboratory at the Faculty of Engineering, University of Rijeka, were primarily used, while the equipment and software at the Faculty of Mechanical Engineering, University of Maribor, were used to a lesser extent. In conducting the research and testing the hypotheses, the following scientific methods are used: induction and deduction, analysis and synthesis, process approach theory, statistical methods, empirical methods, multi-criteria decision-making methods, and simulation modelling in analysing the applied concept.

The value of this research lies in presenting the MIDIT methodology as a novel, integrated approach to manufacturing system design within the context of digital transformation. The methodological contribution is demonstrated by systematically combining the MSD/PSLM lifecycle perspective on manufacturing systems with a clearly defined set of MSD steps, matrix-based linking of these steps with digital technologies, and the integration of a strategic dimension, digital maturity assessment, and multi-criteria decision-making into a single, coherent framework. The originality of the approach is further demonstrated by the conceptual and empirical validation of the methodology through various forms of evidence, including conceptual acceptability, operational applicability, and potential causal effectiveness. The practical contribution of the thesis is to provide concrete, operational support to industrial organisations for planning and implementing the digital transformation of manufacturing systems, through a structured set of steps, tools, and decision points that can be adapted to different levels of industrial maturity.

1.5. Expected scientific contribution of the research

This dissertation introduces the MIDIT methodology, which provides clear frameworks and guidelines for more detailed scientific investigations into the application of individual digital technologies within the MSD process, regardless of an organisation's current level of industrial maturity. Another contribution is the establishment of a framework for future enhancement of the model through the integration of newer generations of digital technologies, such as AI, AE, and AR/VR, across the entire lifecycle of the product and its associated process.

While existing research predominantly addresses only specific segments of digital technology deployment in MSD, and frameworks such as PSLM mainly provide a general conceptual foundation for production systems, MIDIT consolidates these fragmented contributions into a single, coherent, and operational methodology. The methodology explicitly integrates considerations of digital maturity and strategic orientation with a more detailed, MSD-oriented interpretation of the PSLM framework and a systematic mapping of digital technologies onto the 13 steps of the MSD process using the 13x16 MIDIT matrix. Additionally, the MIDIT approach specifies an operational workflow diagram that integrates a two-level KPI framework within a combined validation approach. In this way, this dissertation makes a distinct scientific contribution compared with existing models, which rarely integrate these dimensions into a comprehensive, practically applicable decision-support tool for industrial practice.

1.6. Application of the research results

Applying the proposed methodology to production system design is expected to improve the design process, notably by reducing the total time required, increasing the quality and robustness of the production system, and consequently lowering production costs and enhancing competitiveness.

Integrating digital tools into the design process encourages the use of digital technologies in operations research for application in complex industries that face constant change due to evolving customer requirements. The proposed MIDIT methodology for integrating digital tools into production system design does not require a specific minimum level of digital maturity; it can be used partially within selected organisational processes along the digital transformation pathway, from the lowest levels up to defined target industrial maturity levels.

1.7. Structure of the thesis

The thesis is organised into six interrelated chapters. Chapter 1 introduces the research subject, formulates the main and auxiliary research hypotheses, and outlines the research aim. It also presents the research design and methodology, the expected scientific contribution, and the overall structure of the thesis.

Chapter 2 establishes the conceptual and contextual background by discussing industrial paradigms. It analyses the current state of industrial production from the perspective of digitalisation and examines prevailing trends in manufacturing, providing guidelines for the further development of industrial companies towards I4.0 and I5.0. In this thesis, these terms and abbreviations are used consistently for brevity. The chapter also presents fundamental information on I4.0 and I5.0 based on a review of the relevant literature, including enabling technologies, core design principles, and their human-centric, sustainable, and resilient orientations.

Chapter 3 focuses on digital transformation. It first clarifies fundamental concepts and distinctions between related terms, as a prerequisite for an appropriate and consistent approach to introducing digital transformation. It then discusses key digital dimensions, indices, and digital maturity models, and draws conclusions on the applicability of digital maturity models in industrial companies.

Chapter 4, the central part of the thesis, presents the development of the MIDIT methodology. It begins with an overview of digital technologies associated with I4.0 and I5.0, and summarises key insights regarding the core triad of these paradigms: the smart factory, cyber-physical systems, and the digital thread. This overview is followed by the results of an in-depth investigation into the application of digital technologies in industry and MSD. The second part of Chapter 4 addresses the MSD process in I4.0 and I5.0, starting with the importance of embedding strategic perspectives and objectives at the outset of system design. It introduces the concepts of strategic planning and strategic thinking, clarifies their differences and preventive influence on MSD, and provides a detailed review of MSD elements with examples illustrating the use of digital technologies. The findings on the application of digital technologies to individual design elements are synthesised in a design-element/digital-technology matrix. Based on this synthesis, the PSLM MIDIT methodological framework is defined as a seven-phase structure that serves as a matrix for mapping key decision areas and the role of digital technologies in each phase of production system lifecycle management (PSLM). Further development of this concept results in the final form of the MIDIT framework, which specifies all phases and links them to the FSBCIP perspectives, integrates digital enablers through the TMPE layer, and incorporates explicitly defined design principles for MSD in the context of I4.0 and I5.0. The main activities and typical decisions in each PSLM phase are outlined, and the chapter concludes with a flow diagram for implementing the methodology for integrating digital technologies into MSD.

Chapter 5 presents the empirical validation of the MIDIT methodology in industrial practice. It examines how MSD and digital transformation experts evaluate the proposed KPI framework, assesses the influence of specific digital technologies on KPI expectations, and applies an evidence-informed Delphi approach to the use of VR/AR and AI in selected MIDIT phases. The chapter also compares a traditional MSD workflow (Plan T) with a MIDIT-based workflow (Plan D) to evaluate the effects of systematic digital technology integration on design duration, decision quality, and manufacturing system performance outcomes.

Chapter 6 provides the concluding synthesis of the thesis. It offers a brief retrospective of the overall research process and its main results, evaluates the confirmation or rejection of the main and auxiliary hypotheses, and highlights the scientific and practical contributions of the MIDIT methodology. The chapter also discusses the limitations of the research, outlines recommendations for the use of the methodology in industrial practice, and identifies promising directions for future research on MSD in the context of I4.0 and I5.0.

Chapter 2

2. Conceptual foundations

2.1. Industrial paradigms

Globalisation has created a new environment for the manufacturing industry, characterised by intense competition, shorter product lifecycles, and rapidly changing demand. These conditions require flexible manufacturing systems (FMS) that can quickly adapt in both production structure and volume. Manufacturing remains a cornerstone of economic development in advanced economies, as a strong industrial base generates multiplier effects across other sectors and contributes to long-term technological progress and employment.

Globalisation has also deepened the interdependence among products, manufacturing systems, and business models, making competitiveness increasingly reliant on the ability to optimise them in an integrated way. Early involvement of marketing, design, and production functions in product development enables alignment of specifications, pricing, and production planning, reducing time to market. At the same time, reconfigurable systems support rapid adjustments in product range. Failure in any of these components can jeopardise the sustainability of a business model, which is why contemporary manufacturing development models aim for global positioning, local product customisation, efficient supply chains, and close integration of the product, manufacturing system, and business model (Figure 2.1) [13].

Over the past two centuries, the manufacturing industry has evolved through a series of revolutionary industrial paradigms developed in response to changing market and societal demands, driven by innovations in technology, organisation, and business models. A manufacturing paradigm is an integrated model that connects the manufacturing system, product architecture, and business model into a coherent whole, aligned with prevailing environmental requirements. The evolution of manufacturing is typically described through four key paradigms: craft production, mass production, mass customisation, and global manufacturing. Craft production focused on individual customer needs with a high degree of customisation. Mass production introduced standardisation and significantly reduced costs.

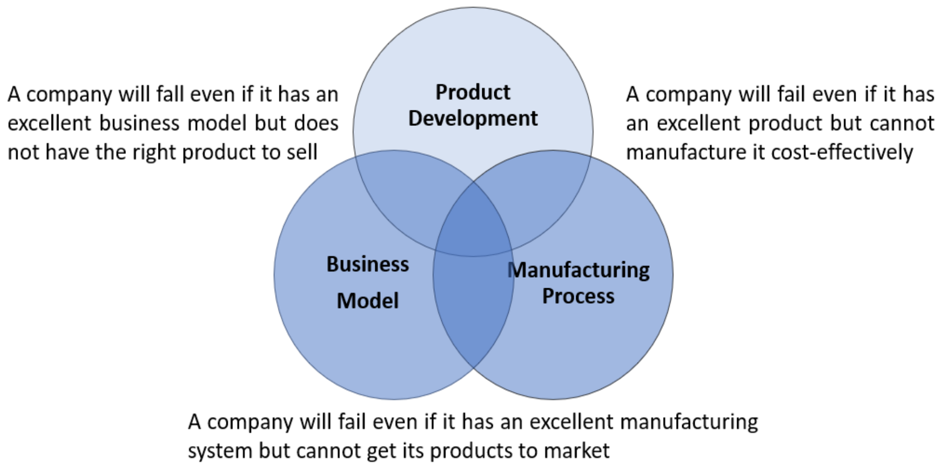


Figure 2.1: Integration of product, manufacturing process, and business model [13]

Mass customisation combined the efficiency of mass production with opportunities for personalisation. Global manufacturing integrates regional and personalised approaches with global supply chains to achieve maximum flexibility and innovation [13].

In the past decade, the manufacturing industry has entered a new phase in which traditional paradigms are being enhanced through intensive digitalisation, the emergence of advanced technologies, increasing sustainability demands, and shifts in workforce composition (Figure 2.2).

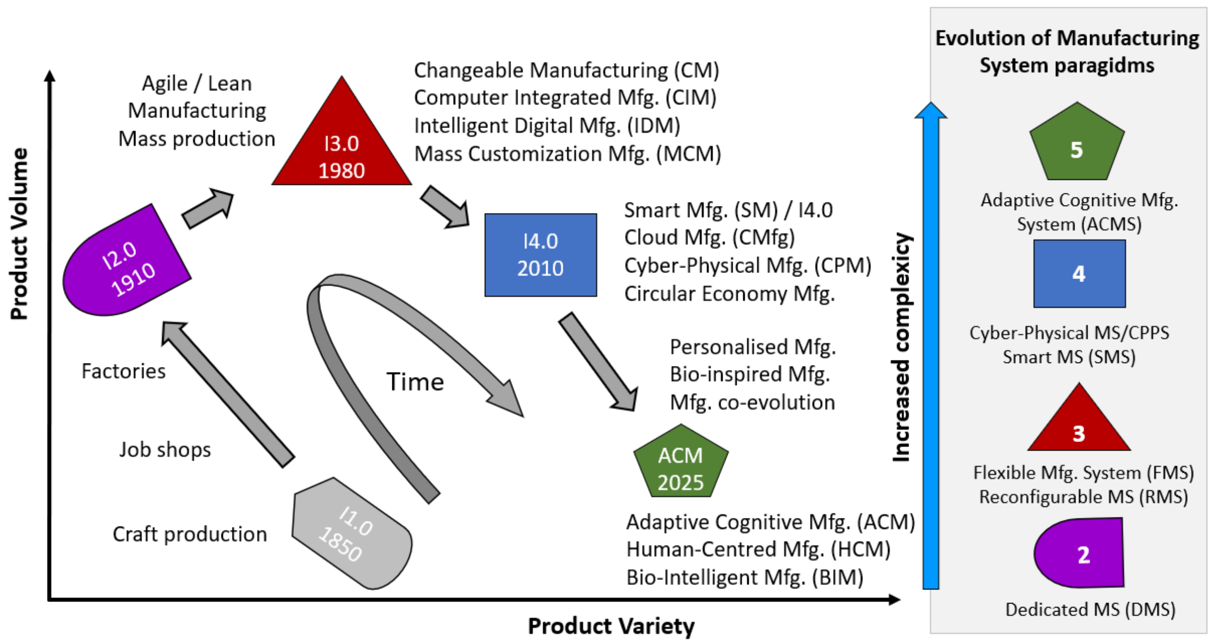


Figure 2.2: Manufacturing and manufacturing system paradigms [14]

This transformation is redefining how manufacturing processes are designed, organised, and executed, laying the foundation for future strategies that incorporate digital transition, green technologies, and human-centred approaches [15].

In this context, the concepts of I4.0 and I5.0 have emerged as contemporary industrial paradigms. Their technological, organisational, and societal implications are examined in greater detail in the following subsections [16].

2.1.1. Current state of industrial manufacturing

Pervasive digitalisation and automation, aligned with I4.0 principles, are driving the integration of digital technologies across almost all areas of manufacturing. Smart factories employ advanced sensors, interconnected devices, and computing systems to monitor and optimise processes in real time. The Internet of Things (IoT) enables the interconnection of machines and systems, while artificial intelligence (AI) and big data analytics support decision-making to enhance efficiency and reduce waste. Collaborative robots (cobots) work alongside humans, performing repetitive or hazardous tasks, thereby increasing productivity and safety, and facilitating the implementation of predictive maintenance, which reduces unplanned downtime and improves equipment reliability. Additive manufacturing (AM) technologies further accelerate prototyping, support product customisation, and reduce material waste, contributing to greater flexibility and manufacturing sustainability [17].

However, increased connectivity and intensive data exchange simultaneously heighten exposure to cyber threats. Consequently, manufacturing companies must systematically invest in cybersecurity measures, including encryption, advanced authentication methods, and, increasingly, blockchain solutions to safeguard data integrity and traceability. At the same time, strong regulatory and consumer pressure to reduce environmental impact encourages the adoption of sustainable manufacturing and circular economy concepts. This includes optimising resource use, reducing CO_2 emissions, and integrating renewable energy sources into manufacturing systems [18].

Operational excellence techniques, such as Lean Manufacturing and Six Sigma, remain critical for improving efficiency, quality, and productivity. In contemporary approaches, they are increasingly combined with I4.0 digital technologies to create data-driven, agile, and robust production systems [19].

Collectively, these technologies and methods define the current landscape of industrial manufacturing and form the foundation for understanding future trends and the ongoing evolution of industrial paradigms.

2.1.2. Trends in industrial manufacturing

Transformations in industrial manufacturing over the past decade have profoundly affected the labour market, as automation and digitalisation reshape required competencies. There is growing demand for expertise in programming, data analysis, and automated systems management, accompanied by a decline in routine occupations. These processes substantially increase efficiency and productivity but also require continuous education and workforce reskilling to mitigate the risks of structural unemployment and ensure adaptability to new technological demands [17].

Broader socioeconomic processes also influence manufacturing trends. Globalisation has expanded markets but increased the vulnerability of manufacturing systems to disruptions caused by pandemics, geopolitical conflicts, and supply chain volatility [18]. Companies are therefore compelled to revise procurement, production, and distribution strategies, diversify supply sources, and invest in the resilience and regionalisation of manufacturing. Although technological advancements and the rise of smart technologies require significant investment in infrastructure and employee training, they also enable process optimisation and cost reduction. Growing consumer awareness of environmental issues further intensifies pressure to adopt sustainable practices that minimise ecological impact and enhance corporate reputation [18].

From a technological perspective, the ongoing development of AI and automation is expected to enable companies to increase productivity and reduce operational costs through predictive maintenance, advanced quality control, and supply chain optimisation [16]. Autonomous and collaborative robots (cobots) are expected to become key drivers of manufacturing efficiency, especially in tasks requiring precision, safety, and flexibility. The I5.0 concept places greater emphasis on ergonomics and human factors in workplace design, using digital tools to enable biomechanically informed adaptation of working conditions to employees' needs [20]. The digital twin concept allows real-time simulation and optimisation of production processes, with smart factories — based on advanced sensors, IoT technologies, and AI systems — gradually becoming an industry standard [21]. These technologies provide deeper data insights, reduce failures, and enhance operational efficiency, laying the foundations for self-optimising production systems capable of dynamically adapting to changing demand and working conditions.

At the same time, the future of industrial manufacturing is strongly oriented towards sustainability. Increased adoption of renewable energy sources, material recycling, and carbon footprint reduction strategies is expected, while regulatory frameworks and consumer pressure further encourage the implementation of environmentally responsible practices and the integration of circular economy principles into industrial strategies [18].

2.2. Production paradigms

Over the past decade, industrial manufacturing has experienced significant digitalisation, automation, and a transition towards sustainable business models, resulting in a shift in production paradigms and the development of smart manufacturing (SM) systems (Figure 2.3). Rapid technological development is transforming managerial paradigms and business models, enabling the collection and analysis of customer-related data, which has become a key source of competitive advantage [22]. In this environment, companies are increasingly pursuing a high degree of product personalisation, involving customers in the design, production, distribution, and assembly phases.

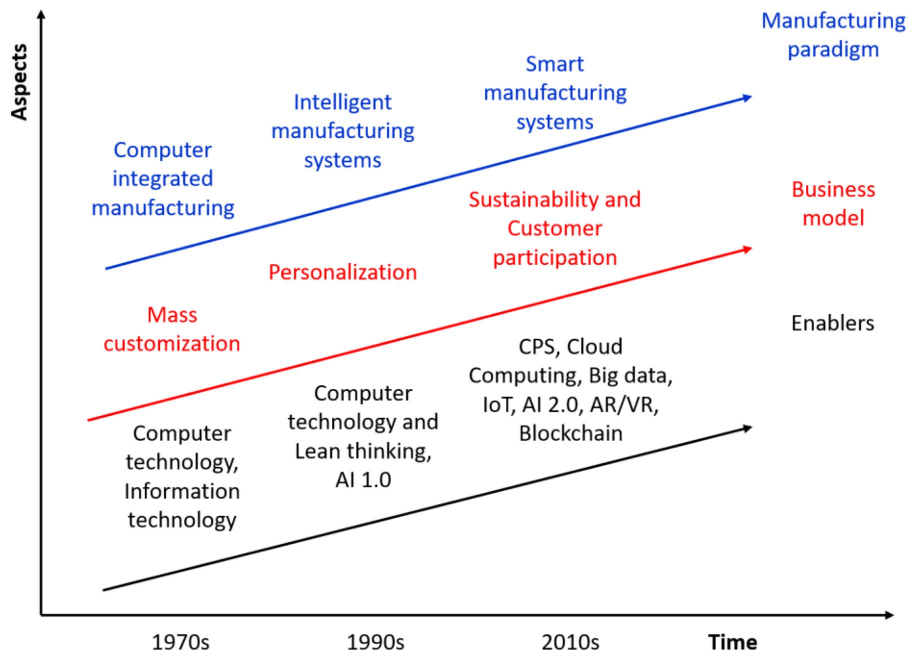


Figure 2.3: The evolution of smart manufacturing systems [22]

Standardised customisation allows product features to be adapted to specific user requirements. At the same time, there is a growing shift from selling standalone products to delivering integrated Product–Service Systems. These systems generate additional value, enhance customer interaction, and support more efficient resource use and collaboration within networked ecosystems. In this context, Business Model 4.0 is emerging as a configuration of a company's technical and social architecture, built on flexible digital processes that enable the creation of cyber-physical collaboration networks (CPSCN) capable of meeting demand for personalised products and complementary services [23]. Business Model 4.0 draws on the megatrends of the Fourth Industrial Revolution (Economy 4.0, smart factories, Society 5.0, sustainable production and consumption) and the core pillars of I4.0, creating value through their application and enabling its monetisation, thus representing an innovative approach to business.

The use of analytical techniques associated with the Big Data concept – such as data mining, visualisation, machine learning (ML), optimisation methods, and social network analysis – increases the operational functionality of processes, while the variety, velocity, volume, veracity, and value of data become key determinants in shaping Business Model 4.0. The impact of I4.0 pillars on value creation is systematised in Table A1 (Appendix A).

The key competitive advantage of Business Model 4.0 is its ability to deliver highly personalised products at costs close to those of mass production, strongly relying on data, innovation, and networked collaboration throughout the entire value chain [23]. While I4.0 drives technological progress through connected systems, the IoT, and AI the I5.0 concept builds on these foundations by focusing on people and sustainability, emphasising ergonomics, quality of the work environment, and social responsibility [17]. Trends such as lean manufacturing and environmentally responsible strategies further enhance efficiency and competitiveness, especially when combined with I4.0 digital tools [19].

Future developments are oriented towards further advancement of AI, smart factories, and sustainable production models, with an emphasis on dynamic optimisation and collaboration between systems at different levels, and on the development of autonomous, adaptive, and self-optimising platforms based on key performance indicators (KPI), ML, and multi-layer architectures [22]. In this process, particular importance is attached to an integrated view of the system – from sensors to strategic business decisions – and to the combination of model-based and data-driven approaches, as well as the standardisation and collaboration of all stakeholders as prerequisites for the next phase of intelligent manufacturing and the continued digital transformation of industry [17].

2.2.1. Industry 4.0

The I4.0 paradigm represents a fundamental transformation of production systems, driven by the digitalisation of business processes. The core characteristic of I4.0 is the fusion of the physical and virtual worlds through cyber-physical systems (CPS), marking the first industrial revolution to be defined and planned a priori rather than analysed exclusively ex post [24].

Since its formal introduction in 2011, I4.0 has evolved from a conceptual vision into a clearly structured technological framework: the Reference Architecture Model Industrie 4.0 (RAMI 4.0), which comprises nine technological pillars and specific implementation principles [25]. RAMI 4.0, registered as standard DIN SPEC 91345, is a three-dimensional reference model for the structured implementation of I4.0 technologies (Figure 2.4). It describes three dimensions: the product lifecycle, hierarchical organisational levels, and functional digitalisation layers.

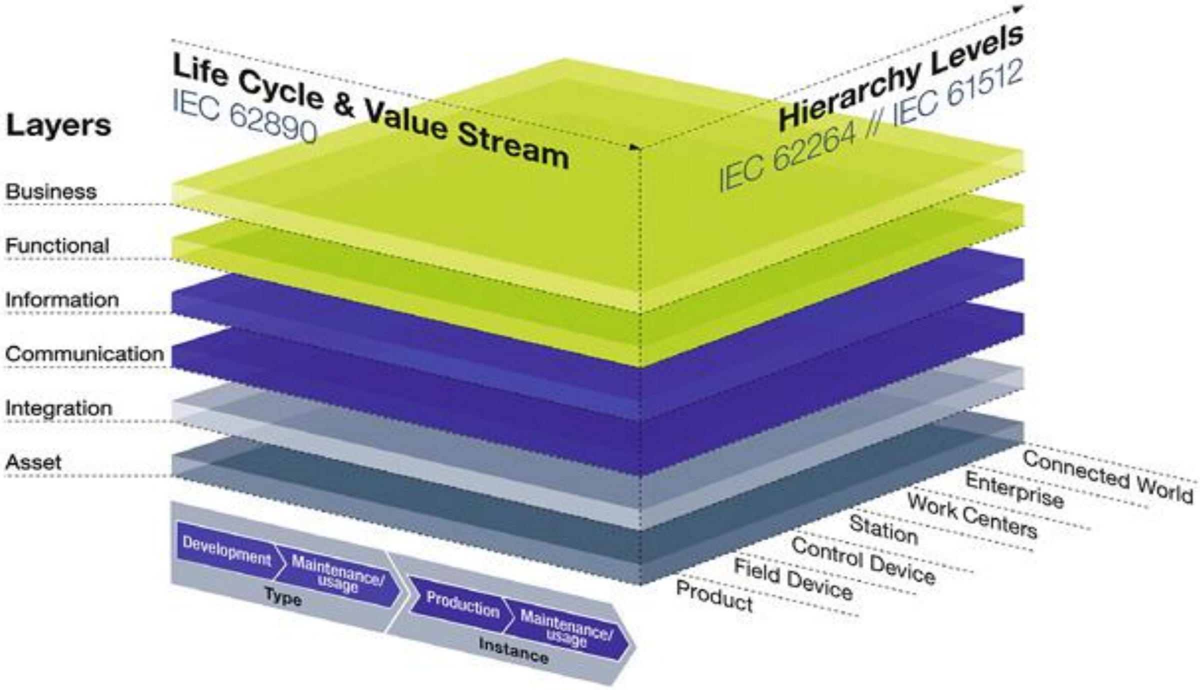


Figure 2.4: Reference model RAMI 4.0 [25]

The structure of each functional layer is shown in Table 2.1.

Table 2.1: Functional layers according to the RAMI 4.0 model [26]:

Layer	Function
Asset Layer	Physical components (robots, PLCs, metal parts, documents)
Integration Layer	Data acquisition and digitalisation (sensors, RFID readers, HMIs)
Communication Layer	Standardisation of communication and data formats
Information Layer	Processing and integration of data into useful information
Functional Layer	Formalisation of functions and business procedures
Business Layer	Mapping of the business model and value chain integrity

Hermann et al. identify four key components of Industry 4.0:

- CPS – integration of computational processes with physical elements, where embedded computers monitor and control physical processes
- IoT – enabling communication between objects, such as RFID tags and sensors, to achieve shared objectives
- Smart Factory – a factory in which CPS communicate via IoT and support humans and machines in performing tasks
- Internet of Services (IoS) – provision of services via the internet, where providers make their services available digitally.

Based on these components, six design principles for the implementation of I4.0 have been proposed (Table 2.2). These principles provide a conceptual framework for designing and implementing I4.0 solutions in manufacturing systems.

Table 2.2: Design principles for implementing Industry 4.0 [24]

	Principle	**Description**
1	Interoperability	Connection of CPS and humans via IoT and Internet of Services
2	Virtualisation	Linking sensor data with virtual models
3	Decentralisation	Ability of CPS to make autonomous decisions
4	Real-time capability	Immediate availability and processing of information
5	Service orientation	Availability of services via the internet
6	Modularity	Flexible adaptation to changing requirements

Alcácer and Cruz-Machado identify three types of integration within the RAMI 4.0 model [26]: horizontal integration (linking companies via digital platforms and supply chain collaboration), vertical integration (linking all levels within an organisation, from machines and production through Manufacturing Execution System (MES)/Enterprise Resource Planning (ERP) systems to management), and end-to-end integration (linking design, production, logistics, and distribution across the entire product lifecycle).

Empirical research on a sample of 92 manufacturing companies indicates a dual structure of I4.0 technologies, organised into two layers [27].

- First layer – front-end technologies: Smart Manufacturing (as the central element), Smart Products, Smart Supply Chain, and Smart Working.
- Second layer – enabling technologies: IoT, cloud services, Big Data, and analytics.

These technologies function complementarily rather than as substitutes; companies achieving higher levels of I4.0 maturity systematically implement most technologies from both layers. Smart manufacturing comprises six key functions, presented in Table 2.3.

Table 2.3: Six functions of Smart Manufacturing [27]:

Function	**Description**
Vertical integration	Advanced ICT systems integrating all levels (PLC, SCADA, MES, ERP)
Virtualisation	Digital process simulation, virtual commissioning, and digital manufacturing
Automation	Robots and AI for predictive maintenance and non-conformity detection
Traceability	Identification of raw materials and products (internal and external traceability)
Flexibility	Additive manufacturing, flexible and autonomous lines, modular machines
Energy management	Monitoring and optimisation of energy efficiency

Successful implementation of I4.0, particularly in SMEs, requires a balanced approach encompassing [28]:

- Technological aspects – selection and integration of appropriate technologies
- Organisational factors – innovation culture and change management
- Financial capabilities – access to capital and assessment of return on investment (ROI)
- Human resources – development of digital competences and talent management
- Strategic support – public policies and collaboration with educational institutions

A tertiary review of the literature indicates that, despite a strong theoretical foundation, there remains a lack of empirical evidence on the measurable effects of I4.0 implementation on enterprise performance, representing an important direction for future research [29]. Future development of I4.0 should focus on integrating model-driven manufacturing with practice, deepening human–machine collaboration and applying these concepts at the level of entire companies and industrial ecosystems.

2.2.2. Industry 5.0

Industry 4.0 emphasises automation, connectivity and digitalisation of production, whereas I5.0 introduces an explicit focus on human–machine collaboration and the integration of human creativity with AI [30].

Crnjac Zizic et al. highlight that I5.0 is a “social and value-oriented enhancement of I4.0, in which technology becomes a tool for societal well-being rather than solely for productivity”, and that it should be understood as an evolutionary phase integrating digital technologies with humanistic values rather than replacing them [31].

I5.0 constitutes a new production paradigm that builds upon I4.0 by embedding a human-centric, sustainable and resilient approach. According to the European Commission, it is based on three fundamental pillars [32]:

1. **Human-centricity** – technology must serve people and enhance their well-being.
2. **Sustainability** – industry must respect environmental boundaries and support the circular economy.
3. **Resilience** – industrial systems must be capable of adaptation and recovery during crises.

A recent report by the European Commission further elaborates this framework by orienting research and innovation policy towards a human-centric industrial transition and by defining concrete technological and societal objectives for the period 2025–2035 [33].

According to Leng et al., Bazel et al., and the European Commission, the transformation towards I5.0 is enabled by a set of technological domains [33–35]:

- Collaborative robotics (cobotics) – robots that safely work alongside humans, increasing productivity and flexibility
- Digital twins – virtual models that enable predictive control and real-time simulations
- Artificial intelligence and data analytics – intelligent decision-making, failure prediction, and process optimisation
- IoT and edge computing – distributed processing and rapid real-time data transmission
- Additive manufacturing (3D printing) – flexible and personalised production.
- Blockchain technology – transparency, traceability, and trust among stakeholders
- Extended reality (VR, AR, and MR) – interactive training and operator support.
- 6G and future networks – ultra-low latency and intelligent connectivity for industrial systems.

Together, these technologies create a co-adaptive human–machine environment that enables personalised and sustainable production. Implementing I5.0 leads to outcomes such as increased product personalisation and opportunities for employee creativity, improved workplace safety and ergonomics, adoption of circular approaches to waste and energy reduction, enhanced resilience of supply chains and industrial systems to disruptions, and strengthened social responsibility and inclusiveness [34].

Despite favourable technological preconditions, I5.0 faces numerous challenges in integrating its elements into existing organisational systems. Research identifies several barriers limiting the adoption of I5.0 [31,33,35]:

- Security and privacy – increased vulnerability of connected systems requires new encryption and authentication mechanisms
- Standardisation and interoperability – the need for global frameworks and data standards
- Human-robot collaboration (HRC) – requires advanced sensing, understanding of human intent, and ethical guidelines for interaction
- Skills gap – workforce transformation and development of the "Operator 5.0" profile
- Organisational resilience and empirical validation of benefits – limited real-world case studies with quantified results
- Ethical issues – responsibility and transparency of AI in industrial decision-making

To overcome these challenges, appropriate preconditions for I5.0 implementation must be ensured [31,35]:

- Strategic orientation – integration of sustainability and human-centric goals into corporate policies

- Competences and education – interdisciplinary skills in AI, data science, ergonomics, and robotics
- Security-ethical infrastructure – standards for privacy, reliability, and cybersecurity
- Pilot projects and living labs – iterative testing of solutions with active operator participation
- Collaborative ecosystem – strong links between industry, academia, and regulatory bodies

I4.0 and I5.0 can be regarded as two sequential yet complementary steps along the pathway of industrial digital transformation: the former focuses on technological connectivity, automation, and data-driven optimisation, while the latter integrates these technologies with human-centric, sustainable, and resilient development (Figure 2.5) [17,31].

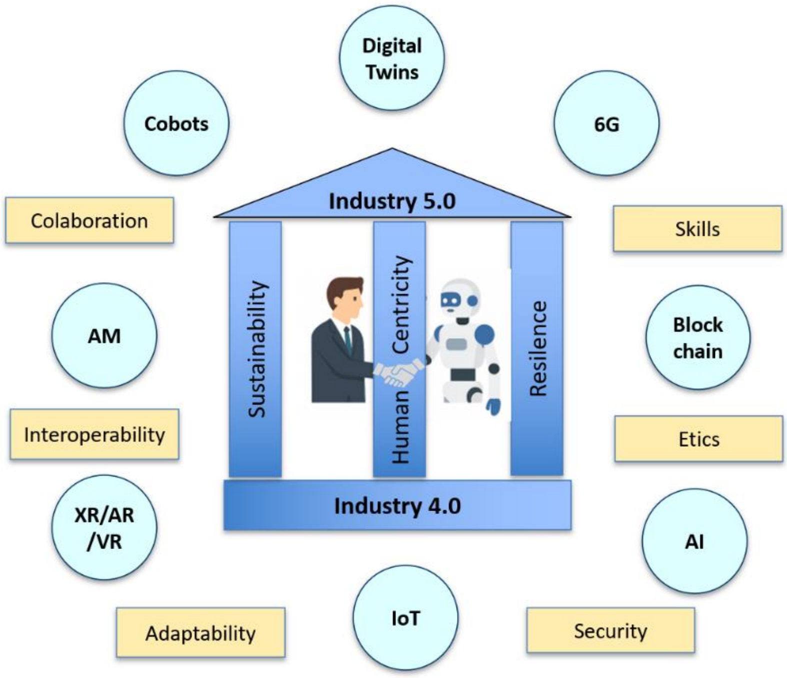


Figure 2.5: Industrial paradigms – Industry 5.0

The following chapter focuses on the concept of digital transformation as a strategic process connecting technological, organisational, and societal dimensions with the level of digital maturity of industrial organisations.

Chapter 3

3. Digital transformation

Digitalisation and digital transformation of business are key processes for the long-term development of the economy and society, and must therefore be approached in a strategic, systematic, and comprehensive manner [36]. Through the intelligent and purposefully targeted application of digital technologies, new business models can be developed and additional value created for the organisation and its stakeholders. Successful digital transformation requires detailed analysis of existing approaches, organisational models, and ways of working, followed by their adaptation to the digital environment [37]. In these circumstances, it is necessary to establish an appropriate governance structure that enables effective use of digital technologies. A conceptual framework is therefore required, one that encompasses key strategic and operational issues, provides an adequate level of security, and supports a systematic and iterative approach to transformation initiatives, particularly when developing an approach tailored to the specific characteristics of an individual company. Such a framework cannot be applied universally to all organisations, as the industrial sector, size, and age of the company, as well as the current level of engagement in digitalisation and digital transformation, largely determine which tasks must be prioritised.

The Three Layer Digital Transformation Framework (3LDT) represents a high-level, company-wide approach to understanding digital transformation. Developed in recent years through collaboration between academic and industrial partners, it adopts a holistic perspective in which digital innovations are the central driver of transformation. As illustrated in Figure 3.1, the framework examines how such innovations influence value creation, organisational structures, and governance mechanisms.

The first layer focuses on changes in value creation enabled by the development and implementation of digital innovations, which allow products, processes, and business models to evolve. However, these developments can only occur when the prerequisites defined in the second layer are in place. These include organisational structures and processes that support innovation, as well as a culture that encourages learning, experimentation, and long-term capability building. Such a culture cannot be established through a single digitalisation initiative; it emerges gradually over time.

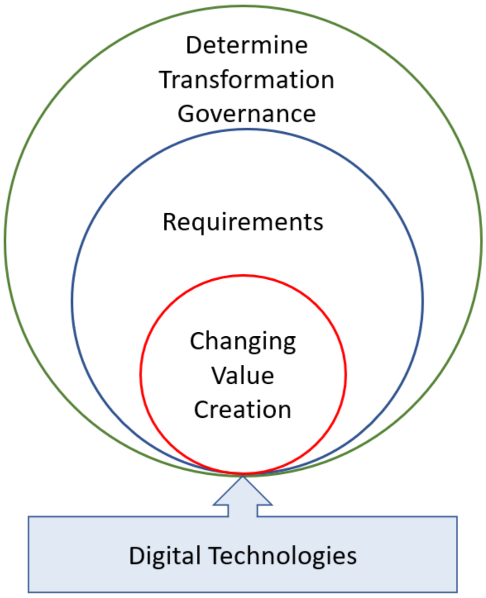


Figure 3.1: Three-layer model of digital transformation - 3LDT framework [36]

Successful implementation and integration of digital innovations therefore depend on a clearly defined transformation governance structure, within which the transformation strategy plays a central role. This strategy sets priorities, considers financial and technological constraints, and aligns the corporate strategy with other strategic guidelines. It must also be distinguished from the IT strategy, which focuses specifically on information and communication technologies. The establishment of a governance structure that integrates these elements and ensures coherence between transformation initiatives and the broader corporate strategy constitutes the third layer of the 3LDT framework.

3.1. Conceptual foundations of digital transformation

Digital transformation is one of the most frequently cited concepts in contemporary business; however, before implementing it, it is essential to have a clear understanding of its meaning, scope, and potential benefits to fully exploit the opportunities that digital technologies offer business systems. Digital transformation and the innovations arising from it reshape organisations, institutions, and society more broadly. At the organisational level, digitalisation triggers disruptive changes within companies and their immediate business environment, accelerating the obsolescence of existing business models [38]. Digital technologies play a central role in creating and amplifying disruptions in society and across different sectors [39]. In response to these disruptions, organisations develop strategic responses and use digital technologies to redefine how they create value, challenging previous assumptions about the sources of their competitiveness. To achieve this, they must implement structural changes and overcome barriers to digital transformation that hinder or slow their progress. Digital tools such as social, mobile, analytics, and cloud technologies (SMAC) can drive and accelerate digital transformation, fundamentally altering established business practices [39]. Digital technologies are therefore becoming increasingly accessible to companies and can enhance their efficiency and profitability, provided their adoption is accompanied by innovative business models or the transformation of traditional models [39]. Understanding the conceptual differences between digitisation, digitalisation, and digital transformation is crucial for achieving the industrial maturity level associated with I4.0 [40]. However, many languages, including German, Spanish, Japanese, and Croatian, do not distinguish between digitisation and digitalisation, even though these activities have little in common. The only similarity between the two concepts, apart from the similarity of their names, is that digitalisation requires the prior completion of digitisation.

Digitisation is the process of converting physical or analogue objects and attributes into a digital format. This includes converting physical documents, audio recordings, images, and other materials into binary data that computers can process.

Digitalisation refers to the use of digitised data to improve business processes, focusing on automating and optimising existing activities by transferring them to digital platforms to increase efficiency and productivity [41].

Digital transformation is a broader concept that encompasses a fundamental change in the way an organisation operates, with digital technologies serving as drivers of strategic and structural change. It involves not only the optimisation of existing processes but also the design of new business models and strategies made possible by digital technologies [42].

Although these terms may appear similar, it is essential to understand the specific characteristics of each and their correct application in the era of digitalisation. Digitisation is central to the Third Industrial Revolution, focusing on converting analogue content into sequences of discrete values such as 0s and 1s, thereby making the basic element of information universal. Digitalisation marks the pathway to the Fourth Industrial Revolution, as it enables the processing of 0s and 1s into meaningful value for practical use, concentrating on improving specific processes. Digital transformation goes beyond the boundaries of individual companies and systems by enabling the combination of various digital and digitalisation solutions. It helps build or select optimal solutions for specific needs and integrate them to create greater value, as the fundamental digital element is universal and encompasses both digital content and its context.

Wen et al. found that manufacturing companies with higher levels of sustainability are more adaptable to digital transformation and tend to apply differentiated competitive strategies, concluding that the stimulus effect on innovation is more pronounced in highly sustainable companies [43]. Furthermore, the antecedents of digital transformation – digital orientation, digital intensity and digital maturity – have been analysed to understand their impact on companies' financial performance [44]. The authors showed that digital orientation and digital intensity alone do not contribute to a company's financial success, whereas digital maturity mediates the relationship between digital orientation and financial performance, as well as between digital intensity and the company's financial performance. Digital transformation therefore presents significant opportunities for companies and entrepreneurs. Moreover, it is strongly shaped by consumer characteristics, particularly the growing demand from digital consumers. Consumers are showing increasing trust in digital technologies in everyday life and interpersonal interactions and expect ubiquitous access to virtual resources [45]. These data enable companies to offer services that better match user needs and to execute their processes more efficiently to gain competitive advantage.

Digital industrial transformation, known as the Fourth Industrial Revolution or I4.0, represents a paradigm shift from a hyper-connected and centralised production ecosystem to a decentralised model [46]. Within I4.0, intelligent physical objects, decentralised subsystems and human components are integrated into an interoperable, hyper-connected and decentralised manufacturing system, enabling greater flexibility, adaptability and autonomy in production processes.

3.1.1. Key dimensions of digital transformation

Digital transformation entails fundamental changes that organisations undertake by integrating digital technologies into all aspects of their operations, enhancing efficiency, competitiveness, and capacity for innovation. Reviews of the available literature indicate that the COVID-19 pandemic has significantly accelerated the need for technological innovation and the adaptation of business models, highlighting the relevance of digital transformation across all business domains. Comparative analyses suggest that six key dimensions are particularly important in defining the digital transformation framework: strategy, organisation, culture, technology, and people [47].

Technological dimension

The technological dimension of digital transformation is central, as it underpins other aspects of transformation by enabling organisations to apply advanced technologies to improve operations, adapt business models, and create new customer experiences (CX). Technological progress, particularly in AI, automation, 5G technologies, and data analytics, has accelerated since 2020, with the pandemic hastening the adoption of digital tools across industries and making cloud computing and digital infrastructure essential for corporate resilience. Verhoef et al. analyse the impact of digital technologies such as AI, blockchain, the IoT and data analytics, emphasising that these technologies enable companies to become more agile and efficient [48]. They act as catalysts for new business models that reshape industries and increase customer engagement through data-driven insights and automation.

Organisational dimension

The organisational dimension of digital transformation involves adapting structures, processes, and internal governance mechanisms to enable and support changes resulting from new technologies [37]. It includes how organisations restructure internal resources, develop new management practices, and reshape the workforce in response to digital change, with increasing emphasis on agile approaches, collaborative governance, and decentralised decision-making. Authors note that organisational adaptability and agility are key success factors in an environment characterised by rapid technological change, while leadership that recognises the need for change and implements it effectively within organisational structures is crucial for successful transformation [49]. Equally important is the innovation that results from redefining organisational boundaries and deeper integration with external partners, as such collaboration further supports digital transformation.

Cultural dimension

With the increasing digitalisation of the work environment, organisational culture must evolve to support innovation, the development of digital competences and resilience to change. The cultural dimension of digital transformation involves changes in values, attitudes, and behaviours within the organisation, aiming to foster digital innovation, flexibility, and agility. Remote work has become common practice and further highlights the importance of digital tools for collaboration and communication [50]. Brynjolfsson and McAfee argue that organisations which systematically invest in digital competences and promote an open culture of change are more successful in adapting to digital technologies [51]. Other authors emphasise that an innovation-oriented culture is crucial for driving digital transformation, as it gives employees the freedom to explore new technologies and business models and requires leadership that actively supports digital innovation and reduces resistance to change [52]. Key components of the cultural dimension include openness to change, encouragement of innovation, collaboration and communication, and strong, supportive leadership, which ultimately shape how employees adopt technologies, innovate and collaborate in the digital transformation process.

Customer-centric dimension

Since 2020, personalisation of the CX and the use of digital channels have become increasingly important, as customers now expect faster, more convenient and integrated interactions through digital platforms [48]. The customer-centric dimension of digital transformation focuses on building competitive advantage through personalised CX and omnichannel strategies that enable consistent and integrated interactions across multiple channels. An omnichannel strategy provides seamless and coordinated experiences across physical and digital channels (stores, websites, mobile applications, social networks, telephone and email support), with customer data and interactions synchronised and used for personalisation. Verhoef et al. highlight the importance of integrating online and offline channels and leveraging customer data to tailor offerings, while digital platforms and data analytics enable a deeper understanding and prediction of customer needs [48]. The customer-centric dimension relies on advanced technologies, including AI, data analytics and ML, to enable real-time interactions, forecast customer behaviour, and dynamically adjust offerings, resulting in higher satisfaction, loyalty, and sales.

Strategic dimension

After 2020, a strategic focus on digital transformation has become a key precondition for the long-term success and development of companies. The strategic dimension of digital transformation highlights the need for organisations to integrate digital technologies into the core of their business strategies to remain competitive and relevant in a digital environment. This requires not only introducing technology but also adapting business models, organisational structures, and culture [37]. Within this dimension, three areas are particularly important: aligning technology with business strategy, transforming business models, and leading the organisation through transformation. Leadership is crucial in defining the vision, priorities, and resources required for the successful implementation of digital initiatives.

