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AI Potential in the Mechatronic Product Development

Identification, Utilization and Evaluation

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Abstract

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This thesis explores the potential of Artificial Intelligence (AI) in mechatronic product development, focusing on the identification, utilization, and evaluation of AI-driven approaches. The increasing complexity of cross-domain collaboration, coupled with the demand for efficiency and reliability, necessitates structured methodologies to systematically integrate AI into engineering processes. While AI offers significant opportunities, challenges related to trustworthiness, robustness, and effective implementation remain critical considerations.

To address these challenges, this work introduces a generalized five-step methodology, providing a structured framework for assessing AI's role in mechatronic development. The methodology enables the targeted identification of AI potential, structured integration into engineering workflows, and systematic evaluation of its impact. By applying this framework to real-world industrial case studies, the thesis demonstrates its practical applicability across different AI use cases, including translation, interpretation, and prediction.

As mechatronic product development continues to evolve, leveraging AI in a structured and validated manner ensures that organizations not only overcome current challenges but also enhance innovation, decision-making, and cross-domain collaboration. The findings of this thesis provide a scalable foundation for AI-driven advancements while maintaining a balance between AI potential and investment considerations.

Keywords: Generalization Framework, Mechatronic Product Development, AI in Engineering, Decision Support Systems, Knowledge Integration, Human-AI Collaboration, Trustworthy AI, AI Potential Assessment, Industrial AI Applications

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To Henry, Mae, Lea, Martina and Thomas

List of Papers

This thesis is based on the following papers, which are referred to in the text by their Roman numerals.

I. **Nüßgen, A.**, Degen, R., Irmer, M., Boström, C., Ruschitzka, M., "Leveraging Robust Artificial Intelligence for Mechatronic Product Development - A Literature Review," *International Journal of Intelligence Science*, Vol. 14, No. 1, January 2024.
II. **Nüßgen, A.**, Degen, R., Irmer, M., Boström, C., Ruschitzka, M., "Intelligent analysis of components with regard to significant features for subsequent classification," *SAE Technical Paper*, June 2023.
III. **Nüßgen, A.**, Richter, F., Lerch, A., Degen, R., Irmer, M., Bos tröm, C., Ruschitzka, M., "Intelligent Component Manufacturability Testing in Virtual Product Development," *Proc. Artificial Intelligence und Machine Learning in der CAE-basierten Simulation*, October 2023, Munich, Germany.
IV. **Nüßgen, A.**, Richter, F., Krach, N., Irmer, M., Degen, R., Boström, C., Ruschitzka, M., "Robustness and Sensitivity of Artifi- cial Neural Networks for Mechatronic Product Development," *Proc. Automotive meets Electronics*, June 2023, Dortmund, Germany.
V. **Nüßgen, A.**, Lerch, A., Degen, R., Irmer, M., de Fries, M., Richter, F., Boström, C., Ruschitzka, M., "Reinforcement Learning in Mechatronic Systems: A Case Study on DC Motor Control," *Circuits and Systems*, Vol. 16, No.1, January 2025.
VI. Metzler, C., Hemel, U., Leibrock, E., **Nüßgen, A.**, Ruschitzka, M., "Künstliche Intelligenz als Co-Pilot – Warum Unternehmen im Fahrersitz bleiben müssen," *IW Policy Paper*, No.1, April 2024.
VII. Degen, R., Tauber, A., Irmer, M., **Nüßgen, A.**, Klein, F., Schyr, C., Leijon, M., Ruschitzka, M., "Integration of Vulnerable Road Users Behavior into a Virtual Test Environment for Highly Automated Mobility Systems," *Proc. Kolloquium Future Mobility*, June 2022, Ostfildern, Germany.

VIII. Degen, R., **Nüßgen, A.**, Irmer, M., Klein, F., Schyr, C., Leijon, M., Ruschitzka, M., "Data Flow Management Requirements for Virtual Testing of Highly Automated Vehicles," *Proc. AVL Ger- man Simulation Conference*, September 2022, Regensburg, Ger- many.

IX. Irmer, M., Degen, R., **Nüßgen, A.**, Thomas, K., Henrichfreise, H., Ruschitzka, M., "Development and Analysis of a Detail Model for Steer-by-Wire Systems," *IEEE Access*, Vol.11, pp. 7229-7236, January 2023.

X. Irmer, M., Rosenthal, R., **Nüßgen, A.**, Degen, R., Thomas, K., Ruschitzka, M., "Design of a Model-Based Optimal Multivariable Control for the Individual Wheel Slip of a Two-Track Vehicle," *SAE Technical Paper*, 2023-01-1219, June 2023.

XI. Irmer, M., Ott, H., Degen, R., **Nüßgen, A.**, Thomas, K., Ruschitzka, M., "Methodical Data Collection for Light Electric Vehicles to validate Simulation Models and fit AI-based Driver Assistance Systems," *Proc. Kolloquium Future Mobility*, June 2022, Ostfildern, Germany.

Other contributions of the author, not included in the thesis.

I. Ruschitzka, M., de Fries, M., Irmer, M., **Nüßgen, A.**, "KI in der Entwicklung & Produktion - Ein Schritt-für-Schritt-Leitfaden zur Programmierung Künstlicher Intelligenz," *Trend-Auto2030plus Guide*, September 2024.

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Contents

Introduction

Parts of the following chapter are adapted from the author's licentiate thesis [1]. An overview of the entire dissertation structure, including which sections build on the prior work and which are newly added, will be provided in the first chapter.

The modern (virtual) product development for mechatronic products has developed steadily in recent years. Complexity has increased throughout, development cycles have become shorter, and demands have become greater. At the same time, however, the knowledge base has also grown continuously: on the one hand, through "real" data and information and, on the other, through virtual or synthetic sources of knowledge - Artificial Intelligence (AI).

> *For the sustainable operation of AI systems, a data-driven mindset must be anchored throughout the company.*
>
> Beate Hofer, CIO, Volkswagen AG

As a result, there are major shifts, propelled by the impressive advancements in AI technologies, as evidenced by [2] and [3]. This technological progress has emerged as a potent force in development, offering augmentation and support throughout the entire lifecycle of mechatronic product development. AI's capacity to analyze extensive datasets, identify patterns, and learn from examples positions it as a formidable catalyst with the potential to revolutionize the industry, as elucidated in [4].

Many large companies are already taking advantage of this circumstance, although in many cases, they may not accurately assess the holistic situation or have thoroughly considered all the challenges. For example, in early January 2024, it was announced that the management, strategy consulting and auditing firm Deloitte is rolling out its internal AI co-pilot to a significant portion of its workforce. As a result, this AI system is intended to assist with daily tasks such as composing emails and creating presentations. However, the company simultaneously cautions its employees to exercise carefulness, as the AI has the potential to generate false statements about real individuals, places, or facts. To counteract this, Deloitte is implementing corresponding training measures. Given that untruths in fields such as medicine, defense, and politics, which are among Deloitte's clients, could have devastating consequences, developing an awareness of the limitations of AI and simultaneously assessing the reliability of the models becomes a logical imperative. [5]

Intelligence-driven Opportunities

Mechatronic product development is a multifaceted endeavor encompassing various disciplines, including mechanical engineering, electrical engineering, control theory, and software engineering. This means that many different domains and thus also human experts as well as domain-specific tools, working methods and even languages must harmonize with each other. [6], [7]

VDI 2206 underscores these observations. In 2021, the document underwent a generous revision with the expanded title "Development of mechatronic and cyber-physical systems". According to the Association of German Engineers, this is due to the fact that mechatronic systems now "also have data interfaces to other components and devices. In this way, they are themselves cyber-physical systems and become part of a higher-level network. The complexity, interdisciplinarity and heterogeneity of such systems is thus constantly increasing." [8]

Subsequently, it is worth looking at the corresponding and current V-model that emerges from VDI 2206. This can be found in Figure 1.

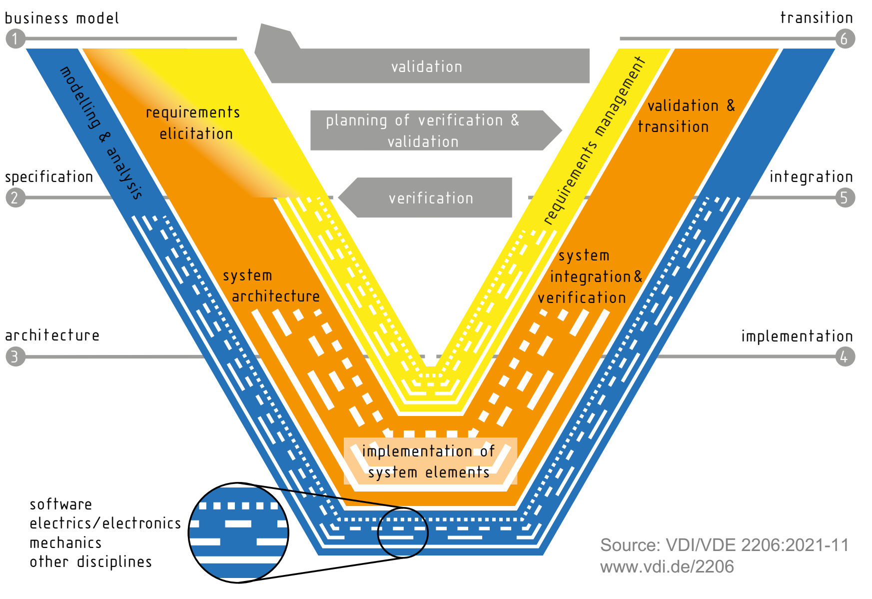


Figure 1: The latest version of the V-model according to VDI/VDE 2206 of November 2021