3.1.2. Indices of digital transformation

Indices of digital transformation are quantitative tools used to assess the level of digital maturity, progress, and performance of organisations, regions, or countries undergoing digital transformation. They cover multiple dimensions of digital advancement, including technological infrastructure, organisational change, innovation, and the effects on the economy and society. The most commonly observed dimensions are technological infrastructure (broadband internet, mobile networks, cloud computing, AI), human capital (digital skills and training opportunities), innovation (investment in research and development, patents, implementation of innovations), and business agility and competitiveness (ability to respond rapidly to change). Several key digital transformation indices are frequently cited in the literature.

The DESI (Digital Economy and Society Index) is an index of the European Commission used to monitor the progress of EU Member States in the digital economy and society. It measures five dimensions: connectivity, human capital, use of internet services, integration of digital technologies in business, and digital public services, enabling cross-country comparisons and the identification of areas requiring additional investment [53].

The DII (Digital Intensity Index) measures the digital readiness of companies through 12 indicators related to the use of digital technologies. It focuses on the degree of adoption of digital solutions, innovation, CX, and organisational agility, providing insight into the contribution of companies to the digital economy [54].

The Digital Transformation Index (DTI), developed by Dell Technologies, tracks the progress of organisations in digital transformation and serves as a benchmark against competitors [54]. It enables the identification of weaknesses in transformation efforts and the definition of investment priorities in areas such as cloud computing, cybersecurity, AI, and data analytics.

Recent research suggests that digital transformation indices serve three key roles: monitoring progress, identifying weaknesses (e.g., in digital skills or infrastructure), and providing a basis for designing policies and strategies to strengthen digital transformation and economic competitiveness. At the same time, several limitations are noted, such as limited adaptability to specific industries and insufficient consideration of organisational culture and leadership, as many indices predominantly focus on technology and skills [48].

Digital transformation indices are important for understanding and monitoring digital progress at national, sectoral, and organisational levels. They provide quantitative data on technological maturity, digital skills, and innovation capacities, helping decision-makers direct resources towards areas with the highest growth potential. However, due to significant differences in the size and organisation of companies, even within the same industry, an individualised approach is necessary, adapting general indices to the specific characteristics of each organisation. At national and sectoral levels, indices are used to identify trends, weaknesses, and opportunities for investment in digital infrastructure and the development of digital skills, while at the company level, digital maturity models (DMM) are increasingly applied as tools for assessing internal readiness for digital transformation.

Digital maturity models and digital transformation indices, although differing in scope and level of application, are complementary: the former provide detailed insight into the internal capabilities and maturity of an organisation, while the latter offer a broader framework for comparing progress at regional, national, or global levels. Together, they are important strategic instruments for raising digital maturity and strengthening competitiveness, and before developing a digital transformation strategy, it is often recommended to carry out an assessment of the current state using a DMM.

3.1.3. Digital maturity models

Digital maturity models are structured frameworks for assessing an organisation's readiness for digital transformation, emphasising not only the extent of technology implementation but also a broader set of organisational characteristics, including culture, strategy, employee competences, technological infrastructure, and innovation potential. They typically define several stages of development, from initial to advanced, enabling organisations to identify their current position, recognise areas for improvement, and plan development in a structured manner. Most DMMs focus on key domains – strategy, technology, people, and culture – with the possibility of adaptation to the specificities of industry, company size, and level of development. In practice, these models serve as operational tools for linking strategic ambitions with concrete digital transformation initiatives: they support the definition of investment priorities, the alignment of organisational capabilities with digital objectives, and the monitoring of progress over time [55].

Among the most widely used models are the Deloitte DMM, BCG's Digital Acceleration Index (DAI), and McKinsey's Digital Quotient (DQ). The Deloitte DMM enables organisations to assess the progress of digital transformation across four key dimensions: strategy, technology, people, and organisation [56]. BCG's DAI compares a company's digital capabilities with the industry average and best practices. McKinsey & Company's DQ model measures the ability to integrate digital technologies into strategies and processes across multiple dimensions, providing insight into strengths, weaknesses, and recommendations for improvement [57].

3.1.3.1. Digital maturity models in industrial and Industry 4.0 contexts

Indices of digital transformation and digital maturity assessment models can also be applied to industrial companies, provided they are adapted to the specific characteristics of the industrial sector, such as dependence on production processes, complex technological infrastructures, and regulatory constraints. In this context, indices such as DESI and the Smart Industry Readiness Index (SIRI) support industrial companies in assessing their capacity for digital transformation, with particular emphasis on technologies critical for manufacturing organisations, including automation, robotics, machine connectivity, and cybersecurity. SIRI is specifically designed for industrial organisations and supports the assessment of progress in areas such as automation, smart manufacturing, and the industrial Internet of Things (IIoT), making it particularly relevant for manufacturing sectors [55].

To enable a more detailed assessment of the operational and technological aspects of industrial production, specialised I4.0-oriented DMMs have been developed, such as the I4.0 Maturity Index (Acatech) and PwC's Digital Operations Maturity Model (DOMM). These models cover the integration of automation, artificial intelligence, digital twins, and supply chain optimisation through connected systems. They are particularly useful for industrial SMEs, as they enable structured planning for the introduction of technologies such as smart manufacturing and predictive maintenance, but are also applicable in large companies with dedicated digital transformation teams. The I4.0 Maturity Index, developed by Acatech, evaluates the maturity of industrial organisations across six levels based on nine dimensions and 62 maturity items, thereby capturing in detail the strategic, organisational, technological, and human aspects of I4.0 [42]. The IMPULS I4.0 Readiness model, developed by Lichtblau et al., comprises six maturity stages and six dimensions: strategy and organisation, smart factory, smart operations, smart products, data-driven services, and employees [58]. Together, these models are key tools for industrial organisations seeking to manage digital transformation systematically and align with the requirements of I4.0, as they enable assessment of maturity with respect to digital technologies and innovation, while taking into account heterogeneity between and within sectors and individual companies [42,58].

The assessment of digital maturity is a crucial step in understanding an organisation's readiness for digital transformation and in identifying opportunities, threats, and the optimal allocation of resources [59]. Maturity levels in most models follow a logical progression from an initial, ad hoc stage to an advanced level, where digital technologies are integrated into core processes and form the basis for continuous innovation. Each level reflects the degree of digital capability and readiness for change, marking the transition from fragmented initiatives to strategically driven, innovation-oriented use of digital technologies.

The literature on digital maturity assessment models in industrial companies highlights that developing a specific set of digital capabilities directly contributes to higher digital maturity and more effective transformation management. In the absence of clearly defined and widely accepted models, much research focuses on conceptualising and constructing new frameworks that address key dimensions of digital transformation and enable practical application in organisations [60]. This topic, including a detailed analysis of model structures, dimensions, maturity levels, and assessment procedures in industrial settings, has been examined in depth by the author in a separate empirical study [61].

The overall conclusion from the scientific literature on digital transformation is clear: digital transformation is a strategic, long-term process that fundamentally reshapes business by integrating digital technologies into products, processes, business models, and customer relationships, with the aim of achieving the target state associated with I4.0. To understand and manage these changes, numerous DMMs and digital transformation indices have been developed to quantify the level of digital readiness of organisations, sectors, and countries, enabling comparison, progress tracking, and identification of weaknesses. DMMs are key tools in a company's digitalisation process, enabling effective assessment of the current state of digitalisation and identification of critical areas when developing a digitalisation strategy towards I4.0 [62]. Most models are based on a multi-stage maturity concept, from the ad-hoc phase, through structured and managed levels, to an innovative stage where digital technologies are fully integrated and drive continuous innovation.

For industrial organisations, especially SMEs, digital transformation acquires an additional dimension through I4.0, where concepts such as smart factories, smart operations, digital twins, predictive maintenance, and data-driven services are combined with limited resources and specific technical requirements. In this context, linking digital transformation indices (to understand market position) with DMMs (for detailed internal diagnosis and planning) enables organisations to set priorities in an informed manner, allocate resources more efficiently, and gradually increase digital maturity through the formulation of a digital strategy.

Chapter 4

4. Design and development of the MIDIT methodology

The literature indicates that RAMI 4.0 and Manufacturing System Design (MSD) share the goal of systematically designing and evolving manufacturing systems, but address this at different levels of abstraction. RAMI 4.0 provides a three-dimensional reference architecture that organises all relevant aspects of an I4.0 system, from physical assets to business processes, across hierarchy levels and lifecycle phases. This offers a common language for stakeholders and guides the structured deployment of digital technologies. In contrast, MSD focuses on configuring the specific manufacturing system for a given product or product family, through coordinated decisions on functions, structures, behaviours, control logic, intelligence, and performance targets over the system lifecycle.

Within this context, MSD decisions can be consistently mapped within the RAMI 4.0 framework, ensuring that choices regarding equipment, IT systems, data flows, control strategies, and services align with standardised architectures and support interoperability, traceability, and gradual migration from conventional to fully digital, connected, and intelligent systems. However, the reviewed studies agree that, despite the availability of RAMI 4.0, numerous guidelines, domain-specific methods, and partial frameworks, there is still no consolidated, widely accepted methodology that systematically links RAMI 4.0 and digital technologies with the complete MSD process across all lifecycle phases. This methodological gap – between high-level reference architectures and fragmented, technology-centric implementations – motivates the development of integrated frameworks such as PSLM MIDIT, which aim to provide a coherent, lifecycle-oriented methodology for the use of digital technologies in MSD and management in the context of I4.0 and I5.0.

In this thesis, the term manufacturing system design (MSD) is used broadly, encompassing what some authors refer to as production system design (PSD), and covering both the structural and operational configuration of the production system throughout its lifecycle. The following sections develop the MIDIT methodology in three steps: (i) analysing key digital technologies of I4.0 and I5.0 and their industrial applications; (ii) structuring MSD in the context of I4.0/I5.0 and defining a PSLM-based lifecycle framework for production systems; and (iii) consolidating these insights into a matrix linking design elements and digital technologies, with a flowchart that operationalises the MIDIT methodology.

4.1. Digital technologies in the Industry 4.0 and Industry 5.0 context

Over the past decade, digital transformation has become a central topic of research for many scholars and practitioners, aiming to accelerate its implementation across various domains and realise its benefits in both private and business environments. According to extensive research, digital technologies are applied in industry through an integrated and comprehensive approach directed towards achieving the levels associated with I4.0 and I5.0. A key element of this approach is the synergy between the digital thread and CPS, which serve as the fundamental building blocks of the smart factory (Figure 4.1). The figure illustrates the concept of a human-centric smart factory, where a network of interconnected cyber-physical systems (CPS), linked via the Industrial Internet of Things (IIoT), forms the fundamental building block of the intelligent production environment. In this system, CPS continuously exchange data between the physical and virtual layers, enabling the implementation of the digital twin and advanced functions for real-time monitoring, optimisation, and self-adaptation of production processes.

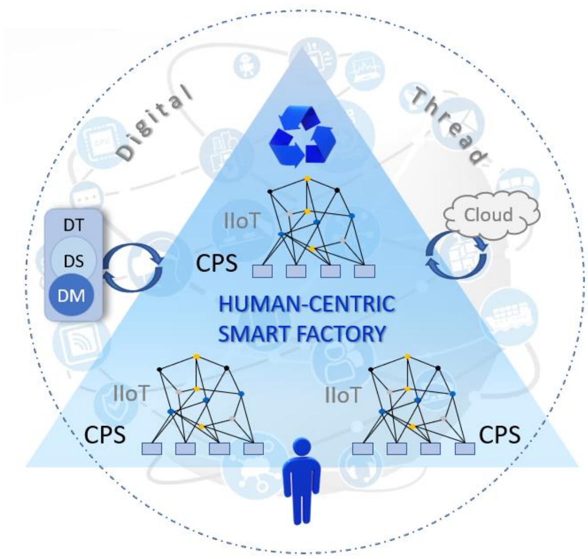


Figure 4.1: Integration of smart factory, CPS, and digital thread

The human remains central role, in accordance with the human-centric principles of I5.0, while cloud infrastructure provides storage and processing for large volumes of data, and the digital thread links all phases of the product and manufacturing system lifecycle into a unified, dynamic, and continuously evolving system.

4.1.1. Smart factory

The concept of Intelligent Manufacturing (IM) is a key element of I4.0 and is broadly defined as the optimisation of production and product transactions through advanced information and manufacturing technologies. Zhong et al. distinguish three interrelated concepts: IM, which focuses on AI-based smart decision-making; IoT-enabled manufacturing, which emphasises real-time data acquisition; and cloud manufacturing, which concentrates on the configuration and sharing of manufacturing services [63]. A commonly cited framework for smart manufacturing systems comprises five dimensions: Smart Design, which uses technologies such as VR and AR to enable real-time interaction between CAD and physical prototyping; Smart Machining, in which CPS-enabled machines collect data and transmit them to cloud-based systems; Smart Monitoring, which provides real-time supervision of key process variables; Smart Control, which offers high-resolution adaptive production control through cyber-physical control systems; and Smart Scheduling, which relies on advanced models and algorithms for intelligent scheduling [64]. From this perspective, a smart factory is an autonomous, digitally networked production environment in which production resources are interconnected via the IIoT, processes are optimised and synchronised through CPS and real-time data, decisions are taken partially or fully in an automated manner using AI and ML algorithms, and products, equipment, workers, and systems are integrated through digital-twin and digital-thread concepts [65,66]. A smart factory is therefore not merely a collection of automated systems but a system with capabilities for self-adaptation and self-learning, and is widely regarded as the target state of I4.0 implementation, in which digital technologies are holistically integrated and operate with a high degree of autonomy [67,68]. Along the pathway towards this target state, various digital technologies can be deployed in hybrid configurations that gradually increase digital maturity and accelerate progress towards a fully realised smart factory [69,70].

In the I5.0 paradigm, the notion of the smart factory builds on I4.0 outcomes rather than being replaced. While I4.0 primarily aims at automation and efficiency, I5.0 emphasises personalisation, human-centricity, and sustainability, leading to concepts such as the “next-generation intelligent factory” or human-centric smart factory [32,71]. In such environments, humans and robots (cobots) collaborate within the same workspace, system design explicitly incorporates ergonomics, safety, and social aspects, AI-supported decisions remain under human supervision, and objectives extend beyond productivity to include resilience and environmental sustainability. Thus, the I4.0 smart factory provides the technological foundation, whereas the I5.0 smart factory represents a socio-technical enhancement that overlays human-centric and sustainability-oriented goals onto the existing digital infrastructure.

4.1.2. Cyber-physical systems (CPS)

Cyber-physical systems (CPS) represent a modern approach to integrating physical production processes with computing and communication technologies, enabling intensive collaboration and real-time interconnection. In manufacturing, cyber-physical production systems (CPPS) use networked sensors, actuators, and control units to provide continuous monitoring, control, and autonomous adaptation of processes in real time, supporting intelligent, networked, self-sustaining systems that form a cornerstone of I4.0 and fully digital lifecycle management [66]. The rapid development and widespread deployment of sensors, data acquisition systems, and industrial networks generate large volumes of Big Data, which CPS exploit through machine-to-machine connectivity to achieve intelligent, resilient, self-adaptive behaviour [66,72]. CPS offer significant benefits, including increased flexibility, the ability to individualise products at batch or lot size one, reduced cycle times and costs, and improved quality through predictive monitoring and rapid response to failures. At the same time, CPS design and implementation face major challenges related to managing system complexity, ensuring interoperability between heterogeneous components, safeguarding security and data protection, and effectively integrating humans into technical processes [72,73]. CPS architectures in factories therefore rely on modular, scalable components, distributed computing technologies for Big Data processing, and increasingly, AI methods to maintain availability, reliability, and resilience. Their integration with digital twins, smart automation, collaborative robots, and Plug-and-Work concepts further accelerates the transformation of manufacturing systems towards highly autonomous, adaptable, efficient configurations [72,73].

Scientific studies and industrial case examples confirm that CPS and CPPS provide substantial economic and operational benefits and are a key step towards future manufacturing systems focused on individualisation and sustainability.

4.1.3. Digital thread

The digital thread has attracted considerable attention as a core concept in digital transformation and industrial infrastructure within the context of I4.0 and I5.0 [74,75]. It provides an extensible, configurable framework for linking authoritative data, information, and knowledge across the entire lifecycle of a manufacturing system, functioning as a continuous data flow that ensures model consistency, supports collaboration along development and operational chains, and enables applications from initial design, planning, and engineering through to production, use, and maintenance of products [74]. Through its architecture, the digital thread spans all phases of digital transformation and connects design, engineering, manufacturing, and post-sales activities, enabling smart factories and smart business systems that maximise the benefits of digitalisation across processes and provide bi-directional connectivity between all actors in the value chain, while shortening response times and improving quality [74,75]. Abdel-Aty and Negri make a significant contribution by offering a methodological synthesis of over a decade of research and proposing a rigorous reference model of the digital thread that links key technologies (IoT, PLM, AI), information structures (ontologies, knowledge graphs), and organisational requirements (collaboration, security), effectively defining the "digital connective tissue" of the smart factory [75]. In the MSD context, this framework connects digital transformation with operational intelligence and provides a basis for integrating the digital thread and digital twin into comprehensive smart-manufacturing systems [74,75]. Building on this, Zhang et al. introduce the surrogate-model digital thread, which connects Model-Based Systems Engineering (MBSE) with ontological data integration and operationally links automated scientific discovery, data linkage, and model integration, turning the digital thread into a formalised meta-model of the industrial digital ecosystem and a platform for future integration with AI, blockchain, and cloud technologies [74].

In manufacturing-system development, the digital thread is increasingly recognised as an integration layer that connects individual digital technologies, such as IoT, digital twins, and advanced analytics, into a coherent whole capable of fully supporting smart factories and advanced production-planning and scheduling (PPS) practices [74,75]. Research and development in this area are therefore crucial for the practical application of I4.0 principles and for embedding continuous, data-driven improvement into manufacturing-system design and operation.

4.1.4. Key digital technologies of Industry 4.0 and Industry 5.0

A wide range of digital technologies is being researched and applied across various industrial domains, yet some form the core and fundamental basis for digital transformation. To achieve substantial benefits from introducing digital technologies, the mutual integration and interconnection of key technologies are as important as their individual deployment. The key digital technologies most frequently cited in the context of I4.0, according to most authors, are shown in Figure 4.2. These include the IIoT, horizontal and vertical system integration, Big Data analytics, cloud computing, simulation and modelling, AI, AR, automation and robotics, and AM [26,76]. The key digital technologies mentioned above are described in more detail in the following sections of this work.

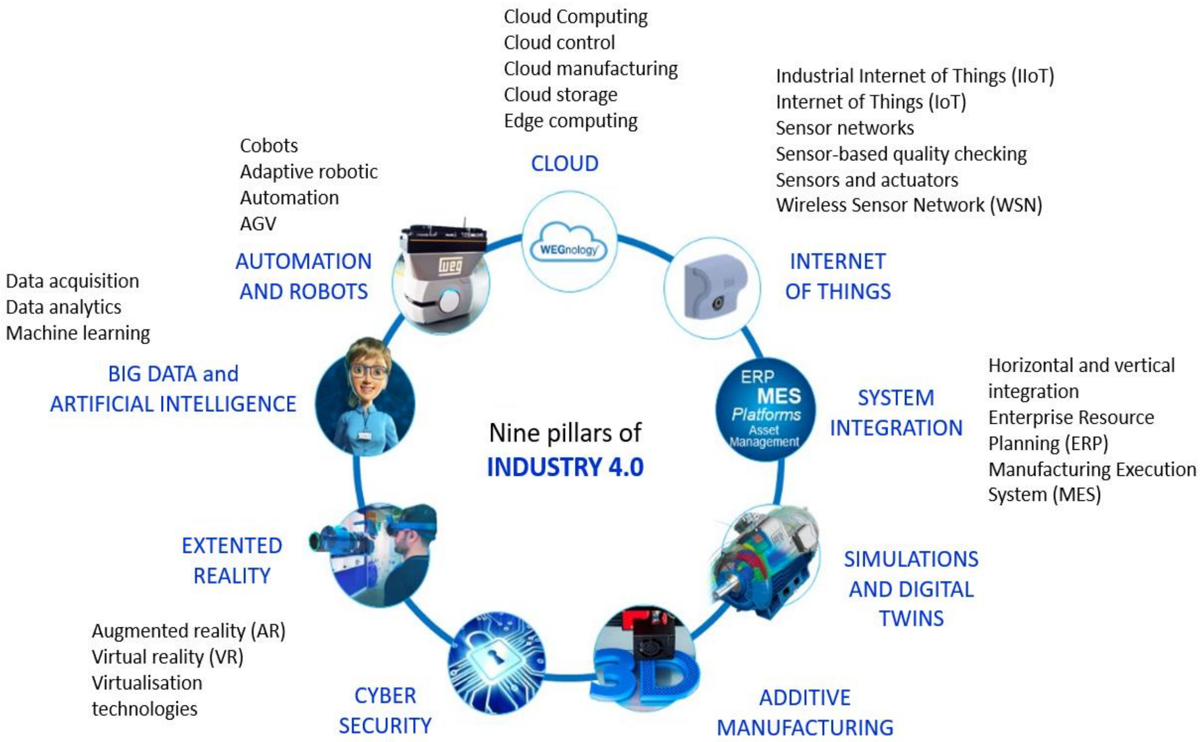


Figure 4.2: Nine pillars of Industry 4.0 [77]

In the context of I5.0, the focus shifts: alongside the digital technologies of I4.0, factors such as a human-centred approach, sustainability, and human-machine collaboration are frequently emphasised. The key technologies include AI with a focus on human-machine collaboration, integrated IoT and cloud solutions, blockchain, digital twins with real-time simulation, as well as robotic solutions and interactive technologies [78,79]. These technologies are illustrated in Figure 4.3.

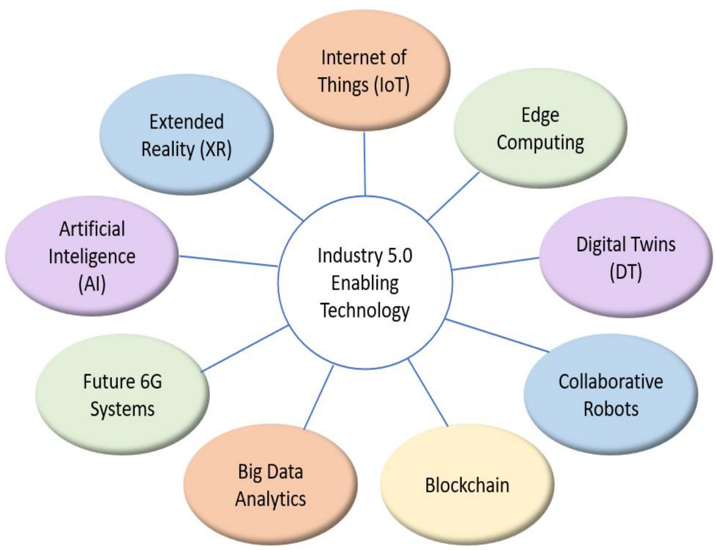


Figure 4.3: Enabling Industry 5.0 technologies [35]

The following section presents a concise overview of selected literature on the application of digital technologies in manufacturing and MSD.

4.1.5. Application of digital technologies in industry and system design

The digital transformation of industrial systems, commonly known to as I4.0, involves the deep integration of information, communication, and physical technologies to create smart, connected manufacturing systems. In this context, key research contributions focus on analysing and formulating guidelines for the use of digital technologies in I4.0 and I5.0 [26]. Numerous studies address product design from a digitalisation perspective, while the associated manufacturing process is often considered only tangentially.

In a literature review on the integration of product design and the corresponding manufacturing process, Shafiee provides valuable insights to support future research and decision-making by experts seeking to enhance manufacturing processes through the integration of products, production, and digital technologies [80]. The author recommends further research to identify the challenges and barriers that hinder effective integration of product design and MSD. Additionally, future studies could examine the role of advanced technologies, such as AI, ML, and data analytics, in optimising this integration. In their investigation of the application of Digital Twin technology in the design and planning of production lines, Lee et al. conclude that most previous research on digital twins has focused on product design rather than on the associated manufacturing systems [81]. Their study highlights how digital twins can enable real-time validation, analysis, and optimisation of production processes, which is particularly important under current conditions of dynamic demand and frequent changes in products and processes. The paper emphasises the need to move from traditional simulations towards digital twin systems that provide real-time data synchronisation and integration with optimisation methods.

Given the limited of relevant literature on the holistic integration of digital technologies into the MSD process, subsequent research has focused on individual examples of digital technology use in industrial environments. The impact and potential integrated application of digital twins and the Design for Six Sigma (DFSS) method for product design have been analysed in the context of MSD [82]. The research addresses the fundamental concepts and classification of digital twins [83], discusses I4.0, and examines various possibilities for using digital twins in industry by reviewing the work of several authors [84,85]. Furthermore, opportunities for integrating digital twins into specific phases of MSD, by analogy with product development processes, have been explored [86]. This analysis resulted in a proposed definition of the DFSS digital model concept for MSD [87]. The DFSSDM* (Design for Six Sigma Digital Model) concept emerged from adapting existing product design models, with some tools and methods enhanced, others retained in their original form, and some replaced with more suitable or new ones, such as digital models. At lower levels of digital maturity, digital models are used, which, as the industrial level of I4.0 is gradually achieved, evolve into digital shadows and, ultimately, digital twins; these concepts and their distinctions are explained in Section 4.1.5.3. The following section provides an overview of selected studies on the application of individual digital technologies in industry and MSD, aiming to explore how specific approaches and solutions can be incorporated into a methodology for integrating digital technologies into the MSD process.

4.1.5.1. Industrial Internet of Things (IIoT)

The terms Internet of Things (IoT) and the Industrial Internet of Things (IIoT) are often used interchangeably, leading to confusion in the context of industrial digitalisation [70]. IoT refers to a broad network of everyday connected devices aimed at improving user comfort and quality of life, while IIoT refers to industry-specific, safety-critical systems for automating, optimising, and maintaining industrial processes, with much higher requirements for availability, reliability, and cybersecurity. A concise comparison of IoT and IIoT is provided in Table A2 (Appendix A) [70]. Functionally, IIoT extends basic IoT principles by integrating cyber-physical systems, advanced analytics, autonomous control, and cloud- and edge-based solutions, enabling smart factories and the digital interconnection of value-chain elements [88]. Typical applications include predictive maintenance, real-time monitoring and optimisation of production processes, and asset, inventory, energy, and quality management. Recent studies indicate that the digital transformation of industrial systems is driven by the evolution of classical SCADA, PLC, MES, and ERP platforms towards decentralised IIoT architectures that integrate CPS, AI, and cloud services to achieve adaptive and autonomous processes, while addressing challenges of interoperability, standardised communication, and cybersecurity [76].

Within I4.0, IIoT forms the technological backbone of the smart factory, while in the emerging I5.0 paradigm it supports human-centricity, sustainability, and resilience by enabling close collaboration between experts, machines, and intelligent systems. In this way, IIoT underpins innovation, personalised manufacturing, and advanced quality and resource management in modern industrial environments.

4.1.5.2. Modelling and simulation of systems

The development of simulation methods in manufacturing systems is closely linked to the evolution and adoption of digital technologies within the I4.0 paradigm. Early work used simulations primarily to translate customer requirements into prototypes for verifying and optimising specifications, but their role has significantly expanded [89,90]. Mourtzis shows that advanced simulation methods, including AR and VR, IIoT-enabled simulations, predictive modelling, hybrid simulations, and digital twins, have become indispensable tools that reduce cost and risk, accelerate experimentation, and support critical decision-making before physical implementation. Digital factories and digital twins further extend the possibilities for production optimisation and control [90].

Recent research integrates systems engineering and object-oriented modelling with optimisation models to simulate alternative system variants and quantitatively assess design decisions in early development phases [91]. These approaches often combine discrete-event simulation (DES), multi-criteria decision-making, and heuristic optimisation to support the design and operation of manufacturing systems, including Lean Six Sigma initiatives in SMEs [87,91–93]. Krulčić et al. demonstrate that a hybrid DFSS digital model, supported by simulation and MCDM, enables the selection of more productive and economical manufacturing configurations, thereby reducing the risk and cost of process changes [87]. Human-centric solutions, such as simulation-based dynamic worker scheduling, align with I5.0 trends by integrating ergonomics and workforce-related constraints into planning [91–93]. Simulation-based modelling and material-flow optimisation during design and reconfiguration confirm that digital models and simulations form the foundation of digital prototyping and early decisions on factory layout and configuration [92,94].

In summary, advanced digital modelling and simulation, including digital twins and AI, play a central role in the design, optimisation, and human-centric operation of smart factories in I4.0 and I5.0. Simulation thus becomes a key tool for digital design, predictive engineering, and the transition towards adaptive, intelligent, and sustainable manufacturing systems.

4.1.5.3. Digital twins

Digital twins are fundamental technologies in advanced manufacturing systems and intelligent industrial environments, as they enable real-time virtual mirroring of physical entities, processes, and systems. Recent reviews indicate that their development and implementation are advancing across several complementary domains [76,95,96]. Core concepts and standardisation requirements are defined in standards such as ISO 23247, which specify the architecture, functional requirements, and interoperability of digital twins in industrial systems [96]. Survey papers highlight their application across the product lifecycle and within smart manufacturing, where real-time data synchronisation between the physical and virtual domains enables predictive maintenance, production process optimisation, and improvements in overall equipment effectiveness (OEE) [76,95,96]. Technological advances include multi-layer reliability models and multi-simulation approaches integrated into digital-twin platforms, supporting dynamic adaptation and real-time optimisation, as well as advanced virtual simulations for planning and managing production resources, which reduce experimentation costs and increase the robustness of manufacturing decisions [81,97,98]. Their growing use in metrology improves estimation of measurement uncertainty and enhances inspection processes, supporting advanced digital monitoring and quality management in I4.0 [99].

The integration of digital twins with IoT technologies, Big Data analytics, and AI enables the creation of smart, adaptive, and sustainable industrial ecosystems [76,96]. In this context, it is important to distinguish clearly between conventional simulation models and digital twins, which function as dynamic systems with multidimensional interactions and are crucial for agile, responsive, and predictive manufacturing environments [97,100]. As organisations vary in their levels of technological maturity, a clear understanding of the degree of data integration between the physical system and its digital representation is essential. To address inconsistent use of terms such as "digital model" and "digital twin", Kritzinger et al. proposed a classification framework distinguishing three levels of digital representation according to the extent of automated data exchange: digital model (DM), digital shadow (DS), and digital twin (DT) [84]. A digital model is a digital depiction of an existing or planned physical object without automatic data exchange, typically realised by CAD, BIM, or simulation models used for visualisation, analysis, and planning with manual data updates. A digital shadow represents a higher level, in which the digital representation is continuously updated with automatically collected data, but the data flow remains unidirectional from the physical to the digital system, providing real-time monitoring and analytics without automatic feedback. A digital twin constitutes the highest level, characterised by bidirectional communication: real-time data acquisition and processing using simulation and predictive models are combined with feedback commands or optimisation recommendations applied to the physical system. The progression from DM to DS to DT illustrates how telemetry, advanced analytics, and closed-loop control increase the functional complexity and utility of digital representations in manufacturing environments [84].

Despite these theoretical distinctions, the digital-twin concept remains subject to debate and varying interpretations among practitioners, particularly in organisations that are only beginning to adopt such technologies, including SMEs [101]. A systematic review of digital twins in manufacturing environments synthesises different approaches, definitions, and maturity models, and emphasises that the digital model, which contains key geometric and structural data, forms the basis of the digital twin [101,102]. Full digital-twin functionality is achieved only through the integration of the digital model, digital shadow, and bidirectional information transfer back to the physical world. A digital twin may refer not only to physical objects but also to processes, services, and other non-physical entities. In this sense, the digital model and digital shadow can be interpreted as constitutive elements of the digital twin rather than its subcategories (Figure 4.4). Depending on technological maturity and strategic needs, organisations may still deploy individual components, such as the digital model or digital shadow, independently of a fully realised digital twin [101].

The limitations of digital twins remain an active research topic. Chinesta et al. trace the evolution of twin concepts in engineering and scientific disciplines, from virtual and digital twins to more recent hybrid twins [103]. The paper describes a transition from classical virtual twins, which rely on numerical simulations and physics-based models for offline analysis and optimisation, to digital twins that incorporate real-time data from physical systems and thus link simulated and real domains. Although digital twins offer high speed and operational capability in real time, their applicability and scientific transparency are constrained by data coverage and quality, and by simplified representations of system physics, whereas virtual twins, although richer from a scientific perspective, are often too slow for real-time control.

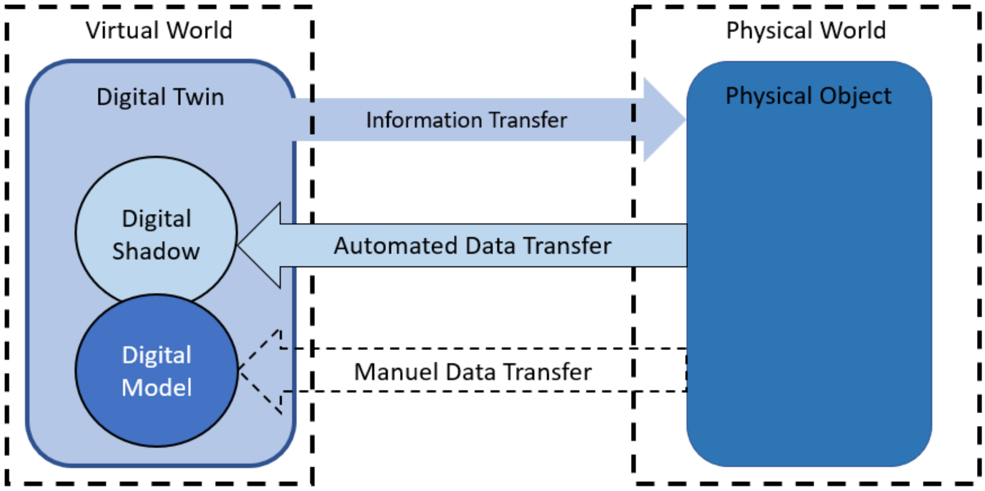


Figure 4.4:Interaction between digital twin and physical world [101]

To address these limitations, the hybrid-twin concept combines the accuracy and explainability of physics-based modelling with the speed and adaptability of data-driven methods [103]. Modern model-order reduction (MOR) techniques, particularly Proper Generalised Decomposition (PGD), enable fast numerical approximations of physics-based models suitable for online use and calibration with real-world data, including real-time adaptation and correction, making hybrid twins a promising direction in digital engineering by combining the predictive power of traditional scientific models with the agility of data-centric computing.

4.1.5.4. Robotics and process automation

The Fourth Industrial Revolution has significantly transformed manufacturing through advanced robotics and process automation. Robotics, combined with automation and integration into IoT infrastructures, forms the foundation of smart and autonomous manufacturing systems by increasing flexibility, productivity, safety, and the quality of human–robot collaboration [104].

Robotic Process Automation (RPA) automates repetitive business processes using software robots that mimic human actions in digital environments [105]. Its core characteristics – work automation, adaptability, ease of use, and integration with existing IT systems – make RPA a key enabler of digital transformation, cost reduction, and improved workflow accuracy. By taking over non-value-adding, repetitive tasks, RPA helps eliminate the “eighth waste” in Lean, defined as underutilised human potential, and enables workers to focus on higher value-added activities [106].

The integration of AI with RPA extends automation from routine tasks to more complex, knowledge-intensive, and adaptive processes by employing ML, natural language processing, and advanced data analytics [107]. In parallel, digital twins enhance the effectiveness of robotic systems and automation by supporting real-time simulation and optimisation of processes, improving process insight, reducing experimentation costs, and strengthening human–robot collaboration. Together, robotics, RPA, AI, and digital twins provide a synergistic foundation for intelligent, flexible, and sustainable manufacturing systems in I4.0 and beyond.

4.1.5.5. Horizontal and vertical integration

Industry 4.0 relies on horizontal and vertical integration to connect manufacturing systems and coordinate activities across hierarchical and functional levels [108–110]. Horizontal integration links production units and business partners into connected value chains, while vertical integration connects organisational layers to enable real-time monitoring, control, and decision-making. ERP and MES systems provide unified platforms for managing resources, data, and production within this integrated architecture, which is typically structured according to standards such as RAMI 4.0 and ISA-95 to ensure interoperability, data consistency, and system flexibility [108–110]. Proper integration of systems and processes increases efficiency, reduces costs, improves quality control, and enhances risk and resource management, although cultural and organisational barriers can still hinder implementation [110].

With the emergence of the I5.0 paradigm, vertical integration is reframed as a dynamic, human-centred, technology-enhanced system that combines tight vertical control with the flexibility required for mass personalisation [111]. Collaborative robots, AI, and digital twins are key enablers of human–machine collaboration, mass customisation, and stakeholder involvement along the production chain, supporting sustainable and resilient manufacturing. Digital twins and distributed MES systems with AI capabilities further enable dynamic automation, continuous optimisation, and real-time reallocation of production tasks, increasing the agility and efficiency of manufacturing systems despite persistent challenges related to interoperability, security, and complexity [112]. The integrated use of ERP, MES, digital twins, AI, and collaborative robots underpins the development of smart, adaptive, human-oriented manufacturing systems essential for sustainable competitiveness and innovation in the era of I4.0 and I5.0.

4.1.5.6. Virtual reality and augmented reality (including mixed reality)

Within the current paradigm of digital transformation, virtual reality (VR) and augmented reality (AR) are emerging as key technologies for the design and operation of manufacturing systems. VR enables immersive simulation of complex objects and processes in computer-generated 3D environments, while AR enhances the user’s perception of the real world with digital information, facilitating interaction between physical and virtual entities [113]. Mixed reality (MR) is typically positioned between VR and AR, combining real and virtual content with persistent spatial anchoring and advanced interaction, and is often treated in industrial contexts as a spatially aware form of AR, such as headset-based overlays aligned with physical assets. Integrated with digital twins and virtual commissioning (VC), these technologies underpin a new generation of cognitive and agile manufacturing systems [113,114]. Recent research demonstrates the feasibility and benefits of VR-based production simulations and digital-factory planning. Studies on collaborative VR environments show that the perceived credibility of VR simulations depends strongly on technical and interaction factors, and that, when appropriately designed, VR can be used effectively for the design and monitoring of production processes in real industrial settings [115]. Dynamic VR platforms for digital factory planning extend VR from passive visualisation to active planning and optimisation by enabling parametrically controlled 3D editing, real-time optimisation, and collaborative simulation, supporting faster adaptation of manufacturing systems and more effective decision-making at various management levels [116,117]. However, analyses of VC tools and digital-twin development reveal that current VR solutions for digital replication of manufacturing systems are still limited by insufficient integration and standardisation between tools and model-exchange standards, so virtual engineering environments do not yet provide fully integrated support for development engineers in early digital-twin design phases [114].

Industrial practice and vendor guidelines also indicate a gradual transition of AR from research to operational use. Implementation frameworks, such as industrial guides that define staged AR deployment with strong emphasis on business validation and integration with MES and ERP systems, provide reference models for the evolution towards “extended-reality factories” and offer industry-validated examples of AR implementation in production [118]. These developments – from early VR solutions based on 3D scanning, through dynamic, real-time factory planning, to industrial AR ecosystems – indicate a clear trend towards integrated, visually supported processes across the MSD lifecycle [116–118]. Collectively, the studies confirm that VR and AR act as complementary tools within the digital-twin context, forming a foundation for integrated, visually enhanced workflows from conceptual engineering to operational exploitation of manufacturing systems, while MR serves as an interaction layer that brings digital-twin content onto the shop floor through spatially anchored, operationally relevant overlays.

4.1.5.7. Big data and artificial intelligence

The combined use of big data analytics and AI is transforming how manufacturing systems are conceived, designed, and operated, from early conceptual modelling and capacity decisions to operational optimisation and continuous improvement [119,120]. In I4.0 environments, MSD is increasingly supported by data-driven feedback loops, where operational data streams from machines, sensors, MES/ERP, and quality systems are converted into actionable knowledge and reintegrated into decisions on layouts, resources, balancing, scheduling rules, and maintenance strategies [119,121]. Reviews of big data analytics in industrial manufacturing explicitly link industrial data and AI methods to product design, planning and scheduling, quality optimisation, and equipment operations and maintenance, highlighting their cross-lifecycle impact.

A key implication is that AI capabilities are limited by the quality of the upstream data pipeline. Manufacturing data are heterogeneous (time series, event logs, images, alarms, machine parameters, operator inputs) and distributed across multiple systems, so significant effort is required in data acquisition, integration, cleaning, contextualisation, and governance before AI models can be trained and deployed reliably [120]. Big data are valuable not only for their volume, but also because they enable systematic transformation of raw signals into information and knowledge across the data lifecycle, from collection, transmission, storage, and pre-processing to analysis, visualisation, and application [120]. Practical industrial-analytics frameworks emphasise architectures that connect data sources, ensure interoperability, and enable scalable processing, as these factors determine whether AI becomes a reliable design and operation tool rather than a set of isolated pilots [119].

Within this integrated perspective, AI can be seen as a set of methods that transform manufacturing big data into decision support for MSD. A commonly used capability ladder distinguishes descriptive and diagnostic analytics (what happened and why) from predictive and prognostic analytics (what is likely to happen) and prescriptive analytics (what should be done). Deep learning surveys in smart manufacturing show that modern AI is particularly effective when the system generates high-volume, high-variety data and when feature extraction can be learned directly from data (e.g., vibration signals, acoustic emissions, thermal images, or visual inspection) [122]. In practice, AI's contribution to MSD is often realised in areas such as planning and control, where ML methods support demand-driven planning, scheduling, dispatching, and process monitoring, provided datasets are prepared and labelled in line with operational realities [123].

A particularly important link between design and operation is the digital twin concept, which consolidates big data flows and AI models into an explicit system representation. For MSD, the distinction between a Digital Model, a Digital Shadow, and a Digital Twin is critical, as many "twin" initiatives in practice correspond to models or shadows; fully coupled twins require robust data integration and governance, as well as a clear strategy for how AI outputs are used to change system behaviour [84]. Recent work on the "digital twin of the factory" further underlines that prerequisites, such as data requirements, interfaces, and model scope, must be addressed already in product development and factory planning, since later retrofitting can be costly and may limit the validity of AI-driven optimisation and monitoring [124].

An additional structuring mechanism for MSD is the use of knowledge graphs (KGs) to integrate heterogeneous manufacturing data and domain knowledge. Recent surveys indicate that KGs support smart manufacturing by enabling semantic interoperability, contextualisation, and reasoning across lifecycle stages, including engineering design, operations, and predictive maintenance, thereby strengthening the link between big data assets and AI-driven decision-making [125]. In an MSD-oriented context, KGs can be described as a "glue layer" connecting design intent (resources, routings, constraints, product structure) with operational evidence (events, conditions, quality outcomes), increasing the robustness and explainability of AI-supported decisions.

Big data analytics thus provides the foundational platform, while AI realises its industrial potential through a set of well-established methodological toolkits [126–128]. For MSD, particularly relevant are ML methods for prediction and classification, such as anomaly detection, predictive maintenance, and predictive quality, as well as deep learning models, including convolutional neural networks for visual inspection and defect detection, recurrent or temporal models (e.g., LSTM) for sensor time series, and unsupervised or self-supervised learning for pattern discovery when labelled failure or quality data are scarce [122,127]. In parallel, RL and hybrid AI optimisation approaches are increasingly explored for prescriptive decision-making in scheduling and control [128]. Collectively, these AI methods provide MSD with mechanisms to transform operational data into predictive insight, faster diagnostics, and actionable recommendations that can be validated through simulation and digital twin models and then embedded into design and planning rules [119,127,128].