New in the 2021 version from Figure 1 is, that the depicted framework illustrates the comprehensive approach to system analysis, modeling, and development, wherein three interrelated strands encapsulate distinct yet interconnected aspects.

The inner strand is devoted to the crucial aspect of requirements engineering, underscoring the perpetual management and refinement of requirements throughout the development lifecycle. The middle strand encompasses the core activities involved in system development. Finally, the outer strand pertains to the modeling and analysis of the system along with its potential subsystems, which operate in parallel to the central development tasks. This systematic representation facilitates a rigorous and holistic scientific examination of the entire development process.

To visually illustrate the interplay between these disciplines, the three strands are depicted as interconnected subareas using various line styles, such as dotted, dashed, or solid lines. This graphical portrayal accentuates that the implementation of system elements relies on profound interconnections between the involved disciplines. The intricate networking between these facets ensures a cohesive and comprehensive approach to system development, bolstering its scientific rigor.

The challenges of effective interdisciplinary collaboration

To operationalize interdisciplinary collaboration effectively, it is imperative for domains to collaboratively advance in unison. However, the practical manifestation of this collaborative spirit often deviates from the ideal. This discrepancy can be attributed to several factors:

Synchronization Imperatives - Instances frequently arise where individual domains necessitate information or knowledge from other domains at specific junctures. However, these domains may not have reached the requisite stage, rendering them unable to provide any information, not even a rudimentary estimate. This intricacy engenders the subsequent phenomenon.

Divergent Work Paces and Sequences - Given that each domain pursues distinct goals, and these objectives may not align resource-wise with those of other domains, the tempo and sequential arrangement of steps can markedly differ. This incongruity poses significant challenges concerning the aforementioned synchronization, making it arduous or delayed.

Impaired Communication through disparate Languages - Owing to the diverse nature of domains, which demand expertise from distinct professionals, variations in knowledge bases and communication styles emerge, resembling a scenario of heterogeneous languages. Consequently, communication may lack precision, leading to the inadvertent loss of crucial details.

Addressing these challenges necessitates a strategic and adept incorporation of AI which holds promise as a robust solution to these multifaceted issues. By deploying these technologies, such as Intelligent Knowledge Management, AI-based Data Analysis Tools and Interface Automation, domains will bridge the gaps in synchronization, expedite workflows, and facilitate more seamless communication. This targeted and judicious utilization of AI not only addresses the outlined challenges but also opens avenues for enhanced efficiency and innovation in interdisciplinary collaboration.

In relation to the preliminary identified use cases for the methodology, which are to be implemented at a later stage in the actual project, an examination of the aforementioned possibilities to address challenges and simultaneously increase efficiency and innovation levels is conducted. A practical application of the presented methods is demonstrated through three real industrial scenarios, each of which showcases a different way in which AI can facilitate mechatronic product development. These scenarios span bridging domain boundaries, interpreting complex manufacturing data, and predicting optimal configurations, demonstrating how AI-driven solutions can reduce departmental friction, improve overall process consistency, and significantly enhance the quality of outcomes. By establishing an AI-based knowledge base early in the development cycle, these approaches contribute to more efficient collaboration among key stakeholders, resulting in smoother coordination from initial concepts through to final production.

Aim and Outline of the Thesis

The Overall Research Question of this thesis is:

> **How can the mechatronic system design be supported and synchronized in the context of Co-Simulation by using predictive information and rules generated by a robustness-checked AI which is fed through the knowledge base?**

This derives into four detailed Research Questions:

- R1 How can the **relevant areas of knowledge and non-knowledge** in mechatronic development processes be identified, evaluated and delimited from each other in order to reach the **acceptable level of ignorance competence** through targeted knowledge mining? (*Paper II-III*)
- R2 How can the critical **analysis parameters for success** and the **ideally suitable segments of the development process** for the use of robust and context-sensitive AI be identified? (*Paper IV*)
- R3 How does the **process for the linking** of diverse mechatronic domains within a co-simulation framework succeed **through translation, interpretation and prediction approaches** using AI? (*Paper V-VI*)
- R4 How can previous development sub-processes for cross-domain tasks evolve with respect to the **new mutual synchronization capabilities** made possible by the robust AI and how do these new requirements **influence the current methodology**? (*Paper I*)

Overview of the Document Structure

The document is organized into the following main chapters:

1. **Introduction** *(Adapted)*
   Provides background information, clarifies the research objectives, and outlines the overall approach. It includes a concise summary of the guiding research questions and their influence on the study.
2. **State of Science and Technology** *(Adapted)*
   Reviews existing literature and industrial practices, AI techniques, and interdisciplinary collaboration challenges.
3. **Conception of the Methodology** *(Adapted)*
   Presents the initial conceptual framework for AI integration in mechatronic development, drawing on insights from the licentiate thesis as the foundation for the structured approach.
4. **Detailing the Methodology** *(Enhanced)*
   Expands on each methodological step, providing theoretical justifications, illustrations, and references to practical examples while refining the earlier methods.
5. **Generalizing the Methodology** *(New)*
   Extends the developed methodology into a generalized framework for AI integration, systematically assessing feasibility and impact. The five-stage approach ensures a coherent process, with the final step incorporating structured AI potential measurement.
6. **Validating the Methodology through Real-World AI Applications** *(New)*
   Demonstrates the methodology's practical applicability by examining real-world AI implementations in industry. The selected case studies illustrate different AI applications and are assessed using the multi-step framework developed in the previous chapter.
7. **Summary and Conclusion** *(Adapted)*
   Synthesizes the central findings, revisits the research questions, and evaluates how the methodology and case studies contribute to advancing knowledge in the field.

A significant portion of the chapters, particularly **Conception of the Methodology** and **Detailing the Methodology**, draw extensively on material from the licentiate thesis. In contrast, **Generalizing the Methodology** and **Validating the Methodology through Real-World AI Applications** represent novel contributions, extending the research framework and applying it to real-world cases. This structure maintains continuity with earlier work while reflecting the expanded scope and contributions of the doctoral study.

Research Design

At the beginning of a thesis, the question usually arises as to which research method should be used to achieve the goals. This method aims to both acquire insights and verify them, thereby aiding in solving scientific challenges. The choice of method significantly influences the process. Therefore, it is important to systematically plan and purposefully design the research approach to generate a coherent argumentation chain and promising results. [9], [10]

The research methodology adopted in this study adheres to the constructive principles of Design Science proposed by [11], while also incorporating the extended methods introduced by [12]. According to these methodologies, Design Science encompasses two primary activities: creation and assessment. "Creation" involves constructing an artifact tailored for a particular purpose, while "assessment" entails evaluating the effectiveness of said artifact.

A conceptual framework for information system research has been developed based on these approaches, as depicted in Figure 2.

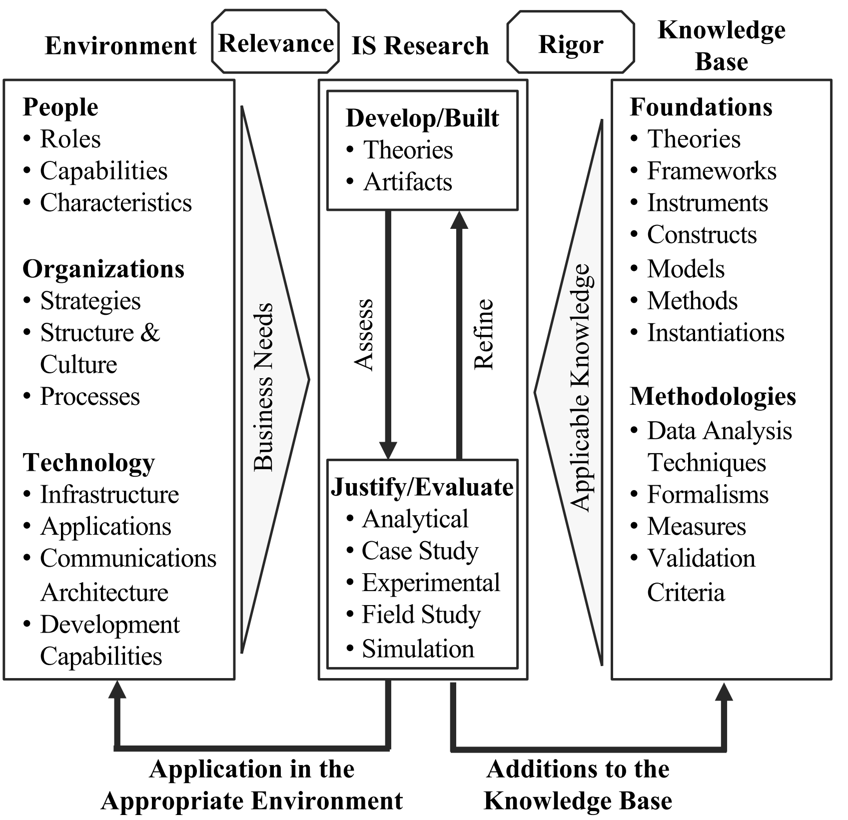


Figure 2: Conceptual framework for information systems research according to [13], layout-matched

The criteria for ensuring quality, as formulated by [14] and pursued in this work, include: relevance, rigor, objectivity, reliability, authenticity, transferability, and action orientation.