Overall, the literature supports a coherent argument: big data provides the material basis, AI supplies the analytical and decision-making machinery, and MSD benefits most when both are embedded in a lifecycle architecture that connects engineering models, operational data, and continuous improvement. This also creates a natural link to CAPP, which can be interpreted as a design-to-operation mechanism that operationalises product and process knowledge (routings, parameters, constraints) and increasingly draws on data-driven and AI methods to improve process-plan generation, validation, and adaptation within I4.0 manufacturing systems.

4.1.5.8. Computer-aided process planning (CAPP)

Digital technologies of I4.0 are transforming manufacturing processes, with Computer-Aided Process Planning (CAPP) playing a strategic role as a bridge between CAD and automated, intelligent production in CAM systems [129]. Modern CAPP solutions are increasingly connected to digital factories and supported by AI, cloud environments, and virtual simulations, forming a foundation for digital integration and advanced production management.

Soori and Asmael provide a comprehensive classification of recent CAPP research, showing how optimisation, AI, energy considerations, and virtualisation together drive the evolution towards collaborative, energy-aware, and intelligent CAPP systems that learn from historical data and leverage cloud computing, virtual planning, and digital twins. They also identify gaps, such as limited integration of neural networks and cloud platforms, and the need for more holistic CAPP concepts aligned with I4.0 and I5.0 [129]. Other studies systematise techniques and optimisation approaches, including feature-based systems, genetic algorithms, artificial neural networks, knowledge-based systems, and STEP-compliant technologies, and demonstrate that automated and flexible CAPP can significantly reduce costs and increase efficiency and quality across the product lifecycle [130]. In the context of additive manufacturing, integrated knowledge-based CAPP frameworks use multi-level models that combine expert knowledge, historical data, optimisation, and AI algorithms to support robust and adaptive process planning for complex multi-component production while maintaining stable quality [131]. Overall, advanced CAPP concepts are becoming critical enablers of competitive digital factories, supporting informed, self-managed, and optimised progression from design concepts to stable, personalised production and quality control.

4.1.5.9. Knowledge-based engineering (KBE)

Knowledge-Based Engineering (KBE) plays a significant role in digital transformation within the context of I4.0 and I5.0 by integrating, automating, and optimising engineering knowledge in complex manufacturing processes [132–135]. Its core value lies in the digitalisation and reuse of expert knowledge, rules, and experience to accelerate product development, enhance cross-disciplinary collaboration, and shorten decision-making time across the product lifecycle. This is particularly important for complex Engineer-To-Order (ETO) and Make-To-Order (MTO) systems [132,133].

Studies indicate that KBE maturity varies across industries: shipbuilding and aerospace already use KBE systems to automate multidisciplinary design tasks and optimisation, while sectors such as prefabricated façades are only beginning to embed manufacturing knowledge into early-stage design decisions and integrate parametric, manufacturing, and logistics constraints, often in combination with BIM [132,134]. Methodological frameworks for KBE development emphasise interactive engineering and the linkage between expert and machine knowledge, for example through graphical matrices that structure objectives, input parameters, and system actions, with a focus on flexibility, SME adoption, and explicit integration of sustainability across the lifecycle [133].

In high-tech domains, KBE is positioned at the core of ontology-based digital threads, working with Model-Based Systems Engineering (MBSE) and ontologies to enable early evaluation of design–production trade-offs and reduce iteration between product-design and production-engineering domains [134]. Hybrid knowledge-acquisition approaches that combine expert-driven and data-driven learning increase the scalability and interoperability of knowledge, reinforcing KBE's role in knowledge modelling, management, and orchestration of digital information flows across the product lifecycle.

Practical implementations based on ontologies and CAD tool APIs (e.g., Siemens NX) demonstrate that platform-independent KBE tools can automate 3D model generation and design tasks in construction and manufacturing engineering, enabling modular and scalable solutions tailored to SMEs, accelerating the development of individualised products, and supporting configuration of designs according to customer needs [135]. Overall, KBE – especially when combined with ontologies, digital threads, BIM, MBSE, and sustainability-oriented practices – emerges as a key enabler of future digital factories by supporting automation, coherent integration of engineering knowledge, increased production flexibility, and progress towards I5.0 through more human-centred and user-driven innovation processes.

4.1.5.10. Additive manufacturing (AM)

Additive manufacturing (AM) provides an alternative to traditional production by fabricating complex geometries layer by layer directly from digital CAD models, simplifying and improving the accuracy of prototype production [136]. Compared with subtractive methods such as CNC machining, AM offers a more efficient way to shape products, with empirically confirmed advantages in product development and production, particularly through reduced material waste and support for sustainable, flexible manufacturing.

Recent reviews highlight AM's capability to produce complex, customised parts and its growing application in selected subsystems and components of manufacturing systems, where rapid prototyping and local production offer clear benefits [136]. Integrating 3D printing into automated lines enhances tooling and auxiliary components, maintenance, and in house spare part production, provided that technological, organisational, and regulatory aspects are aligned [137]. Systematic studies show that 3D-printed jigs and fixtures have become mainstream, especially in the automotive sector, reducing lead time and cost and accelerating iterations in line balancing and workplace ergonomics [138]. Overall, additively manufactured fixtures (AMF) have become a key instrument in early MSD, with the greatest impact in tooling, spatial layout simulations, maintenance and repair, and digital integration with automation.

4.1.5.11. Cloud computing

Cloud technology is a cornerstone of digital transformation in manufacturing, enabling scalable, flexible, and distributed access to engineering and production resources, data, and expertise across globally networked value chains. In MSD and product lifecycle management (PLM), cloud-oriented platforms decouple data, software tools, and simulation and optimisation processes from local infrastructure, supporting service-oriented business models, digital collaboration, and faster innovation cycles in agile, personalised systems [139,140].

Research shows that cloud solutions bridge gaps between globally distributed industrial partners, improving utilisation of expertise, resource flexibility, and process integration, thus redefining collaboration and innovation in digital environments [139]. The Cloud-Based Design and Manufacturing (CBDM) paradigm frames this as a service-oriented, collaborative, and configurable architecture in which resources and data are accessible via the cloud and shared across organisations to enable mass customisation and scalable innovation [140]. To address data-exchange risks, service-oriented infrastructures with advanced encryption and intellectual property protection have been proposed for the secure sharing of CAD models without compromising confidentiality [141].

Cloud platforms are increasingly combined with mixed reality (MR) systems, intelligent virtual manufacturing cells (IVMC), IoT, and AI analytics. MR-based cloud applications support collaborative part design with simultaneous, interactive work and automatic conversion into manufacturing documentation [142]. IVMC concepts use multi-agent systems, heuristics, and intelligent task mapping in the cloud to dynamically configure manufacturing cells according to current production needs, constraints, and user priorities, increasing flexibility, modularity, and resource utilisation, and accelerating the formation of new lines [143]. Integrated cloud–IoT–AI monitoring platforms process real-time sensor data to detect deviations, enable predictive maintenance, and support continuous operational improvement in smart manufacturing [144]. Overall, the integration of cloud technology with MR, virtual cells, IoT, and AI-driven analytics underpins a new generation of adaptive, digitally driven manufacturing systems, spanning the path from design to autonomous control and optimisation while expanding opportunities for innovation and global collaboration.

4.1.5.12. Cybersecurity

Cybersecurity is a crucial aspect of modern industry and smart manufacturing plants, as industrial systems are increasingly exposed to sophisticated attacks due to growing digitalisation, IoT connectivity, and the integration of IT and OT layers. Resilience to cyber threats therefore extends beyond traditional data protection to include continuous access management, multi-layered security policies, adherence to recognised standards, and methods for early detection and response to incidents [145,146].

Recent studies show that legacy perimeter-based ("zoned") defence models, where trust depends on network location, are no longer effective in dynamic networks and digital production chains [145,147]. Instead, zero-trust architectures with micro-segmentation, identity verification at every interaction, and automated anomaly detection and blocking systems are recommended as suitable frameworks for protecting legacy equipment, IoT devices, virtualised services, and production data flows [147]. The shift towards digitally driven production and AM, including 3D printing and related design and CAM processes, introduces new attack vectors – from intellectual property theft to manipulation of code and manufactured parts – which require security models that address technological, organisational, and human factors together. In this context, the implementation and convergence of international standards such as ISO/IEC 27001, NIST 800-53, and IEC 62443 are considered essential for robust protection and proactive forensics in heterogeneous industrial environments [145,146]. Advanced quantitative methods, AI, and ML are increasingly used to detect and classify attacks on IIoT, SCADA, and CPS, while research on insider threats highlights the importance of enhanced authentication, behavioural analysis, and anomaly detection mechanisms in distributed, collaborative, and virtualised settings where conventional safeguards are inadequate [146,148,149]. Overall, the literature emphasises that effective industrial cybersecurity is fundamental to innovation, productivity, and the long-term sustainability of digitally driven and smart manufacturing systems, and that success depends on combining technically advanced protection mechanisms with a security-oriented organisational culture and consistent application of international security standards and protocols.

4.1.5.13. Blockchain

Blockchain has become a transformative technology in smart and sustainable manufacturing and digital collaboration by enabling decentralised data management, secure information exchange, and automated execution of transactional rules without central intermediaries. This increases trust among business partners and participants in industrial ecosystems. While early applications focused on finance and logistics, recent studies demonstrate its value in product quality management, traceability, and collaborative manufacturing platforms [150,151].

In smart manufacturing, Blockchain-based Product Quality Management (BPQM) frameworks provide immutable, transparent, and secure recording of key events across the product lifecycle. These frameworks are often combined with smart contracts and AI to enable automated decision-making and end-to-end quality traceability, as shown in practical case studies [151,152]. Engineering practice further shows that integrating blockchain with edge computing can accelerate processes, increase data exchange speed, and strengthen security in applications ranging from production flow control to digital twins and remote machine operation [152]. Blockchain is also increasingly used as infrastructure for collaborative industrial platforms, where consensus-oriented cloud manufacturing models based on federated blockchain and smart contracts support secure matching and interaction between users and service providers (e.g., 3D printing services), thereby enhancing trust, scalability, and solution quality [153].

Review papers on blockchain in I4.0 and I5.0 highlight a growing range of opportunities – from transparency and digital traceability to support for circular economy models, human-centric approaches, and resilience across value chains – while also emphasising persistent challenges related to standardisation, efficiency, and integration with existing systems, which remain key directions for future development.

The reviewed digital technologies, collectively form the technological backbone of I4.0 and the emerging I5.0. These technologies enable real-time data acquisition and analysis, virtual-physical integration, autonomous and collaborative operation, and secure, distributed value-chain coordination, thereby supporting agile, highly customised, and increasingly sustainable manufacturing systems. In MSD, they shift the focus from static, equipment-centred layouts to cyber-physical, model-driven, and human-centric architectures, where design, planning, operation, and continuous improvement are tightly integrated. As these technologies diffuse into industrial practice, their actual impact on manufacturing systems is increasingly determined by the organisation's level of digital maturity and its position along the digital-transformation pathway. Companies with low maturity typically implement isolated, locally optimised solutions, whereas more advanced organisations embed digital technologies into integrated, data-driven architectures that support real-time decision-making and continuous improvement. This reinforces the need to explicitly consider digital capabilities and organisational readiness when addressing MSD in the context of I4.0 and I5.0.

The following chapter examines methods and principles for designing manufacturing systems in I4.0 and I5.0, showing how these technologies can be systematically embedded into engineering practice to achieve greater flexibility, resilience, and alignment with human and environmental requirements.

4.2. Design of manufacturing systems in the context of Industry 4.0 and Industry 5.0

In the broadest sense, MSD encompasses the systematic definition of the structure and operation of a production system, including products, processes, resources, layouts, control logic and performance targets. In the literature, the terms manufacturing system design (MSD) and production system design (PSD) are not used consistently; some authors treat manufacturing as a subsystem of production, while others adopt the opposite hierarchy. In practice, however, the distinction is often blurred, and both terms are used to denote the design of the system that transforms inputs into finished products. Cochran et al. introduce the Manufacturing System Design Decomposition (MSDD) as a formal framework for MSD [154,155], while ElMaraghy et al. offer a similarly broad, evolutionary view of manufacturing systems and their design in dynamic environments [14]. In this thesis, MSD is therefore used as an umbrella term for the design of the production system within the defined system boundary.

Manufacturing environments are characterised by the continual adoption of new production paradigms, which often overlap or compete, alongside innovations that generate a range of promising technologies. Simultaneously, these environments are marked by large-scale digitalisation of production and assembly processes, generating vast volumes of highly heterogeneous data at high speed, whose latent but substantial value can be exploited through appropriate analytical and integrative approaches (Figure 4.5).

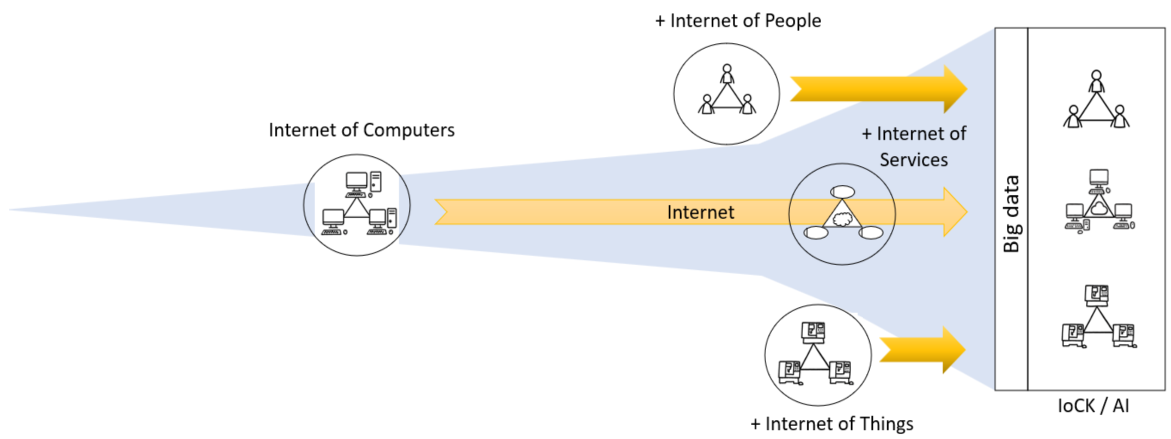


Figure 4.5: Digital data volume in manufacturing [156]

The recent evolution of MSD clearly reflects a transition from the technology-centred paradigm of I4.0 to the value-oriented paradigm of I5.0, as highlighted by Leng et al. [157]. They provided the foundation for MSD digital transformation through the introduction of CPS, IoT, digital twins, simulation, and AI, enabling virtualisation, optimisation, and analytical modelling of manufacturing systems.

However, MSD within the I4.0 framework has remained primarily focused on efficiency and automation, with limited consideration of human, organisational, and sustainability dimensions. I5.0 builds on these technological foundations by introducing three core values: human-centricity, resilience, and sustainability, which become integral elements of design criteria. According to Leng et al., this shift is operationalised through extended design processes, particularly the FSBCIP model (Function–Structure–Behaviour–Control–Intelligence–Performance), which links structural and functional design with intelligent control, autonomy, and performance. In this way, MSD is transformed from a predominantly technological activity into a multidisciplinary process that integrates human factors, system resilience, and environmental sustainability [158]. I4.0 thus provides the digital enablers, while I5.0 defines the broader purpose of design. Their relationship is complementary: I4.0 technologies make it possible to operationalise the values of I5.0, while I5.0 reshapes design priorities and criteria beyond mere automation, towards manufacturing systems that are simultaneously intelligent, human-centred, and sustainable.

To realise these I4.0 and I5.0 ambitions in practice, implementation must begin as early as possible in the lifecycle of a manufacturing system, specifically during the design phase of the production system. When digital enablers (such as CPS, IoT, digital twins, and advanced analytics) and I5.0 value criteria (human-centricity, resilience, and sustainability) are embedded from the outset, their positive effects on performance, learning, and adaptability can be achieved much earlier in the operational phase. This requires a deliberate strategic approach from the very beginning of each manufacturing system development effort: rather than treating digitalisation and I5.0 values as later “add-ons”, they must inform concept definition, architecture choices, and capacity decisions from the start. In this context, the next subsection examines strategic thinking as a key integrative mechanism for aligning early-stage MSD decisions with long-term competitiveness in an I4.0 and I5.0 context.

4.2.1. Strategic thinking for manufacturing system competitiveness

The use of digital technologies in MSD enables the generation of multiple acceptable alternatives, shifting further research towards the role of digitalisation in strategic thinking when defining the strategic concept of a manufacturing system for a given family of related products, with the potential to extend it to the remaining product portfolio with minimal adaptations [159,160]. As every industrial system is unique in its structure, knowledge base, and operating environment, its development strategy and long-term survival in a competitive market must be tailored to these specificities, drawing on appropriate approaches to strategic competitiveness. The literature most frequently highlights two fundamental perspectives: the resource-based view and the dynamic capabilities approach, which are examined in the following sections in the context of their integration with digital technologies and the MSD process.

4.2.1.1. Different strategic perspectives on competitiveness in digital transformation

According to the resource-based paradigm, competitive advantage is rooted in a company's internal resources, meaning the exploitation of its own potential and strengths rather than primarily pursuing external market opportunities. Resource strength is evident in various forms: specific skills and expertise, the ability to produce competitively, valuable assets such as advanced plants and technologies, human resources, and proven quality systems [161]. It is not simply a static asset base but the result of continuous learning and accumulated experience, that is, organisational expertise. In a dynamic environment, however, such competitive advantage is limited, and the resource-based view has been criticised for its internal focus and static nature. Digital technologies enable more effective exploitation of resource strengths and transform them into core competences. Higher levels of digital transformation and progress towards I4.0 further reinforce resources; competent I4.0 specialists enhance other resources by applying digital technologies to decision-making at all organisational levels, accelerating development, reducing the cost of product and technology innovation, and increasing flexibility in responding to market changes. Nevertheless, the resource-based approach only weakly explains how resources are developed and renewed over time. Long-term sustainability requires not only resource accumulation and favourable strategic positioning, but also continuous learning, periodic optimisation of the resource base, and active management of intangible assets. The ability to create new forms of competitive advantage is termed dynamic capability and is defined as the company's capacity to integrate, build, and reconfigure internal and external competences to address rapidly changing environments [162]. Initial work situates these capabilities within the temporal triad of past (position), present (processes) and future (scenarios), and groups them into three key activities: sensing, seizing, and transforming. These are forward-looking capabilities that cannot be bought; they must be built up over the long term, as illustrated by the example of the Toyota Production System. Dynamic capabilities are necessary but not sufficient for sustained competitive advantage: their effects are temporary and require constant adaptation. In this process, the role of managers and experts is crucial in understanding and leveraging the potential of digitalisation at all stages of decision-making.

Digital transformation has progressed rapidly over the past decade, particularly with the advent of 4G and 5G wireless communication networks. One of its core tasks is the conception and implementation of new business models [48]. Digital transformation accelerates preparatory activities in various types of projects, from developing new products and processes to improving existing business processes. Incorporating dynamic capabilities into digital transformation enhances the quality of defining optimal solutions in all these project types. The objectives of digital transformation, such as digital connectivity and automated data exchange between physical and virtual systems, ensure fast and transparent access to key information required by decision-makers for high-quality decisions. Digital technologies further accelerate the testing and refinement of hypotheses about customers and technologies, which is particularly important in "generic reappraisal" phases [163]. At all stages of application, they play a crucial role by enabling rapid virtual data collection and analysis, as well as concept testing in both new product and process development and continuous improvement initiatives. This increases the volume and quality of input indicators that influence the choice of the target configuration of the manufacturing system and allows different scenarios and their impact on outputs and product competitiveness to be evaluated.

The implementation of a new business model, supported by an appropriate strategy, relies on the capacity for reconfiguration. Reconfiguration entails a critical assessment of the adequacy of existing capacities and the search for solutions to identified gaps through internal development, acquisition, or contracting of required capacities from partners. The speed of business model reconfiguration can be crucial. To avoid falling behind leading competitors, it is necessary to engage in strategic thinking already in the initial phase of conceptual design of the production system, as well as in the optimisation of existing systems.

4.2.1.2. Relationship between strategic planning and strategic thinking

Strategic thinking has appeared in the strategic management literature for about three decades, yet its precise content and definition remain ambiguous, and it is often conflated with strategy, strategic management, or strategic planning. Jelenc defines strategic thinking as a process in which an individual perceives, senses, understands, accepts, and critically questions the characteristics that affect the future of the business system, assigns meaning to them, and acts accordingly, shaping impressions, approaches, and behaviours [164].

Strategic thinking is therefore a continuous, process-based approach which, unlike strategic planning with its varying intensity, occurs throughout the entire year. The individual, typically at the highest management levels, is central, but emphasis is also placed on transferring strategic thinking capabilities through interaction with colleagues, subordinates, and superiors. The key idea of strategic management remains that the business system should be different and more successful than its competitors by creating and continuously adapting its own models. Professional competence is a fundamental prerequisite for any form of strategic thinking and includes knowledge of the industry, the wider environment, and business and technological processes. In practice, successful outcomes are often attributed to “good” strategic thinking, while failures are ascribed to its absence.

Sloan defines strategic thinking as a problem-centred approach to strategy, grounded in the theory of criticality and supported by specific cognitive abilities that differ from those required for strategic planning [160]. The emphasis is on correctly identifying the problem before seeking solutions and rigorously questioning the underlying assumptions of the strategy to open up new possibilities. Sloan’s “strategy triad” consists of strategic thinking, strategic planning, and strategy execution as three mutually interdependent, dynamically balanced domains. The dynamic model shown in Figure 4.6 is a highly interactive triangle with “floating points” that move into or out of focus depending on the organisation’s needs at a given time.

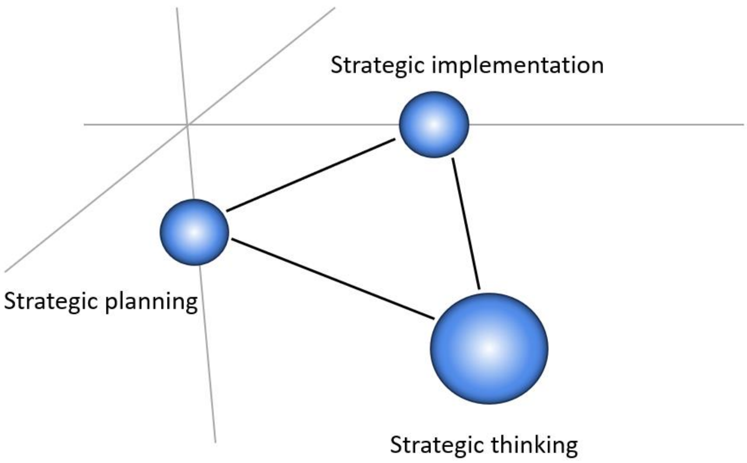


Figure 4.6: Sloan Triad model for strategy [160]

The links between the domains are “elastic” and not strictly defined, serving as a reminder that all three are necessary for a successful strategy. The domains are inseparable and mutually dependent; each is important for business success but plays a different role as the focus shifts in response to changing business needs. The duration of focus on each domain varies, and the rhythm of movement across domains differs for every strategic case because the underlying factors and environmental conditions vary [160].

Applying this model requires cognitive agility, disciplined learning, and a constant interplay between intuition and data-driven analytical insight, as well as the involvement of as many experts as possible in decision-making processes at all organisational levels.

4.2.1.3. Strategic thinking in an industrial environment

Increasing environmental turbulence in recent years has exposed the limitations of classical strategic planning tools and highlighted the need to develop strategic thinking capabilities at lower organisational levels, particularly when modern digital technologies are involved. In practice, strategic thinking is often neglected, typically justified by a lack of time or the perception that it is a “luxury” activity. However, successful organisations seek to balance thinking, planning and execution, and to include experts and key stakeholders from different business areas in strategic dialogue. It is possible to think strategically without formal methods, but it is not possible to formulate a high-quality strategy without strategic thinking. Experienced strategists accept the existence of complex questions without complete answers, observe system behaviour patterns, and shape future states by developing scenarios [159]. The use of strategy formulation tools combined with modern digital technologies enables the exploration of multiple scenarios for the same strategy and their comparison in a virtual environment. Digital technologies, particularly digital models and digital twins, provide credible virtual representations of existing or planned physical systems. Hybrid models, in which classical methods are complemented by digital tools, create opportunities to simulate different scenarios, analyse results, and make more informed decisions in complex business processes. The essence of strategic thinking lies in adopting a broad perspective and anticipating future situations rather than focusing on isolated problem-solving.

Viewed through the lens of dynamic capabilities theory, digital technologies play a role in all three phases: sensing, seizing, and transforming [159]. In the sensing phase, when assessing the impact of new or adapted technologies on the system and its environment, digital technologies enable faster and more accurate testing of multiple variants, provided that key information and their interrelationships are appropriately captured in the model. In the seizing phase, digital technologies provide information that accelerates organisational learning and prepares the ground for the transformation phase, in which the organisation uses acquired insights to adjust structures and processes. In many industries, especially when developing new products and technologies, this process occurs under time-critical conditions in competition with other companies. Figure 4.7 shows the potential use of digital technologies in different phases of competitive capabilities, depending on the level of digital maturity. The higher the level of maturity, the greater the range of digital technologies available, enabling stronger synergetic effects both in the optimisation of installed systems and during MSD. At the same time, a higher level of maturity creates the preconditions for greater involvement of experts at all organisational levels, leading to higher-quality solutions in the definition and management of production systems. Digital technologies also enable earlier detection of performance deviations and potential errors.

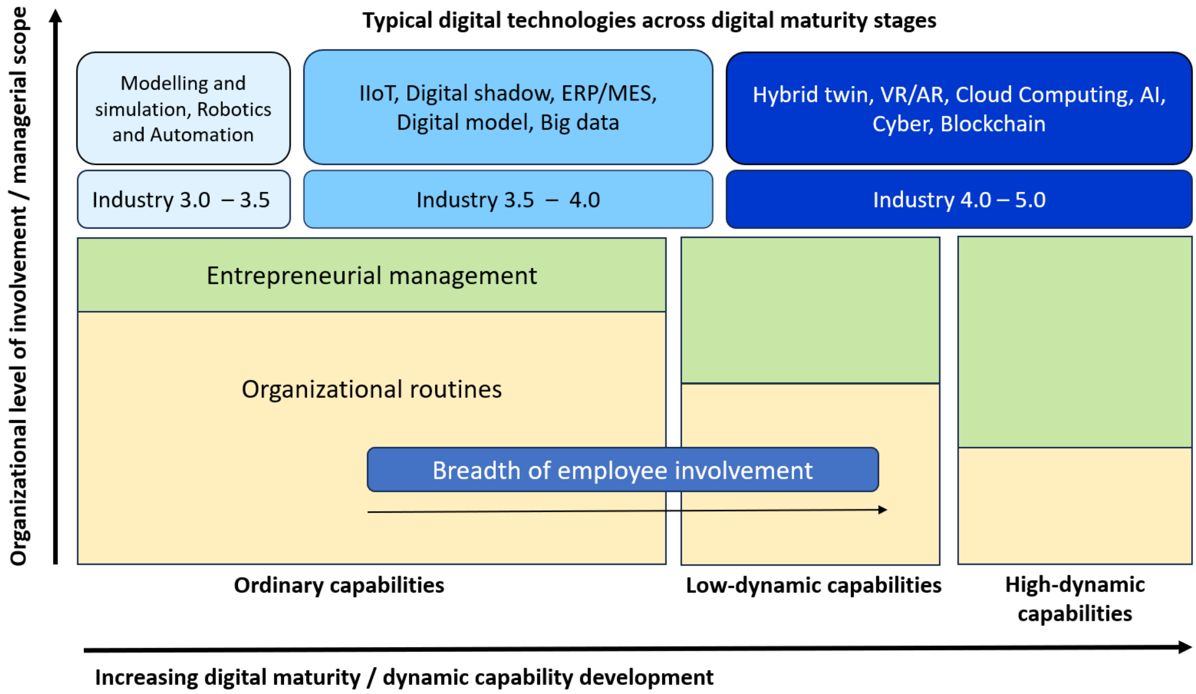


Figure 4.7: Involvement of experts in dynamic capabilities with integrated digital tools – adapted [165]

Figure 4.8 illustrates the area where errors originate below the threshold of acceptable performance, which in practice often goes unnoticed or is ignored until the consequences become apparent (D) [159]. Timely identification of deviations and elimination of root causes can prevent entry into the danger zone or the occurrence of failure (A, C), while delayed or ineffective responses increase the likelihood of serious failures (B, D).

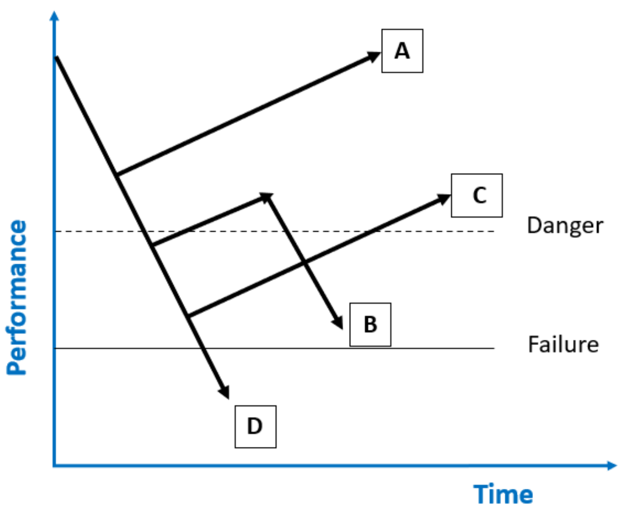


Figure 4.8: Timely recognition of hazards [159]

Monitoring and analytics systems based on digital tools support early detection of such deviations, while simultaneously tracking internal processes and the external environment. Some errors can be prevented or their impact mitigated through a combination of well-considered strategy, strategic thinking, modern methods, digital tools, and consistent planning and monitoring of implementation. This approach is universally applicable, from process conception in the early design stages, to continuous improvement phases.

For example, a robotic car-body welding line demonstrates that, over a factory's lifetime, only about 25% of costs are incurred before commissioning, while planned costs account for around 44% and unplanned costs about 31%, with the latter exceeding the initial investment, as shown in Figure 4.9 [166].
It is estimated that the total costs of future plants can be reduced by approximately 30% through improved planning and equipment procurement, orienting product development towards manufacturability, changing production organisation, and reducing unplanned costs by around 85%.

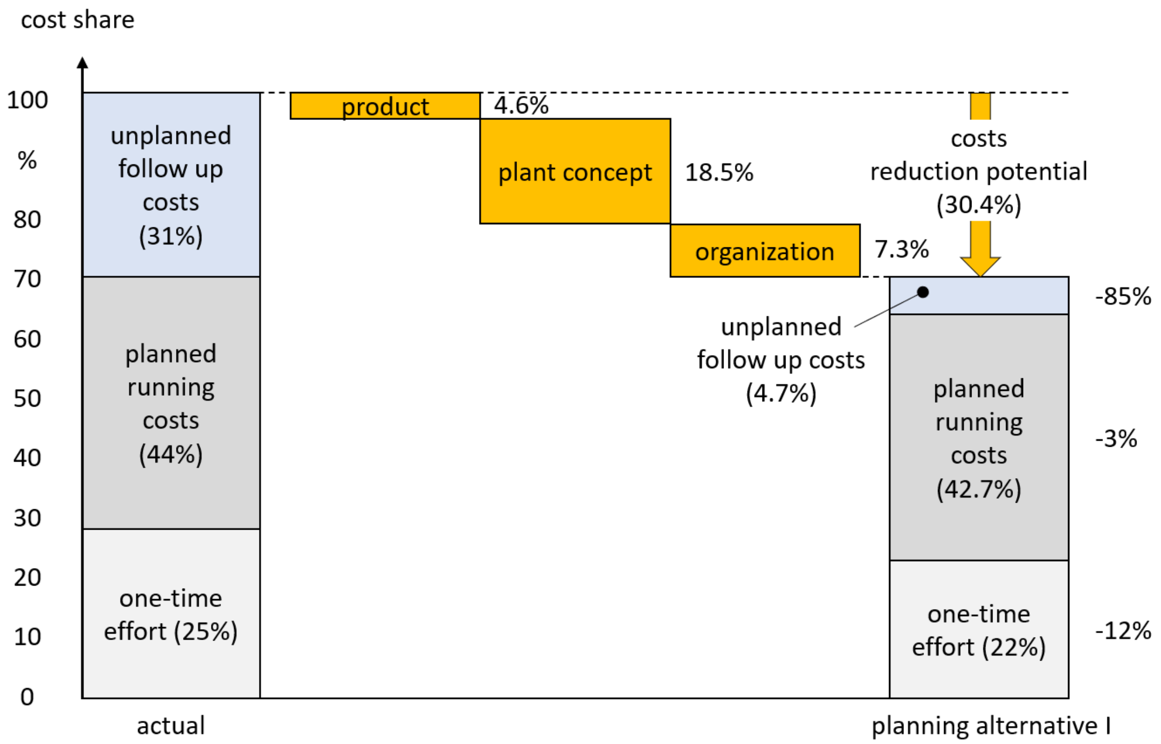


Figure 4.9: Potential for reducing lifecycle costs [166]

Modern digital technologies, available from the earliest stages of product and MSD, enable the creation, verification, and optimisation of virtual replicas of physical systems, thereby directly supporting strategic thinking and cost reduction throughout the entire lifecycle [167].

4.2.2. Elements of manufacturing system design

In classical literature, MSD is regarded as the integration of physical resources, human resources, and information-management functions. Groover defines a manufacturing system as a combination of facilities (space, machines, material-handling equipment, measurement and information systems) and manufacturing support systems (planning, control, quality, administration), emphasising that target performance levels can be achieved only through coordinated design of all these subsystems [168].

A similar holistic perspective is presented by Hitomi, who, within the scope of manufacturing systems engineering, connects three fundamental dimensions: production technology, production management, and industrial economics [169]. These works already identify elements such as product, process, resources, information, and cost, which are now essential inputs for MSD in the context of I4.0 and I5.0.At the factory and spatial-layout level, Wiendahl et al. propose a methodological approach to factory planning and design, in which the system is considered hierarchically, from the workplace, through production areas, up to the building and site [170]. Their framework covers programme and volume planning, selection of the production concept, flow, layout, logistics, and workplace design, integrating ergonomics, safety, and environmental requirements. This directly supports elements in the proposed framework such as input requirements and market, product structure (bill of materials-BOM), space and layout, material flow and logistics, and HSE (health, safety, and environment). In this thesis, these elements are systematised and grouped into an operational design guideline that facilitates structured design; a concise overview is provided in Table 4.1.

Hopp and Spearman emphasise flow dynamics, specifically, the relationships between work in progress (WIP), throughput time, capacity, variability, and inventory levels, and demonstrate how different planning and scheduling policies affect system performance [171]. Their approach closely links material flow, information flow (planning and scheduling), and performance (OEE, productivity, lead time, inventory), which in the present framework is reflected in the elements “material flow and logistics”, “information flow and PPC”, and “performance, costs and economics”. By introducing typical indicators (e.g., WIP, on time delivery (OTIF), OEE, unit costs, ROI), the framework operationalises the “physics of the factory” as concrete metrics that can be defined and monitored already in the design phase, rather than only retrospectively during system operation. Literature on the design of quality and maintenance systems further highlights the need for an integrated approach.

Colledani et al. propose the “production quality” paradigm, demonstrating that MSD must consider line structure, maintenance strategies, machine unreliability, buffer sizing, and information flow, rather than treating quality as an isolated end-of-line control activity [172]. Gola, in a review of MSD and management, highlights the multi-level nature of the problem, spanning capacity and flexibility planning, maintenance, and environmental aspects [173].

This justifies the inclusion of separate elements for quality control, maintenance, and HSE in the proposed framework, with Table 4.1 explicitly listing typical indicators (first pass yield - FPY, scrap rate, mean time between failure - MTBF, mean time to repair - MTTR, energy consumption, waste) that classical authors usually mention only implicitly or in a fragmented manner. With the modernisation of manufacturing systems, the role of digital technologies and CPPS has become increasingly prominent. Monostori emphasises that the Fourth Industrial Revolution is fundamentally based on integrating physical resources (machines, logistics, maintenance) with advanced information and communication technologies, sensor systems, and analytics [174]. Later work by Monostori et al. elaborates on CPPS architectures, the role of sensors, communication networks, models and analytics, and the implications for planning, control, maintenance, and quality [72]. These contributions provide the theoretical basis for including a dedicated element - digital technologies, I4.0 and I5.0, and CPPS - in the framework, which builds on classical elements such as machines, processes, logistics, quality, and maintenance, not replacing them but interconnecting them and making them transparent and adaptive.

Research on Reconfigurable Manufacturing Systems (RMS) further highlights the need to address flexibility and adaptability explicitly during the design phase. Mehrabi et al. define RMS as a design paradigm that enables rapid adjustment of capacity and functionality "exactly as much as needed and when needed" [175]. This requires that modularity, scalability, and diagnosability be incorporated from the outset when specifying elements such as machinery and equipment, layout, logistics, and digital infrastructure. In the proposed framework, this approach is reflected in the criteria for evaluating individual elements (e.g., proportion of modular machines, scalability of capacity, level of CPPS integration), which are also summarised in Table 4.1.

The proposed framework, comprising thirteen elements (ranging from input requirements, product and process, through resources, layout, logistics, quality, maintenance and HSE, to performance and digital technologies), represents a synthesis of classical approaches to MSD [168–171], enhanced by contemporary emphases on quality, maintenance, reconfigurability, and CPS [72,172,173,175].

Table 4.1 operationalises these dimensions through a set of key questions and indicators, transforming the framework into a practical guideline for structured MSD in the context of I4.0 and I5.0. Combined with the information on the applicability of digital technologies in Table A3 in Appendix A, it enables consistent linkage between the classical elements of the manufacturing system, the deployed digital technologies, and the targeted performance outcomes. Table A3 summarises the key design questions and representative digital solutions that support decision-making in the design phase, as well as the monitoring and improvement of performance during system operation.

Table 4.1: Key elements framework of manufacturing system design

System/process element		Key design questions	Representative indicators (examples)
1.	Input requirements and market	What products and variants are required, and in what volumes? What delivery performance and regulatory constraints must be met? Are there specific customer requirements?	Annual or monthly demand; batch size; OTIF (%); target order-to-delivery lead time.
2.	Product and product structure (BOM)	How is the product structured (BOM)? Which characteristics are critical and which product variants must be supported?	Number of BOM levels; number of parts per product; proportion of common parts; number of CTQ characteristics.
3.	Process and flow of activities	What are the main operations and their sequence? What takt time is required, and where are the potential bottlenecks?	Number of operations and stations; line takt time; operation cycle time; process lead time; proportion of value-adding time (%).
4.	Resources: machines, equipment and tools	Which machines and technical resources are required, and what are their capacities and capabilities? What is the level of automation and the setup effort involved?	Machine capacity (pcs/h); utilisation (%); setup and changeover time; number of breakdowns per month; proportion of automated operations (%).
5.	People and work organisation	What staffing levels and skill profiles are required? How are tasks, responsibilities, and competences allocated across workstations and shifts?	Number of operators per shift; output per labour hour (pcs/h); proportion of multi-skilled workers (%); training hours per employee per year; staff turnover rate (%).
6.	Space and layout	Which layout concept is appropriate (line, cell, functional, or hybrid)? How much space is required for equipment, buffers, and the movement of people and materials?	Total production area (m^2); area per workstation (m^2); material flow path length (m); number of flow crossings; space utilisation (%).
7.	Material flow and logistics	How are materials supplied, stored, and moved within the system? What levels of work-in-process (WIP) and inventory are acceptable?	WIP (pieces or days of production); number of material handlings per unit; internal transport time; inventory accuracy (%); buffer size per station.

System/process element		Key design questions	Representative indicators (examples)
8.	Information flow and control (PPC, IT)	How is production planned, scheduled, and monitored? Which IT systems are used (ERP, MES, etc.), and to what extent are they integrated?	Plan adherence (%); response time to disturbances; level of system integration (e.g., number of integrated modules); proportion of manual data entry (%); data update frequency (real-time, hourly, daily).
9.	Quality control	At which points is quality inspected (incoming, in-process, final) and by which methods? How are non-conforming products handled?	First-pass yield (%); scrap rate (%); rework rate (%); defects per million (PPM); number of customer complaints; inspection cycle time.
10.	Maintenance	Which maintenance strategy is applied (reactive, preventive, predictive)? How are interventions and spare parts planned, executed, and recorded?	MTBF; MTTR; technical availability (%); share of preventive maintenance in total maintenance effort (%); number of breakdown-related stoppages per month; maintenance cost per unit.
11.	Safety, ergonomics and environment (HSE)	What are the main safety risks and ergonomic requirements in workplaces? In environmental impacts of system?	Number of work accidents per year; TRIR; ergonomic assessment scores; energy consumption per unit; waste per unit; recycling rate (%).
12.	Performance, costs and economics	Which performance levels are targeted and at what cost? How is the economic viability of the system or investment evaluated?	OEE (%); line productivity (pcs/h or pcs/shift); unit manufacturing cost; return on investment (ROI); net present value (NPV); break-even point; total order-to-delivery lead time.
13.	Digital technologies and I4.0/I5.0 integration	Which assets and processes are connected through sensors and IIoT? Where are digital models, such as simulation and digital twins, and data analytics or AI applied? Is VR/AR used for commissioning or training?	Number of connected machines and sensors; proportion of operations under digital monitoring (%); number of analytics or AI use cases; reduction in downtime or scrap rate due to digital solutions (%); data refresh rate; VR/AR training hour per year.

4.2.3. Matrix of digital technology applicability across design elements

Building on the proposed framework of thirteen MSD elements and the set of sixteen selected digital technologies, the next step is to examine how these technologies are deployed across the different elements of system design. While previous tables provided qualitative links and examples of applications, a more detailed view is needed to distinguish between technologies that are structurally central to a given element and those that play a more supportive or marginal role. This distinction is particularly important for identifying where their impact on system design is most significant. The analysis is based on the design guidelines for each digital technology.

Industrial Internet of Things (IIoT)

When designing manufacturing systems with IIoT, it is essential to define which assets and processes will be instrumented, which variables will be measured (status, condition, environment), and how data will be transmitted and integrated with MES/ERP and analytics platforms. Particular attention should be paid to sensor placement, communication architecture, and data granularity to ensure IIoT data can effectively support process control, maintenance, quality, and logistics decisions.

Modelling and simulation

When applying modelling and simulation, designers should first clarify the questions to be answered (capacity, bottlenecks, quality, availability, WIP, lead time, ergonomics, etc.) and then define the required level of model detail for processes, resources, layout, and control logic. Simulation models should be calibrated, parameterised, and reusable so they can support scenario analyses, sensitivity studies, and later serve as a basis for digital twins.

Digital twin (digital model, digital shadow, digital twin)

Incorporating digital twins into system design requires defining which parts of the system will have a twin, which data streams will update it in real time, and which decisions it will support (e.g., commissioning, scheduling, maintenance, quality). Designers should specify data models, synchronisation mechanisms, and validation procedures to ensure the digital twin remains an accurate and useful representation of the physical system throughout its lifecycle.

Robotics and automation

When designing with robotics and automation, it is essential to determine which tasks should be automated, the desired human–robot collaboration pattern, and the implications for layout, safety, and skills. Robot and automated guided vehicle (AGV/AMR) selection must align with cycle time requirements, payloads, reach, and path constraints, while safety concepts, ergonomics, and maintenance access are considered from the outset of the design process.

Horizontal and vertical integration (ERP/MES, etc.)

For horizontal and vertical integration, the design should define information flows and responsibilities across levels (shop floor, MES, ERP) and standardise interfaces and data structures. Early decisions on integration architecture, such as which planning logic resides in each system, reduce later rework and ensure that performance, cost, and traceability indicators are generated consistently from operational data.