After selecting the methodology, the question arises of which research approach the scientific work belongs to and consequently, how it should be structured. The approach of this work is inductive in nature and can be classified in the field of applied research. The aim of this genre is to develop and shape a new theory, or in the case of this work, a new methodology or solution, based on research. Works in this field typically address significant practical challenges. In relation to the project presented here, this therefore concerns the integration of efficient and robust AI into mechatronic product development, including the resulting effects and the outlook for the future and the corresponding prospects.

The criteria for a contribution to the state of the art include the following points according to [13] and therefore especially the Guideline 4:

- new process, product or design object
  → **synchronize newly linked cross-domain tasks smarter through robust AI**
- important unsolved problem class to be solved
  → **existing asynchrony of domains and different language**
- proposes generalizable solution
  → **positively influence the current methodology over time**
- investigates the solution empirically
  → **proof of concept through appropriate data and examples**

Four steps are derived from these circumstances, shown in Figure 3.

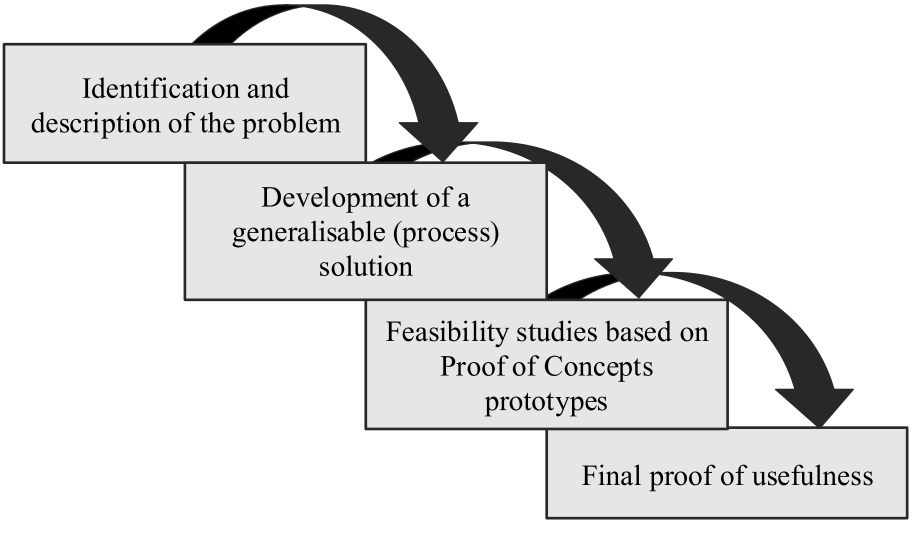


Figure 3: The four identified steps for this work in the context of Applied Research based on [11], [13], [15]

Having successfully accomplished the identification and description of the problem at hand, the next phase of the investigation involves a comprehensive examination of the current state of the art within both the research landscape and industrial practices. This analysis aims to provide a contextual backdrop for the subsequent development of the methodical approach, which is designed to facilitate a broad and generalized integration of AI within the developmental process.

The Methodical Approach is a pivotal component of the research, serving as a strategic framework for the application of AI across diverse facets of the development process. This involves a systematic and carefully designed approach to harnessing AI's capabilities, thereby enhancing efficiency and effectiveness.

Following the formulation of the Methodical Approach, the research will delve into the exploration of individual aspects related to potential application areas. This detailed investigation seeks to unravel the intricacies of applying AI, providing insights into its nuances, challenges, and potential synergies with existing practices. The focus here is not only on theoretical considerations but also on practical assessments to confirm the real-world effectiveness of AI applications.

As the research progresses, the conclusive proof of the utility of the proposed method will be a critical juncture. Positive results from the explorations will serve as the empirical foundation to substantiate the benefits of integrating AI within the development process. This final step aims to provide a compelling case for the adoption of the method, underscoring its value and significance in addressing the identified problem. [15], [11]

State of Science and Technology

The following chapter provides an overview of the state of the art both in the field of research and in the context of industrial utilization and is adapted from the author's licentiate thesis [1].