Virtual technologies (VR/AR)

When integrating VR and AR, designers should specify which design reviews, training activities, or shop-floor tasks will use VR/AR, and what digital content and interaction modes are required (such as 3D models, annotations, instructions). This includes planning how VR/AR tools will be maintained and updated as layouts, processes, and work instructions evolve, ensuring they remain aligned with the actual system.

Big data

For big data applications, it is essential to determine which data sources will be captured, at what frequency, and which analytical use cases are prioritised (such as forecasting, anomaly detection, optimisation). From a design perspective, data models, retention policies, and governance rules must be defined so that the resulting data lake or platform can reliably support simulation, digital twins, and AI models.

Artificial intelligence (AI)

When designing AI-enabled systems, engineers should identify specific decision problems where learning models add value (e.g., predictive maintenance, quality prediction, scheduling) and ensure that suitable training data and feedback signals are available. The design must also address model deployment (edge vs cloud), monitoring and update procedures, as well as fallback strategies when AI recommendations are unavailable or uncertain.

Computer-aided process planning (CAPP)

For CAPP, the design guideline is to formalise the link between product structures and process plans, including rules for operation selection, sequencing, resource allocation, and parameter setting. Integrating CAPP with CAD, CAM, and MES enables consistent propagation of product changes into the process and reduces manual effort and variability in process planning.

Knowledge-based engineering (KBE)

When using KBE, designers should identify which engineering rules, constraints, and heuristics need to be captured (product, process, quality) and define how they will be represented and executed (rule engines, templates, configurators). A clear governance process is required for updating and validating knowledge bases, ensuring that KBE supports standardisation and scalability rather than codifying outdated practices.

Additive manufacturing (AM)

Incorporating AM into system design requires identifying where in the process chain AM adds value (end-use parts, prototypes, tooling, spares) and adapting product designs, BOM structures, and workflows accordingly. Designers must assess AM implications for quality control, post-processing, material logistics, and cost, and ensure that AM resources are properly integrated into layout, planning, and maintenance concepts.

Cloud computing

For cloud-based solutions, the design effort should clarify which functions and data will reside in the cloud (e.g., analytics, digital twins, data storage) and which latency, availability, and security requirements must be met. This includes defining hybrid architectures (edge and cloud), application programming interface (API) strategies, and cost models, ensuring that cloud services can scale with system complexity and data volume.

Cyber security and Blockchain

When considering cyber security and blockchain, designers must identify the critical assets, communication channels, and data sets that require protection or immutability, and select appropriate security controls and trust mechanisms. Security and integrity requirements should be integrated into the architecture (such as network segmentation, authentication, encryption, and logging) and, where blockchain is applied, into the design of traceability processes and data structures.

To provide a clearer representation of how each technology can be applied within each design element, a 13 × 16 matrix was constructed, with each row corresponding to a design element and each column to a digital technology. For each element–technology pair, the relative importance of that technology in designing the given element was assessed based on the literature review and the conceptual analysis presented in previous sections. The assessment considered the frequency, directness and consistency with which a given technology was linked to the corresponding design element, using a predefined ordinal scale ranging from no evident relevance to high relevance. This systematic procedure enhances the transparency and replicability of the assessment. The assessment distinguishes three levels of importance: dominant, significant but supportive, and minimal or occasional. These levels are represented using simple graphical symbols to provide a concise and visually accessible overview, as shown in Table 4.2. The resulting matrix thus serves as a link between the generic design framework and the technology-specific chapters, indicating where each digital technology should be considered a key design concern and where it primarily complements other central technologies. The matrix should be interpreted as a set of recommendations and guidelines derived from the results of the literature review and long-term experiential knowledge regarding the use of individual technologies. The guidelines reflect conclusions about the current state, with an inherent tendency to evolve over time due to the continuous development and deployment of digital technologies in industry, in line with the advancement of digital transformation.

The matrix in Table 4.2 links the thirteen MSD elements (rows), with the sixteen digital technologies considered in this dissertation (columns). The symbols indicate the relative relevance of each technology for a given element: (●) denotes a dominant role, where the technology is structurally central to the design of that element; (◐) indicates a significant but supporting role, where the technology contributes important functionality without being the primary enabler; and (○) represents a minimal, rare, or practically irrelevant role. Thus, the matrix provides a concise overview of where each digital technology should be primarily addressed within the design framework and where it plays a complementary or marginal role. The following paragraphs provide a concise justification for the classification of each technology's role within the respective elements of the MSD framework.

Input requirements and market

For the input requirements and market element, Big Data and AI (●) are dominant, as demand analysis, forecasting, and segmentation directly depend on large historical datasets and predictive models [119]. ERP/MES integration, modelling and simulation, cloud computing, digital thread, and cyber-security (◐) play a supporting role by providing structured order and capacity data, enabling scenario analyses (e.g., capacity versus demand), and offering scalable infrastructure for running forecasting and "what-if" experiments [45,74,91,108,176].

Product and product structure (BOM)

In the product and BOM element, modelling and simulation and digital thread (●) are central as they support virtual product validation, behaviour analysis and structural consistency of the BOM [74,90]. KBE, AM, CPS, Big Data, digital twins, cyber security, and blockchain (◐) provide secure complementary support by codifying design rules, enabling new product geometries and mass customisation, and supplying empirical field data that can be fed back into design [66,72,131,151,177,178].

Process and flow of activities

For process and flow of activities, IIoT, modelling and simulation, CAPP, CPS, and digital thread (●) are dominant, as they jointly define, instrument, and virtually validate the process sequence, cycle times, and routing [12,70,130,134,176]. Robotics and automation, ERP/MES integration, KBE, digital twins, Big Data, AI, and cyber security (◐) enhance this by enabling data-driven process improvement, automatic process plan updates and advanced analytics for bottleneck detection, scheduling, and optimisation [107,112,135,149,178].

Table 4.2: Matrix: Design element versus Digital Technology

	Basic digitalisation						Core Industry I4.0							Advanced I4.0/I5.0		
System/process element \ Digital Technology	Modelling and Simulation	Robotics and Automation	ERP/MES (Manufacturing Execution System) Integration	Computer-aided process planning (CAPP)	Knowlwdge-based engineering (KBE)	Additive Manufacturing (AM)	Industrial Internet of Things (IIoT)	Digital Twin	Virtual/Augmented Reality (VR/AR)	Big Data	Cloud Computing	Cyber-phisical system (CPS)	Digital thread	Artificial Inteligence (AI)	Cyber Security	Blockchain
1. Input requirements and market	◐	○	◐	○	○	○	○	○	○	●	◐	○	◐	●	◐	○
2. Product and product structure (BOM)	●	○	○	○	◐	◐	○	◐	○	◐	○	◐	●	○	◐	◐
3. Process and flow of activities	●	◐	◐	●	◐	○	●	◐	○	◐	○	●	●	◐	◐	○
4. Resources: machines, equipment and tools	◐	●	○	●	◐	◐	●	●	○	○	◐	●	◐	◐	●	○
5. People and work organisation	●	◐	◐	◐	◐	○	○	○	●	◐	○	○	◐	◐	◐	○
6. Space and layout	●	○	○	○	○	○	○	●	●	◐	◐	○	○	◐	○	○
7. Material flow and logistics	●	●	●	○	○	○	●	◐	○	◐	◐	◐	◐	◐	◐	●
8. Information flow and control (PPC, IT)	○	○	●	◐	◐	○	●	◐	○	●	◐	●	●	◐	◐	◐
9. Quality control	○	◐	○	◐	◐	◐	●	◐	◐	●	○	◐	●	●	◐	◐
10. Maintenance	◐	◐	○	○	○	◐	●	●	○	●	◐	◐	●	●	◐	○
11. Safety, ergonomics and environment (HSE)	◐	◐	○	○	○	○	●	○	●	◐	○	◐	◐	◐	●	○
12. Performance, costs and economics	●	○	◐	●	○	○	○	◐	○	●	◐	◐	●	●	◐	◐
13. Digital technologies and I4.0/I5.0	●	◐	●	●	◐	◐	●	●	◐	●	●	●	●	●	●	◐

Legend:

● dominant role

◐ significant supporting role

○ minimal/rare/irrelevant role

Resources: machines, equipment and tools

Within the resources element, IIoT, robotics and automation, digital twins, CAPP, CPS, and cyber security (●) are key, as they determine the automation level, connectivity, and virtual representation of critical assets [70,129,174,176,179]. Modelling and simulation, KBE, AM, cloud computing, AI, and digital thread (◐) support resource design and management through VC, capability analysis, utilisation prediction, tooling, prototyping, and scalable processing of machine and sensor data [74,91,113,135,136,140].

People and work organisation

For people and work organisation, modelling and simulation and VR/AR (●) are dominant, as they directly shape training concepts, digital work instructions, and human–machine interaction at the workplace [91,180]. Robotics and automation, ERP/MES integration, CAPP, Big Data, AI, digital thread, cyber security, and KBE (◐) play a supporting role by influencing task allocation between humans and machines, skill requirements, competency management, and knowledge capture in standard operating procedures and decision rules [148].

Space and layout

In the space and layout element, modelling and simulation, digital twins, and VR/AR (●) are central tools for virtual factory layout design, ergonomic validation and stakeholder walkthroughs [94,117]. AI, Big Data, and cloud computing (◐) support layout decisions by providing empirical flow and utilisation data, as well as computational resources for large-scale layout optimisation and 3D model management [143,181].

Material flow and logistics

For material flow and logistics, IIoT, modelling and simulation, robotics and automation (AGV/AMR), blockchain, and ERP/MES integration (●) are dominant, as they provide real-time tracking of materials, virtual evaluation of flow concepts, and close integration between logistics processes and production planning [94,105,112,182,183]. Digital twins, Big Data, AI, cloud computing, CPS, digital thread, and cyber security (◐) further enhance routing, buffering, and inventory policies through optimisation, predictive analysis, and flexible control of automated logistics resources [69,94,102,144,149].

Information flow and control (PPC, IT)

In information flow and control, ERP/MES integration, IIoT, Big Data, CAPP, CPS, and digital thread (●) form the backbone, defining how transactional data, shop-floor events, and planning information are captured and propagated across levels [70,75,129]. AI, cloud computing, cyber security, blockchain, KBE, and digital twins (◐) play a key supporting role by enabling advanced scheduling and decision support, scalable data processing, secure and traceable information exchange, and virtual validation of control strategies [45,183–185].

Quality control

For quality control, IIoT, Big Data, AI, and digital thread (●) are dominant, enabling in-line data capture, statistical monitoring, and predictive quality analytics [119,127,134]. Robotics and automation, CAPP, digital twins, KBE, VR/AR, AM, CPS, cyber security, and blockchain (◐) support the definition of control strategies, rule-based inspection plans, and trustworthy, tamper-proof traceability of quality-relevant data, as well as supporting tooling and prototyping [99,131,138,146,151,186,187].

Maintenance

Within the maintenance element, IIoT, Big Data, AI, digital thread, and digital twins (●) form the core of condition-based and predictive maintenance, enabling continuous monitoring, fault prediction, and virtual degradation modelling [69,75,88,188]. Modelling and simulation, cloud computing, robotics and automation, CPS, and cyber security (◐) provide additional support by enabling "what-if" analyses of maintenance policies, scalable processing of maintenance data, tooling, spare parts, and the use of robots for inspection and intervention in hazardous or hard-to-reach areas [12,26,67,176].

Safety, ergonomics, and environment (HSE)

For HSE, VR/AR, IIoT, and cyber security (●) are dominant as they influence how risks are visualised, how workers are assisted in real time, and how environmental and safety-relevant parameters are monitored [189–191]. Modelling and simulation, Big Data, AI, CPS, robotics and automation, and digital thread (◐) support this domain by enabling ergonomic simulation, analysis of incident and near-miss data, risk prediction, and automation of high-risk tasks [72,74,170].

Performance, costs, and economics

In the performance, costs, and economics element, Big Data, modelling and simulation, CAPP, AI, and digital thread (●) provide the analytical foundation for KPI tracking, cost analysis, scenario evaluation, and optimisation [74,119,129,192]. Digital twins, ERP/MES integration, cloud computing, CPS, cyber security, and blockchain (◐) complement this by supplying reliable operational data, ensuring end-to-end data consistency, and providing scalable computational resources for complex economic and performance evaluations [66,96,112,146,150].

Digital technologies and I4.0/I5.0 (meta-element)

In the meta-element of digital technologies and I4.0/I5.0, IIoT, modelling and simulation, CAPP, digital twins, Big Data, CPS, AI, ERP/MES integration, digital thread, cloud computing, and cyber security (●) form the core digital infrastructure and architecture of an I4.0/I5.0-ready manufacturing system [72,74,112,119,129,148,186]. Robotics and automation, VR/AR, KBE, AM, and blockchain (◐) are specialised enablers that, depending on the application context, enhance this infrastructure with advanced physical automation, immersive interfaces, rule-based process planning, knowledge capture, and novel manufacturing capabilities [9,107,136,150,193].

4.2.4. Principles for designing production systems in Industry 4.0 and 5.0 context

The proposed framework of thirteen elements offers a structured approach to MSD, covering input requirements and product structure, processes, resources, layout, logistics, information and control, quality, maintenance, HSE, overall performance, and the role of digital technologies. By systematically mapping each element to the set of thirteen digital technologies, it becomes clear that I4.0/5.0 is not achieved through isolated "technology add-ons", but through a coherent redesign of system structures, flows, and decision processes. Some technologies, such as AM or CAPP, are closely linked to specific elements, while IIoT, Big Data, AI, simulation, digital twins, ERP/MES integration, and cloud computing act as transversal enablers across most elements of the framework.

From a design perspective, this integrated view indicates that digitalisation should be addressed as a system-level architectural challenge rather than as a series of individual projects. Decisions regarding sensors and connectivity (IIoT), data models and platforms (Big Data, cloud), models and analytics (simulation, digital twin, AI), and transactional systems (ERP/MES integration) must be aligned with the physical configuration of machines, logistics, layouts, and workplaces. At the same time, human factors – organisation of work, competencies, ergonomics, and safety – remain central and are increasingly supported by VR/AR, robotics, and knowledge-based systems. In the context of I5.0, this alignment extends to human-centricity, resilience, and sustainability, shaping how HSE, maintenance, and environmental performance are integrated into the design.

Based on the framework and technology mapping, a set of high-level design principles for I4.0/I5.0-ready manufacturing systems can be formulated:

- Systemic integration of physical and digital layers

Design physical structures (processes, resources, layout, logistics) and digital layers (sensing, data, models, applications) together, ensuring that IIoT, Big Data, simulation and digital twins are incorporated into the system architecture from the outset, rather than added retrospectively.

- Data-driven and model-based design

Use historical and experimental data, as well as simulation and digital twins, to determine capacity, buffers, and resources, evaluate alternative configurations, and support investment decisions, rather than relying primarily on deterministic calculations and expert judgement.

- Clear allocation of decision logic across levels and systems

Explicitly define which planning and control functions reside at machine/PLC, MES/CPPS, and ERP levels, and how they interact. This reduces ambiguity, simplifies integration, and enables consistent performance measurement and optimisation.

- Human-centric automation and decision support

Combine robotics and automation with VR/AR, KBE, and AI to support operators and engineers, rather than replacing them without redesigning work. This requires attention to skills, training, ergonomics, and human–machine interfaces alongside technical automation choices.

- Lifecycle and adaptability orientation

Design systems with reconfigurability, maintainability, and upgradability in mind, so that digital technologies (IIoT, analytics, security, cloud services) can evolve over time without disrupting core operations. Simulation and digital twins should be conceived as assets spanning design, ramp-up, and operation phases.

- Security, traceability and trust by design

Incorporate cyber security and data integrity requirements into the architecture from the outset, particularly for elements handling information flow, quality, and external connectivity. Where appropriate, use blockchain or similar mechanisms to ensure traceable and tamper-resistant records.

- Alignment of KPIs, economics, and technology choices

Link the selection and configuration of digital technologies to explicit performance and cost targets (OEE, lead time, flexibility, energy, quality, lifecycle cost), and use economic evaluation tools to justify and prioritise technology investments.

Taken together, these principles show that designing an I4.0/I5.0-ready manufacturing system requires co-designing products, processes, physical infrastructures, and digital infrastructures within a unified architectural and decision framework. The thirteen-element model and its mapping to sixteen digital technologies provide a practical scaffold for this co-design, ensuring that no critical dimension is overlooked and that digitalisation efforts are grounded in the concrete structure and objectives of the manufacturing system.

4.3. Framework for managing the production system lifecycle in the context of Industry 4.0 and 5.0

In this dissertation, the system of interest is the production system considered across its entire lifecycle. The production system comprises the manufacturing facilities and the associated support functions required to plan, operate, maintain, and evolve production. A lifecycle perspective is adopted, aligning with the maintenance of a consistent (digital) representation of the production system throughout its evolution [154]. Accordingly, the term Production System Lifecycle Management (PSLM) is used as the umbrella concept, covering the full range of management activities from initial planning and requirements specification, through design, implementation, and commissioning, to operation, continuous improvement, and planned decommissioning [14,155].

Existing standardisation-oriented work on the digital factory and SM – including frameworks such as IEC 62832-1 and NISTIR 8107—emphasises data integration and interoperability across product, production, and business lifecycles [194]. These contributions, together with reference architectures such as RAMI 4.0, provide important structural viewpoints and interoperability guidelines, but do not themselves constitute a complete, operational methodology for MSD. Rather, they must be complemented by process-oriented frameworks that define objectives, design decisions, and their interrelations over the production system lifecycle.

Related work on Manufacturing System Lifecycle Management (MSLM), such as the formalisation by Lavi et al. using Object-Process Methodology, demonstrates that lifecycle approaches can be rigorously modelled at the manufacturing system level [195]. However, these efforts typically address a narrower scope than PSLM, focusing on the core manufacturing system rather than the entire factory and its socio-technical and sustainability dimensions. In this thesis, such MSLM insights are adopted with respect to modelling and traceability, but are embedded within a broader PSLM framework that explicitly integrates organisational, human, and environmental aspects of the production system.

In the preceding sections of this chapter, the research has progressed from the general concepts of the smart factory, CPS, and the digital thread to specific digital technologies that implement these concepts in industry. The analysis of individual technologies in Section 4.1 has shown that their impact depends less on the mere availability of tools and more on how they are integrated into the holistic design and management of the production system throughout its entire lifecycle. Accordingly, Section 4.2 has broadened the focus to MSD in the context of I4.0 and I5.0, emphasising the importance of strategic thinking, an extended performance set (economic, environmental, and social), and the need to systematically map digital technologies to design phases and typical decision points.

The analysis of MSD elements, the review of examples from the literature, and the defined matrix of digital technologies indicate that fragmented approaches – whether technological or organisational – are no longer sufficient. Instead of the ad hoc introduction of individual solutions, an integrated framework is required that links strategic framing, design, implementation, operation, and reconfiguration of the production system, while upholding the values of a human-centric, sustainable, and resilient industry. On this basis, there is a need for a clear definition of PSLM in the context of I4.0 and I5.0, as a conceptual and methodological framework that connects decisions throughout the entire lifecycle of the system, drawing on digital twins, integrated data flows, and sociotechnical principles.

This chapter builds on these insights and proposes an operationalised PSLM MIDIT framework that synthesises the previously defined principles, MSD phases, and the role of digital technologies in the comprehensive management of the production system lifecycle.

4.3.1. PLM and PSLM

The terms PLM and PSLM are used consistently throughout this work. Product Lifecycle Management (PLM) is defined as a concept and management discipline that covers the planning, development, design, industrialisation, operation, maintenance, and retirement of products, together with the associated methods, processes, and organisational structures. When it is necessary to highlight the procedural aspect, the terms PLM process or PLM methodology are used, while PLM systems or PLM software platforms refer exclusively to information systems that support the execution of PLM. Similarly, PSLM refers to the concept and discipline of managing the entire lifecycle of a production system, from strategic framing and conceptual design, through structural and detailed engineering, commissioning and operational management, to reconfiguration and decommissioning. In this dissertation, the proposed seven-phase framework is interpreted as a PSLM process model or PSLM methodology for production systems in the context of I4.0 and I5.0, while the digital systems that support PSLM (PLM, MES, ERP, IIoT, and DT platforms) are treated as technological enablers rather than as a separate category of "PSLM systems".

In the literature on MSD, numerous variants of lifecycle models exist, but they essentially converge on a similar sequence of phases, from initial planning to end-of-life and reuse of the system. Islam et al. argue that the key decisions determining future operational performance are made in the early lifecycle phases, particularly in the design phase [196,197]. Based on the synthesis developed in this dissertation, the production system lifecycle is structured into the phases of planning, design and implementation, operation, and end-of-life or reuse, with the design phase further divided into preparatory and detailed design, drawing on the production development perspective and comparative reviews of lifecycle models reported in the literature [198,199]. In recent years, the term PSLM has appeared more frequently in the literature as an extension of the logic of classical PLM from the product to the production system. Documents published under the Plattform Industrie 4.0 initiative explicitly place PSLM alongside PLM and supply chain management, and define it as the management of all production planning and engineering processes (conceptual and basic design, detailed engineering, construction, commissioning) as well as the entire in-operation lifecycle of the production system (operation, maintenance, upgrades, decommissioning) [200]. Within European I4.0 initiatives, the prevailing view is that PLM manages the evolution of the product, while PSLM manages the development and change of the factory or production system that realises that product.

A related line of research develops the concept of MSLM, in which international standards for the lifecycle of production systems are operationalised through MBSE approaches, such as Object–Process Methodology [195]. However, existing works largely remain at the level of high-level definitions and reference architectures, offering relatively few detailed proposals on how to structure the phases and decisions in the lifecycle of a production system in the context of I4.0 and I5.0. In response to this gap, this dissertation proposes a seven-phase PSLM framework that synthesises the dominant approaches identified in the literature and provides a process-oriented matrix for mapping key decision areas and the role of digital technologies in each phase. The following sections briefly describe each phase and summarise the main findings of the literature review on the use of digital technologies in the corresponding lifecycle stages. This seven-phase structure is adopted as the reference PSLM model for the subsequent development and refinement of the detailed MIDIT framework.

4.3.2. Strategic analysis and objectives definition (Phase 1)

The strategic analysis and objectives definition phase establishes strategic objectives, the business case, and high-level requirements for a new or reconfigured production system, and includes a preliminary assessment of the existing production system. This phase corresponds to Phase 1 of the proposed PSLM MIDIT framework and to Phase 1 in Table A4 in Appendix A, where the strategic analysis of markets and product portfolios is explicitly linked to the definition of business objectives, I4.0/5.0 ambitions, and key KPIs for the production system. In this way, the initial PSLM phase sets the functional and performance targets against which all subsequent design decisions are evaluated. In this phase, decision-makers define target capacities, required flexibility, target costs, and performance indicators. Key decision areas include aligning the manufacturing strategy with the product portfolio, determining the required degree of automation, and choosing between implementing a new system or upgrading an existing one. Rather than treating planning in the traditional sense as an exercise in estimating volume and cost, this dissertation frames Phase 1, in the context of I4.0 and I5.0, as a step in which the target type of production system, the desired level of digital maturity, and the degree of human-centrism and sustainability are explicitly specified. In an I4.0 and I5.0 context, planning increasingly relies on data analytics, integration with PLM/ERP systems, and scenario modelling (for example, digitally supported demand and capacity analysis) [198]. Qin et al. introduce a categorical framework that classifies production systems according to flow type, degree of automation, and level of connectivity, allowing planners already in Phase 1 to position whether the target is a classical line, a reconfigurable cellular network, matrix production, or a highly networked CPPS [7]. Based on the synthesis developed in this dissertation, production system planning is therefore treated as a non-neutral activity in which resilience, worker wellbeing, and environmental footprint must be considered from the outset, together with productivity, cost, and quality [157,158]. The proposed perspective further situates the planned production system within a broader sociotechnical context, viewing it as a node embedded in social and natural flows, consistent with the concepts of sociotechnical systems and social metabolism [201]. In an I4.0 environment, Phase 1 also covers technology road mapping and the selection of digital technologies (IIoT platforms, digital twins, advanced robotics, analytics, etc.) that constitute strategic priorities, rather than focusing solely on required capacity. In this phase, the selection of digital technologies is addressed using multi-criteria analysis methods that combine technical and economic aspects, risk, and organisational readiness, rather than relying on intuition or prevailing “fashion trends” [202]. At the same time, integration frameworks for management processes indicate that it is necessary to define, already at this stage, the target level of vertical and horizontal digital integration of the future system, as well as the required capabilities for monitoring, predictive analytics and coordination [203].

In this dissertation, Phase 1 is the point at which the company’s strategic goals, the technological vision of I4.0, and the socio-ecological ambitions of I5.0 converge. Understanding the difference between strategic planning and strategic thinking, and applying the Sloan Triad model to define the optimal production system, becomes essential at this stage. The outcome of Phase 1 is not merely an investment decision, but a structured set of targeted system capabilities (flexibility, reconfigurability, human-centric workplaces, energy efficiency, digital integration, resilience, and environmental performance) that subsequently feeds into the formal specification of requirements and serves as the entry point for the remaining phases of the MIDIT framework.

4.3.3. Conceptual and structural design of the production system (Phase 2)

This phase corresponds to Phase 2 of the PSLM MIDIT framework and to Phase 2 in Table A4 in Appendix A, where alternative production system concepts are generated and their basic structure is defined in terms of flows, layouts, and human-machine collaboration. Building on the structured set of targeted system capabilities defined in Phase 1, this phase translates high-level objectives (e.g., flexibility, reconfigurability, human-centric workplaces, energy efficiency, digital integration and resilience) into a consistent set of conceptual solutions and structural principles for the production system. The conceptual and structural choices made here provide the main FSBCIP viewpoints on function and structure, which will later be tested in terms of behaviour, control, and performance.

In this conceptual design phase, the requirements specified at the end of Phase 1 are converted into alternative structures and modes of operation for the production system.

Phase 2 therefore covers the generation of alternative line, cellular, RMS and matrix concepts, the definition of main material and information flows, and the development of rough layouts at the level of zones, halls, and cells. In an I4.0 and I5.0 environment, this includes the integrated development of the physical configuration (material flow, layout, resource types) and the digital configuration (sensor network, software service structure, communication protocols, scheduling and control algorithms). Conceptual design in this thesis follows the principle that functional requirements are decomposed into hierarchies of sub-requirements and mapped to design parameters in a way that minimises coupling and supports modularity and reconfigurability [204,205]. Conceptual decisions also allocate intelligent functions (perception, analytics, decision-making, execution) to appropriate hierarchical levels, from equipment and cells to lines, factories, and cloud platforms, rather than treating "intelligence" as a monolithic layer [206]. Conceptual alternatives are explicitly classified by flow type, degree of automation, and level of connectivity, enabling a structured comparison of line, cellular, RMS, and matrix concepts from the standpoint of flexibility and digital integration [7]. Furthermore, rough layouts are derived from modular functional units (production, logistics, quality, maintenance) that can be combined and virtually tested for their impact on performance [207], and a reference discrete-event simulation model is prepared already in this phase to explore robust scaling paths by varying capacity, automation levels, and working-time patterns [192]. For highly reconfigurable systems such as matrix production, Phase 2 explicitly accounts for dynamic routing, universal cells, and rapid reconfiguration capabilities when defining and comparing alternatives [208]. From an I5.0 perspective, conceptual design additionally incorporates worker-related constraints and objectives (ergonomics, cognitive load, participation), so that human-centric scenarios form an integral part of conceptual thinking rather than an ex-post correction [20].

Based on this body of work, this dissertation adopts Phase 2 as a conceptual and structural design step in which alternative production system concepts, rough layouts, and work-organisation principles are systematically derived from the capabilities defined in Phase 1, classified by flow, automation, and connectivity, and prepared as reference scenarios for subsequent simulation and digital-twin-based refinement in later MIDIT phases. The outcome of Phase 2 is a set of classified conceptual alternatives, each defined by flows, layouts, degrees of automation and connectivity, and human–machine collaboration, which serves as structured input for the feasibility analysis and requirements specification conducted in Phase 3 of the PSLM MIDIT framework.

4.3.4. Feasibility analysis and concept selection (Phase 3)

Building on these conceptual alternatives, Phase 3 of the PSLM MIDIT framework translates them into preliminary engineering calculations, feasibility assessments and a concrete set of system requirements. In this feasibility and concept selection phase, takt and capacity calculations, investment and risk evaluations, and the specification of detailed requirements form the basis for selecting the preferred concept and defining the initial data and integration blueprint for subsequent design phases. In this dissertation, Phase 3 links the conceptual alternatives developed in Phase 2 with a formally justified choice of the reference concept for further MIDIT development.

During this phase, target takt times, the required level of modularity, ergonomic and safety requirements, and regulatory constraints are defined, as the quality of decisions made here has a decisive impact on ramp-up success and subsequent operational performance [196]. In an Industry 4.0 and Industry 5.0 context, requirements extend beyond demanded volumes and takt rate to include the system's ability to support the product configuration space, market dynamics, digital services, and new forms of work. Consequently, the requirements specification also includes information on planned product configurations, the expected rate of introduction of new variants, and the desired degree of personalisation [80]. Conceptual frameworks for SM system design further expand the classical requirement set (capacity, quality, cost) with "smart" requirements such as adaptability, transparency, self-monitoring, learning capability, and interoperability, which then serve as a basis for structured mapping to design parameters [204,205]. From an I5.0 perspective, the requirements specification additionally incorporates normative aspects, including limits on the maximum permissible cognitive load of operators, minimum standards for worker participation in decision-making, and explicit targets related to circularity and local social impact [201]. Reviews of MSD research at the I4.0 and I5.0 interface consistently report a shift towards extended performance sets (economic, environmental, and social), making this feasibility and requirements phase critical for avoiding downstream trade-offs that are effectively "built in" through inadequately defined requirements.

In this dissertation, digital technologies in Phase 3 are treated primarily as information infrastructure for feasibility analysis and requirements specification. PLM/PDM systems provide access to product data, while MES/ERP data offer insights into the actual performance of current systems. Digital models and preliminary simulations are used to analyse capacity, spatial constraints, and sensitivity to demand variability. In this way, the requirements specification and the selection of the preferred concept are grounded in data and models rather than assumptions and "best guess" estimates. The outcome of Phase 3 is a justified selection of the preferred production system concept, supported by quantified capacity and takt calculations, feasibility and risk analysis, and an agreed set of functional and non-functional requirements. In addition, Phase 3 produces initial decisions on make-or-buy, the prioritisation of automation and digital functions, and baseline standards for interoperability and data requirements, in line with Phase 3 in Table A4 in Appendix A. This outcome represents the formal requirements baseline and reference concept that guide the detailed design and validation activities in the subsequent MIDIT phases. This formally justified reference concept and the associated requirements baseline constitute the starting point for the detailed multi-domain engineering activities in Phase 4 of the PSLM MIDIT framework.

4.3.5. Detailed design and virtual validation (Phase 4)

Based on the selected reference concept and the agreed requirements from Phase 3 of the PSLM MIDIT framework, Phase 4 specifies the production system in detail and validates it using integrated digital models and simulations. Detailed process design, layout, resource selection, and IT/OT architecture are consolidated into integrated digital twins that support virtual validation of system behaviour, control strategies, and human–system interaction. In this dissertation, Phase 4 therefore represents the transition from a selected concept to a fully specified and virtually verified reference design for implementation.

In this phase, detailed design decisions include the selection of specific technologies and suppliers, the choice of control logic and scheduling approaches, the determination of capacities (machines, operators, and buffers), and the alignment of ergonomics, safety, and human roles [199,209]. In an Industry 4.0 context, these activities are increasingly organised within a model-centric paradigm, where an integrated digital twin – rather than a set of isolated tools – links product, processes, equipment, layout, logistics, and control, and serves as the main artefact through which detailed design is conducted. Generic design methodologies for smart manufacturing specify design parameters at the level of machines and cells, sensor and actuator types, IIoT network configuration, software service structures (MES, MOM, analytics), scheduling algorithms, and work-organisation patterns, while axiomatic design principles are used to limit unnecessary coupling between these parameters and thereby support reconfigurability and maintainability [205]. Results of simulation-based sizing from the conceptual phase are transferred into detailed design by iteratively optimising buffer sizes, the number of machines per station, and the arrangement of lines and auxiliary areas using simulation experiments and criteria such as profit, reliability, and changeability [192]. Integrated product–production design requires that detailed product models (for example, modular platforms) and process models are aligned so that the product configuration space remains compatible with system capabilities without hidden adaptation costs [80]. From an I5.0 perspective, detailed design also covers workplaces and human–machine interaction, where digital human models, VR/AR for evaluating ergonomics and collaboration, and value-sensitive design methods are used to embed human-centric values into design decisions [158,201].

Based on this body of work, this dissertation adopts Phase 4 as a multi-domain engineering step in which the physical and digital layers of the production system are designed in an integrated manner. The validated digital twin and the fully specified reference design produced in this phase form the operational blueprint for implementation, commissioning, and subsequent lifecycle management in the following phases of the MIDIT framework.

4.3.6. Industrialisation and integration design (Phase 5)

Phase 5 of the PSLM MIDIT framework, corresponding to Phase 5 in Table A4 in Appendix A, focuses on industrialisation and integration design: design freeze, finalisation of system specifications, integration planning, preparation of test protocols, cybersecurity measures, and work instructions. This phase operationalises the transition from digitally validated designs and models to an implementable integration and industrialisation plan, and in this dissertation, represents the bridge between virtual validation in Phase 4 and physical implementation in Phase 6 of the PSLM MIDIT framework. In practical terms, Phase 5 consolidates technical specifications for machines, automation, and IT/OT systems; plans interfaces between PLC, SCADA, MES, and IIoT platforms; and defines system integration and acceptance test strategies (SIT and UAT), including criteria for pilot scope and commissioning readiness [209]. Integration and cybersecurity requirements are translated into concrete interface specifications, API definitions, access-control concepts, and governance rules, while work instructions and training materials are developed to prepare operators and engineers for the future digitalised environment [203]. In an I4.0 context, industrialisation and integration design increasingly rely on the digital thread and virtual commissioning tools, which allow control logic and interfaces to be tested on digital twins of the line or factory before physical installation, thereby reducing integration risks and improving commissioning readiness [209]. Recent studies also stress the need to embed cybersecurity and data-governance measures directly into integration design, rather than treating them as ex-post add-ons, and to align training and work instruction development with the target human-machine collaboration patterns in the digitalised system.

Based on these insights, this dissertation adopts Phase 5 as the stage in which the validated digital twin is translated into a coherent industrialisation package: a frozen design baseline, complete technical and integration specifications, defined SIT/UAT procedures and criteria, cybersecurity and governance concepts, and operator-oriented documentation and training materials. This package provides structured input for commissioning, ramp-up, and performance monitoring activities in the subsequent phases of the MIDIT framework.

4.3.7. Implementation, commissioning and ramp-up (Phase 6)

This phase corresponds to Phase 6 of the PSLM MIDIT framework and Phase 6 in Table A4 in Appendix A, where the designed production system is implemented, commissioned, and ramped up to target performance. During this phase, equipment and IT systems are procured and installed, automation and information systems are integrated, virtual and physical commissioning are conducted, and ramp-up to the planned capacity is executed while operators and engineers receive training. In this dissertation, Phase 6 is treated as a stress test of the decisions made in Phases 3–5, verifying the robustness of the concept, detailed design, and integration plan under real operating conditions.

Structured use of the preceding design phases reduces ramp-up problems and stabilisation time [197]. In the I4.0 paradigm, Phase 6 relies heavily on the digital thread, which connects models and data across the life cycle, and on digital twins that support VC, emulation of logic controllers, and early monitoring of actual performance in combination with the IIoT infrastructure [209]. Implementation is understood as the step in which concretised design parameters are transformed into installed resources and configured software modules, while traceability to the functional-requirements hierarchy is preserved to verify whether adaptability, transparency and interoperability objectives are met [205]. Scaling paths defined in the conceptual phase are operationalised during implementation. Instead of a one-off start-up, capacity is increased gradually by adding resources according to predefined scenarios and demand thresholds. This approach reduces risk and improves economic performance [192]. Implementation also includes configuring the integration framework for management processes. Data sources from machines, sensors, and information systems are linked with edge and cloud layers, and with analytical and visualisation applications that support control and continuous improvement [203]. Within this context, virtual commissioning is a key activity. PLC, SCADA, and MES logic are tested on the digital twin of the line or factory under different load and failure scenarios, which shortens adaptation time and reduces commissioning risks [209].

From an I5.0 perspective, ramp-up has a pronounced human-centric dimension. The introduction of new technologies is aligned with training plans, co-creation of work methods with operators, and systematic assessment of impacts on psychosocial working conditions. Typical decision areas in this phase therefore include the sequence of installation and commissioning, the equipment testing and acceptance strategy (FAT/SAT), performance thresholds and exit criteria for ramp-up, and the worker training programme for a digitalised environment, as indicated for Phase 6 in Table A4 in Appendix A.

On this basis, this dissertation adopts Phase 6 as the lifecycle step in which the digitally validated design is translated into a functioning production system and the interplay between technical performance and human-centric, socio-ecological objectives is verified before the system enters routine operation. In doing so, Phase 6 closes the initial design–implementation loop and establishes the baseline conditions from which operational performance, continuous improvement, and future redesign activities are managed over the remaining lifecycle of the production system.

4.3.8. Operations management, continuous improvement and redesign (Phase 7)

Phase 7 of the PSLM MIDIT framework, corresponding to Phase 7 in Table A4 in Appendix A, treats operation as an ongoing design–execute–learn–redesign cycle rather than a static end state. Continuous monitoring, improvement, and reconfiguration activities use operational data and digital models to adjust system structure, control, and intelligence, and to trigger new design iterations when required. In this dissertation, Phase 7 represents the stage in which the production system is managed as a dynamically evolving system, and the feedback loop to earlier PSLM and MIDIT phases is closed.

In the operation phase, the production system functions in real time. However, in I4.0 and I5.0 approaches, design explicitly extends into operations instead of ending with commissioning. Typical decision areas include resource allocation, maintenance strategies, adaptations of layout and working methods, and the evolution of IT and automation solutions. Operation is strongly supported by IIoT sensing, MES systems, real-time analytics, predictive maintenance, and adaptive controls. These technologies provide the data foundation for continuous improvement and reconfiguration. Digital twins, integration frameworks, and real-time analytics enable the system to adapt dynamically to changes in demand, product portfolio, equipment condition, and workforce availability [209]. In this view, design is no longer a one-off project but an iterative design–execute–learn–redesign cycle in which the boundary between engineering and operations is gradually blurred [157].

Conceptual and empirical work on operations management in smart factories suggests viewing the operational system through functions (production, maintenance, quality, logistics) and their interactions, using simulation models and empirical data to assess policy changes such as modified maintenance schedules, warehouse centralisation, or new quality rules [207]. Layered integration architectures further structure operational management into device, edge, platform, and application levels, allowing decisions to be taken at the lowest possible but still well-informed level, while preserving overall management visibility [203]. Smart manufacturing design methodologies emphasise that continuous improvement and redesign should use operational data to adjust design parameters, redefine requirements where necessary, and reconfigure the system structure when changes in performance, demand, or context justify such interventions [204,205]. From an I5.0 perspective, continuous improvement in Phase 7 also encompasses worker wellbeing and societal impact: interventions are assessed not only against economic and environmental, but also social indicators, with meaningful worker participation playing an important role [201].

End-of-life decisions such as line shutdown, equipment relocation and reuse, and recycling or remanufacturing of components are treated as specific forms of major redesign within Phase 7. In this way, termination and reuse are integrated into the continuous improvement and redesign logic rather than being left to ad hoc decisions, and the final phase of one system's lifecycle naturally feeds into the strategic analysis and objectives definition of the next cycle.

On this basis, this dissertation proposes a seven-phase PSLM MIDIT framework that treats the lifecycle of the production system as a digitally supported, iterative design–execute–learn–redesign process rather than a linear path from planning to end-of-life. Strategic and requirements phases (1–3) are explicitly linked to detailed design, industrialisation, and ramp-up (4–6) through digital twins and the digital thread, while the operations and redesign phase (7) closes the loop by feeding human-centric, sustainable, and resilient improvement insights back into new design cycles in line with I4.0 and I5.0 principles.

4.3.9. MIDIT production system lifecycle management framework

The seven-phase framework is inherently cyclical: completing one production system simultaneously serves as strategic preparation for the next. Digital models, accumulated operational data, and sociotechnical insights from the previous lifecycle provide the foundation for more informed, robust, and sustainable decisions in the subsequent design iteration. In this dissertation, the seven-phase framework shown in Figure 4.10 is adopted as an operationalised PSLM model for smart and human-centric production systems, providing the reference lifecycle structure for the MIDIT methodology. It defines the phases (from strategy to reconfiguration), links them to the FSBCIP perspectives (Function–Structure–Behaviour–Control–Intelligence–Performance), and explicitly incorporates digital enablers for I4.0 and I5.0 values through the TMPE meta-layer (Thinking–Modelling–Process–Enabler) [157]. The TMPE meta-layer also serves as a unifying design logic across all lifecycle phases and tools, ensuring that strategic intentions, modelling choices, process activities, and enabling technologies remain consistent and traceable throughout the entire lifecycle.

The horizontal axis represents the seven MSD phases, which correspond to the PSLM MIDIT framework phases summarised in Table A4 in Appendix A: Strategic analysis and objectives definition (Phase 1), Conceptual and structural design of the production system (Phase 2), Feasibility analysis and concept selection (Phase 3), Detailed design and virtual validation (Phase 4), Industrialisation and integration design (Phase 5), Implementation, commissioning and ramp-up (Phase 6), and Operations management, continuous improvement and redesign (Phase 7). These phases align with product PLM phases (concept, design and industrialisation, ramp-up and operation, and improvement and reconfiguration). Phases 1–3 of the PSLM MIDIT framework largely correspond to the product-concept phase, Phases 4–5 to design and industrialisation, Phase 6 to ramp-up and early operation, and Phase 7 to the improvement and reconfiguration phase. In this way, the framework embeds the logic of product PLM within a production-system PSLM perspective, ensuring that decisions on the factory and product lifecycle remain synchronised.

Along the left edge of the framework, the FSBCIP perspectives indicate what is examined in each phase: the system's function, structure, dynamic behaviour, control mechanisms, embedded intelligence, and target performance. FSBCIP does not introduce an additional sequence of design steps; instead, it provides a stable set of viewpoints from which each PSLM phase is analysed, making trade-offs between alternative design options more explicit and comparable. The roles of the six FSBCIP perspectives are summarised in Table 4.3. In Table A4 in Appendix A, the main activities and decisions of each phase are linked to these FSBCIP perspectives, so that structural, behavioural, control, and performance implications of design choices become visible across the lifecycle. The bottom layer of the framework is formed by the TMPE meta-perspective, which emphasises the systematic application of design principles (such as modularity, reconfigurability, human-centric design, and green design), appropriate models (conceptual, simulation, digital twins), structured design processes, and suitable digital enablers. The four TMPE layers and their roles are outlined in Table 4.4.

Table 4.3: Brief description of FSBCIP perspectives – adopted [157]

Perspective	Concise description
Function	The system's required achievements: its role, purpose, and expected value for users and the organisation, including required levels of service, quality, flexibility, and responsiveness.
Structure	The system's composition and organisation: physical and logical elements, resources, layout, and the arrangement of lines, cells, and flows of materials and information.
Behaviour	The system's dynamic operation over time: flows, states, variability, and interactions between resources, operators, and materials under realistic operating conditions.
Control	The system's monitoring and direction: organisational and technical mechanisms for planning, scheduling, performance monitoring, and responding to disturbances and deviations.
Intelligence	The system's intelligence: the degree of embedded analytics, learning, and autonomy, such as sensors, AI/ML models, digital twins, and decision-support or optimisation algorithms.
Performance	The system's success: key performance indicators for efficiency, productivity, quality, cost, sustainability, ergonomics, and reliability relative to the specified design objectives.