In the context of the research landscape, significant activities are evident. However, when it comes to mechatronic product development, the situation is different. While looking at current and past publication titles there are occasional attempts to leverage AI profitably, but these efforts typically focus on individual aspects, neglecting a holistic examination of the entire development process. Examples for this would be [16], [17], [18].

To thoroughly investigate and substantiate this observation, a compilation of pertinent categories with the target of a detailed analysis has been undertaken. These categories are crucial for the meaningful utilization of intelligent methods for the product development. They include:

- **Consideration of the Holistic Cycle** - Evaluate the extent to which AI is already integrated into the overall mechatronic product development process. This involves assessing the incorporation of AI at various stages, from conceptualization to prototyping, testing, and deployment.
- **Domain Linking** - Investigate how AI facilitates the integration and linking of diverse domains involved in mechatronic product development, such as mechanics, electronics, controls, and software. Assess the impact on decision-making, interoperability, and the identification of design conflicts or trade-offs.
- **Replacement for Human Expert Knowledge** - Analyze the role of AI in complementing or potentially replacing human expert knowledge in mechatronic product development. Evaluate how AI models, trained on big data and domain-specific knowledge, contribute to consistent and reliable decision-making.
- **Differentiation from non-relevant Knowledge** - Assess the capability of AI databases to differentiate between relevant and non-relevant knowledge. Explore how advanced search algorithms, Natural Language Processing (NLP), and semantic analysis contribute to prioritizing pertinent information and reducing information overload.

- **Consideration of Knowledge Gaps -** Investigate how AI databases assist in identifying and bridging knowledge gaps within mechatronic product development. Explore the use of knowledge graphs and machine learning algorithms to infer missing information and validate the data to ensure accuracy and reliability.
- **Robustness of Prediction Quality -** Evaluate approaches to quantify and predict uncertainties inherent in AI, especially within Artificial Neural Networks (ANNs). Examine methods to calculate additional output values reflecting the network's confidence in predictions, providing users with insights into potential deviations.
- **Consideration of Optimization Proposals with AI -** Explore the opportunities provided by AI databases for suggesting optimization proposals in mechatronic product development. Assess how AI analyses data to identify areas for improvement, propose design modifications, and enhance performance based on historical data, simulations, and benchmarks.
- **Application to one or more Proofs of Concept -** Examine the application of AI concepts and methods to one or more proofs of concept.

In order to be able to provide an assessment of the respective research activities, a corresponding scale is introduced. The evaluation will employ a five-level scheme represented by circles, each indicating the degree of consideration for a specific characteristic:

1. **No consideration** (circle not filled): The literature lacks attention to the characteristic, with no meaningful reference or discussion.
2. **Rudimentary consideration** (circle 1/4 filled): The literature provides a basic acknowledgment of the characteristic, with minor references or brief discussions lacking depth or analysis.
3. **Balanced consideration** (circle 1/2 filled): The literature exhibits a moderate and well-rounded consideration, with reasonable attention, various aspects, and a relatively comprehensive analysis.
4. **High focus** (circle 3/4 filled): The literature demonstrates a substantial focus on the characteristic, dedicating a significant portion of content to in-depth exploration, offering valuable insights and extensive discussions.
5. **Holistic consideration** (circle fully filled): At the highest level, the literature exemplifies a comprehensive and all-encompassing consideration of the characteristic. Thorough analysis covers every aspect, showcasing a profound understanding and valuable contributions to the field.

Figure 4 illustrates the outcomes of the conducted investigation regarding the theoretical deficit.