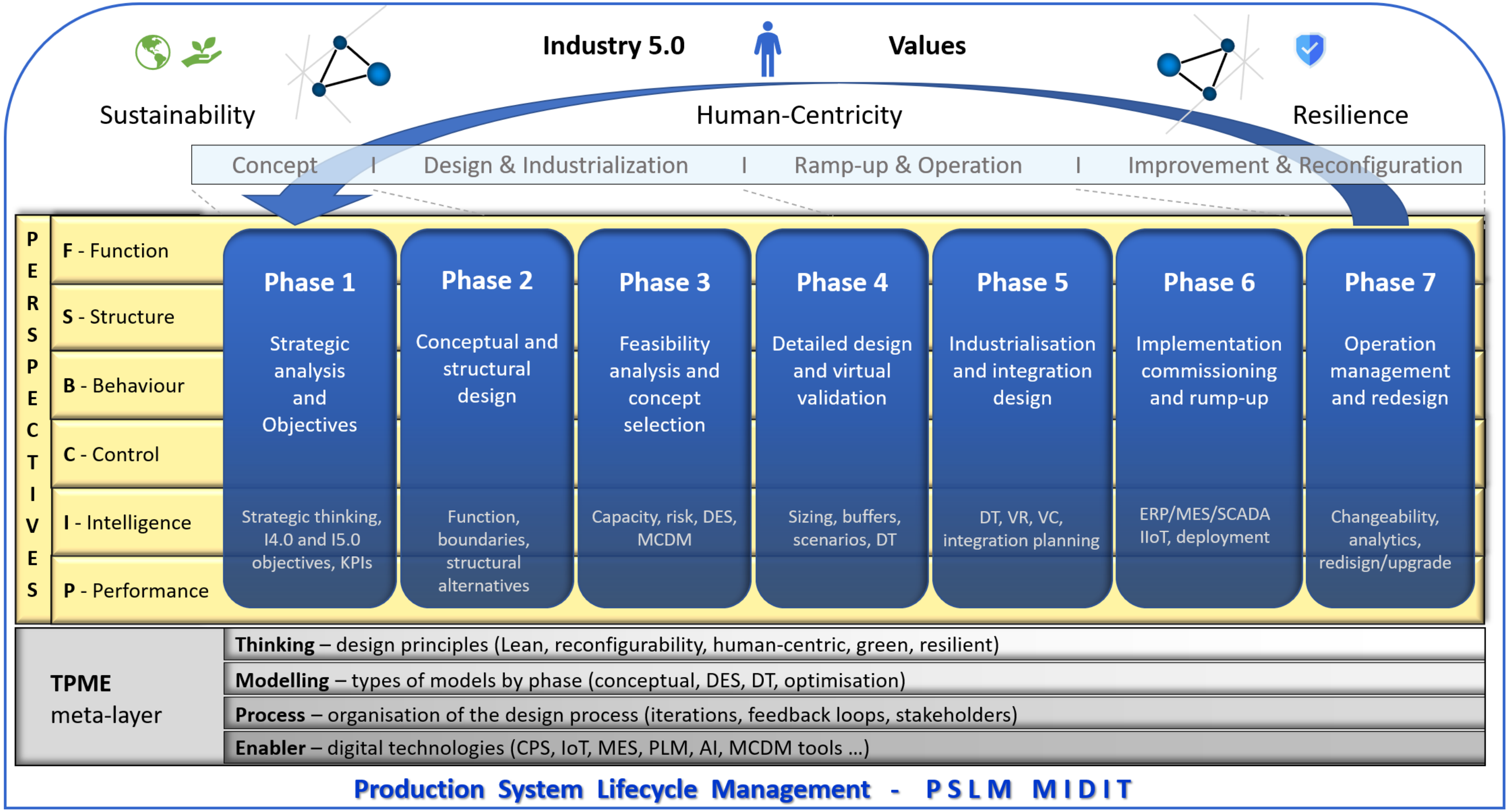
The "Typical digital tools" column in Table A4 in Appendix A lists specific enablers for each TMPE dimension across the seven phases: business-intelligence dashboards and maturity-assessment tools in Phase 1 mainly support Thinking and Modelling; simulation and digital-twin platforms in Phases 2–4 reinforce Modelling and Process; while MES, SCADA, IIoT, and analytics platforms in Phases 5–7 serve as key enablers for executing and sustaining the designed processes. Thus, TMPE offers a coherent design logic that links phases, viewpoints, and digital technologies into a single, traceable MSD approach.

Table 4.4: TMPE meta-layer perspectives and their roles in MSD - adopted [157]

Meta layer	Concise description
Thinking	The framing of problems and formulation of objectives: systematic and holistic reasoning with explicit human-centric and circular principles, and the definition of goals, values, and criteria for manufacturing system design.
Modelling	The conceptual and computational representation of the system: the use of formal, simulation, and digital-twin models to explore design alternatives, scenarios, and what-if analyses.
Process	The organisation of design work: phases, tasks, iterations, and responsibilities in the design process, from strategic framing and conceptualisation to detailed design, implementation, and reconfiguration.
Enabler	The technologies and tools that support implementation, including digital platforms, software, automation, data analytics, and collaborative infrastructures (such as distributed collaboration, knowledge automation, simulation, and intelligent optimisation tools) that sustain the TMPE approach throughout the entire lifecycle.

The entire framework is guided by I5.0 values, human-centricity, sustainability, and resilience, which shape the formulation of objectives, criteria, and decisions in all phases of MSD. Strategic thinking is present throughout all phases, steps, and activities. In practical terms, end-of-life, termination, and reuse scenarios are treated as an extension of Phase 7, where improvement and reconfiguration activities explicitly include decisions on system decommissioning, equipment reuse, remanufacturing, and recycling in line with circular-economy and I5.0 principles.

In this way, the framework respects the logic of the PSLM lifecycle while extending it to meet the requirements of I4.0 and I5.0: strong reliance on digital models and digital twins, integration of management processes, and explicit inclusion of human-centric, green, and resilient objectives. The proposed model thus serves as a conceptual representation of PLM for the production system, where decisions on design, management, and system evolution are systematically connected throughout the entire lifecycle. Together, Figure 4.10 and Table A4 provide an operationalised PSLM MIDIT view of MSD, in which lifecycle phases, FSBCIP perspectives, TMPE meta-layers, and digital technologies are tightly coupled and mutually traceable, and in which the final phase of one system's lifecycle naturally becomes the starting point for the strategic analysis of the next system.



Source: Author's framework based on Qin (2016), Leng (2024, 2025), Bi (2021), Stark (2017), Schäfer (2024), Mohr (2024), Pereira (2025)...

Figure 4.10: Operational PSLM MIDIT in the context of Industry 5.0

4.4. Functional description of the MIDIT methodology

Following the introduction of digital technologies in the context of I4.0 and I5.0 (Section 4.1), the principles and elements of MSD (Section 4.2), and the PSLM MIDIT framework (Section 4.3), this section provides a functional description of the proposed MIDIT methodology, based on the flowchart developed in Appendix B. The flowchart presents an integrated methodological structure that connects strategic intent, digital maturity, MSD activities, and the purposeful use of digital technologies into a coherent decision-support framework. Unlike predominantly linear or technology-specific MSD approaches, the MIDIT workflow explicitly formalises decision gates, KPI gates, feedback loops, and governance logic, thereby structuring how MSD activities are executed and revised in digitally enabled industrial environments. A description of the individual decision questions associated with the decision gates is provided in Table B1 in Appendix B.

The proposed MIDIT methodology is organised into three main methodological steps, interconnected through iterative feedback loops rather than executed as a strictly linear sequence. At the highest level, the first step establishes the strategic and maturity-related basis for the procedure; the second step defines the MIDIT framework and the corresponding applicability logic; the third step operationalises the methodology through the MSD/MIDIT execution mechanism and KPI-based decision structure. The bidirectional links indicate that the procedure is not strictly linear, but includes iterative feedback between the three main steps. This high-level representation is shown in Figure 4.11 and serves as an overview of the overall procedural architecture of the methodology.

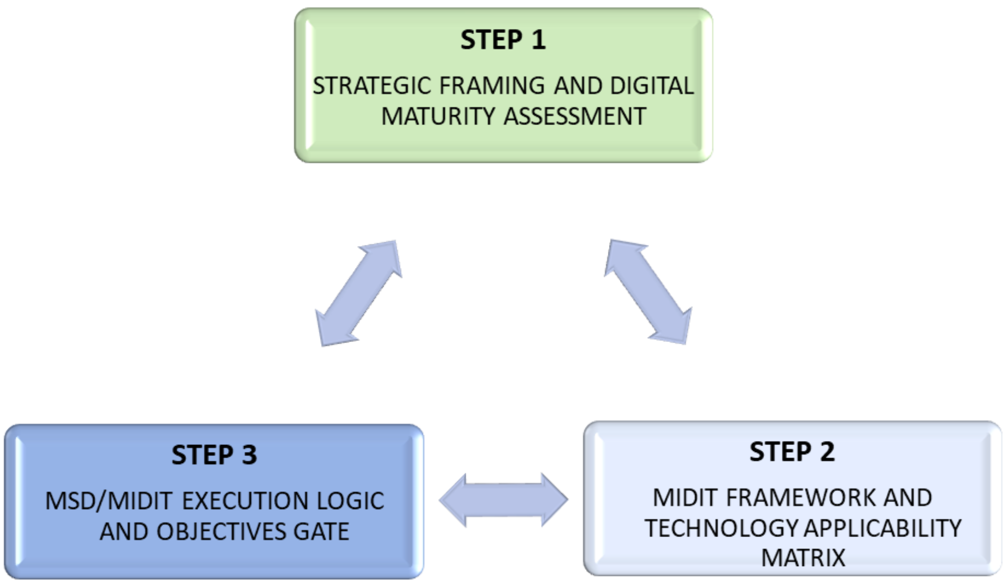


Figure 4.11: High-level three-step structure of the proposed MIDIT methodology

This gate-based, KPI-oriented, and feedback-driven structure distinguishes MIDIT from more linear or technology-fragmented MSD approaches, as it explicitly links digital tools, KPI information, and root-cause analysis into a single, governable decision workflow.

Methodologically, Step 1 establishes the strategic and organisational foundation for applying the proposed approach by defining target objectives, clarifying the strategic context, and assessing the company's digital maturity. Step 2 translates these inputs into a structured methodological basis using the MIDIT framework and the associated applicability matrix, providing the logic for aligning digital technologies with relevant design needs, decision points, and lifecycle phases. Step 3 forms the operational core of the methodology, governing the MSD/MIDIT execution process through iterative element-level assessment, analytical decomposition, and KPI-oriented decision support. While Figure 4.11 summarises the methodology at a high procedural level, the internal execution logic is concentrated mainly in Step 3. Therefore, Figure 4.12 provides a synthesis-level representation of the core MSD/MIDIT execution mechanism, illustrating how the methodology progresses through the seven MIDIT phases and how the evaluation of MSD elements is structured through repeated element-level assessment, the analytical role of the FSBCIP perspectives, the cross-phase role of strategic thinking, and the transversal function of the TMPE meta-layer.

As shown in Figure 4.12, Step 3 forms the operational core of the methodology, translating the previously established strategic and methodological foundations into the execution of MSD activities. Its role extends beyond simple implementation to coordinating how design decisions are progressively formed, evaluated, and refined throughout the lifecycle-oriented MIDIT logic. Accordingly, this figure does not present the full operational detail of the methodology but instead synthesises its principal execution logic.

At the outer level, the procedure advances through the seven MIDIT phases defined within the framework. Within each phase, all MSD elements are systematically revisited, so the same design issues are not addressed only once but are repeatedly reassessed as the process advances. This repeated reassessment enables continuity between conceptual reasoning, detailed preparation, implementation, and subsequent improvement or reconfiguration. Simultaneously, the level of analytical depth evolves across the phases: in earlier stages, the elements are considered more broadly and exploratively, while in later stages they are addressed in a more detailed, operational, and implementation-oriented manner.

At the inner analytical level, each selected MSD element is examined through the FSBCIP perspectives, which provide a structured basis for considering different dimensions of the design problem and for making trade-offs between alternative solutions more explicit. In parallel, strategic thinking remains present across all phases as a guiding logic that continuously aligns design choices with the broader strategic direction of the company. The TMPE meta-layer complements this logic by linking thinking, modelling, process activities, and enabling technologies into a coherent transversal structure spanning the entire lifecycle.

Together, these mechanisms ensure that the execution of Step 3 is iterative, context-sensitive, and methodologically consistent, rather than a purely technical application of isolated digital tools.

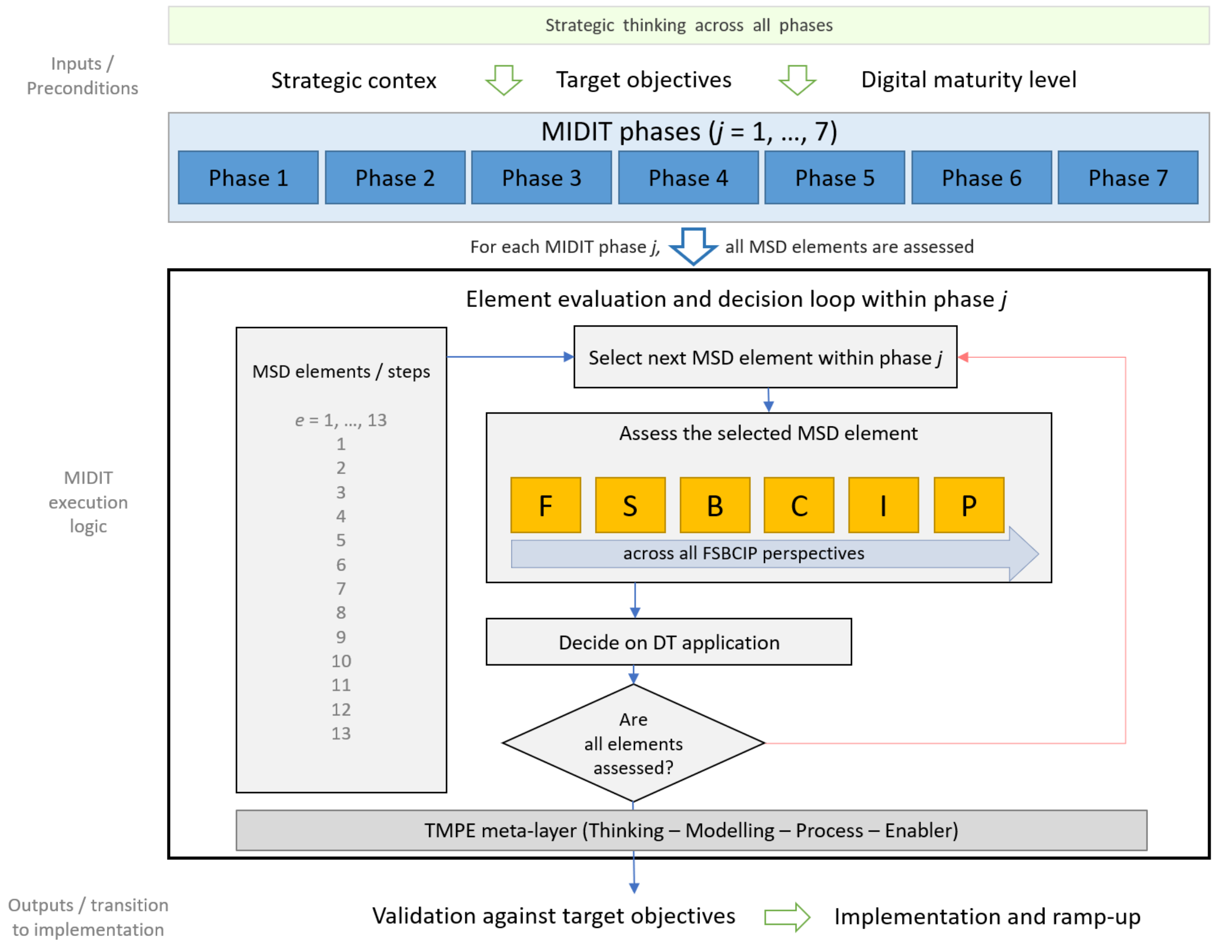


Figure 4.12: Synthesis of the execution logic of the MIDIT methodology for integrating digital technologies into manufacturing system design

A more detailed operational representation of the MIDIT procedure, including its underlying activity flow, decision points, and iterative structure, is provided in the flowchart in Appendix B. This flowchart complements, rather than duplicates, the representations in Figures 4.11 and 4.12. While the figures in the main text present a high-level, synthesis-oriented view of the methodology, the appendix flowchart offers a more explicit procedural elaboration of its execution logic by specifying the detailed activity sequence, decision gates, feedback loops, and governance structure. Thus, it serves as an operational reference for the practical application and interpretation of the MIDIT methodology. The flowchart demonstrates that the MIDIT methodology functions as an adaptive reference model for structured and context-sensitive decision-making in MSD. Methodologically, this structure goes beyond the predominantly linear or technology-focused MSD approaches found in the literature. Existing models typically prescribe either a one-directional sequence of design steps or focus on the deployment of individual technologies without an integrated governance logic. By contrast, the MIDIT flowchart combines three types of gates in a single, governable loop: decision gates on design progression (D-gates), KPI gates that explicitly test whether current concepts satisfy the required indicator levels, and dedicated root-cause gates that distinguish between conceptual design issues, data and model quality problems, and execution or resource constraints. This explicit differentiation of deviation types determines whether the process should return to earlier MSD elements, trigger improvements in data and models, or adjust implementation and ramp-up plans, thereby providing a structured and repeatable mechanism for managing iterations. In this way, MIDIT not only integrates digital tools into MSD, but also introduces a novel gate and KPI-based control logic that systematically links digital technologies, KPI information, and feedback loops into a single methodological whole.

4.5. Impact of digital technologies on design-related KPIs in the PSLM context

In the previous chapter, a framework for managing the PSLM in the context of I4.0 and I5.0 was defined, with particular emphasis on the interrelationship between PSLM, PLM, and the MSD methodology within the MIDIT framework. This section shifts focus to the performance dimension of that framework, specifically the design-related KPIs relevant to the design, evaluation, and continuous improvement of production systems. Particular attention is given to the role of digital technologies in enabling these KPIs to serve not only as reactive operational measures but also as design criteria and validation instruments throughout the PSLM, with emphasis on MSD.

The starting assumption is that companies at an intermediate level of digital maturity typically already monitor a basic set of operational KPIs, such as OEE, lead time, FPY, scrap rate, cost per unit, and safety. However, the role of digital technologies in supporting the design of production systems to achieve these target values has not yet been sufficiently systematised. The purpose of this chapter is therefore to define a core set of KPIs relevant to MSD in the context of I4.0 and I5.0, relate these indicators to the phases of the PSLM/MIDIT framework, explain how digital technologies support the setting and validation of target KPI values during MSD, and introduce a complementary set of advanced MSD design KPIs that capture the impact of digital technologies on the performance of the design process itself.

Thus, the chapter establishes a conceptual link between the PSLM-based MIDIT framework and the practical implementation of MSD. For this purpose, a distinction is made between core KPIs, which reflect the expected operational performance of the designed production system, and advanced MSD design KPIs, which describe the quality, speed, robustness, and maturity of the design process.

4.5.1. Core KPIs in manufacturing system design and their digital support

The core KPIs proposed for companies at an intermediate level of digital maturity include OEE, availability, throughput, capacity utilisation, lead time, on-time delivery, FPY, scrap rate, rework rate, cost per unit, cost of quality, safety, and schedule adherence. Detailed descriptions of these indicators, along with the main classes of digital technologies that support the definition and validation of their target values in the MSD phase, are provided in Table A5 in Appendix A.

4.5.1.1. Defining target KPI values using digital technologies in manufacturing system design

A key contribution of digital technologies to MSD is the ability to verify the achievability of KPI target values during the conceptual and detailed design phases, before physical implementation. In this way, digital technologies enable ex ante validation of target values and allow core KPIs to serve as design criteria rather than merely ex post operational measures.

For time and capacity-related KPIs such as OEE, throughput, lead time, availability, and capacity utilisation, digital models and simulation tools enable examination of how alternative configurations of equipment, layout, work organisation, buffering, and scheduling affect the expected performance of the future system. By analysing alternative design scenarios under varying load conditions and product mixes, designers can assess whether targeted performance levels are realistically achievable and identify potential bottlenecks, excessive waiting times, or underutilised resources. These KPIs directly support the selection and dimensioning of system concepts.

For quality-related KPIs, including FPY, scrap, and rework rates, digital quality planning tools, process modelling, and design approaches such as DfM/DfA and robust design enable early estimation of process capability and the expected quality performance of alternative system concepts. By analysing process variations, tolerance chains, and sensitivity to input disturbances, it is possible to assess whether intended quality targets can be achieved and to use these indicators as criteria for selecting process alternatives, defining control points, and specifying capability requirements.

Economic KPIs such as cost per unit and cost of quality can also be addressed in advance through digital cost models integrated with cycle time estimates, utilisation assumptions, expected defect levels, and alternative automation scenarios. These models support evaluation of design trade-offs between investment and operating costs and allow the expected economic consequences of different system configurations to be assessed before implementation.

Safety-related KPIs can be addressed in the design phase through ergonomics and safety analyses performed in digital environments, including 3D modelling and VR-based assessment. These approaches allow hazardous situations, ergonomic overload, and unsafe interactions between operators, machines, and robots to be identified before the physical system is realised. As a result, safety targets can be treated as design constraints and validation criteria during MSD.

Overall, these examples demonstrate that digital technologies extend the role of core KPIs within MSD from retrospective performance measures to forward-looking design and validation tools. This is particularly relevant for companies at an intermediate level of digital maturity, where the basic KPI structure is typically already established, but the systematic use of digital tools for validating design targets is still developing.

4.5.1.2. Linking core KPIs and MIDIT phases

The defined set of core KPIs is linked to the phases of the MIDIT-based PSLM framework to reflect the evolving role of performance indicators throughout the production system lifecycle. In the earlier, more conceptual phases, KPIs such as throughput, lead time, OEE, delivery performance, and safety primarily serve as target constraints guiding the selection of system concepts, basic flow structures, and resource configurations. In the more detailed design phases, these indicators are more explicitly connected to process parameters, quality plans, ergonomic solutions, and control-related design decisions. During implementation and ramp-up, the focus shifts from projected values to verifying whether the realised system achieves the designed targets. In the subsequent operational and improvement phases, the achieved KPI values provide feedback for further optimisation, redesign, and reconfiguration.

Accordingly, core KPIs function as a consistent performance thread across the MIDIT phases: they guide conceptual design choices, support digital validation in the design phase, and provide the basis for verification and feedback in implementation and operation. In this way, the core KPI set establishes a direct link between the logic of the PSLM/MIDIT framework and the practical performance orientation of MSD.

The proposed set of core KPIs and its links to the PSLM/MIDIT phases form part of the conceptual basis for the empirical work presented later in the thesis, where expert interviews and case-based analysis are used to validate, refine, and prioritise these indicators in industrial contexts with varying levels of digital maturity.

4.5.2. Advanced KPIs in manufacturing system design

In addition to the core KPIs describing the expected operational performance of the designed production system, a second group of indicators is needed to assess the performance of the design process itself. This is particularly relevant for companies that have moved beyond basic digitalisation and now systematically use simulation, digital twins, advanced analytics, knowledge-based engineering, collaborative platforms, and related digital technologies within MSD. In such environments, the contribution of digital technologies should be evaluated not only in terms of operational gains, but also in relation to their impact on the speed, robustness, quality, and organisational maturity of the design process. For this reason, the proposed framework introduces a complementary set of advanced MSD design KPIs. These indicators capture the extent to which digital technologies enhance how production systems are conceived, analysed, validated, and continuously redesigned throughout the lifecycle. They therefore complement the core KPI set by shifting the focus from the performance of the designed system to the performance of the MSD process itself.

The advanced MSD design KPIs are grouped into five categories. The first category addresses the time performance of the MSD process. The second captures the quality and robustness of design outcomes. The third focuses on data and analytics in design. The fourth covers human-centric and collaborative aspects of MSD. The fifth concerns digital risk management and system resilience. Together, these categories provide a structured basis for assessing not only whether digital technologies are present, but also whether they are effectively exploited as enablers of a more capable and mature MSD process.

For each KPI, Table A6 in Appendix A provides a brief definition, identifies the main classes of digital technologies supporting its use in the MSD context, and summarises what it indicates about the performance and maturity of the design process.

The first category of advanced MSD design KPIs concerns the time performance of MSD. Indicators such as MSD Lead Time, Time-to-Concept Alternatives, and Time-to-Ramp-up Prediction describe how quickly an organisation can generate and evaluate design alternatives, converge on a robust system concept, and produce reliable projections of ramp-up behaviour. Collectively, these indicators demonstrate whether digital technologies are effectively used to shorten design and validation cycles.

The second category addresses the quality and robustness of design outcomes. Indicators such as Accuracy of Designed KPIs, Design Iteration Efficiency, and Reuse of Digital Assets in MSD reflect whether digitally supported design activities result in realistic and stable performance targets, reduce unnecessary redesign loops, and systematically build on previously developed models and knowledge. These indicators are particularly useful for distinguishing between organisations that simply use digital tools and those that have integrated them into a coherent, learning-oriented design process.

The third category focuses on data and analytics in MSD. Data-driven Design Decisions Share, Model Calibration Level, and Scenario Coverage Index indicate the extent to which design decisions are based on calibrated models, empirical data, and systematic scenario analysis rather than intuition alone. High values in this group suggest that digital technologies such as

IIoT, analytics platforms, simulation environments, and digital twins are genuinely used as decision-support tools within MSD.

The fourth category focuses on human-centric and collaborative aspects of design. Indicators such as Operator Involvement in MSD, Ergonomic Risk Reduction in Design, and Cross-functional Design Collaboration Index measure the extent to which operator knowledge, ergonomics, safety considerations, and cross-functional coordination are integrated into the design process. In this way, the advanced KPI framework reflects the I5.0 emphasis on human-centricity and collaborative design supported by digital technologies.

The fifth category addresses digital risk and system resilience in MSD. Cyber-physical Risk Consideration in Design, Design for Reconfigurability Index, and Predictive Maintenance Design Integration indicate whether cyber-physical risks, OT/IT integration challenges, future reconfigurability, and predictive maintenance requirements are proactively addressed at the design stage. This category distinguishes organisations that use digital technologies solely to optimise current operations from those that design production systems for long-term flexibility, resilience, and secure digital integration.

Together, the core KPIs and advanced MSD design KPIs form the conceptual measurement framework of the MIDIT-based PSLM. While the core KPIs capture the expected operational performance of the designed production system, the advanced MSD design KPIs assess the performance of the design process itself and the extent to which digital technologies are effectively leveraged within MSD. However, the practical relevance, applicability, and perceived usefulness of this framework and its proposed indicators cannot be established solely on conceptual grounds. The following chapter therefore presents their empirical validation through expert interviews and an industrial case study.

Chapter 5

5. Empirical validation of the MIDIT methodology

5.1. Research design and data collection

This chapter presents the empirical validation of the MIDIT methodology in industrial practice, focusing on the effects and applicability of digital technologies in MSD. The empirical research pursues four objectives:

1. To examine how MSD and digital-transformation experts evaluate the relevance and practical value of the proposed core and advanced KPI sets within MSD;
2. To assess expert judgements on how specific digital technologies influence the evaluation and expected values of KPIs during MSD;
3. To evaluate, using an evidence-informed Delphi approach, the feasibility and anticipated impact of VR/AR and AI technologies in selected MIDIT phases;
4. To quantify the impact of systematic digital technology-integration on design duration and design quality by comparing a traditional MSD workflow (Plan T) with a MIDIT-based workflow (Plan D).

A mixed-methods research design combining qualitative and quantitative techniques is applied. The validation comprises four mutually reinforcing components:

- Expert assessment (Section 5.2): semi-structured interviews and two structured questionnaires assess the KPI framework and the impact of digital technologies on core and advanced KPIs.
- Case study (Section 5.3): an industrial case illustrates how digital models enable earlier detection of bottlenecks and more reliable KPI prediction during design.
- Evidence-informed Delphi (Section 5.4): domain experts evaluate VR/AR and AI applicability and expected impact using standardised scenarios, briefing evidence, and structured metrics.
- Schedule comparison (Section 5.5): a comparative analysis of Plan T and Plan D assesses expected effects on timeline, iterations, and decision-gate progression.

Together, these components provide convergent evidence for evaluating whether MIDIT can shorten design lead times, improve decision quality, and enhance manufacturing-system KPI outcomes in the context of digital transformation. Table 5.1 summarises how the empirical components relate to the predefined hypotheses and the type of evidence they provide.

Table 5.1: Empirical validation components and their linkage to research hypotheses

Component type	Section	Hypotheses addressed	Main evidence
Expert assessment perceptions, structured survey data	5.2	H1, H1a	Expert
Case study (digital model) in a real MSD project	5.3	H1a	KPI comparison
Evidence-informed Delphi expert consensus	5.4	H1b, H1c	Scenario-based
Schedule comparison Plan T/D time and effort estimates	5.5	H1	Project -level

The main hypothesis H1 is evaluated cumulatively, drawing on the specific findings for H1a, H1b, and H1c together with the Plan T vs. Plan D schedule comparison.

5.1.1. Industrial environment and profile of participating SMEs

The empirical validation was conducted in a regional industrial environment dominated by SMEs that had previously participated in digital maturity research. In an earlier project, three manufacturing companies from the same region contributed to the development and validation of a digital maturity assessment model for SMEs [61]. By collaborating with the research team, these companies developed a shared understanding of digital transformation and provided domain knowledge to ensure that the maturity dimensions and assessment criteria reflected real industrial needs.

For this dissertation, the same industrial environment serves as the starting point, with a continued focus on discrete manufacturing. The sample includes companies from several sectors: metal machining and machine tool manufacturing, metal manufacturing, automotive components manufacturing, and the glass industry. These companies operate in competitive international markets and face demanding customer and industry requirements, increasing the pressure for efficient and reliable manufacturing systems. All participating companies recognise the strategic importance of digital transformation and demonstrate at least a basic level of digital capability, ranging from fundamental digital tools to more advanced horizontal and vertical system integration, simulation solutions, IoT technologies, and cybersecurity measures.

This industrial background provides a relevant and demanding testing ground for the MIDIT methodology: the companies are sufficiently engaged in digitalisation to meaningfully assess the role of digital technologies in MSD, while also exhibiting a moderate level of digital maturity typical for SMEs across the wider region. Consequently, issues of methodological support, KPI definition, and the improvement of MSD performance are particularly significant.

Table 5.2 presents the key characteristics of the participating companies, including their sector, number of employees, implemented digital technologies, and digital maturity (DM) level. The DM value represents the overall digital maturity score of the company, while the value in brackets indicates its technology-specific maturity, distinguishing general progress in digital transformation from concrete technological capability. All companies use at least basic digital tools (e.g., CAD, CAM, CAE, and MRP/ERP systems), while some also demonstrate more advanced features such as simulation tools, IoT solutions, and MES systems. Based on these characteristics, the sample consists of typical companies in a phase of active yet incomplete digital transformation, making them a particularly suitable context for the empirical validation of the MIDIT methodology, as they have sufficient experience with digital technologies to provide informed assessments of their impact on MSD, while also exhibiting a clear need for structured methodological support and more clearly defined KPIs.

Table 5.2: Description of selected companies for validation

Company	Industry Sector	Number of Employees	Implemented Digital Technologies	DM
Company C01	Automotive	695	CAD/CAM/CAE, horizontal and vertical system integration (ERP, MES); cloud, IoT, simulations	2.09 (2.16)
Company C02	Metal manufacturing	140	CAD/CAM/CAE, horizontal and vertical system integration (ERP, MES); IoT	2.25 (1.89)
Company C03	Machine tool manufacturing	35	MRPII Pauk software, CAD/CAM/CAE	1.69 (1.73)
Company C04	Glass industry	240	CAD/CAM/CAE, horizontal and vertical system integration (ERP); IoT	2.57 (2.13)

5.2. Expert assessment of the impact of digital technologies on KPIs

The expert panel consisted of specialists responsible for designing, managing, and improving manufacturing systems, including those in production management, technology or engineering leadership, quality management, production planning, maintenance, and HR or HSE roles. Participants worked in SMEs of various sizes, with most employed at companies with 35–695 employees and possessing intermediate to advanced familiarity with MSD or manufacturing system management. Self-assessed familiarity with digital technologies ranged from basic to expert, with most respondents reporting intermediate to advanced familiarity.

5.2.1. Questionnaire design and measurement scales

The expert assessment was supported by two complementary questionnaires that operationalise the KPI framework developed in the previous chapter and relate it to the use of digital technologies in MSD. The first questionnaire focuses on digital technologies in defining and improving core operational KPIs, while the second addresses advanced, design-related KPIs that describe the performance and maturity of the MSD process itself. Both instruments include respondent and company profile items (sector, enterprise size, role, MSD experience, digital familiarity) and a confidentiality statement clarifying voluntary participation and aggregated reporting.

Core KPI questionnaire (impact on operational KPI-driven decisions)

The core questionnaire is organised into KPI blocks aligned with the framework: production/capacity/time (e.g., OEE, throughput, availability, capacity utilisation), quality (FPY, scrap rate, rework), cost, flexibility, and human-centric aspects (safety, ergonomics). For each block, relevant digital technologies are listed (simulation and modelling, digital twins, ERP/MES integration, robotics/automation, IIoT/CPS, CAPP/KBE). Respondents rate the impact of each technology on MSD decisions that determine the feasibility of reaching target KPI values using a five-point Likert scale: 1 no impact, 2 small, 3 moderate, 4 large, 5 very large. Closed-ended items are complemented by short open questions within each block and concluding open questions about underused technologies, hard-to-estimate KPIs in early design phases, and recommendations for better integration within MIDIT.

Advanced KPI questionnaire (application and sensitivity)

The advanced questionnaire targets KPIs that measure MSD process performance rather than only downstream operational outcomes. KPI groups include: time-related indicators (MSD lead time, time to concept alternatives), design quality and robustness (accuracy of KPI estimates, iteration efficiency), data maturity and analytics (proportion of data-driven decisions, model calibration), collaboration and human-centricity (operator involvement, cross-functional collaboration), and digital risk/resilience (cyber-physical risk consideration, design for reconfigurability).

For each advanced KPI, respondents provide two ratings:

- **Application level (0–5)**: 0 not used; 1–5 from rare or ad hoc to systematic formal usage.
- **Sensitivity to digital technologies (1–5)**: 1 no impact; 5 very strong impact.

Each KPI group includes one open question to capture realised benefits and obstacles, such as data availability, competence gaps, and integration barriers. The questionnaires are provided in Appendix C (core KPIs) and Appendix D (advanced KPIs).

Together, the two questionnaires establish a structured link between the conceptual KPI framework and practitioners' experience. The first maps how specific digital technologies influence MSD decisions related to core KPI outcomes, while the second characterises how MSD processes are measured and improved through advanced, design-oriented KPIs. This structure enables subsequent cross-company comparison, supports quantitative analysis of response patterns, and provides a rich qualitative basis for interpreting the empirical findings presented in Sections 5.2.2 - 5.2.4.

5.2.2. Data processing, aggregation and statistical tests

All questionnaire responses underwent a structured data-cleaning procedure. Records were checked for internal consistency, and respondent identifiers had to match the master respondent list for each company. Entries associated with unknown or duplicate identifiers were removed from the analysis. Missing or inapplicable ratings were flagged using the IsNA indicator; all such cases (IsNA = 1) were excluded from the computation of descriptive statistics. Not all digital technologies were evaluated in every KPI block, as respondents were instructed to rate only those technologies, they considered meaningful and significant for the respective KPI area. Consequently, the number of observations per technology and KPI block varies, reflecting practical relevance rather than a fully balanced experimental design.

After cleaning, the data were aggregated in several steps. At the most granular level, each observation represents a single respondent's rating of a specific digital technology within a given KPI block and company. These observations were then summarised at the level of KPI blocks, digital technologies, and companies using standard descriptive statistics: number of ratings (N), arithmetic mean, median, standard deviation, interquartile range (IQR), and Top Box share (percentage of ratings ≥ 4 on the five-point scale). Company-level summaries were further combined into overall aggregates across all four companies. Medians and Top Box percentages are emphasised throughout because they are more robust to skewness and ceiling effects than the mean and provide a more management-oriented interpretation of "high perceived impact".

Company maturity was operationalised as a numerical index on a four-level scale and assigned to each respondent via the company identifier. In this analysis, maturity is used descriptively to support interpretation of patterns in the ratings across companies with different digital-transformation profiles. No formal regression or covariance modelling with maturity as a predictor was performed, given the small number of companies and respondents. Therefore, differences between companies are interpreted as indicative of combined contextual and maturity-related effects rather than as statistically isolated impacts of maturity alone.

For inferential analysis, non-parametric tests were chosen to reflect the ordinal nature of the Likert-scale data and the modest sample size in each company. Within each company, comparisons between KPI blocks were treated as paired or repeated-measures designs because the same respondents rated multiple blocks. These within-company differences were tested using the Friedman test, and effect sizes were quantified using Kendall's W as a measure of within-panel agreement.

Between-company comparisons for each KPI block were treated as independent samples and analysed using the Kruskal–Wallis test, with epsilon-squared (ε^2) reported as an approximate effect size. In interpreting the results, values of Kendall's W above approximately 0.5 were taken to indicate strong agreement, while ε^2 values in a similar range were interpreted as medium to large effects.

The combination of robust descriptive summaries and non-parametric tests provides the statistical basis for the empirical results and interpretations presented in Section 5.2.3, where the corresponding tables are reported and discussed in detail.

5.2.3. Results: impact on core operational KPIs

The analysis was conducted on an unpaired multi-company sample, with each company evaluated by a different set of respondents (C01: 4, C02: 4, C03: 3, C04: 4).

Experts assessed the impact of relevant digital technologies on six KPI blocks: production/capacity/time (A1), quality (B1), costs (C1), supply/planning (D1), safety and human-centred aspects (E1), and advanced technologies (F1). Ratings were collected on a five-point Likert scale from 1 (no impact) to 5 (very strong impact). At the overall sample level, all KPI blocks achieved a median of 4 (large impact), with high Top Box shares (ratings 4 and 5) ranging from 71.4% (E1) to 90.6% (C1), as summarised in Table 5.3. These findings indicate that respondents generally perceive digital technologies as a powerful means of achieving target KPI values in MSD. Table 5.3 shows that production/capacity/time (A1), costs (C1), and supply/planning (D1) have the highest Top Box shares (87.7–90.6%), while safety and human-centred aspects (E1) receive slightly lower, though still predominantly positive, ratings (Top Box 71.4%). The advanced-technologies block (F1) records a median of 4 and a Top Box share of 74.2%, indicating that more novel technologies are also regarded as influential, with somewhat greater variability.

When results are examined by company, most blocks retain a median of 4 across all companies, with more pronounced differences in the E1 and F1 blocks (Appendix E).

Table 5.3: Perceived impact by KPI block - overall

KPI Group	KPI block	N	Mean	Median	Top Box %
A1	Production / Capacity / Time	81	4.20	4	87.7%
B1	Quality	93	4.02	4	81.7%
C1	Costs	96	4.25	4	90.6%
D1	Supply / Planning	80	4.19	4	88.8%
E1	Safety / Human-centric	84	3.95	4	71.4%
F1	Advanced technologies	31	3.90	4	74.2%
Legend: N – number of ratings; Top Box % – share of ratings ≥ 4					

The least mature company (C03, maturity 1.69) shows a median of 3 and a Top Box share of 0.0% for safety and human-centred aspects (E1), whereas the most mature company (C04, maturity 2.57) consistently assigns the highest ratings across blocks, with Top Box shares of 100.0% in all six blocks. In the advanced-technologies block (F1), the more mature companies reach medians of 4 and Top Box values between 66.7% and 100.0%, while C01 shows a median of 3 with a Top Box share of 41.7%. These company-level patterns are detailed in Appendix E and complement the maturity overview in Table 5.4, suggesting that organisations with more developed digital practices more clearly recognise the potential of advanced technologies, particularly in domains related to safety and "industry 5.0" use cases.

Table 5.4: Sample and digital maturity by company

Company ID	Digital Maturity Level (1–4)	Respondents (N)
C01	2.09	4
C02	2.25	4
C03	1.69	3
C04	2.57	4

At the level of individual technologies, the five highest-ranked solutions by overall mean impact are listed in Table 5.4. AI and ML, IIoT/CPS, ERP/MES integration, and digital twins form the leading group, each with overall means above 4.0 and Top Box shares of at least 85.7% (Table 5.5). The minimum and maximum medians across companies for these technologies range from 4.0 to 5.0, indicating broad consensus on their importance despite differing maturity levels. Robust design and DoE tools, robotisation and automation, Digital Thread, APS/PPC tools, and Big Data/Analytics/Cloud also achieve high mean scores, confirming that both data-centric and model-based technologies are regarded as central enablers of KPI-driven design.

Table 5.5: Top five digital technologies ranked by overall mean

Rank	DT name	N	Mean	Median	Top Box %	Min company median	Max company median
1	AI and ML	36	4.44	4.0	100.0%	4.0	5.0
2	ERP/MES	45	4.42	5.0	93.0%	4.0	5.0
3	IIoT / CPS	24	4.42	4.0	100.0%	4.0	5.0
4	Digital twin	56	4.36	4.5	85.7%	4.0	5.0
5	Robust design / DoE	12	4.33	4.0	100.0%	4.0	4.5

A more nuanced picture emerges when technologies are considered within specific KPI blocks. In the production, capacity, and time (A1) and cost (C1) blocks, simulation and modelling, digital twins, ERP/MES integration, and AI/ML receive particularly high ratings, reflecting their role in quantifying throughput, utilisation, and cost behaviour. In the quality block (B1), CAPP/KBE, advanced statistical tools (DoE), and AI/ML are especially prominent, whereas supply and planning (D1) is dominated by ERP/MES, APS/PPC tools, Digital Thread, and big data analytics. For safety and human-centred aspects (E1), VR/AR, robotisation and automation, and IIoT stand out, while the advanced technologies block (F1) unsurprisingly favours AI/ML and additive manufacturing.

The non-parametric tests (Table 5.6 and Table 5.7) confirm that the patterns are not random.

Table 5.6: Non-parametric test: Friedman tests

Company ID	N respondents	χ^2	p	Kendall W
C01	4	18.406	0.002	0.920
C02	4	12.695	0.026	0.635
C03	4	11.373	0.044	0.758
C04	4	10.639	0.059	0.532

Within each company, Friedman tests reveal statistically significant differences between KPI blocks for three out of four companies, with Kendall's W values indicating strong within-panel agreement. Between companies, Kruskal–Wallis tests for each block yield statistically significant differences with medium to large effect sizes (ε^2 between 0.51 and 0.83; Table 5.6).

Taken together, these results show that experts systematically distinguish between KPI domains and that their judgements vary in line with company-level digital maturity.

Table 5.7: Non-parametric test: Kruskal - Wallis test

KPI Group	KPI Block Name	Total respondents	H	p	ε^2
A1	Production / Capacity / Time	15	9.014	0.029	0.547
B1	Quality	15	11.468	0.009	0.770
C1	Costs	15	8.641	0.034	0.513
D1	Supply / Planning	15	11.743	0.008	0.795
E1	Safety / Human-centric	15	12.145	0.007	0.831
F1	Advanced technologies	15	10.301	0.016	0.664

In addition to scalar impact ratings, respondents selected two technologies they considered most important for decision-making in each KPI block. Top1 and Top2 selections were aggregated using Borda scoring (Top1 = 2 points, Top2 = 1 point), as shown in Table 5.8. Overall, technologies with the highest mean impact ratings also tend to be among the most frequently selected Top2 tools for decision-making in their respective KPI blocks. This convergence between perceived impact and decision-making priority suggests that digital technologies are viewed not merely as supporting infrastructure, but as integral components of key design decisions that determine the feasibility of achieving target KPI values.

Table 5.8: Top 2 decision-making priorities

Block	DT Name	Overall Count	Overall Borda	% Respondents Top 2
A1	Modelling and simulation	13	23	0.93
A1	ERP/MES integration	10	11	0.71
A1	CAPP / KBE	3	5	0.21
B1	CAPP / KBE	7	13	0.47
B1	Modelling and simulation	6	10	0.40
B1	Digital quality planning tools	6	10	0.40
C1	ERP/MES integration	8	12	0.53
C1	Modelling and simulation	5	9	0.33
C1	Big Data / Analytics / Cloud	5	9	0.33
D1	ERP/MES integration	14	26	0.93
D1	APS / PPC tools	12	15	0.80
D1	Big Data / Analytics / Cloud	3	3	0.20
E1	VR/AR	13	22	0.87
E1	Robotisation and automation	9	13	0.60
E1	Modelling and simulation	5	6	0.33

When the results are interpreted in relation to company-level digital maturity, a clear pattern emerges. The least mature company (C03, maturity 1.69) generally gives lower ratings, particularly in the safety block (E1: median 2, Top Box 0.0%) and the advanced technologies block (F1: median 4, Top Box 66.7%), whereas the most mature company (C04, maturity 2.57) consistently evaluates the impact of digital technologies as large or very large across all blocks (medians 4–5, Top Box 100.0% in all blocks). This pattern aligns with the expectation that greater exposure to and experience with digital technologies leads to a clearer understanding of their contribution to KPI outcomes. Exploratory Dunn post hoc tests with Holm correction confirmed that the largest contrasts occur between the least and most digitally mature companies, particularly in E1 and F1 (detailed results in Appendix E).

Open-ended responses broadly confirm the quantitative findings. Respondents most frequently associate AI and advanced analytics with shorter design times, faster decision-making, and higher solution quality. However, they note that specialised AI agents, digital twins, VR/AR solutions, and broader PLM/PSLM support remain insufficiently developed or not yet fully available in practice. The most difficult KPIs to define reliably in early design stages are those dependent on incomplete, low-quality, or non-digitalised data, particularly OEE, availability, and quality indicators. Overall, the responses suggest that the main barrier is not the perceived relevance of digital technologies, but the lack of robust data foundations and sufficiently operational digital support structures.

Taken together, the descriptive and inferential results show that experts in all participating companies perceive digital technologies as a relevant and practically valuable means of supporting KPI-driven MSD. Importantly, the highest-ranked technologies – simulation and modelling, ERP/MES integration, IIoT/CPS, AI/ML, and VR/AR – are simultaneously recognised as key decision-making tools, supporting the concept of systematic, scenario-based integration of digital technologies within the MIDIT methodology. This pattern of perceptions and preferences provides an empirical basis for arguing that structured deployment of these technologies can shorten design lead times, improve decision quality, and increase the likelihood of achieving target KPI values in MSD.

5.2.4. Results: impact on advanced, design-related KPIs

This subsection analyses how advanced, design-oriented KPIs are currently applied in MSD, their perceived sensitivity to digital technologies, and where the greatest untapped potential for improvement can be identified using the gap indicator. The analytical procedure combined descriptive analysis of data on the original response scales with the calculation of composite indicators based on normalised values. Descriptive measures of KPI application and sensitivity were calculated on the original scales to preserve the interpretability of expert assessments. In contrast, values used for composite indicators were normalised to the 0–1 interval to ensure comparability between the application and sensitivity dimensions. Based on these transformed values, impact and gap indicators were calculated, with impact reflecting the joint presence and importance of a KPI, and gap representing the difference between perceived importance and actual implementation level. This methodological approach preserves the substantive meaning of the original ratings while enabling comparability of higher-level derived indicators.

5.2.4.1. Overall level of use, sensitivity, and gaps

Analysis of the five conceptual groups of advanced KPIs reveals distinct patterns in their current use and perceived sensitivity to digital technologies during the MSD phase (Table 5.9). The highest Mean A value is observed for human-centric and collaboration (2.733), followed by quality of design (2.600) and risk and resilience (2.417), while data and analytics (2.200) and time performance (2.089) show lower average levels of formal implementation. This indicates that the adoption of advanced KPIs in MSD is uneven across conceptual domains.

Table 5.9: Indices of advanced MSD KPIs by group – use (A), sensitivity (B) and unused potential

KPI Group	N A (>0)	Mean A	Mean B	Mean Impact	Mean Gap
Human-centric and collaboration	15	2.733	3.978	0.171	0.613
Data and analytics	25	2.200	3.978	0.214	0.551
Risk and resilience	24	2.417	3.667	0.228	0.476
Quality of design	30	2.600	3.711	0.290	0.396
Time performance	45	2.089	3.956	0.356	0.373

Note: Scale A (0–5); scale B (1–5). Mean A and Mean B are calculated using the original response scales. Mean Impact and Mean Gap are based on normalised values (A_norm = A/5, B_norm = B/5). Mean Gap represents the average KPI-level opportunity gap (B_norm – A_norm). N denotes the number of observations where A > 0.

In contrast, Mean B values remain consistently high across all groups, ranging from 3.667 to 3.978. The highest perceived sensitivity to digital technologies is recorded for the human-centric and collaboration group and the data and analytics group (both 3.978), closely followed by time performance (3.956). These results suggest that respondents broadly recognise the relevance of digital technologies for improving advanced MSD performance, even in areas where current KPI use remains limited.

The Mean Impact index provides an important integrative perspective by combining current use and perceived digital relevance. The highest Mean Impact is observed for time performance (0.356), followed by quality of design (0.290), while human-centric and collaboration shows the lowest value (0.171). This suggests that time-related advanced KPIs currently demonstrate the strongest combined digital effect, whereas human-centric and collaboration-related KPIs, despite their recognised relevance, have not yet translated into equally strong practical impact.

The Mean Gap results highlight the main areas of unrealised potential. The largest gap is recorded for human-centric and collaboration (0.613), followed by data and analytics (0.551), while time performance shows the lowest gap (0.373). This indicates that the greatest opportunity for further development lies primarily in human-centric and data-related dimensions, where the expected contribution of digital technologies clearly exceeds current formal KPI implementation.

Overall, the results indicate three broad patterns. Time performance demonstrates the strongest current combined digital effect among the analysed groups. Human-centric and collaborative aspects, as well as data and analytics, represent the strongest opportunity areas, combining high perceived relevance with the largest remaining gaps. Quality of design and risk and resilience occupy an intermediate position, indicating moderate implementation, substantial relevance, and considerable scope for methodological development. Collectively, these findings suggest that further development of the MIDIT-based PSLM methodology should prioritise human-centric, collaborative, and data-driven KPI structures in MSD.

5.2.4.2. Maturity differences at the individual KPI level

At the level of individual advanced KPIs, a more differentiated maturity pattern emerges. Some indicators that are relatively close to traditional performance logic, such as MSD Lead Time (A1_1), Time-to-Ramp-up Prediction (A1_3), and Accuracy of Designed KPIs (B1_1), show comparatively higher levels of current use. This suggests that organisations are more likely to formalise advanced KPIs that remain closely linked to established concerns such as timing, ramp-up, and the consistency between designed and realised system performance.

In contrast, several KPIs that are conceptually central to a mature, digitally enabled MSD approach still show limited practical adoption. This is particularly evident for Operator Involvement in MSD (D1_1), Model Calibration Level (C1_2), and Reuse of Digital Assets in MSD (B1_3), which combine very low current use with high perceived relevance of digital technologies. Similar patterns are also seen for Cross-functional Design Collaboration (D1_3) and Design for Reconfigurability Index (E1_2). These results indicate that human-centric, data-driven, collaborative, and adaptability-oriented aspects of MSD are already recognised as important, but have not yet been systematically translated into formal KPI structures. The dispersion of results across individual KPIs further suggests that organisational practice is heterogeneous, with some companies already applying more advanced MSD metrics, while others still rely on limited or ad hoc measurement approaches.

Table 5.10 presents the advanced MSD KPIs with the highest average opportunity gap between current use and perceived sensitivity to digital technologies, thus identifying indicators with the greatest unrealised improvement potential. The largest gap is observed for

Operator Involvement in MSD (D1_1), which is not used in practice (Mean A = 0.00), despite a clearly positive assessment of its digital relevance (Mean B = 3.73). Similarly high gaps are found for Model Calibration Level (C1_2), Reuse of Digital Assets in MSD (B1_3), Cross-functional Design Collaboration Index (D1_3), and Design for Reconfigurability Index (E1_2). Collectively, these results indicate that the strongest unmet potential lies in human-centric, data-driven, collaborative, and reconfigurability-oriented aspects of MSD, where the importance of digital technologies is already recognised, but their translation into formal KPI practice remains limited.

Table 5.10: Advanced MSD KPIs with the highest average opportunity gap

KPI Code	KPI Group	KPI Name	Mean A	Mean B	Mean Gap
D1_1	Human-centric and collaboration	Operator Involvement in MSD	0.00	3.73	0.75
C1_2	Data and analytics	Model Calibration Level	0.80	4.27	0.69
B1_3	Quality of design	Reuse of Digital Assets in MSD	0.47	3.93	0.69
D1_3	Human-centric and collaboration	Cross-functional Design Collaboration Index	0.93	4.27	0.67
E1_2	Risk and resilience	Design for Reconfigurability Index	1.07	3.67	0.52

Overall, the KPI-level results confirm that the maturity of advanced MSD measurement remains uneven. While some organisations have already begun to operationalise selected advanced indicators, many of the more distinctive I4.0/5.0-oriented KPIs are still at an early stage of implementation. A complete overview of KPI-level descriptive results is provided in Appendix F, while Table 5.10 highlights those advanced KPIs with the greatest unrealised potential.

5.2.4.3. Relationships at KPI and company maturity levels

Correlation analysis between the use of advanced KPIs (A) and their perceived sensitivity to digital technologies (B) was conducted for individual KPI groups and for the overall data set. The results show positive and statistically significant correlations across all KPI groups, with coefficients ranging from approximately 0.46 to 0.69 and p-values below 0.05. The strongest relationships are observed for time-related KPIs and for risk and resilience, while the data and analytics group shows a somewhat lower, but still clearly positive, correlation (Appendix F).

These findings indicate a consistent association between the maturity of advanced KPI use and the perceived role of digital technologies in MSD. Organisations that make more intensive use of advanced KPIs also tend to perceive digital technologies as more relevant for shaping design processes and outcomes. This may reflect a mutually reinforcing relationship: digitally supported design environments can improve the visibility and measurability of design decisions, while more developed KPI systems may, in turn, enable organisations to make better use of digital tools in MSD practice.

At the level of the full KPI set, the overall correlation between A and B confirms this pattern. In general, organisations that demonstrate a higher level of maturity in the use of advanced design-oriented KPIs also report a stronger perceived contribution of digital technologies to these performance dimensions. Although this result should not be interpreted causally, it does suggest that KPI development and digitally supported MSD tend to evolve in parallel rather than independently.

This broader relationship is also reflected in the company-level comparison presented in Table 5.11. The results show clearly differentiated organisational profiles.

Company C04 achieves the highest average level of advanced KPI use (Mean A = 2.43), the highest perceived sensitivity to digital technologies (Mean B = 4.73), and the highest Mean Impact value (0.46), indicating the most advanced observed profile in the sample. In contrast, C03 records the lowest Mean A (0.62), the lowest Mean B (2.76), and the lowest Mean Impact (0.08), suggesting a considerably less developed integration of advanced KPIs and digital technologies in MSD. C01 and C02 occupy intermediate positions: C01 shows a moderate level of KPI use with relatively high perceived digital relevance, while C02 combines very low practical use with a comparatively high Mean Gap (0.59), indicating substantial unrealised potential.

Table 5.11: Company-level comparison of advanced KPI maturity

Company	Mean A	Mean B	Mean Impact	Mean Gap	N Respondents
CO1	1.65	3.85	0.29	0.44	4
CO2	0.88	3.82	0.14	0.59	4
CO3	0.62	2.76	0.08	0.43	3
CO4	2.43	4.73	0.46	0.46	4

These differences confirm that the proposed set of advanced KPIs is sufficiently sensitive to distinguish between varying levels of MSD maturity across organisations. Thus, the KPI framework can serve not only as a measurement structure but also as a comparative diagnostic tool within the broader MIDIT-based PSLM model. The observed company profiles also provide a useful basis for selecting case studies in subsequent chapters, where the co-evolution of KPI systems and digital technology use in real MSD projects can be examined in greater depth.

Open-ended responses regarding advanced KPIs provide a valuable qualitative complement to the quantitative findings. Respondents primarily associate advanced KPI structures with shorter design times, higher solution quality, and better-informed decision-making, particularly through faster analysis of alternatives, more accurate prediction of results and costs, and reduced decision risk. Specific value is attributed to KPIs related to the reuse of digital assets, time to ramp-up, accuracy of targeted KPIs, data-driven design decisions, and cross-functional collaboration. This suggests that respondents view advanced KPI systems not only as measurement tools but also as enablers of more effective MSD management. The most frequently emphasised limitation is the lack of integrated and reliable data, often linked to insufficient system integration, which constrains the early definition and practical application of advanced KPI structures. The responses also indicate that advanced KPIs and related digital technologies can improve collaboration, transparency, and the overall quality of coordinated solutions, while aspects such as digital risk and reconfigurability are still not sufficiently embedded in early design phases. Recommendations for further methodological development focus on interoperability, data collection standards, further integration of technologies, specialised AI agents, and a clearer definition of human roles and competencies within the MSD process.

Overall, the findings confirm that the proposed set of advanced KPIs is analytically robust and sufficiently sensitive to capture both the current maturity of digitally supported MSD practice and the key priority areas for further development of the MIDIT-based PSLM methodology.

5.3. Case study: Manufacturing system design optimisation using a digital model

To demonstrate the applicability of digital models and digital twins throughout the manufacturing system lifecycle, a case study from the author's long-term industrial practice in the automotive sector was selected. The observed manufacturing system aligns with I4.0 principles and already used digital models at the equipment level (e.g., tooling and 3D equipment modelling), but not previously at the overall manufacturing system level.

This section analyses improvement alternatives for a critical subsystem, focusing on productivity and the required number of direct operators using a digital model. The case concerns the improvement or reconfiguration of an existing manufacturing system; within the MIDIT–PSLM framework, this corresponds to Phase 7, which also serves as the starting point of a new design cycle.

The manufacturing system for machining aluminium housings consists of three stages: turning on CNC lathes; milling, drilling, and tapping on CNC machining centres; and washing, leak testing, visual inspection, and packaging. To increase productivity and reduce costs, new solutions were considered, and the second stage was identified as the critical element.

In the alternative concept, stages one and three were retained, while a different solution was pursued for the critical second stage. The concepts differed in machine count and direct operator requirements to achieve the target takt time and output volume. Initially, alternatives were defined without digital modelling and were expected – based on manual calculations – to meet target KPIs.

A multidisciplinary team selected a supplier from seven nominated bidders whose offers satisfied techno-commercial conditions [167]. After installation, the system failed to achieve the planned takt time due to two main reasons: lower-than-expected equipment reliability, partly due to component quality but primarily due to the selected system concept; and a lower actual takt time that resulted in insufficient operator capacity for post-machining deburring.

Digital modelling could have identified both issues during conceptual design. Digital models were developed for the original and alternative concepts. The results of observed KPIs are shown in Table 5.12 for: productivity, reliability, quality and number of direct operators.

Table 5.12: KPI results of the digital models

KPIs	Productivity (parts)	Reliability (%)	Number of direct operators	Quality scrap rate (%)
Original system	348,331	88.7	8	6.2
Alternative system	307,894	76.5	4	6.2

Simulation results revealed reliability issues and the occurrence of a new bottleneck, as shown in Figures 5.1 and 5.2 [87].

Figure 5.1: Digital model of the original manufacturing system

Visual inspection of simulation flows indicated the formation of a linear buffer, which disrupted workload balance and prevented the desired productivity. Simulated annual productivity deviated by approximately 13% from expected values. The first issue was partially mitigated by improved machine components, while the second was resolved by introducing a robotic station for automatic deburring. Development, procurement, installation, and commissioning of this station took approximately ten months (Figure 5.3). These interventions increased investment and resulted in unplanned costs, including higher maintenance expenses and productivity losses during the transition, which reduced the originally expected economic advantages of the alternative concept.

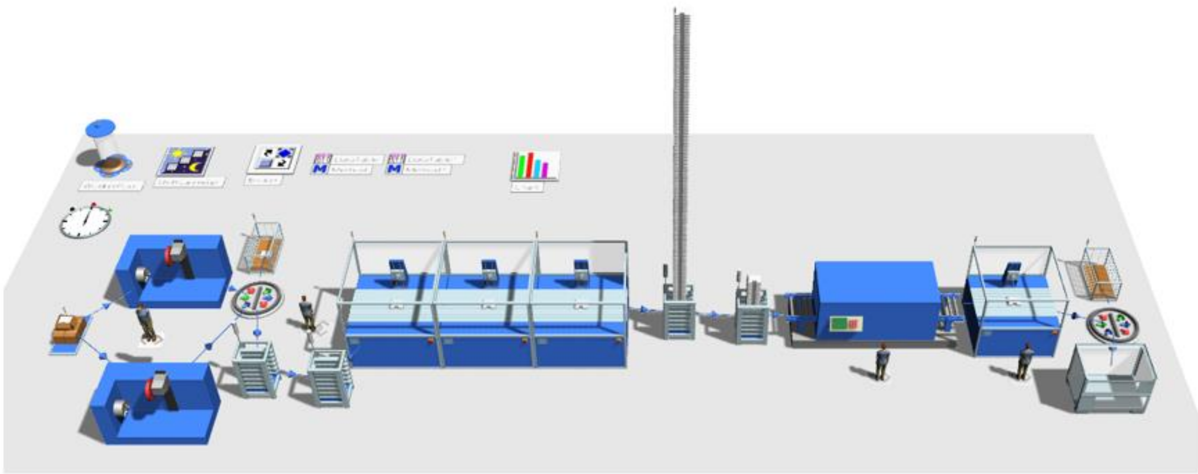


Figure 5.2: Digital model of the alternative manufacturing system after installation

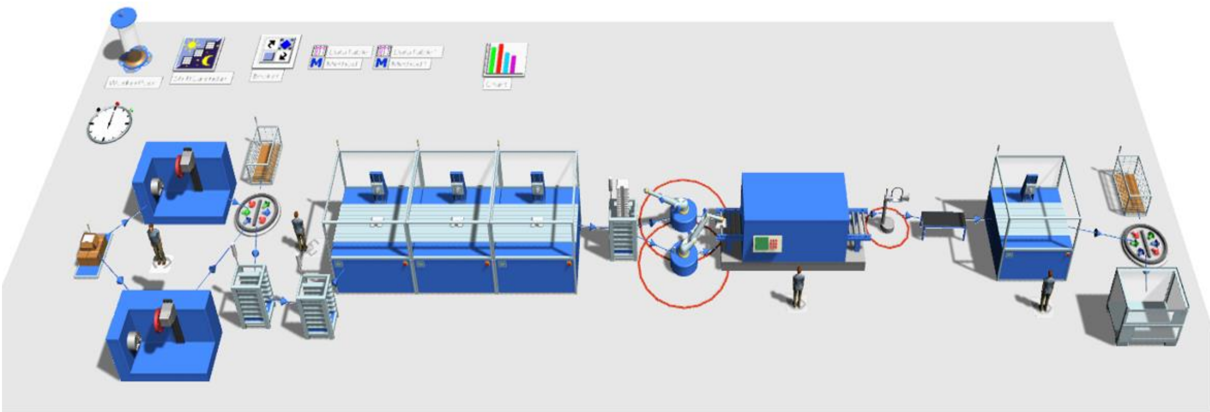


Figure 5.3:Digital model of the alternative manufacturing system after optimisation

Digital models allow scenario testing and concept validation without disrupting current operations or introducing commissioning risk. Collaborative use of simulation-supported strategic thinking enables the identification of more favourable solutions in a virtual environment, potentially saving time and resources. Digital twins further enhance decision quality by providing live data for calibration and validation, reducing errors compared to relying solely on static digital models.

Using the developed digital model during design enabled early prediction of key KPIs, including machine utilisation, throughput, and work-in-process levels. The deviation between designed KPI values and realised values after implementation remained within approximately 6%, which is considered satisfactory accuracy for early-stage MSD decision-making. These findings support Auxiliary Hypothesis I, which states that digital models enable reliable KPI prediction during the design phase.

5.4. Evidence-informed Delphi validation of VR/AR and AI within MIDIT framework

5.4.1. Evidence-informed Delphi design and briefing package

This section defines a structured and reproducible validation protocol for Hypotheses H1b and H1c within the proposed MIDIT methodology and the MIDIT-based PSLM framework. Due to the limited availability of industrial experts with practical experience in applying VR/AR and AI to MSD tasks, an evidence-informed Delphi approach was adopted. The panel comprised domain experts in MSD and operations (section 5.2.1.), who, before rating, received a standardised briefing package derived from relevant literature, specifying clear technological assumptions and constraints [180,190,210–213].

The purpose of the briefing package is to provide domain experts (MSD, production, logistics, quality, maintenance, HSE) with a standardised, comparable, evidence-based understanding of what simulation, VR/AR, and AI can realistically contribute to MSD, including prerequisites and limitations. This ensures informed judgements while controlling for uneven familiarity with these technologies.

The protocol focuses on two key outcomes explicitly stated in the hypotheses: speed and quality of MSD results.

- **Hypothesis H1b:** The application of simulation modelling and the use of Virtual/Augmented Reality (VR/AR) directly impact the speed and quality of manufacturing system design.
- **Hypothesis H1c:** The integration of Artificial Intelligence (AI) into selected MIDIT steps accelerates analysis and supports the proposal of better-justified solutions.

Impact is evaluated by comparing two standardised workflows for an identical MSD scope: a baseline workflow with minimal digital support (Plan T) and a MIDIT-enhanced workflow with systematic technology integration (Plan D). To ensure comparability, both workflows are assessed under controlled boundary conditions: identical scope and deliverables, identical input data package, fixed decision gates aligned with MIDIT/PSLM, and consistent team competence assumptions.

Data were collected using a scenario-based instrument (V1–V6). Each scenario represents a standardised MSD task fragment aligned with MIDIT decision-gate logic and focuses on measurable speed and quality outcomes under Plan T versus Plan D assumptions (Appendix G). Table G1 in Appendix G, defines the dependent variables used to evaluate Hypotheses H1b and H1c. “Speed” is measured using time-related metrics and iteration intensity; “quality” is measured using early issue detection, rework, KPI-estimate robustness, and rubric-based expert scoring.

Rubric scoring uses clearly described 1–5 levels for each criterion; all reviewers receive the same rubric and briefing package. Criteria include feasibility and implementability, robustness, safety and ergonomics (human-centric), flexibility, and sustainability. All reviewers receive the same rubric and evidence package (Appendix G).

To increase objectivity and reduce bias, four safeguards were applied:

1. Expert calibration through self-assessed familiarity and calibration questions.
2. Standardised scenarios to reduce abstract speculation and improve comparability.
3. Separation of feasibility and potential impact to reduce conflation bias.
4. Triangulation with external experts to provide an additional validation layer.

To increase realism and reduce role-specific bias, each company conducted group-based consensus ratings with experts from multiple functions. As MSD decisions in practice are interdisciplinary and driven by trade-offs, consensus rating is considered closer to real decision-gate behaviour than isolated individual judgement. Key disagreements and conditions affecting ratings (such as data readiness, integration readiness, and competence availability) were documented during the discussion, while final ratings were recorded as a jointly agreed consensus outcome for each company.

5.4.2. Operationalisation of Hypotheses H1b and H1c

Hypotheses H1b and H1c were operationalised using two outcome dimensions: speed and quality. As these hypotheses concern the effects of digital technology application relative to a traditional approach, the instrument employed a relative scale E0–E3, where E represents the estimated intensity of change when applying the MIDIT-enhanced workflow (Plan D) compared to the reference traditional workflow (Plan T).

For Hypothesis H1b (simulation + VR/AR), scenarios V2, V3, V4, and V6 were selected, as they cover key MSD steps where reduced iteration loops and earlier issue detection are expected through simulation and immersive reviews. For Hypothesis H1c (AI), scenarios V1, V2, V4, V5, and V6 were chosen, as they address the generation and ranking of alternatives, accelerated decision-making, and transparent trade-off explanation under a human-in-the-loop approach.

Two aggregate indicators were constructed for each hypothesis: H1b Speed and H1b Quality, and H1c Speed and H1c Quality. Aggregation was performed across relevant metrics and scenarios; for each company, the median was computed to increase robustness to small sample sizes and potential extreme ratings.

Data were collected in four industrial companies using the scenario-based briefing package with questionnaire (Appendix G). For each metric within each scenario, participants rated the relative effect of Plan D versus Plan T on the E0–E3 scale. As convergent validation of overall design quality, a final global rubric (Likert 1–5) was used, in which Plan T and Plan D were rated separately and a difference score was computed as Δ = Plan D – Plan T across criteria K1–K6.

For each company, the following indicators were defined:

- **H1b Speed**: median E ratings for speed metrics (T total, T dec, #Iter) in scenarios V2, V3, and V6.
- **H1b Quality**: median E ratings for quality metrics (#Issues_pre, T rework, Err KPI, Q rubric) in scenarios V2, V3, V4, and V6.
- **H1c Speed**: median E ratings for speed metrics (T dec, #Iter, T total) in scenarios V1, V5, and V6.
- **H1c Quality**: median E ratings for quality metrics (Q rubric – selected criteria and total, Err KPI, T rework) in scenarios V1, V2, V4, V5, and V6.

A priori inference rules: A hypothesis is considered supported within a company if both conditions are satisfied:

1. the aggregate speed indicator (H1b Speed or H1c Speed) shows at least a medium effect (median E ≥ 2), and
2. the aggregate quality indicator (H1b Quality or H1c Quality) shows at least a medium effect (median E ≥ 2).

At the sample level (four companies), a hypothesis is considered generally supported if the above criterion is met in at least three out of four companies, with pooled results reported additionally. The final global rubric serves as convergent evidence: a positive Δ is expected in criteria theoretically related to the evaluated technologies (e.g., H1b with robustness and human-centricity; H1c with validity/transparency of KPI estimates and decision justification).

Due to lower digital maturity and limited direct experience with advanced digital technologies (VR/AR and AI in MSD), prerequisite and barrier assessment was performed at a global readiness level (implementation readiness of Plan D), rather than scenario-by-scenario phase diagnostics. This reduces respondent cognitive load and limits speculative ratings while producing comparable, actionable insights into organisational, data, and competence prerequisites. A phase-specific prerequisite analysis is proposed for future work in higher-maturity organisations.

A total of fifteen industrial experts participated; in each company, three to four experts from MSD, production, quality, planning, maintenance, and HSE functions contributed. In each of the four companies, results represent a consensus position agreed among multiple functional experts. Therefore, findings are interpreted primarily as a multi-case consensus assessment rather than an individual survey.

5.4.3. Results for Hypothesis H1b (simulation and VR/AR)

Hypothesis H1b was tested using scenarios V2, V3, V4, and V6, which cover capacity and takt analysis through simulation, ergonomics and safety assessment through VR/AR, intralogistics flow simulation, and the final design-freeze evidence package. The aggregated results for the H1b Speed and H1b Quality indices are presented in Table 5.13.

Table 5.13: Results for Hypothesis H1b (simulation and VR/AR)

Company	H1b Speed (median E)	Speed support	H1b Quality (median E)	Quality support	ΔK2	ΔK5
C1	3.0	✓	3.0	✓	+1	+2
C2	1.5	Δ	2.0	✓	+1	0
C3	1.5	Δ	3.0	✓	+1	+1
C4	3.0	✓	3.0	✓	+1	+1
SUM	-	-	-	-	+1 (all)	varies
Legend: ✓ – supported (median E ≥ 2); Δ – partially supported (1 ≤ median E < 2); X – not supported (median E < 1)						

Results show that H1b Quality achieves at least medium support (median E ≥ 2) in all four companies, whereas H1b Speed reaches this threshold in only two of the four companies. This indicates a robust and consistent effect on design quality, but a more context-dependent effect on speed. The quality-related effect suggests that simulation modelling and VR/AR-based reviews support earlier identification of design issues, such as clashes, ergonomics or safety misalignments, and intralogistics bottlenecks, thereby reducing downstream rework.

Convergent support is also evident in the final global rubric. Criterion K2 (robustness) improves in all four companies (ΔK2 = +1), while K5 (human-centricity) improves in three companies and remains unchanged in one (ΔK5 = 0 in C2). These shifts reinforce the interpretation that simulation and VR/AR primarily strengthen the quality, robustness, and human-centredness of MSD decisions.

By contrast, the speed effect is not universal. Two companies report a high effect (median = 3.0), while the other two assess the effect as between small and medium (median = 1.5). This suggests that the expected time gains from simulation and immersive reviews may be partly offset by the initial effort required for model preparation, parameterisation, and organisation of review sessions, especially in contexts with lower digital maturity or limited resources.

For H1b, the results indicate a strong and consistent positive effect of simulation and VR/AR on the quality and robustness of MSD decisions. The expected positive impact on speed is present, but more variable and clearly depends on modelling effort, data availability and organisational readiness. In this sense, H1b is supported primarily in its quality dimension, while the speed dimension is confirmed only under favourable conditions rather than uniformly across all contexts. Accordingly, Hypothesis H1b is interpreted as partially supported: support for the quality dimension is strong and consistent, whereas support for the speed dimension is only partial and depends on the implementation context.

5.4.4. Results for Hypothesis H1c (AI integration)

Hypothesis H1c was tested using scenarios V1, V2, V4, V5, and V6, focusing on AI support for the generation and ranking of alternatives (V1), parameter optimisation and scenario exploration (V2/V4), transparent trade-off decisions with a human-in-the-loop approach (V5), and integration of AI-generated evidence into the design-freeze package (V6). The results presented in Table 5.14 show that both H1c Speed and H1c Quality reach at least medium intensity (median E ≥ 2) in all four companies, providing consistent support for Hypothesis H1c.

Table 5.14: Results for Hypothesis H1c (AI integration)

Company	H1c Speed (median E)	Speed support	H1c Quality (median E)	Quality support	ΔK3	AI risk
C1	3.0	✓	3.0	✓	+1	2
C2	2.0	✓	2.0	✓	+1	1
C3	2.0	✓	2.0	✓	+1	2
C4	3.0	✓	3.0	✓	+1	0
SUM	-	-	-	-	+1 (all)	low-moderate
Legend: ✓ – supported (median E ≥ 2); Δ – partially supported (1 ≤ median E < 2); X – not supported (median E < 1)						

Convergent support is also evident in the final global rubric, where criterion K3 (validity/transparency of KPI estimation) improves in all four companies (ΔK3 = +1). This aligns with the expected AI mechanism: faster and more transparent decision-making through structured alternative generation, ranking, and clearer justification of KPI trade-offs.

The perceived risk of incorrect decisions associated with AI-supported recommendations, as measured by the control item in scenario V5, ranges from low to moderate. This indicates that AI integration is generally acceptable within the Delphi panel, provided its use remains embedded in human-in-the-loop decision logic and that AI outputs are validated before the final design freeze.

The empirical findings for H1c show that AI is consistently associated with faster analysis, a broader range of alternatives, and more transparent justification of MSD decisions. This supports the hypothesis that AI facilitates the proposal of better-justified and more systematically evaluated alternatives, rather than strictly mathematically optimal solutions. In this context, H1c can be considered supported at the level of multi-company expert consensus. These conclusions are based on structured, scenario-based expert assessments of expected performance improvements, rather than on direct experimental or longitudinal measurements in real projects.

Cross-cutting Delphi panel insights on prerequisites and barriers

Beyond the scenario-based hypothesis testing, the Delphi panel also identified several cross-cutting conditions for successful DT integration in MSD. The most frequently emphasised prerequisites are management support, process adaptation, and high-quality data, while the main barriers are resistance to change and lack of time and resources. These findings suggest that the critical challenges of DT adoption in MSD are primarily organisational and data-related rather than purely technological. Given the small number of Delphi responses, these insights should be interpreted as indicative rather than statistically generalisable; nevertheless, they provide a useful qualitative complement to the multi-case assessment results.

Overall, the Delphi panel results indicate that simulation, VR/AR, and AI are all seen as capable of improving MSD performance, but with different effect profiles: simulation and VR/AR make particularly strong and consistent contributions to design quality, while AI offers broader simultaneous support for both speed and quality, provided its use is embedded in appropriate organisational conditions, high-quality data foundations, and human-in-the-loop decision governance. These findings reflect expert scenario-based judgements about expected effects, rather than directly observed longitudinal measurements of realised time savings.

Experts explicitly highlighted the value of MIDIT's gate-based and feedback-oriented structure, including KPI gates and differentiated root-cause categories, as a distinctive feature compared with more linear or technology-fragmented approaches. This confirms that the conceptual structure of MIDIT is not only theoretically coherent but also perceived as practically useful for organising MSD decisions during digital transformation.

5.5. Comparative analysis of MSD scheduling plans

The comparative analysis of MSD scheduling plans is based on a reference schedule derived from industrial practice. The baseline plan (Plan T) was obtained from a company that manufactures various aluminium components for original equipment in the automotive industry and concerns the design of a manufacturing system for an electric vehicle e-motor housing cover. This plan was subsequently extended by analysing the potential application of individual digital technologies and defining their expected effects based on research findings, resulting in a MIDIT-enhanced plan (Plan D). The numerical results of the comparison between Plan T and Plan D are presented in tabular form in the following section, while a graphical representation of the achieved time reductions by activity and design phase is provided in Appendix H. The aim of this comparison is to quantify the expected effects of systematic digital technology integration on project duration, effort, and decision-gate progression within the MSD process.

The analysis is based on process mapping and project scheduling data captured during empirical validation, using equivalent design tasks and milestones to ensure comparability. Plan T represents a traditional sequence of conceptual, detailed, and implementation design phases, following established engineering procedures and making limited use of digital tools. In contrast, Plan D incorporates digital enablers such as simulation-based layout validation, early-stage digital models, and collaborative modelling platforms aligned with MIDIT principles. The comparative schedule analysis identifies specific points in the design timeline where digital technologies are expected to reduce rework, enable faster decision-making, and improve synchronisation between design and validation activities. The findings provide quantitative evidence for evaluating the third research objective and contribute to understanding how digital integration can enhance overall design efficiency and project outcomes in MSD.

The results of the schedule comparison are presented in tabular summaries at the level of main project phases and individual activities. For each activity, baseline durations from Plan T are compared with the digitally supported Plan D, expressed in working hours and relative percentage change. At the project level, total design duration and total projected cost are reported, highlighting the combined effect of multiple local improvements and a small number of intentionally extended activities. In addition to the activity-level comparison, the analysis aggregates time and cost data by major project phases: project preparation, final product development, prototype production, process planning, process preparation, pilot production, and process qualification. This phase-level view enables clearer identification of where digital technologies generate the most pronounced benefits in terms of lead-time reduction and cost savings, and where their primary contribution is improved quality and risk reduction rather than shorter duration. For example, phases strongly supported by simulation, virtual validation, and collaborative modelling typically show both time and cost reductions, while phases involving in-depth process optimisation may have slightly longer durations but lower expected rework and higher KPI performance. The cost comparison is performed at both the overall project and phase levels, accounting for the additional effort and resources required for digital model creation, simulation runs, and data analysis. Although some digitally enhanced activities in Plan D, such as casting simulation and scenario-based optimisation, require more working hours than their counterparts in Plan T, these investments are offset by reduced iteration cycles, fewer physical prototypes, and earlier detection of design and process issues. Consequently, the total project cost in Plan D either remains comparable to or decreases relative to Plan T, while providing greater confidence in meeting target KPI values. The tabular results therefore support a nuanced interpretation: digital integration does not uniformly shorten every activity, but systematically improves the overall efficiency, robustness, and economic performance of the MSD project.

Table 5.15 compares project duration and effort between Plan T and Plan D at the level of the main MSD phases. The overall MSD project duration decreases from 431 to 286 working days and from 13,247 to 9,707 working hours, corresponding to a 34% reduction in lead time and a 27% reduction in total effort. These improvements result primarily from changes in activities on the critical path, while time reductions in non-critical activities mainly reduce resource demand and cost without affecting the project completion date.

Table 5.15: Results of MSD plans duration comparison

MSD PHASE	Duration Plan T (days)	Duration Plan D (days)	Working hours Plan T	Working hours Plan D	Index (days)	Index (hours)
MSD project overall	431	286	13,247	9,707	-34%	-27%
Product development	163	94	680	680	-42%	0%
Internal product validation	10	7	80	56	-30%	-30%
Input data	10	5	160	80	-50%	-50%
Prototype manufacturing	142	73	2,328	1,508	-49%	-35%
Process planning	130	60	3,380	2,356	-54%	-30%
Process preparation	189	135.5	5,243	3,779	-28%	-28%
Trial production	46	35	808	696	-24%	-14%
Manufacturing process qualification	9	7	104	88	-22%	-15%

Interpreting product development results requires particular attention. The reduction in working days (−42%) reflects a shorter and better synchronised interface between product development and the subsequent prototyping phase, while working hours remain unchanged because detailed product development activities were not within the scope of this analysis and remain on the critical path. In other words, digital technologies in this context primarily improve temporal coupling and overlap between phases rather than reducing the absolute effort of product development itself.

Prototype manufacturing and process planning phases show substantial reductions in both duration and effort. In prototype manufacturing, the time is reduced from 142 to 73 days and working hours from 2,328 to 1,508 (−49% and −35%), mainly due to digital support in the design and manufacture of casting tools and clamping fixtures, as well as in the measurement and analysis of prototype results. In process planning, reductions from 130 to 60 days and from 3,380 to 2,356 working hours (−54% and −30%) are achieved in similar areas: digital design and validation of casting and trimming tools, clamping fixtures for machining, and special equipment for leak testing and DMC marking.

In the process preparation phase, both duration and effort decrease by 28%, reflecting the use of digital technologies to implement and refine the elements defined in the process planning phase. Some activities, such as casting simulations or VR-based operator training, require more time than in Plan T, but this additional effort is intended to improve solution quality and process robustness, which subsequently reduces the need for rework and disturbance handling in downstream phases. Trial production and manufacturing process qualification show more moderate cumulative improvements due to their inherently shorter duration and the dominance of physical production time; their main benefits from digital integration are a more stable ramp-up and fewer iterations rather than drastic schedule compression.

It should be noted that the impact assessment of digital technologies was performed on core MSD design activities within each phase. Administrative tasks and activities driven by external lead times (such as procurement and delivery of tools and equipment) were not explicitly optimised in this study, indicating further potential for improvement in future applications. Detailed information on the analysed activities, including critical-path positioning and mapping to MSD steps, is provided in the Gantt chart in Appendix H.

Overall, the comparison between Plan T and Plan D demonstrates that systematic digital technology integration within the MIDIT framework can substantially shorten MSD project lead time and effort, while simultaneously enhancing the robustness and quality of design decisions. The results further indicate that higher levels of digital technology adoption are associated with significantly shorter MSD design time and improved planning performance, thereby supporting Hypothesis H1.

Chapter 6

6. Conclusion

The research methodology integrates theoretical analysis, conceptual modelling, the author's industrial experience, and empirical validation in industrial companies. The theoretical component is based on an extensive multi-year investigation of digital maturity in industrial companies in the region, which resulted in the development of an adapted digital maturity model aligned with the actual state of digital transformation in small and medium-sized enterprises. Insights from this prior work – particularly recurring obstacles, lack of data, limited digital competences, and fragmented technology investments – further shaped the methodological approach of this dissertation and confirmed the need for frameworks grounded in the real constraints of industrial practice. In the chapter on digital transformation, the distinctions between digitisation, digitalisation, and digital transformation are clarified, and the main dimensions of digital transformation (technological, organisational, cultural, customer-centric, and strategic) and their interdependencies are described. The most important digital transformation indices and maturity models used in industrial environments are briefly presented, with emphasis on their role in quantifying digital readiness, tracking progress, and identifying critical areas for investment. Building on these findings and the author's extensive experience in designing and optimising manufacturing processes in real industrial contexts, especially in the automotive sector, the conceptual part of the research was complemented by detailed case-study analyses using digital models and by a comparison of a traditional manufacturing system design plan (Plan T) with a MIDIT-based approach (Plan D), providing an additional level of validation beyond the formal empirical studies in companies.

In this context, manufacturing system design is no longer simply a technical task of defining capacities and flows, but a point where strategic thinking, expertise from different organisational levels, and digital tools converge to co-create the future configuration of the manufacturing system. The framework extends traditional MSD perspectives by explicitly integrating strategic orientation and dynamic capabilities into the core design logic, rather than treating them as external management concerns. On this theoretical and empirical foundation, a structured framework of manufacturing system design elements was defined, comprising thirteen interrelated elements: from input requirements, product and process, through resources, layout, logistics, quality, maintenance, and HSE, to performance and digital technologies. The chapter also highlights the role of strategic thinking in manufacturing system design: the use of digital technologies enables the generation of multiple acceptable design alternatives and shifts the research focus from purely operational optimisation to the role of digitalisation in shaping the strategic concept of the manufacturing system for a given product family, with the potential to extend it to other portfolio segments with minimal adaptations. Adopting the dynamic-capabilities perspective, digital technologies support the sensing, seizing, and transforming phases by enabling rapid and reliable scenario comparison in virtual environments, accelerating organisational learning, and supporting structural and process adjustments under time-critical competitive conditions.

On this basis, a 13×16 MIDIT matrix was developed, linking each manufacturing system design element to a set of sixteen representative digital technologies. For each element–technology pair, the relative importance of that technology (dominant, significant supportive, or minimal/occasional) was assessed, resulting in an overview that enables designers to identify critical and supportive digital tools in each design phase. The matrix serves as a set of recommendations and guidelines grounded in the literature review and the author's long-term industrial experience, with an inherent tendency to evolve as new technologies enter practice. Based on this framework and matrix, key design principles for I4.0 and I5.0 ready manufacturing systems were formulated, including systemic integration of physical and digital layers, data and model-driven design, clear allocation of decision logic, human-centric automation and decision support, lifecycle orientation and adaptability, security, transparency and trust by design, and alignment between key performance indicators, economics, and technology choices. Together, these principles form a practical guide for designing digitally ready manufacturing systems.

To integrate manufacturing system design with lifecycle management, the PSLM MIDIT framework was developed, defining seven phases in the production system lifecycle, from strategic framing to reconfiguration, and linking them to the FSBCIP perspectives (Function–Structure–Behaviour–Control–Intelligence–Performance) and the TMPE meta-layer (Thinking–Modelling–Process–Enabler). The TMPE layer serves as a unifying design logic that connects strategic intent, modelling choices, process activities, and digital technologies into a coherent whole, ensuring traceability of key decisions across all lifecycle phases. Strategic thinking is embedded throughout all seven PSLM phases, with explicit adherence to the three core principles of I5.0: human-centricity, sustainability, and resilience. This reinforces the cyclical nature of the framework: the seventh phase is not an endpoint, but a stage where experiences, data, and insights from the previous lifecycle become the starting point for the next first phase of a successor or reconfigured manufacturing system. PSLM MIDIT thus operationalises a form of "PLM for the production system", in which decisions on design, management, and system evolution remain systematically interconnected and are supported by digital twins, integrated data flows, and socio-technical principles. Complementing this framework, a two-layer key performance indicator system was developed: a core set of operational key performance indicators describing the performance of the designed system, and a set of advanced, design-oriented key performance indicators measuring the effectiveness and maturity of the manufacturing system design process itself and the degree of digital-technology utilisation. This key performance indicator framework is conceptually linked to all PSLM MIDIT phases, allowing key performance indicators to be used not only as reactive measures in the operational phase but also as active management tools throughout design, evaluation, and continuous improvement. This combination of PSLM MIDIT, TMPE, and FSBCIP perspectives therefore provides a novel, lifecycle-oriented view of manufacturing systems that complements product-focused PLM with an equally systematic "PLM for the production system".