Theory Deficit		Consideration of the Holistic Cycle	Domain Linking	Replacement for Human Expert Knowledge	Differentiation from Non-relevant Knowledge	Consideration of Knowledge Gaps	Robustness of Prediction Quality	Consideration of Optimization Proposals with AI	Application to one or more proofs of concept
[16]	An Artificial Intelligence approach for the multicriteria optimization in mechatronic products design	◑	○	◑	○	○	○	●	●
[19]	Application and research of artificial intelligence in mechatronic engineering	◑	◑	◕	○	○	○	●	○
[20]	Application of Intelligent Systems in Multi-modal Information Analytics (…)	◔	◔	○	○	○	○	◕	○
[21]	Application Research of Mechatronics System Based on Computer Artificial Intelligence Technology	○	○	◔	○	○	○	●	●
[22]	Concept for an integrated product and process development of electric drives using a knowledge-based system	◑	●	●	◔	◔	○	○	○
[23]	Difficulties of mechanical engineering students in developing integrated knowledge for the cross-discipline of mechatronics: a conceptual investigation	○	◕	◔	◔	◔	○	○	◑
[24]	Early reliability estimation in automotive industry	◕	○	◑	○	○	●	○	●
[25]	Exploration of the Application of Artificial Intelligence Technology in Mechatronics Technology Based on	◑	◑	◕	○	○	○	◕	○
[26]	Grundlagen für einen mechatronischen Effektkatalog	◑	◑	◕	○	◔	○	○	○
[27]	Industrial Artificial Intelligence in Industry 4.0 - Systematic Review, Challenges and Outlook	◑	◑	◑	◑	◔	◕	●	○
[28]	Integration of Artificial Intelligence Techniques in Mechatronic Systems for Smart Manufacturing	◑	◔	◔	○	○	○	●	○
[29]	Introducing the Electronic Knowledge Framework into the Traditional Automotive Suppliers' Industry: From Mechanical Engineering to Mechatronics	◑	◑	◑	◔	◔	○	○	◕
[30]	Knowledge capitalization in mechatronic collaborative design	◑	●	◕	◔	◔	○	○	◕
[31]	Knowledge sharing for mechatronic systems design and optimization	◕	◕	●	◑	◑	○	○	●
[32]	Knowledge-based engineering for multidisciplinary systems: Integrated design based on interface model	◑	●	◕	◔	◔	○	○	◕
[33]	Konzept für eine simulationsgetriebene-wissensbasierte Produktentwicklung im Umfeld mechatronischer Produkte	◕	◕	◕	◔	◑	◑	○	◑
[17]	Mechatronic Design and Optimization Using Knowledge Based Engineering Applied to an Inherently Unstable and Unmanned Aerial Vehicle	◔	◑	◕	○	◔	○	○	●
[34]	Mechatronics - A unifying interdisciplinary and intelligent engineering science paradigm	●	●	◕	◔	◔	○	○	○
[18]	Overview of the Relationship between Mechatronic Engineering and Artificial Intelligence	◔	◔	○	○	○	○	●	○
[35]	Requirements Management When Introducing New Mechatronic Sub-systems - Managing the Knowledge Gaps	◔	●	◕	◑	◕	○	○	◑
[36]	Special Issue on Application of Artificial Intelligence in Mechatronics	◔	◔	◔	○	○	○	◑	○
[37]	Systemorientierte Visualisierung disziplinübergreifender Entwicklungsabhängigkeiten mechatronischer Automobilsysteme	●	●	◕	◑	◑	○	○	◔
[38]	The science and education of mechatronics engineering	◑	●	◔	○	○	○	○	○
[39]	Towards an Integrated Conceptual Design Evaluation of Mechatronic Systems: The SysDICE Approach	◕	●	◑	◔	◔	○	◑	◕
[40]	Transdisciplinary Approach of the Mechatronics in the Knowledge Based Society	◑	●	●	○	◔	○	○	○
[41]	Verknüpfungsmodell zuverlässigkeitsrelevanter Informationen in der Produktentwicklung mechatronischer Systeme	◕	●	●	◑	◕	○	○	●
[42]	Wissensmanagement: Zwischen Wissen und Nichtwissen	○	○	○	●	◕	○	○	◔
[43]	Zuverlässigkeitsbewertung mechatronischer Systeme in frühen Entwicklungsphasen	◕	◕	◔	◔	○	●	○	●

Figure 4: The literature analysis in detail, developed in Paper I

The visual result is emphasizing the anticipated observation that while individual aspects are occasionally explored in detail, a comprehensive perspective on the overall context is still lacking.

Consequently, there is an absence of a recommended course of action that stakeholders can follow to effectively harness the potential of AI. This deficit in a holistic approach impedes the identification of a strategic pathway to fully exploit the opportunities presented by the intelligent methods. Additional investigations and aspects can be found in **Paper I**.

In practice, the situation is analogous, with substantial expectations concerning current and future potentials. This is corroborated by trend reports from leading global consulting companies. For instance, **McKinsey & Company**, in their document titled *The economic potential of generative AI*, published in June 2023, explore various future impacts of the ongoing mega-trend of generative AI. They shed light on diverse scenarios, including the transformation of software engineering and R&D resulting from the effective use of AI, as seen in Figure 5. [44] The prevailing expectation is unequivocally oriented towards holistically supporting the development processes in both areas - commencing from initiation and planning, extending to system design, and culminating in maintenance and diagnosis.