The empirical and conceptual validation of the MIDIT methodology was designed to combine multiple complementary sources of evidence, explicitly aiming to assess quality, independence, and understanding from different perspectives. The starting point was that evaluating a new methodology cannot be reduced to a single survey or case study, especially in an environment of limited digital maturity and varied experience with advanced technologies. A mixed-methods design was therefore adopted, combining experiential expert knowledge, structured quantitative assessments, scenario-based analyses, and the author's long-term industrial experience. An important feature of the sample is that the interviewees, key performance indicator focus group members, and Delphi panellists were experts who had previously participated in developing the adapted digital maturity model DAMA-AHP for companies in the region, ensuring a deep understanding of digital transformation, industrial challenges, and the role of digital technologies in manufacturing system design, thereby enhancing the credibility of their assessments.

In the initial phase of the empirical work, semi-structured interviews and two structured questionnaires were used to assess experts' views on the relevance of the proposed KPI framework and the impact of specific digital technologies on achieving target KPIs in the design phase. On average, all KPI blocks were rated as strongly influenced by digital technologies, with AI/ML, IIoT/CPS, ERP/MES integration, and digital twins identified as having the highest perceived impact. These findings primarily reflect practitioners' perceptions and expectations under current organisational conditions, rather than experimentally measured performance changes, but they provide a structured empirical basis for subsequent quantitative and case-based analyses. The analysis of advanced, design-oriented key performance indicators showed that many of these indicators enjoy broad conceptual acceptance and are perceived as highly sensitive to digital technologies, yet remain only weakly implemented in formal measurement systems, positioning them as "under-used opportunities" for further development of the MIDIT-based PSLM framework. Positive and statistically significant correlations between the level of use of advanced key performance indicators and their perceived sensitivity to digital technologies indicate that the development of key performance indicator frameworks and digitally enabled manufacturing system design are synergistic processes, where investment in one area facilitates progress in the other. The quantitative analysis used descriptive statistics, non-parametric tests, and measures such as Kendall's W and epsilon-squared, with medians and Top-Box shares highlighted as managerially relevant indicators of perceived impact. In the next step, a case study of a real manufacturing system design and optimisation project using a digital model tested these concepts on a concrete example: simulation experiments demonstrated that target key performance indicator values can be reliably estimated in the design phase, bottlenecks identified early, and unnecessary costs and delays after physical installation avoided. This provides empirical confirmation that optimisation activities can be shifted significantly from the operational to the virtual design phase, directly operationalising and confirming Hypothesis H1a.

The second part of the validation focused on advanced digital technologies – simulation, VR/AR, and AI – for which the participating companies had limited direct implementation experience. An evidence-informed Delphi approach was therefore used: experts from four companies, after receiving a standardised briefing package based on the literature and clearly defined assumptions, jointly assessed the impact of simulation, VR/AR, and AI on the speed and quality of manufacturing system design outcomes by comparing two standardised workflows, the baseline Plan T and the MIDIT-enhanced Plan D. Triangulation with independent external experts, who reviewed the conceptual assumptions, briefing materials, and measurement instruments, further strengthened methodological soundness and reduced the risk of systematic bias. The results show that integrating simulation modelling and VR/AR into MIDIT consistently improves design quality, primarily through earlier problem detection and reduced rework, while the effect on process speed depends on context, digital maturity, and available resources. Thus, digital technologies do not automatically guarantee shorter design lead times, as the initial effort required for model preparation, data consolidation, and review sessions can partly offset the expected time savings in less mature or resource-constrained environments. In two companies, experts estimated a strong reduction in project duration, whereas in the other two, the additional effort required to build models and prepare digital artefacts partially offset the time savings; accordingly, Hypothesis H1b is considered partially supported for speed and fully supported for quality. In contrast, Hypothesis H1c is supported in all four companies: integrating AI into selected MIDIT steps accelerates analysis and decision-making and improves the quality of solution selection, particularly by providing more transparent explanations of key performance indicator trade-offs. Convergent support is evident in the global rubric, where the validity and transparency of key performance indicator estimation improve across all companies, while the perceived risk of erroneous decisions remains low to moderate due to the human-in-the-loop approach.

The final part of the empirical work focused on a comparative analysis of manufacturing system design schedules for the same project, developed using a traditional approach (Plan T) and a MIDIT-based approach (Plan D). An analysis of the actual activities, mapped to the thirteen defined manufacturing system design steps, and an assessment of the potential use of individual digital technologies based on the MIDIT matrix, showed that systematic integration of digital technologies substantially shortens key design phases and reduces the number of iterations. Based on conservative estimates grounded in the literature and the author's industrial experience, it was found that Plan D, compared with Plan T, shortens the conceptual and detailed design phases by approximately 30%, reduces the need for physical prototypes, and lowers the risk of costly post-installation corrections. These findings quantitatively complement the expert assessments, case study results, and Delphi analysis, and provide strong, albeit context-specific, empirical support for the main hypothesis H1, which states that applying the MIDIT methodology in the manufacturing system design process accelerates digital transformation and improves measurable system performance. Indirect evidence from advanced design-related key performance indicator surveys and Delphi assessments of the effects of simulation, digital twins, VR/AR, and AI further confirms that the structured use of key digital technologies embedded in MIDIT accelerates the transition towards more mature digital practices and enables more systematic management of business outcomes.

Taken together, the components of the empirical work provide complementary evidence for the validity of the MIDIT methodology. The alignment of MIDIT with established theoretical frameworks, the internal consistency of its steps, and positive assessments by domain experts primarily support the conceptual soundness of the approach. Pilot applications, case studies, and implementation-oriented analyses addressing data availability, tooling requirements, and process feasibility demonstrate its operational applicability in realistic industrial contexts. Comparative applications, simulation experiments, and before-and-after analyses of key performance indicators, where MIDIT-based decisions are contrasted with conventional approaches, indicate the methodology's potential causal impact on manufacturing system performance.

Based on the theoretical and empirical work, several scientific contributions of this dissertation can be clearly identified. First, the MIDIT methodological framework for integrating digital technologies into manufacturing systems design has been developed. The framework links the requirements of I4.0 and 5.0 with specific manufacturing system design activities and decisions, and is intended to be applicable in both lower and higher maturity companies. Second, a structured set of thirteen manufacturing system design elements has been defined, with clearly described typical activities and key decisions, and a 13×16 matrix has been developed linking these elements to a representative set of sixteen digital technologies. This matrix provides an original practical tool for designers and managers when selecting dominant and supporting technologies and prioritising investments in digital solutions. Third, the PSLM MIDIT lifecycle framework has been proposed, comprising seven phases linked to the FSBCIP perspectives and the TMPE meta-layer. This introduces a new type of "PLM for the production system" that integrates strategic thinking, digital models, performance management, and I5.0 socio-technical principles throughout the system's lifecycle. Fourth, a detailed MIDIT flowchart has been developed, operationalising the methodology through decision gates, feedback loops, and governance mechanisms. At each step, digital maturity, key performance indicator governance, and technology selection are explicitly considered, translating the theoretical concept into a concrete reference model for practical implementation. Fifth, a two-layer key performance indicator framework has been defined, comprising a core set of operational key performance indicators and a set of advanced, design-oriented manufacturing system design key performance indicators. This framework has been empirically validated through expert panels in four industrial companies and has proved sensitive enough to distinguish different levels of practice maturity and perceived digital technology impact on performance. Finally, the combination of conceptual development of MIDIT, an in-depth case study, an evidence-informed Delphi approach, and comparative analysis of traditional and MIDIT-based workflows constitutes a methodological contribution in its own right, offering a replicable pattern for evaluating the effects of digital technologies on the speed and quality of manufacturing system design in environments with limited digital maturity.

The limitations of this research must be considered in relation to the scope, sample, and developmental stage of the MIDIT methodology. Empirical validation was conducted in a limited number of small and medium-sized enterprises from a single geographical region, which restricts direct generalisation to large companies, other sectors, or industrial environments with significantly different structures and resource levels. The digital maturity of the participating companies and the quality of available key performance indicator data depend heavily on internal monitoring and reporting systems, which in many industries are still not fully adapted to the requirements of digital transformation. This aligns with other studies highlighting shortcomings in data quality, digital skills, and infrastructure readiness as key challenges. At this stage, MIDIT has been validated through a combination of expert assessments, scenario analyses, and a detailed case study, but a full longitudinal implementation of the methodology in a larger number of companies has not yet been undertaken. Although this evidence is convergent, it does not yet allow for definitive causal attribution across all performance dimensions, particularly in complex multi-factor industrial environments. Such implementation would be necessary to quantify its impact on key performance indicators over longer periods and across diverse contexts. Furthermore, although the effects of simulation, VR/AR, and AI have been analysed, some experiments and scenarios are based on a limited set of assumptions and standardised situations, while actual implementation in practice often depends on organisational, technological, and financial factors beyond the scope of this dissertation. Finally, despite the use of an evidence-informed Delphi approach and the involvement of independent experts in reviewing conceptual assumptions and instruments, direct hands-on experience with advanced digital technologies in manufacturing system design remains heterogeneous among participants, especially in lower-maturity environments, which may result in conservative or cautious evaluations in some cases.

For industrial practice, the results of this research provide several concrete recommendations. Companies in the early or intermediate stages of digital transformation are encouraged to use MIDIT as a reference framework for structuring their manufacturing system design processes, without needing to implement the methodology fully from the outset. Adoption can instead begin selectively – through chosen PSLM phases, priority manufacturing system design elements, or key performance indicator blocks – and be progressively expanded as experience and digital maturity increase, with partial implementation explicitly recognised as a legitimate and valuable use of the framework. It is particularly important to integrate digital enablers and I5.0 values (human-centricity, sustainability, resilience) into manufacturing system design from the earliest stages, rather than adding them as afterthoughts to already defined system concepts. Systematic use of simulation models, digital twins, and analytical tools for key performance indicator forecasting should become an integral part of standard workflows when defining system concepts, so that optimisation shifts as much as possible from the operational to the design phase. Establishing a two-layer key performance indicator framework, which also measures the performance of the design process itself, is crucial for identifying and reducing unproductive iterations, hidden costs, and the risk of missed opportunities. The introduction of VR/AR and AI technologies should follow a gradual, pilot-based approach, guided by the human-in-the-loop principle and supported by adequate data readiness, organisational backing, and competence development, to fully leverage the benefits of faster and more transparent decision-making.

The directions for future research follow logically from the identified limitations and opportunities. One avenue is to expand the empirical base by including a larger number of companies of different sizes, sectors, and regions, enabling a more detailed assessment of MIDIT’s effects in diverse digital transformation contexts and maturity levels. Another is the development of longitudinal studies that track changes in core and advanced key performance indicators and in digital maturity over longer periods, allowing more precise quantification of the impact of specific digital technologies and organisational interventions on business performance. A further avenue is to deepen the integration of VR/AR and AI within MIDIT, for example by developing digital-factory and extended-reality environments that simultaneously support system design, operator training, and operational decision-making. Finally, research should address organisational and societal aspects of digital transformation – the development of new competences, changes in organisational culture, participatory design, and worker involvement in decision-making – to further strengthen the link between the technological and human-centred dimensions of I5.0 and to provide a more complete picture of the potential impact of the MIDIT methodology in industrial practice.

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List of symbols and abbreviations

χ^2	Chi-square statistic
p	p-value
H	Kruskal–Wallis H statistic
ε^2	Epsilon-squared effect size

8D	Eight Disciplines Problem Solving
ACM	Adaptive Cognitive Manufacturing
AGV	Automated Guided Vehicle
AM	Additive Manufacturing
AMR	Autonomous Mobile Robot
API	Application Programming Interface
APQP	Advanced Product Quality Planning
APS	Advanced Planning and Scheduling
AR	Augmented Reality
BIM	Bio-Intelligent Manufacturing
BOM	Bill of Materials
BPM	Business Process Management Tools
CAE	Computer-Aided Engineering
CAI	Computer-Added Inspection
CAPP	Computer-Aided Process Planning
CIM	Computer Integrated Manufacturing
CMMS	Computerised Maintenance Management System
CONWIP	Constant Work in Process
CPPS	Cyber-Physical Production System
CPS	Cyber-Physical System

CRM	Customer Relationship Management
CTQ	Critical to Quality
CV	Coefficient of variation
CX	Customer Experience
DES	Discrete Event Simulation
DESI	Digital Economy and Society Index
DfA	Design for Assembly
DfM	Design for Manufacturing
DFSS	Design for Six Sigma
DFSSDM	Design for Six Sigma Digital Model
DfX	Design for X
DM	Digital Model
DMC	Data Matrix Codes
DMM	Digital Maturity Model
DoE	Design of Experiments
DS	Digital Shadow
DT	Digital Twin / Digital Transformation / Digital Technology (depends on context)
EAM	Enterprise Asset Management
EMS	Energy Monitoring System
ERD	Entity Relationship Diagram
ERP	Enterprise Resource Planning
ETO	Engineer-to-Order
FAT	Factory Acceptance Test
FMEA	Failure Modes and Effects Analysis
FPY	First Pass Yield
FSBCIP	Function–Structure–Behaviour–Control–Intelligence–Performance
GDM	Generic Design Methodology

HCM	Human-Centred Manufacturing
HiL	Hardware-in-the-Loop
HR	Human Resources
HSE	Health, Safety and Environment
I1.0	Industry 1.0
I2.0	Industry 2.0
I3.0	Industry 3.0
I4.0	Industry 4.0
I5.0	Industry 5.0
IACS	Industrial Automation and Control Systems
IIoT	Industrial Internet of Things
IM	Intelligent Manufacturing
IoCK	Internet of Construction Knowledge
IoT	Internet of Things
IQR	Interquartile Range
IT-OT	Information Technology – Operational Technology
KBE	Knowledge-Based Engineering
KBS	Knowledge-Based Systems
KG	Knowledge Graph
KPI	Key Performance Indicator
LCA	Life Cycle Assessment tool
MBSE	Model-Based Systems Engineering
MCDM	Multi-Criteria Decision Making
MES	Manufacturing Execution System
Mfg	Manufacturing
MIDIT	Methodology for the Integration of Digital Technologies
ML	Machine Learning
MODIA	Model for Organisational Diagnosis and Improvement Analysis

MOM	Manufacturing Operations Management
MQTT	Message Queuing Telemetry Transport
MR	Mixed Reality
MRP	Material Requirements Planning
MRPII	Manufacturing Resource Planning
MSD	Manufacturing System Design
MTBF	Mean Time Between Failures
MTTR	Mean Time To Repair
NPV	Net Present Value
OEE	Overall Equipment Effectiveness
OPC UA	Open Platform Communications Unified Architecture
OPI	Original Prototype Introduction for Manufacturing System Design
OT	Operational Technology
OTIF	On Time In Full
PDM	Product Data Management
PLC	Programmable Logic Controller
PLM	Product Lifecycle Management
PPC	Production Planning and Control
PPM	Parts Per Million
PRSEL	Final Product Definition and Selection for Series Production
PSLM	Production System Lifecycle Management
RAMI 4.0	Reference Architecture Model Industrie 4.0
RFID	Radio-Frequency Identification
RMS	Reconfigurable Manufacturing System
ROI	Return on Investment
RPA	Robotic Process Automation
RTLS	Real-Time Location System
SAT	Site Acceptance Test

SCADA	Supervisory Control and Data Acquisition
SD	Standard Deviation
SiL	Software-in-the-Loop
SIT	System Integration Testing
SM	Smart Manufacturing
SME	Small and Medium-sized Manufacturing Enterprises
SMS	Smart Manufacturing System
SPC	Statistical Process Control
STEP	Standard for the Exchange of Product Data
SySML	Systems Modelling Language
TDP	Technical-Delivery Preconditions
TPME	Thinking-Modelling-Process-Enabler
TRIR	Total Recordable Incident Rate
UAT	User Acceptance Testing
UML	Unified Modelling Language
VC	Virtual Commissioning
VR	Virtual Reality
WIP	Work in Progress
WMS	Warehouse Management Systems

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Curriculum Vitae

Elvis Krulčić holds a degree in Mechanical Engineering and has over thirty years of professional experience in industry, production system management, quality assurance, maintenance, and technical management. Since 2021, he has been a teaching and research assistant at the Department of Industrial Engineering and Management, Faculty of Engineering, University of Rijeka, where he is currently pursuing doctoral studies.

He obtained his first degree in Mechanical Engineering from the Faculty of Engineering, University of Rijeka (1993), and graduated from the Faculty of Mechanical Engineering, University of Ljubljana in 2001. His degree was formally recognised by the University of Rijeka in 2004.

Throughout his career, Mr Krulčić has gained extensive experience in four companies of various sizes, mainly in the automotive industry, as well as in mechanical engineering, installation, and maintenance of engines for marine and transport applications. He has held several professional and managerial positions involving production management, quality management, manufacturing system design, project management, process optimisation, and implementation of continuous improvement methodologies, particularly Lean and Six Sigma. He holds an international Six Sigma Black Belt certificate and has extensive experience in developing and maintaining management systems based on ISO 9001, IATF/ISO TS 16949, ISO 14001, and ISO 45001 standards.

His academic and research activities focus on industrial engineering, digital transformation, Industry 4.0, digital maturity, and digital twins, with additional interests in production system design and process improvement. He is the author or co-author of several scientific and professional papers published in national and international journals and conference proceedings.

Mr Krulčić possesses strong analytical, organisational, and communication skills, as well as experience in teamwork and public presentations. He is fluent in English and Slovenian.

List of Publications

Scientific papers in peer-reviewed journals:

1. Krulčić, Elvis; Dobovićek, Sandro; Pavletić, Duško; Čabrijan, Ivana. A Dynamic Assessment of Digital Maturity in Industrial SMEs: An Adaptive AHP-Based Digital Maturity Model (DMM)with Customizable Weighting and Multidimensional Classification (DAMA-AHP) // Technologies (Basel), 13 (2025), 7; 1-31. doi: 10.3390/technologies13070282.
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Appendices

Appendix A: Tabular data representations

Table A1: Industry 4.0 pillars value creation;

Table A2: Overview of key differences between IoT and IIoT;

Table A3: Key questions and examples of the use of digital technologies;

Table A4: MSD framework: phases, activities, decisions and typical digital tools;

Table A5: Impact of digital technologies on targeted KPI design;

Table A6: Information about Advanced MSD KPIs

Appendix B: Flowchart for the MIDIT methodology

Appendix C: Questionnaire: The Role of Digital Technologies in Analysing and Improving KPI Indicators in the MSD Phase

Appendix D: Questionnaire: Advanced KPIs for Assessing the Impact of Digital Technologies on the MSD Process

Appendix E: Results of perceived impact by Core KPI block

Appendix F: Descriptive Statistics for Advanced KPIs

Appendix G: Scenario based instrument; Evaluation metrics; Evidence-Informed Delphi: Questionnaire (H1b and H1c)

Appendix H: Gant chart for manufacturing system design Plan D versus Plan T analyse

Appendix A

Table A1: Industry 4.0 pillars value creation [214]

Industry 4.0 Pillars	Value creation
Autonomous robots	Increase process efficiency
	Increase production efficiency
	Reduce production costs
	Increase process flexibility
	Increase employee safety
Big Data	Lower infrastructure costs (through outsourcing)
	Protect data against cyber-attacks
	Use additional services in advanced analytics and AI (ML)
	Make the flow of information and data between production and business systems more effective
Systems Integration	Create a network of cooperating companies
	Shorten delivery times for personalised orders
	Accelerate decision-making processes between teams
	Increase profitability
Additive Production	Reduce prototyping costs
	Reduce storage costs
Industrial Internet of Things	Create reliable information on the progress of process implementation
	Provide unlimited (time and place) access to information
	Increase the quality of personalised products
Augmented and Virtual Reality and Simulations	Save time in the physical preparation of new product prototypes
	Shorten the time required to introduce new employees
	Increase work safety
	Reduce operating costs
	Lowering the costs of introducing new employees
Cybersecurity	Protect data, information and networks against cyber-attacks and unauthorised access

Table A2: Overview of key differences between IoT and IIoT [70]

Aspect	IoT (Internet of Things)	IIoT (Industrial Internet of Things)
Application domain	consumer and social sectors: smart homes, healthcare, transport, personal devices	industrial sectors: manufacturing, energy, logistics, mining, agriculture
Primary objective	improving comfort and user experience	optimising efficiency, safety, reliability, and process productivity
Reliability and security	moderate security and fault-tolerance requirements	stringent real-time performance, safety, and resilience requirements
Technological focus	connecting smart devices via the internet (Wi-Fi, cloud)	integration of CPS, SCADA, IACS, 5G, edge, and fog computing
System architecture	three-layer architecture: sensor → network → application	multi-layer architecture with additional control, analytics, and real-time security layers
Standards and protocols	MQTT, CoAP, Zigbee, Wi-Fi	OPC UA, ISA-95, Modbus, LPWAN, 5G
Data criticality	data loss is usually not critical	data loss can cause financial or physical damage
Typical applications	smart thermostats, wearables, home automation	smart factories, automated production lines, predictive maintenance
Role in I4.0 / I5.0	basic digital networking layer	key infrastructure of the smart factory (I4.0) and a foundation for human-centric production (I5.0)

Table A3: Key questions and examples of the use of digital technologies

System - process element		Key design questions	Examples of digital technology applications
1.	Input requirements and market	Which products and variants are required, and in what volumes? What delivery performance and regulatory constraints must be met?	Demand forecasting using advanced analytics or ML (from ERP or CRM data); digital sales and order management platforms linked to production planning; scenario tools for capacity planning; online configuration tools feeding demand data into design [173], [215].

System - process element		Key design questions	Examples of digital technology applications
2.	Product and product structure (BOM)	How is the product structured (BOM)? Which characteristics are critical, and which product variants must be supported?	PLM systems for managing product structures and versions; CAD/CAE tools for product/tool design and virtual validation; configuration management systems (rule-based configurators); digital definition of CTQ characteristics linked to quality and MES [110], [156].
3.	Process and flow of activities	What are the main operations and their sequence? What takt time is required, and where are the potential bottlenecks?	DE simulation of process flows (virtual commissioning of lines/tools); ML models for process parameter defining; process mining from MES/ERP logs to identify actual routes and bottlenecks; process digital twins for what-if analysis; BPM tools for modelling and optimising routing and workflows [90], [112] [211]
4.	Resources: machines, equipment and tools	Which machines and technical resources are required, and what are their capacities and capabilities? What is the level of automation and the setup effort involved?	CNC/robot simulation and offline programming; IIoT sensors on machines for utilisation and state monitoring; digital twin of critical equipment for capability analysis; tool management systems with RFID-tagged tools and automatic identification [72], [215].
5.	People and work organisation	What staffing levels and skill profiles are required? How are tasks, responsibilities, and competences allocated across workstations and shifts?	Digital work instructions on tablets or wearables; AR-assisted assembly and inspection; skill and competence management modules in HR/MES; AR/MR training environments for complex operations; collaborative robots (cobots) with digital safety and guidance systems [216], [186].
6.	Space and layout	Which layout concept is appropriate (line, cell, functional, or hybrid)? How much space is required for equipment, buffers, and the movement of people and materials?	3D factory layout and simulation tools; VR/AR for virtual walkthroughs and ergonomic assessments; automatic layout optimisation using algorithms (e.g., minimising material flow); digital clash detection between layout, building, and utilities (BIM integration) [116], [217].
7.	Material flow and logistics	How are materials supplied, stored, and moved within the system? What levels of work-in-process (WIP) and inventory are acceptable?	Warehouse management systems (WMS) and in-plant logistics control; AGV/TED fleet management platforms; RFID/barcode and RTLS for tracking materials and containers; digital twin of internal logistics for routing and buffer sizing; e-kanban systems [182,218].

System - process element		Key design questions	Examples of digital technology applications
8.	Information flow and control (PPC, IT)	How are production planning, scheduling and monitoring carried out? Which IT systems are used (ERP, MES, etc.) and to what extent are they integrated?	Integrated ERP–MES–SCADA/PLC architectures; APS systems for advanced finite-capacity scheduling; CPPS platforms combining shop-floor data and control logic; IoT platforms and data lakes for real-time data acquisition; digital dashboards for PPC and exception management [219,220].
9.	Quality control	At which points is quality inspected (incoming, in-process, final) and by which methods? How are non-conforming products handled?	In-line machine vision systems and automated inspection; SPC software connected to measurement devices; ML-based anomaly and pattern detection in quality data; full traceability via barcode/RFID, and serialisation; electronic non-conformance management and 8D workflows [221], [187].
10.	Maintenance	Which maintenance strategy is applied (reactive, preventive, predictive)? How are interventions and spare parts planned, executed, and recorded?	CMMS/EAM systems for planning and recording maintenance; condition monitoring using IIoT sensors (vibration, temperature, energy); predictive maintenance models use ML; digital twins of critical assets are used for degradation modelling; mobile apps for technicians manage work orders and checklists [72], [222].
11.	Safety, ergonomics and environment (HSE)	What are the main safety risks and ergonomic requirements in workplaces? What are the environmental impacts of the system?	Digital risk assessment tools; ergonomic simulation of postures and loads in 3D work-cell models; wearables and proximity sensors for worker safety; environmental and energy monitoring systems (EMS) for emissions, waste and energy; digital incident reporting and analysis platforms [189], [223].
12.	Performance, costs and economics	Which performance levels are targeted and at what cost? How is the economic viability of the system or investment evaluated?	Business Intelligence and analytics dashboards for real-time KPIs (OEE, productivity, lead time, cost); automated data collection from ERP/MES for cost and variance analysis; simulation-based economic evaluation of design scenarios; digital scenario and sensitivity analysis tools for investment decisions [224] [225].

System - process element		Key design questions	Examples of digital technology applications
13.	Digital technologies and I4.0/I5.0 integration	Which assets and processes are connected through sensors and IIoT? Where are digital models (such as simulation digital twins) and data analytics/ AI applied?	Cyber-physical production system architectures [72]; IIoT platforms (edge/cloud) integrating machines [72], logistics [226], and quality [110]; system-level digital twin of line or factory for holistic optimisation [81]; AI and analytics services for scheduling, energy optimisation, and decision support [223]; human-centric HMIs, AR/VR interfaces, and collaborative decision-support tools [142].

Table A4: MSD framework: phases, activities, decisions and typical digital tools

MD framework phase	Main activities	Typical decisions	Typical digital tools (examples)
Phase 1 - Strategic analysis and objectives definition	Market and product portfolio analysis; definition of business objectives (cost, quality, flexibility, sustainability); Industry 4.0/5.0 trend analysis; preliminary assessment of the existing production system.	Define target capacities and required flexibility; select target markets and segmentation; determine the intended level of digitalisation and autonomy; define key KPIs and Industry 5.0 goals (human-centricity, resilience, environmental impact).	Business intelligence and descriptive analytics (BI dashboards, spreadsheets); maturity/readiness assessment tools (I4.0/I5.0 maturity models); sustainability pre-assessment and LCA tools; knowledge and collaboration platforms (shared repositories, visual canvases).
Phase 2 - Conceptual and structural design of the production system	Generation of alternative production system concepts (line, cellular, RMS, matrix/network); definition of material and information flows; rough layout (zones, halls, cells); concept of work organisation and human-machine collaboration.	Select the production system type; decide on the automation level and the role of collaborative robotics; choose the basic layout and internal logistics concept; define target levels of variability and reconfigurability.	Concept modelling and systems engineering tools (process modelling, SysML/UML); early-stage discrete-event simulation for what-if analysis; rough factory layout tools; value stream mapping and flow-visualisation tools.
Phase 3 - Feasibility analysis and concept selection	Preliminary engineering calculations (takt, capacity, balancing); feasibility and investment assessment; risk analysis and requirements specification; initial definition of data and integration blueprint (target architecture).	Select the preferred concept and define scope; decide on make/buy strategy; set preliminary investment envelope; prioritise automation and digital functions; select baseline standards for interoperability and data requirements.	Capacity planning and line-balancing tools; optimisation and decision-support tools (OR/constraints); costing and feasibility modelling; FMEA/risk assessment tools; company and IT-OT architecture modelling; data modelling tools (ERD and requirements management).

MD framework phase	Main activities	Typical decisions	Typical digital tools (examples)
Phase 4 - Detailed design and virtual validation	Process detailing (operations, routes, times, bottlenecks); detailed layout (stations, lines, warehouses, buffers); selection of machines, robots, equipment and sensors; IT/OT architecture design (MES, SCADA, IIoT, DT); development and validation of simulation and digital twin models.	Select specific technologies and suppliers; choose control logic (push/pull, Kanban/CONWIP, scheduling approaches); determine capacities (machines, operators, buffer sizes); align ergonomics, safety and human roles; complete the cost and performance analysis.	CAD/CAE for equipment and layout detailing; digital factory tools; discrete-event simulation; robotics simulation and offline programming; human modelling and ergonomics tools; IIoT integration toolchains (e.g., OPC UA/MQTT); MES/SCADA prototyping; digital twin platforms and model management.
Phase 5 - Industrialisation and integration design	Design freeze and finalisation of technical specifications; detailed integration planning; implementation of control logic and interfaces; preparation of test protocols and cybersecurity measures; development of work instructions and training materials.	Select integration strategy (greenfield/brownfield, phased rollout); define system integration and acceptance test strategy (SIT/UAT preparation); determine cybersecurity controls and governance; select pilot scope and readiness criteria for commissioning.	PLC/SCADA engineering environments; version control and DevOps toolchains; virtual commissioning (SiL/HiL) tools; interface specification and API management; cybersecurity assessment frameworks (IEC 62443-oriented checklists); digital work instruction and training authoring (AR-enabled where appropriate).
Phase 6 - Implementation, commissioning and ramp-up	Procurement and installation of equipment and IT systems; integration of automation and information systems; virtual and physical commissioning; ramp-up planning and execution; training of operators and engineers.	Determine the sequence of installation and commissioning; define equipment testing and acceptance strategy (FAT/SAT); set performance thresholds and exit criteria for ramp-up; define the worker training programme for a digitalised environment.	Project planning and execution tools; commissioning and test tracking systems; deployment and configuration tools for MES/SCADA/IIoT stacks; operator training platforms (digital work instructions, AR-based guidance); operational data pipeline activation (historians/streaming, where applicable).

MD framework phase	Main activities	Typical decisions	Typical digital tools (examples)
Phase 7 - Operations management, continuous improvement and redesign	Performance monitoring (productivity, quality, energy, ergonomics, sustainability); continuous improvement (Lean, Six Sigma, Kaizen); predictive maintenance and asset management; adjustment of layouts, processes and control rules; initiation of redesign cycles.	Determine improvement priorities; select reconfiguration or reconstruction projects; decide when to initiate a major redesign; update targets and launch the next design cycle.	Manufacturing analytics and KPI dashboards (OEE/SPC); MES, SCADA and historians; AI and ML pipelines for predictive maintenance and quality analytics; process mining; continuous improvement management tools (A3, Kaizen digital boards); re-simulation and scenario analysis for redesign.

Table A5: Impact of digital technologies on targeted KPI design

KPI	Brief definition	Dominant digital technologies in MSD with impact on KPI design
OEE	Effectiveness of equipment compared to its theoretical maximum, combining availability, performance, and quality.	Simulation tools for manufacturing systems, digital modelling and layout tools, specialised OEE planning modules, and scenario analysis.
Availability / Downtime	Proportion of time the equipment is available for operation, including a breakdown of downtime.	Reliability and FMEA software, maintenance planning tools, failure scenario simulation, and analytical tools for availability assessment.
Throughput	Number of units produced within a given time period.	Discrete event simulation of production, flow optimisation and line balancing tools, and process modelling tools.
Capacity Utilisation	The extent to which the available capacity is used compared to the nominal or planned capacity.	Capacity planning in specialised MSD tools, capacity simulation, and analytical tools for product mix and volume scenarios.
Lead Time	Time from order to delivery (end-to-end).	Value stream mapping and simulation tools, process modelling, and tools for planning material and information flows.
On-Time Delivery (OTIF)	Proportion of orders delivered on time and in full compared to the total number of orders.	Planning and scheduling software in the conceptual phase (APS), simulation of demand and capacity scenarios, and supply chain modelling tools.
First Pass Yield (FPY)	Proportion of units meeting quality specifications on the first attempt.	Digital quality planning tools (APQP, control plan), statistical and simulation tools (DoE, robust design), and process modelling.
Scrap Rate	Proportion of units that must be discarded as scrap.	DfM/DfA software, process and variation simulation, tolerance analysis tools, and process simulation tools.
Rework Rate	Proportion of units requiring additional operations or reworking.	Digital work instruction planning tools, 3D/VR tools for assembly verification, DfX software (design for assembly/service).
Cost per Unit	Average cost of producing a single unit.	Costing modules in MSD tools, CAD process planning–costing integration, simulation of resource loading and automation scenarios.
Cost of Quality	Costs of prevention, appraisal, and non-quality.	Digital tools for modelling quality costs, software for planning and analysing control activities, and statistical modelling of defect scenarios.

KPI	Brief definition	Dominant digital technologies in MSD with impact on KPI design
Safety	Number of accidents, incidents, and lost workdays.	Ergonomics software (3D, VR), tools for simulating human–machine–robot interaction, and digital tools for risk assessment and safety analysis.
Schedule Adherence	Degree of alignment between actual execution and the production plan.	Planning and simulation tools for scheduling (schedule simulators), digital models of flows and capacities, and tools for testing schedule robustness under change.

Table A6: Information about Advanced MSD KPIs

	KPI	Brief definition	Dominant digital technologies in MSD with impact on KPI	What it indicates for MSD
Time performance	MSD Lead Time	Time from formal project start to freezing the manufacturing system design or concept decision.	Simulation tools, digital twins, MSD planning tools, PLM/ERP integration, and collaborative design platforms.	Speed of the MSD process; how quickly the organisation can arrive at a validated system design.
	Time-to-Concept Alternatives	Time required to generate and quantitatively evaluate a specified number of system design alternatives (e.g., the top three concepts).	Generative MSD tools, parametric models, digital twin, automated scenario-based simulation.	Ability to efficiently explore the design space and compare alternative system concepts.
	Time-to-Ramp-up Prediction	Time required during the design phase to obtain a reliable estimate of the ramp-up duration, from installation to achieving target performance.	Digital twin for virtual commissioning, ramp-up simulation, and analysis of historical ramp-up projects.	Maturity in anticipating ramp-up performance and incorporating it into design decisions.
Quality of Design	Accuracy of Designed KPIs	Deviation between designed and actual values of core operational KPIs (OEE, throughput, lead time, FPY) after stabilisation.	Simulation, digital twin, MSD–MES/ERP data integration, and advanced analytics.	Quality and credibility of MSD outputs; how realistic the designed targets are.
	Design Iteration Efficiency	Number of major design iterations (concept or layout changes) per project, normalised by project complexity.	Collaborative design platforms, configurable digital twin models, and variant management tools.	Efficiency of the design process and effectiveness of early digital validation.

	KPI	Brief definition	Dominant digital technologies in MSD with impact on KPI	What it indicates for MSD
	Reuse of Digital Assets in MSD	Proportion of reused digital models (layouts, simulations, standard modules) compared to all models used in a project.	PLM and knowledge bases, KBE, libraries of standard cells and lines, digital thread.	Level of standardisation and learning in MSD; ability to capitalise on previous digital work.
Data maturity and analytics	Data-driven Design Decisions Share	Proportion of key MSD decisions explicitly based on quantitative outputs from digital tools (simulation, AI, analytics, digital twin).	Big data and analytics platforms, AI and ML, integration of ERP and MES data with MSD tools.	Degree to which MSD is data-driven rather than based on experience.
	Model Calibration Level	Proportion of critical model parameters (cycle times, failures, scrap rate, demand) calibrated using real data compared with expert estimates.	ERP/MES integration, IIoT/IoT, data lakes, digital thread.	Credibility and robustness of MSD models as decision support tools.
	Scenario Coverage Index	Number of analysed scenarios (mix, volume, failures, takt changes) relative to a reference set of relevant scenarios.	Automated scenario generation in simulation tools, AI-based "what-if" support, and digital twin.	Thoroughness of design risk analysis and readiness for variability and disturbances.
	Operator Involvement in MSD	Share of projects in which operators and end users participate in design evaluation using digital tools (e.g., VR, 3D reviews).	VR/AR, collaborative review platforms, workplace digital twins.	Human centricity of MSD and quality of practical feedback before implementation.

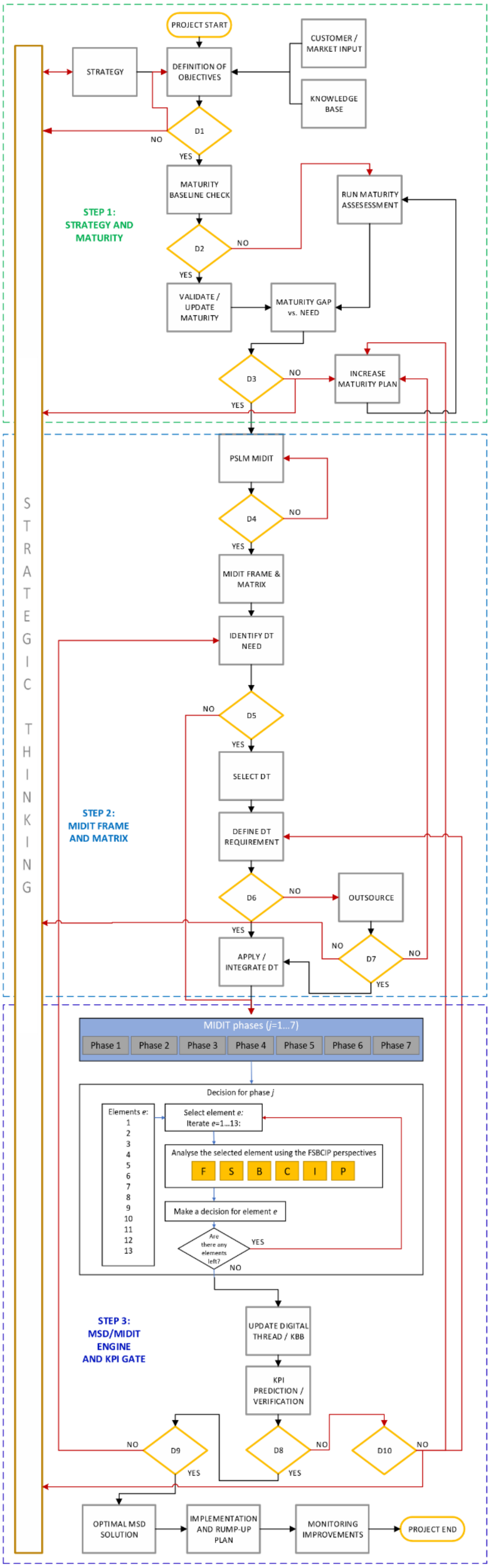
	KPI	Brief definition	Dominant digital technologies in MSD with impact on KPI	What it indicates for MSD
I5.0 perspective	Ergonomic Risk Reduction in Design	Difference between initial and designed ergonomic risk levels (according to ergonomic indices) before implementation.	3D ergonomics software, VR simulations, human–task digital twins.	Extent to which MSD systematically improves ergonomics and safety through design.
	Cross-functional Design Collaboration Index	Proportion of design decisions made collaboratively by multiple functions (production, quality, maintenance, HSE) using shared digital models.	Collaborative MSD/PLM platforms, digital thread, and cloud-based co-design tools.	Integration of perspectives in MSD and the development of cross-functional digital collaboration maturity.
Digital risk and Resilience	Cyber-physical Risk Consideration in Design	Proportion of MSD projects in which cybersecurity, OT/IT integration risk, and network reliability are explicitly included in the design criteria.	Cybersecurity assessment tools, OT/IT architecture modelling, network and digital twins.	Awareness and management of digital risks at the design stage, not just during operation.
	Design for Reconfigurability Index	Degree to which the system is designed for future reconfiguration (modular cells, plug-and-produce, software-defined flows).	Modular MSD tools, digital twins, CPS/IIoT platforms, and line configurators.	Long-term adaptability and alignment of MSD with reconfigurable and Industry 5.0 concepts.
	Predictive Maintenance Design Integration	Proportion of new systems where predictive maintenance requirements (sensors, algorithms, integrations) are already specified in the MSD and linked to availability-related KPIs.	IIoT and AI/ML for predictive maintenance, integrated with CMMS/EAM at the design stage.	Proactiveness of MSD in incorporating maintainability and predictive capabilities into system design.

Appendix B

Table B1: Decision gate questions

Decision gate	Decision question
D1	Is the MSD scope and KPI target set approved?
D2	Is a valid digital maturity assessment available?
D3	Is the current maturity level sufficient for the intended digital technologies utilisation and KPI achievement approach?
D4	Is the MIDIT lifecycle alignment acceptable?
D5	Is a digital technology intervention required for the current MSD step?
D6	Is the required digital technology available in-house?
D7	Is outsourcing or partnering feasible under the defined constraints?
D8	Does the design solution satisfy the KPI gate for the current step?
D9	Is the final MSD step completed (i = 13)?
D10	Which root-cause category explains the KPI deviation?

Figure B1: Flowchart for MIDIT methodology



Appendix C

Questionnaire: The Role of Digital Technologies in Analysing and Improving KPI Indicators in the MSD Phase

Respondent Information (optional, for research purposes only)

Please provide basic information about your organisation and your role. The data will be used exclusively in aggregate form, without specifying company names or individuals.

- Company name: ___________________________________
- Industrial sector (e.g., automotive, mechanical engineering, food processing...): ____
- Company size (number of employees):
    - ☐ < 50
    - ☐ 50–249
    - ☐ 250–999
    - ☐ ≥ 1000
- Your current function/position (e.g., production manager, industrial engineering manager, production process designer, DT manager): _________________________________
- Years of experience in production system design:
    - ☐ < 3 years
    - ☐ 3–5 years
    - ☐ 6–10 years
    - ☐ > 10 years
- Level of familiarity with digital technologies in manufacturing (self-assessment):
    - ☐ Basic
    - ☐ Intermediate
    - ☐ Advanced
    - ☐ Expert

Confidentiality and Participation Statement

This questionnaire is part of doctoral research on the design of production systems and the impact of digital technologies on shaping design decisions that determine the feasibility (potential for achievement) of targeted KPI values in the production system design (MSD) phase.

- Participation in this research is voluntary.
- You may refuse to answer individual questions or withdraw from participation at any time without consequence.

- All collected data will be processed confidentially and used exclusively for research purposes.
- Results will be presented in aggregate form, without specifying company names or individuals.
- Reports, publications, and the doctoral thesis will not include information that could enable identification of individual companies or respondents.

By completing and submitting this questionnaire, you consent to participate in the research under the conditions stated above.

General Instructions for Completing the Questionnaire

This questionnaire concerns the production system design phase and the key performance indicators (KPIs) used to define target production system performance.

For each KPI block and its associated digital technologies, please assess the impact of applying that technology during the design phase on your ability to set target values for the specified KPI indicators.

Assess the impact in comparison to the period before the introduction of the technology in question (i.e., how much the technology has improved your ability to achieve KPI indicators in the past 2–3 years).

Use the following impact scale (1–5):

1 – No significant impact
2 – Small impact
3 – Medium impact
4 – Large impact
5 – Very large impact

Please mark one value (1–5 or N/A) for each technology in the tables.

A) KPI: Production, Capacity, Time - *OEE, Throughput, Availability, Capacity Utilisation*

Question A1: Please assess the impact of the following digital technologies on decisions in the design process that determine the feasibility of targeted KPI indicator values by selecting a rating for each technology:

A.1 Production / Capacity / Time *(OEE, Throughput, Availability, Capacity Utilization)*	**Impact on targeted KPI (1-5)**					
	1	**2**	**3**	**4**	**5**	**N/A**
1. Modelling and simulation (production system simulation, bottleneck analysis, line balancing)	☐	☐	☐	☐	☐	☐
2. Digital twin (digital model of a production system for performance verification in different scenarios)	☐	☐	☐	☐	☐	☐

A.1 Production / Capacity / Time *(OEE, Throughput, Availability, Capacity Utilization)*	**Impact on targeted KPI (1-5)** **1 2 3 4 5 N/A**
3. ERP/MES integration (using historical data for model and target calibration)	☐ ☐ ☐ ☐ ☐ ☐
4. Robotisation and automation (designing the level of automation and the structure of stations and lines)	☐ ☐ ☐ ☐ ☐ ☐
5. IIoT / Cyber-physical systems (using actual performance data to redefine design assumptions)	☐ ☐ ☐ ☐ ☐ ☐
6. CAPP / KBE (computer-aided process planning and knowledge-based engineering for optimising operation sequences and times)	☐ ☐ ☐ ☐ ☐ ☐

Question A2: Which digital technologies do you consider most important for making decisions in the design process to achieve target KPI values for OEE, Throughput, Availability, and Capacity Utilisation?

Please select up to two technologies:

- ☐ Modelling and simulation
- ☐ Digital twin
- ☐ ERP/MES integration
- ☐ Robotisation and automation
- ☐ IIoT / Cyber-physical systems
- ☐ CAPP / KBE

B) KPI: Quality – First Pass Yield (FPY), Scrap Rate, Rework Rate

Question B1: Please assess the impact of the following digital technologies on decisions in the design process that determine the feasibility of achieving targeted KPI indicator values by selecting a rating for each technology:

B.1 Quality *(First Pass Yield (FPY), Scrap Rate, Rework Rate)*	**Impact on targeted KPI (1-5)** **1 2 3 4 5 N/A**
1. CAPP / KBE (planning control points, process parameters for quality)	☐ ☐ ☐ ☐ ☐ ☐
2. Modelling and simulation (process simulation including variability and defect aspects)	☐ ☐ ☐ ☐ ☐ ☐

B.1 Quality *(First Pass Yield (FPY), Scrap Rate, Rework Rate)*	**Impact on targeted KPI (1-5)** **1 2 3 4 5 N/A**
3. Digital twin (process simulation and quality verification before production)	☐ ☐ ☐ ☐ ☐ ☐
4. Tolerance analysis and variability analysis tools (tolerance stack-up)	☐ ☐ ☐ ☐ ☐ ☐
5. Statistical and simulation tools for robust design and Design of Experiments (DoE)	☐ ☐ ☐ ☐ ☐ ☐
6. Digital quality planning tools (e.g., digital control plan, APQP software linked with process models)	☐ ☐ ☐ ☐ ☐ ☐
7. AI and machine learning (predictive models for estimating the probability of defect scenarios)	☐ ☐ ☐ ☐ ☐ ☐

Question B2: Which digital technologies do you consider most important for making decisions in the design process to achieve target KPI values for FPY, Scrap Rate, and Rework Rate?

Please select up to two technologies:

- ☐ CAPP / KBE
- ☐ Modelling and simulation (process)
- ☐ Digital twin
- ☐ Tolerance analysis
- ☐ Robust design / DoE tools
- ☐ Digital quality planning tools
- ☐ AI and machine learning

C) KPI: Costs - *Cost per unit of product, cost of quality*

Question C1: Please assess the impact of the following digital technologies on decisions in the design process that determine the feasibility of targeted KPI indicator values by selecting a rating for each technology:

C.1 Costs *(Cost per unit of product, cost of quality)*	**Impact on targeted KPI (1-5)** **1 2 3 4 5 N/A**
1. ERP/MES integration (cost and performance data as inputs to cost models)	☐ ☐ ☐ ☐ ☐ ☐

C.1 Costs *(Cost per unit of product, cost of quality)*	**Impact on targeted KPI (1-5)** **1 2 3 4 5 N/A**
2. CAPP / KBE (process cost planning based on specified technology and parameters)	☐ ☐ ☐ ☐ ☐ ☐
3. Modelling and simulation (capacity, utilisation, and cost per unit scenarios)	☐ ☐ ☐ ☐ ☐ ☐
4. Digital twin (simulation of costs for various system configurations)	☐ ☐ ☐ ☐ ☐ ☐
5. Big Data / Analytics / Cloud (advanced cost and performance analytics, what-if scenarios)	☐ ☐ ☐ ☐ ☐ ☐
6. Digital Thread (data connectivity from product design to manufacturing and cost)	☐ ☐ ☐ ☐ ☐ ☐
7. AI / Machine learning (cost scenario optimisation based on data)	☐ ☐ ☐ ☐ ☐ ☐

Question C2: Which digital technologies do you consider most important for making decisions in the design process to achieve target KPI values for cost per unit of product and cost of quality?

Please select up to two technologies:

☐ ERP/MES integration
☐ CAPP / KBE
☐ Modelling and simulation
☐ Digital twin
☐ Big Data / Analytics / Cloud
☐ Digital Thread
☐ AI / Machine learning

D) KPI: Supply, Planning - *Lead Time, On-Time Delivery (OTIF), Schedule Adherence*

Question D1: Please assess the impact of the following digital technologies on decisions in the design process that determine the feasibility of targeted KPI indicator values by selecting a rating for each technology:

D.1 Supply / Planning *(Lead Time, On-Time Delivery (OTIF), Schedule Adherence)*	**Impact on targeted KPI (1-5)** **1**	**2**	**3**	**4**	**5**	**N/A**
1. Modelling and simulation (flow, WIP, bottleneck simulation, what-if scenarios)	☐	☐	☐	☐	☐	☐
2. Digital twin (virtual verification of the feasibility of the plan and schedule)	☐	☐	☐	☐	☐	☐
3. ERP/MES integration (actual data on times, WIP, and deliveries as input to design)	☐	☐	☐	☐	☐	☐
4. APS / PPC tools (advanced planning and scheduling, digital planning and scheduling)	☐	☐	☐	☐	☐	☐
5. Digital Thread (information connectivity via PSLM for material and information flow planning)	☐	☐	☐	☐	☐	☐
6. Big Data / Analytics (demand and capacity scenario analysis to redefine lead time targets)	☐	☐	☐	☐	☐	☐

Question D2: Which digital technologies do you consider most important for making decisions in the design process to achieve target KPI values for lead time, OTIF, and schedule adherence?

Please select up to two technologies:

- ☐ Modelling and simulation
- ☐ Digital twin
- ☐ ERP/MES integration
- ☐ APS / PPC tools
- ☐ Digital Thread
- ☐ Big Data / Analytics

E) KPI: Safety, Human-Centred Approach – Safety, Ergonomics, HSE

Question E1: Please assess the impact of the following digital technologies on decisions in the design process that determine the feasibility of achieving the targeted KPI indicator values by selecting a rating for each technology:

E.1 Safety / Human-centred approach *(Safety, Ergonomics, HSE)*	**Impact on targeted KPI (1-5)** **1**	**2**	**3**	**4**	**5**	**N/A**
1. VR/AR (ergonomic analysis, work simulation, human-machine interaction simulation)	☐	☐	☐	☐	☐	☐
2. Digital twin (simulation of human and robot work in a virtual environment before implementation)	☐	☐	☐	☐	☐	☐
3. Robotisation and automation (reducing risk exposure, collaborative robotics)	☐	☐	☐	☐	☐	☐
4. Modelling and simulation (simulation of human flows and human-machine-robot interactions)	☐	☐	☐	☐	☐	☐
5. Cyber-physical systems / IIoT (data on working conditions, load, and safety events as input to design)	☐	☐	☐	☐	☐	☐
6. Cyber security (protection of data and systems from security threats)	☐	☐	☐	☐	☐	☐

Question E2: Which digital technologies do you consider most important for making decisions in the design process to achieve target KPI values for safety and ergonomics?

Please select up to two technologies:

- ☐ VR/AR
- ☐ Digital twin
- ☐ Robotisation and automation
- ☐ Modelling and simulation
- ☐ Cyber-physical systems / IIoT
- ☐ Cyber security

F) Impact of Advanced Technologies (Industry 5.0, Special Cases)

Question F1: Please assess the impact of the following advanced technologies on overall production system design (transversal impact on a group of KPI indicators):

F.1 Impact of advanced technologies (Industry 5.0 / special cases)	Impact on targeted KPI (1-5) 1	2	3	4	5	N/A
1. AM / Additive manufacturing (where applicable: new product design, new business models)	☐	☐	☐	☐	☐	☐
2. Blockchain (supply chain transparency, data security, new business models)	☐	☐	☐	☐	☐	☐
3. AI and advanced analytics (cross-functional optimisation of multiple KPIs simultaneously, predictive capabilities)	☐	☐	☐	☐	☐	☐

Question F2: How would you describe the impact of AI and advanced analytics on the quality and duration of decision-making in the design process that affects the feasibility of targeted KPI values?

____

Concluding Questions (open-ended)
Question G1

Which digital technologies do you consider still insufficiently developed or accessible to contribute significantly to the MSD phase, particularly regarding the selection, definition, and improvement of KPI indicators?

Please specify which technologies you would prioritise for development or implementation.

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Question G2

Which KPI indicators are most difficult for you to estimate reliably in the early phase of production system design, even with available digital technologies? What do you find most lacking in this context?

(e.g., relevant data, quality models or simulations, standardised definitions and formulas, tool integration, reliable input assumptions, competencies, etc.)

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Question G3

What recommendations would you make to improve the integration of digital technologies into a MIDIT-based methodology for managing the production system lifecycle, in accordance with the principles of Industry 4.0 and 5.0?

For example, consider interoperability and data standards, digital twin, knowledge management, human roles and competencies, cybersecurity, sustainability, and a human-centric approach.

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Thank you for your time and expert contribution to this research.

Appendix D

Questionnaire: Advanced KPIs for Assessing the Impact of Digital Technologies on the MSD Process

Respondent information (optional, for research purposes only)

Please provide some basic information about your organisation and your role. The data will be used only in aggregated form, without naming companies or individuals.

- Company name: ________________________________
- Industry sector (e.g., automotive, machinery, food, electronics…):

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- Company size (number of employees):
  - ☐ < 50
  - ☐ 50–249
  - ☐ 250–999
  - ☐ ≥ 1000
- Your current position/role (e.g., production manager, industrial engineering manager, MSD engineer, digital transformation manager):

  ____
- Years of experience in manufacturing system design (MSD):
  - ☐ < 3 years
  - ☐ 3–5 years
  - ☐ 6–10 years
  - ☐ > 10 years
- Self-assessed familiarity with digital technologies in manufacturing:
  - ☐ Basic
  - ☐ Intermediate
  - ☐ Advanced
  - ☐ Expert

Confidentiality and Participation Statement

This questionnaire forms part of a doctoral research project on manufacturing system design (MSD) and the impact of digital technologies on design-related KPIs during the design phase.

- Participation in this study is voluntary.
- You may choose not to answer any question or withdraw from the study at any time without consequence.
- All data collected will be treated as confidential and used solely for research purposes.
- Results will be reported in aggregate form, without identifying companies or individual respondents.
- No information that could identify a specific company or respondent will be disclosed in reports, publications, or the doctoral thesis.
- By completing and returning this questionnaire, you consent to participate in the study under the conditions described above.

General Instructions for Completing the Questionnaire
This questionnaire concerns advanced KPIs that measure the process and quality of MSD, rather than only the operational performance of the system. The aim is to assess:

- the extent to which these KPIs are used in your practice
- your view of the impact of digital technologies on their improvement.

Please complete the questionnaire based on your personal experience and that of your organisation. For each KPI, please evaluate two aspects:

A – Level of KPI application in the MSD phase

N/A – Not applicable or not measurable in our context

1 – Very rarely or on an ad hoc basis

2 – Occasionally

3 – Moderately often

4 – Systematically in most MSD projects

5 – Systematically and formally (a standard part of the methodology)

B – KPI sensitivity to digital technologies in MSD

1 – No significant impact

2 – Small impact

3 – Medium impact

4 – Large impact

5 – Very large impact

You are not required to calculate exact values; use the definitions to guide your judgement.
If your organisation has no experience with digital technologies in this KPI area, select 1 (no impact) or leave blank.

Please mark one value for A and B for each KPI.

A) Time-related KPIs of MSD Design – MSD Lead Time, Time to Concept Alternatives, Time to Ramp-up Prediction

Question A1: Please assess:

A.1 Time-related KPIs of MSD Design	**A) Application in MSD phase (0–5)**						**B) Sensitivity to DT (1–5)**				
1. **MSD Lead Time** (the period from the formal start of the MSD project to the design freeze or concept decision)	N/A	1	2	3	4	5	1	2	3	4	5
	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
2. **Time to Concept Alternatives** (time required to generate and quantitatively evaluate a specified number of alternative concepts, such as the top three)	N/A	1	2	3	4	5	1	2	3	4	5
	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
3. **Time to ramp-up prediction** (the time required during the design phase to obtain a reliable estimate of the ramp-up duration)	N/A	1	2	3	4	5	1	2	3	4	5
	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Question A2: To what extent has the use of digital technologies (e.g., simulation, digital twin, collaborative tools) shortened the duration of the MSD process in your recent projects?

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B) Design Quality and Robustness KPIs - Accuracy of targeted KPIs, Design Iteration Efficiency, Reuse of Digital Assets

Question B1: Please assess:

B.1 Design Quality and Robustness KPIs	**A) Application in MSD phase (0–5)**						**B) Sensitivity to DT (1–5)**				
1. **Accuracy of targeted KPIs** (percentage deviation between targeted and achieved KPIs after system stabilisation)	N/A	1	2	3	4	5	1	2	3	4	5
	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
2. **Design Iteration Efficiency** (major redesign loop affecting layout, capacity, or technology selection)	N/A	1	2	3	4	5	1	2	3	4	5
	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

3. **Reuse of Digital Assets in MSD** (share of reuse of existing digital models in MSD projects)	N/A 1 2 3 4 5 ☐ ☐ ☐ ☐ ☐ ☐	1 2 3 4 5 ☐ ☐ ☐ ☐ ☐

Question B2: Which of these KPIs do you consider most useful for assessing the quality of the MSD process when using digital technologies, and why?

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C) Data Maturity and Analytics in Design – Data-driven Design Decisions Share, Model Calibration Level, Scenario Coverage Index

Question C1: Please assess:

C.1 Data Maturity and Analytics KPIs	**A) Application in MSD phase (0–5)**	**B) Sensitivity to DT (1–5)**
1. **Data-driven Design Decisions Share** (percentage of key MSD decisions based on quantitative analyses from digital tools)	N/A 1 2 3 4 5 ☐ ☐ ☐ ☐ ☐ ☐	1 2 3 4 5 ☐ ☐ ☐ ☐ ☐
2. **Model Calibration Level** (percentage of key model parameters calibrated using real data rather than estimates)	N/A 1 2 3 4 5 ☐ ☐ ☐ ☐ ☐ ☐	1 2 3 4 5 ☐ ☐ ☐ ☐ ☐
3. **Scenario Coverage Index** (number of analysed scenarios relative to the reference set of relevant scenarios for the project; e.g., demand ±X%, breakdown scenarios, product mix, staffing variation)	N/A 1 2 3 4 5 ☐ ☐ ☐ ☐ ☐ ☐	1 2 3 4 5 ☐ ☐ ☐ ☐ ☐

Question C2: In your experience, what is the greatest barrier to achieving a high level of data-driven design: lack of data, systems integration, competencies, or time pressure?

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D) Human-centric and Collaborative Aspects of MSD - Operator Involvement, Ergonomic Risk Reduction, Cross-functional Design Collaboration

Question D1: Please assess:

D.1 Human-centric and Collaborative KPIs	A) Application in MSD phase (0–5)	B) Sensitivity to DT (1–5)
1. **Operator involvement in MSD** (percentage of projects in which operators actively participate in design evaluation using digital tools such as VR or AR)	N/A 1 2 3 4 5 ☐ ☐ ☐ ☐ ☐ ☐	1 2 3 4 5 ☐ ☐ ☐ ☐ ☐
2. **Ergonomic Risk Reduction in Design** (change in ergonomic risk from the initial to the designed state before implementation, expressed as a percentage reduction)	N/A 1 2 3 4 5 ☐ ☐ ☐ ☐ ☐ ☐	1 2 3 4 5 ☐ ☐ ☐ ☐ ☐
3. **Cross-functional Design Collaboration Index** (percentage of decisions made collaboratively by multiple functions using shared digital models)	N/A 1 2 3 4 5 ☐ ☐ ☐ ☐ ☐ ☐	1 2 3 4 5 ☐ ☐ ☐ ☐ ☐

Question D2: How are digital technologies (such as VR/AR, collaborative platforms, and digital twin) changing the way functions collaborate (production, quality, maintenance, HSE, logistics) in MSD projects?

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E) Digital Risk and Resilience in MSD – Cyber-physical Risk Consideration, Design for Reconfigurability, Predictive Maintenance Integration

Question E1: Please assess:

E.1 Digital Risk and Resilience KPIs	A) Application in MSD phase (0–5)	B) Sensitivity to DT (1–5)
1. **Cyber-physical Risk Consideration in Design** (percentage of MSD projects in which cyber security and OT/IT risks are explicitly considered)	N/A 1 2 3 4 5 ☐ ☐ ☐ ☐ ☐ ☐	1 2 3 4 5 ☐ ☐ ☐ ☐ ☐
2. **Design for Reconfigurability Index** (the extent to which the system is designed for future digitally enabled configuration changes)	N/A 1 2 3 4 5 ☐ ☐ ☐ ☐ ☐ ☐	1 2 3 4 5 ☐ ☐ ☐ ☐ ☐
3. **Predictive Maintenance Design Integration** (proportion of new systems with predictive maintenance requirements defined during the MSD phase)	N/A 1 2 3 4 5 ☐ ☐ ☐ ☐ ☐ ☐	1 2 3 4 5 ☐ ☐ ☐ ☐ ☐

Question E2: To what extent are digital risks (cybersecurity, OT/IT integration, data security) and future reconfigurability actually considered in the early design phases, and to what extent are they still addressed only during implementation or operation?

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Concluding Questions

Question F1
Which two or three advanced KPIs from this questionnaire do you consider most important for your organisation over the next three to five years, and why?

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Question F2
Are there any additional design-related KPIs you consider important that are not included in this questionnaire? Please list them.

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Question F3
How would you recommend improving the MIDIT-based MSD methodology for measuring and tracking advanced KPIs, particularly in the context of Industry 4.0 and 5.0?

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Thank you for your time and expert contribution to this research.

Appendix E

1. Perceived impact by KPI block (median and Top Box%)

KPI Group	KPI block	Overall Median	Overall Top Box %	C01 Median	C01 Top Box %	C02 Median	C02 Top Box %	C03 Median	C03 Top Box %	C04 Median	C04 Top Box %
A1	Production / Capacity / Time (OEE, Throughput, Availability, Capacity utilisation)	4	87.7%	4	87.5%	4	100.0%	3	22.2%	4	100.0%
B1	Quality (FPY, Scrap rate, Rework rate)	4	81.7%	4	75.0%	4	75.0%	4	66.7%	4	100.0%
C1	Costs (Cost per unit, Cost of quality)	4	90.6%	4	85.7%	4	89.3%	4	83.3%	5	100.0%
D1	Supply / Planning (Lead time, OTIF, Schedule adherence)	4	88.8%	4	83.3%	4	95.0%	4	66.7%	5	100.0%
E1	Safety / Human-centric (Safety, ergonomics, HSE)	4	71.4%	4	66.7%	4.5	83.3%	3	0.0%	5	100.0%
F1	Advanced technologies (Industry 5.0 / special cases)	4	74.2%	3	41.7%	4	100.0%	4	66.7%	4	100.0%

2. Results of Dunn test

KPI Group	KPI Block Name	Pair	z	p raw	p holm
A1	Production / Capacity / Time	C01 vs C02	0.536349916	0.591716738	1
A1	Production / Capacity / Time	C01 vs C03	2.813860021	0.004895054	0.029370323
A1	Production / Capacity / Time	C01 vs C04	0.536349916	0.591716738	1
A1	Production / Capacity / Time	C02 vs C03	2.317296488	0.020487586	0.081950346
A1	Production / Capacity / Time	C02 vs C04	0	1	1
A1	Production / Capacity / Time	C03 vs C04	-2.317296488	0.020487586	0.081950346
B1	Quality	C01 vs C02	-0.525739355	0.599069316	0.599069316
B1	Quality	C01 vs C03	1.460220186	0.144229569	0.288459139
B1	Quality	C01 vs C04	-2.022074441	0.043168662	0.206158003
B1	Quality	C02 vs C03	1.946960248	0.051539501	0.206158003
B1	Quality	C02 vs C04	-1.496335087	0.134566356	0.288459139
B1	Quality	C03 vs C04	-3.332297347	0.000861322	0.005167931
C1	Costs	C01 vs C02	-0.599383808	0.548916972	0.882359273
C1	Costs	C01 vs C03	0.147979087	0.882359273	0.882359273
C1	Costs	C01 vs C04	-2.517411992	0.01182205	0.065940377
C1	Costs	C02 vs C03	0.702900664	0.482117658	0.882359273
C1	Costs	C02 vs C04	-1.918028185	0.055107437	0.220429750
C1	Costs	C03 vs C04	-2.478649709	0.013188075	0.065940377
D1	Supply / Planning	C01 vs C02	-0.159255514	0.873467568	0.873467568
D1	Supply / Planning	C01 vs C03	1.548140540	0.121588463	0.243176927
D1	Supply / Planning	C01 vs C04	-1.990693929	0.046514547	0.232572733
D1	Supply / Planning	C02 vs C03	1.695582496	0.089964975	0.243176927
D1	Supply / Planning	C02 vs C04	-1.831438415	0.067035132	0.243176927
D1	Supply / Planning	C03 vs C04	-3.391164992	0.000695962	0.004175771
E1	Safety / Human-centric	C01 vs C02	-1.593999638	0.110936116	0.332808348
E1	Safety / Human-centric	C01 vs C03	1.033029833	0.301589938	0.523734190
E1	Safety / Human-centric	C01 vs C04	-2.231599493	0.025641445	0.102565781
E1	Safety / Human-centric	C02 vs C03	2.508786737	0.01211466	0.060573300

KPI Group	KPI Block Name	Pair	z	p raw	p holm
E1	Safety / Human-centric	C02 vs C04	-0.637599855	0.52373419	0.523734190
E1	Safety / Human-centric	C03 vs C04	-3.099089498	0.001941164	0.011646982
F1	Advanced technologies	C01 vs C02	-1.842495476	0.065402708	0.261610831
F1	Advanced technologies	C01 vs C03	-0.87875542	0.379533902	0.408200830
F1	Advanced technologies	C01 vs C04	-3.098742391	0.001943439	0.011660635
F1	Advanced technologies	C02 vs C03	0.827063925	0.40820083	0.408200830
F1	Advanced technologies	C02 vs C04	-1.256246915	0.209026462	0.408200830
F1	Advanced technologies	C03 vs C04	-1.99012257	0.046577435	0.232887176

Appendix F

1. Descriptive statistics by Advanced KPI (mean, SD, IQR, CV)

KPI Code	KPI Group	KPI Name	Mean A	SD A	IQR A	CV A	N A	Mean B	SD B	IQR B	CV B	N B	Mean Gap
A1_1	Time performance	MSD Lead Time	2.00	0.93	2	0.463	15	4.07	0.96	1.5	0.236	15	0.41
A1_2	Time performance	Time-to-Concept Alternatives	1.73	1.28	1	0.738	15	3.93	0.80	1.5	0.203	15	0.44
A1_3	Time performance	Time-to-Ramp-up Prediction	2.53	1.06	1	0.418	15	3.87	0.83	1.5	0.216	15	0.27
B1_1	Quality of design	Accuracy of Designed KPIs	2.93	1.62	1	0.554	15	3.87	1.06	0.5	0.274	15	0.19
B1_2	Quality of design	Design Iteration Efficiency	1.80	1.57	2.5	0.871	15	3.33	1.11	1	0.334	15	0.31
B1_3	Quality of design	Reuse of Digital Assets in MSD	0.47	0.52	1	1.107	15	3.93	0.70	0.5	0.179	15	0.69
C1_1	Data and analytics	Data-driven Design Decisions Share	1.67	1.29	2.5	0.775	15	4.00	0.93	2	0.231	15	0.47
C1_2	Data and analytics	Model Calibration Level	0.80	0.94	2	1.176	15	4.27	0.59	1	0.139	15	0.69
C1_3	Data and analytics	Scenario Coverage Index	1.20	1.66	2	1.380	15	3.67	0.72	1	0.197	15	0.49
D1_1	Human-centric and collaboration	Operator Involvement in MSD	0.00	0.00	0		15	3.73	1.10	1.5	0.295	15	0.75
D1_2	Human-centric and collaboration	Ergonomic Risk Reduction in Design	1.80	1.78	3	0.989	15	3.93	0.96	2	0.244	15	0.43
D1_3	Human-centric and collaboration	Cross-functional Design Collaboration Index	0.93	1.22	1.5	1.310	15	4.27	0.96	1	0.225	15	0.67
E1_1	Risk and resilience	Cyber-physical Risk Consideration in Design	0.80	1.37	1.5	1.717	15	3.07	1.28	2	0.417	15	0.45
E1_2	Risk and resilience	Design for Reconfigurability Index	1.07	1.03	2	0.968	15	3.67	0.90	0	0.245	15	0.52
E1_3	Risk and resilience	Predictive Maintenance Design Integration	2.00	1.36	2	0.681	15	4.27	0.80	1	0.187	15	0.45

Legend: SD – standard deviation; IQR – interquartile range; CV – coefficient of variation; N - number of observations

2. Indices by KPI Group (mean, SD, IQR)

KPI Group	Mean A index	SD A index	IQR A index	Mean B index	SD B index	IQR B index	Mean A norm	Mean B norm	Mean Impact Index	Mean Gap
Data and analytics	1.22	0.88	1.33	3.98	0.58	0.83	0.24	0.80	0.21	0.55
Human-centric and collaboration	0.91	0.34	0.17	3.98	0.88	1.00	0.18	0.80	0.17	0.61
Quality of design	1.73	0.77	1.17	3.71	0.82	0.67	0.35	0.74	0.29	0.40
Risk and resilience	1.29	1.11	1.83	3.67	0.76	1.00	0.26	0.73	0.23	0.48
Time performance	2.09	0.91	0.83	3.96	0.70	0.83	0.42	0.79	0.36	0.37

3. Gap (B - A) Ranking - Priority KPIs (N=15)

KPI Code	KPI Group	KPI Name	Mean A	Mean B	Mean Gap	Ranking Gap
D1_1	Human-centric and collaboration	Operator Involvement in MSD	0.00	3.73	0.75	1
C1_2	Data and analytics	Model Calibration Level	0.80	4.27	0.69	2
B1_3	Quality of design	Reuse of Digital Assets in MSD	0.47	3.93	0.69	2
D1_3	Human-centric and collaboration	Cross-functional Design Collaboration Index	0.93	4.27	0.67	4
E1_2	Risk and resilience	Design for Reconfigurability Index	1.07	3.67	0.52	5
C1_3	Data and analytics	Scenario Coverage Index	1.20	3.67	0.49	6
C1_1	Data and analytics	Data-driven Design Decisions Share	1.67	4.00	0.47	7
E1_3	Risk and resilience	Predictive Maintenance Design Integration	2.00	4.27	0.45	8
E1_1	Risk and resilience	Cyber-physical Risk Consideration in Design	0.80	3.07	0.45	8
A1_2	Time performance	Time-to-Concept Alternatives	1.73	3.93	0.44	10
D1_2	Human-centric and collaboration	Ergonomic Risk Reduction in Design	1.80	3.93	0.43	11
A1_1	Time performance	MSD Lead Time	2.00	4.07	0.41	12
B1_2	Quality of design	Design Iteration Efficiency	1.80	3.33	0.31	13
A1_3	Time performance	Time-to-Ramp-up Prediction	2.53	3.87	0.27	14
B1_1	Quality of design	Accuracy of Designed KPIs	2.93	3.87	0.19	15

4. Correlation Analysis (N=15)

KPI Group	Correlation A-B	P value	N observations	Interpretation
Data and analytics	0.479	0.0009	45	Significant
Human-centric and collaboration	0.455	0.0017	45	Significant
Quality of design	0.505	0.0004	45	Significant
Risk and resilience	0.662	<0.0001	45	Significant
Time performance	0.692	<0.0001	45	Significant
Overall (all KPIs)	0.513	<0.0001	225	Significant

Appendix G

Scenario based instrument

V1 – Layout alternatives (AI)

Context: In conceptual design, it is necessary to generate and compare layout alternatives for the same process sequence. Constraints include available space, flows, safety zones, and available equipment.

V2 – Capacity, takt time and buffers (simulation + AI)

Context: It is necessary to verify that the design achieves the required takt time and throughput under variations in demand and product mix.

V3 – Ergonomics and Safety (VR/AR Review)

Context: The workstation requires manual loading and unloading, with areas where personnel and internal logistics operate. Late rework due to ergonomics and safety issues occurs frequently.

V4 – Intralogistics (flow simulation and AI routing)

Context: The design of intralogistics (routes, buffers, supply) affects WIP, delays, and safety. Conflicts are often detected late.

V5 – AI recommendation and trade-off (human-in-the-loop)

Context: There are three competing solution variants (more resources, larger buffers, or a different logistics concept). A decision must be made considering KPI trade-offs.

V6 – Design freeze (integrated evidence package)

Context: The design freeze should be completed with minimal surprises during ramp-up.

Table G1: Evaluation metrics (speed and quality)

Category	Metric (code)	Definition	Measurement approach	Interpretation
Speed	Total design lead time (T total)	Time from start to design freeze (gate completion)	Schedule model / measured time	Lower is better
Speed	Decision cycle time (T dec)	Time to reach key gate decisions (layout, capacity, logistics concept)	Per-gate durations	Lower is better
Speed	Iteration count (#Iter)	Number of iteration loops until completion criteria	Count of revisions	Lower is better
Speed	Iteration effort (T iter)	Time spent per iteration / cumulative iteration time	Schedule model / logs	Lower is better
Quality	Early issues detected (#Issues_pre)	Conflicts or defects detected before implementation (e.g., bottlenecks, clashes, safety or ergonomics issues)	Structured checklist and review records	Higher is better (earlier detection)
Quality	Rework effort (T rework)	Time spent on rework after review, simulation or VR review	Schedule model or measured	Lower is better
Quality	KPI estimate robustness (Err KPI)	Deviation between predicted KPI values and reference (simulation output or known benchmark)	Absolute or relative error	Lower is better
Quality	Expert quality score (Q rubric)	Rubric-based score (1–5) across defined criteria	Standard rubric	Higher is better

Evidence-informed Delphi: Questionnaire

MIDIT / PSLM validation of auxiliary hypotheses H1b (Simulation + VR/AR) and H1c (AI)

A) General Information

Confidentiality and Participation Statement

This questionnaire is part of doctoral research on the design of production systems and the impact of digital technologies on shaping design decisions that determine the feasibility (potential for achievement) of targeted KPI values in the production system design (MSD) phase.

- Participation in this research is voluntary.
- You may refuse to answer individual questions or discontinue participation at any time without consequence.
- All collected data will be processed confidentially and used exclusively for research purposes.
- Results will be presented in aggregate form, without specifying company names or individual persons.
- Reports, publications, and the doctoral thesis will not include information that could enable identification of individual companies or respondents.

By completing and submitting this questionnaire, you agree to participate in the research under the conditions stated above.

Definitions of metrics (summary):

- T total: total design lead time up to the Design Freeze gate (D11).
- T dec: time to reach key design decisions (layout, capacity, logistics).
- Err KPI: reliability of KPI estimation in the design phase (e.g., incorrect measurement definition/formula, KPI not linked to the target, non-operational KPI due to lack of data, inappropriate target leading to wrong decisions).
- #Iter: number of iterations/revisions required to meet the gate completion criteria.
- T rework: time spent on rework after the formal review/validation.
- #Issues_pre: number of issues identified before implementation (collisions, bottlenecks, ergonomics, safety).
- Q rubric: quality of the solution according to the rubric (K1–K6) on a 1–5 scale.

Rules: The gate criteria and required outputs (evidence) are identical for Plan T and Plan D. Experts evaluate the difference (Plan D relative to Plan T) based on the described scenarios and briefing.

B) Delphi questionnaire - scenarios

Please answer for each scenario:

1. (E) Potential impact of Plan D compared to Plan T, assuming that the preconditions are met.
2. (F) Feasibility of implementing Plan D in your environment (SME, digital maturity, resources).
3. Provide a brief justification (1–2 sentences).

B1) Calibration (1 minute)

Item	Rating (0-4)	Comment
Familiarity with simulation in MSD		
Familiarity with VR/AR in MSD		
Familiarity with AI in MSD		
Role/position (e.g., process engineering, logistics, quality, HSE)		

Scale 0–4: 0 = no experience, 1 = basic familiarity, 2 = occasional use/exposure, 3 = regular use, 4 = expert.

B2) Rating scales

Effect scale (E): E0 = no effect,
E1 = small effect,
E2 = medium effect,
E3 = large effect.

Feasibility scale (F): F0 = not feasible within 1–2 years,
F1 = difficult to implement,
F2 = feasible with investment or training,
F3 = immediately feasible.

V1 – Layout alternatives (AI)

Context: In conceptual design, it is necessary to generate and compare layout alternatives for the same process sequence. Constraints include available space, flows, safety zones, and available equipment.

Plan T (traditional):

1–2 engineers manually create 2–3 variants and select the best one based on their experience and basic criteria.

Plan D (MIDIT-enhanced):

An AI tool helps generate 8–16 variants, filters out those that violate the constraints, and ranks the top 3 according to weighted KPI criteria, thereby accelerating the evaluation

Evaluation (Plan D relative to Plan T):

Question / metric	**Effect E0–E3**	**Justification (1–2 sentences)**
Impact on T dec (speed of the layout decision)		
Impact on #Alternatives (number of evaluated variants)		
Impact on #Iter (later layout revisions)		
Impact on Q rubric (K1 feasibility, K4 flexibility)		
General comment: the most critical precondition/risk for AI at this step		

Feasibility (I) for this scenario (Plan D); (F0–F3): ___

Brief justification of feasibility (1–2 sentences):

____

____

V2 – Capacity, takt time and buffers (simulation + AI)

Context: It is necessary to verify that the design achieves the required takt time and throughput under variations in demand and product mix.

Plan T (traditional):

Capacity is calculated in Excel and confirmed by expert judgement; buffer policy is selected heuristically.

Plan D (MIDIT-enhanced):

Discrete-event simulation (DES) is used to test scenarios, and AI proposes a set of parameters (buffer sizes, number of resources, control rules) to achieve the optimal KPI performance.

Evaluation (Plan D relative to Plan T):

Question / metric	**Effect E0–E3**	**Justification (1–2 sentences)**
Impact on Err KPI (reliability of KPI estimation in the design phase)		
Impact on #Iter (fewer patches/rework in later stages)		
Impact on T rework (reduced need for subsequent corrections)		
Impact on T total up to Design Freeze (D11)		
General comment: which precondition is most often missing in an SME environment		

Feasibility (I) for this scenario (Plan D); (F0–F3): ___

Brief justification of feasibility (1–2 sentences):

____

____

V3 – Ergonomics and Safety (VR/AR Review)

Context: The workstation requires manual loading and unloading, with areas where personnel and internal logistics operate. Late rework due to ergonomics and safety issues occurs frequently.

Plan T (traditional):

2D/3D review on a screen, along with a standard HSE review and checklist.

Plan D (MIDIT-enhanced):

VR/AR immersive review with stakeholders (production, HSE, process engineering) to assess reachability, visibility, collisions, and safety zones.

Evaluation (Plan D relative to Plan T):

Question / metric	**Effect E0–E3**	**Justification (1–2 sentences)**
Impact on #Issues_pre (earlier detection of issues: collisions, reach, safety zones)		
Impact on T rework (subsequent ergonomics/safety corrections)		
Impact on T dec (faster alignment and decision-making)		
Impact on Q rubric K5 (human-centric)		
General comment: Are 3D models available, and who would participate in the review?		

Feasibility (I) for this scenario (Plan D); (F0–F3): ___

Brief justification of feasibility (1–2 sentences):

____

____

V4 – Intralogistics (flow simulation and AI routing)

Context: The design of intralogistics (routes, buffers, supply) affects WIP, delays, and safety. Conflicts are often detected late.

Plan T (traditional):

Routes and supply are planned manually, based on a rough estimation of logistics workload.

Plan D (MIDIT-enhanced):

Flow simulation (AGV/forklift) combined with AI-based optimisation of routes and supply schedules under safety constraints.

Evaluation (Plan D relative to Plan T):

Question / metric	**Effect E0–E3**	**Justification (1–2 sentences)**
Impact on #Issues_pre (collisions, congestion, infeasible routes)		
Impact on Err KPI (lead time / WIP estimation)		
Impact on T rework (late layout changes due to logistics)		
Impact on Q rubric (K2 robustness, K4 flexibility)		
General comment: the greatest organisational risk for implementation		

Feasibility (I) for this scenario (Plan D); (F0–F3): ___

Brief justification of feasibility (1–2 sentences):

____

____

V5 – AI recommendation and trade-off (human-in-the-loop)

Context: There are three competing solution variants (more resources, larger buffers, or a different logistics concept). A decision must be made considering KPI trade-offs.

Plan T (traditional):

The team makes the decision through discussion and manual spreadsheets.

Plan D (MIDIT-enhanced):

An AI system generates a top-N set of recommendations with explanations of the trade-offs and warnings about constraint violations; the team then confirms the decision (human-in-the-loop).

Evaluation (Plan D relative to Plan T):

Question / metric	**Effect E0–E3**	**Justification (1–2 sentences)**
Impact on T dec (faster decision-making)		
Impact on Q rubric K3 (transparency and validity of KPI assessment)		
Impact on #Iter (fewer decision reversals)		
Risk of wrong decision due to AI (E0 no risk - E3 high risk)		
General comment: what is the key prerequisite for trusting an AI recommendation		

Feasibility (I) for this scenario (Plan D); (F0–F3): ___

Brief justification of feasibility (1–2 sentences):

____

____

V6 – Design freeze (integrated evidence package)

Context: The design freeze should be completed with minimal surprises during ramp-up.

Plan T (traditional):

Final layout, calculations, and standard review minutes.

Plan D (MIDIT-enhanced):

Additionally: simulation scenario reports, VR/AR ergonomics and safety review log, and an AI report on alternatives and the rationale for the selected option (log = list of issues with screenshot/marker in the scene, responsible person, and due date). The AI output must be verified and validated before the design freeze.

Evaluation (Plan D relative to Plan T):

Question / metric	Effect E0–E3	Justification (1–2 sentences)
Impact on T total up to Design Freeze (may also be negative due to additional work)		
Impact on T rework after the freeze		
Impact on #Issues_pre before implementation		
Impact on Q rubric overall		
General comment: would this evidence package increase confidence in the decision, and why		

Feasibility (I) for this scenario (Plan D); (F0–F3): ___

Brief justification of feasibility (1–2 sentences):

____

____

B3) Final global rubric

Selection of key preconditions (select two): What must be in place in your organisation for the scenario (Plan D) to work at all?

<u>Select two preconditions:</u>

Preconditions (Mark "X")	**Specify**
☐ Available 3D model / digital layout	
☐ High-quality data (process times, routing, demand)	
☐ Defined KPI criteria and constraints	
☐ Competences (AI/VR/simulation)	
☐ IT/infrastructure and tools	
☐ Management support / process change	
☐ Other (specify):	

Selection of the main barriers/risks (select two):

Main Barriers/risks (Mark "X")	**Specify**
☐ Lack of time and resources	
☐ Poor data quality / unavailable data	
☐ Resistance to change / organisational culture	
☐ Cost / unclear ROI	
☐ Technical integration (IT/OT, compatibility)	
☐ Trust / explainability of AI results	
☐ Cybersecurity / security requirements	
☐ Other (specify):	

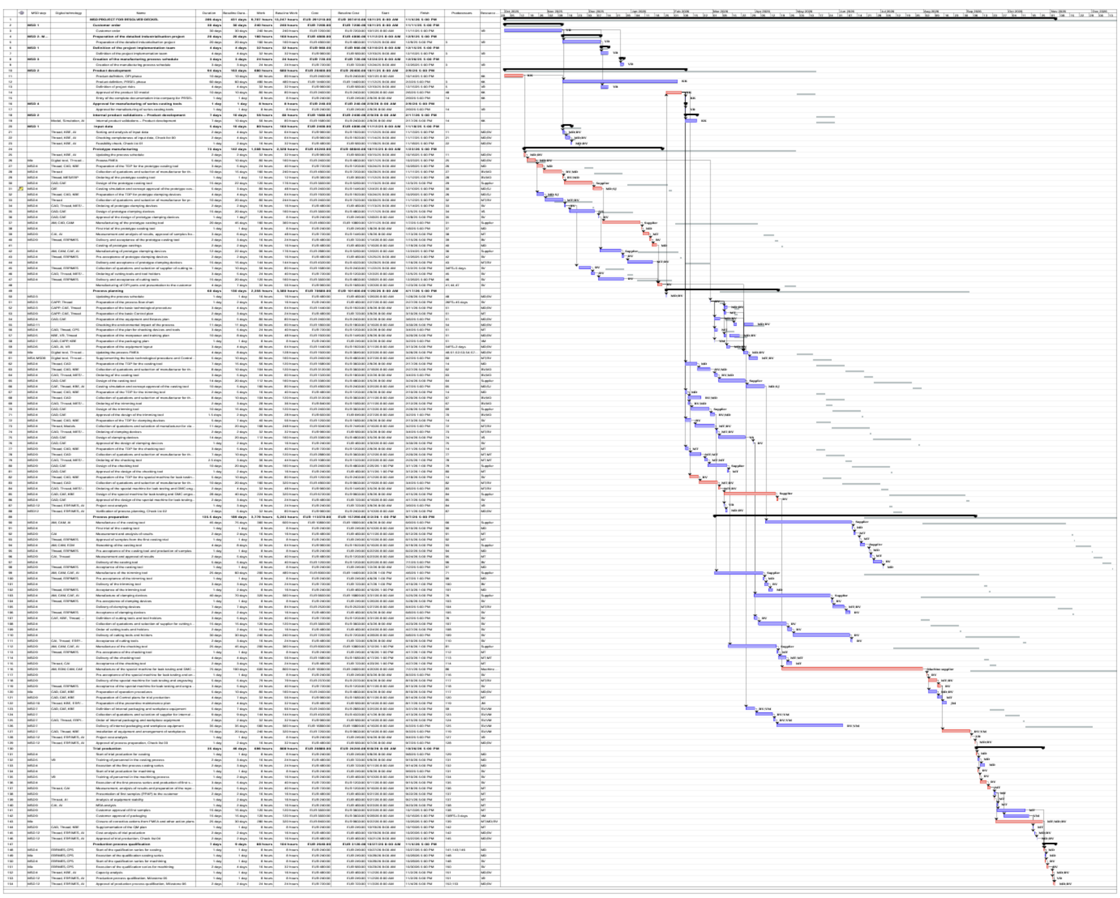
This section provides an overall assessment of the quality of the final solution after reviewing all scenarios for Plan T (current way of working) and Plan D (MIDIT). Criteria K1–K5 are rated on a scale of 1–5.

Criterion	Plan T (1–5)	Plan D (1–5)	Comment
K1 Feasibility and implementability			
K2 Robustness and stability of performance			
K3 Validity and reliability of KPI assessment			
K4 Flexibility and scalability			
K5 Human-centric (ergonomics, safety)			
K6 Resilience and sustainability			

Thank you for your time and expert contribution to this research.

Appendix H

Gant chart for manufacturing system design Plan D versus Plan T analyse



Note: This Gantt chart is shown for information only. The complete Gantt chart in its original size and resolution is available as a separate PDF attachment, suitable for clear reading.