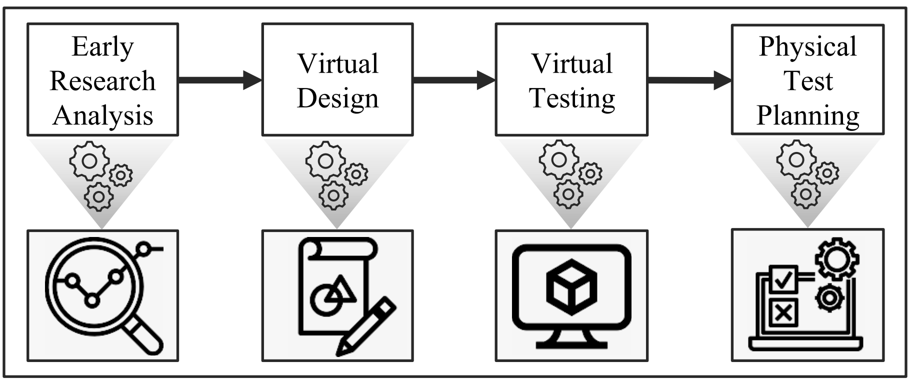


Figure 5: The possible transformation fields of product R&D through AI according to the report of McKinsey & Company [44]

As emphasized Research and Development stands on the brink of transformation, with the integration of cutting-edge technologies promising to revolutionize traditional processes.

Early-stage analysis is undergoing a profound shift as researchers leverage generative AI to augment market reporting, ideation, and the initial drafting of products or solutions. This application empowers them to delve deeper into market insights and swiftly generate innovative concepts.

The virtual design phase sees a significant evolution as generative AI enables researchers to swiftly generate drafts and designs based on prompts, thereby facilitating rapid iteration with a plethora of design options. This acceleration not only expedites the design process but also enhances creativity and exploration.

Virtual testing, a crucial aspect of product development, is also benefiting from advancements in generative AI. By integrating new deep learning techniques, researchers are streamlining and optimizing simulations, leading to faster and more precise outcomes.

Furthermore, in the realm of physical testing, generative AI is revolutionizing test planning. Researchers are now able to optimize test cases, resulting in more efficient testing processes and reduced time requirements for physical build and testing. This optimization not only saves time and resources but also enhances the overall efficacy of the testing phase.

Similarly, **Gartner**, a trend research company, annually publishes so-called *Hype Cycles* for a general technology radar and specific disciplines. The *Hype Cycle for Artificial Intelligence, 2023,* as well as the others, comprises phases such as

1. Innovation Trigger,
2. Peak of Inflated Expectations,
3. Trough of Disillusionment,
4. Slope of Enlightenment
5. and Plateau of Productivity.

As shown in Figure 6 the time axis is represented on the abscissa, while the degree of expectation is depicted on the ordinate.

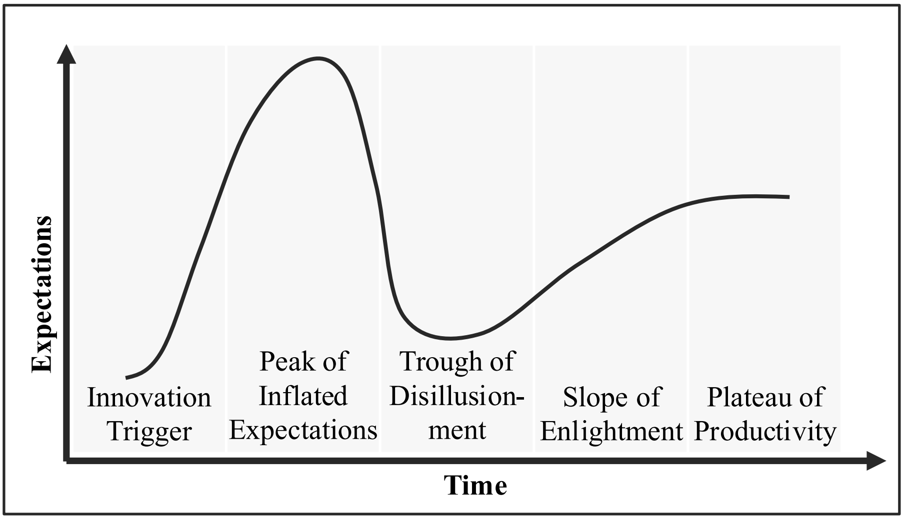


Figure 6: The scheme of the 2023 Gartner Hype Cycle™ for Artificial Intelligence (AI) [45], layout-matched

It is important to emphasize that the temporal categorization is symbol-based. For instance, Artificial General Intelligence is currently transitioning between

Phase 1 and 2 but is anticipated to reach the plateau in more than ten years which is a significant temporal duration in the realm of technologies.

Turning attention to technologies relevant to mechatronic product development, terms like AI Engineering and AI Simulation quickly emerge. According to Gartner's assessment, these technologies are currently in the first phase and are expected to reach the plateau in five to ten years. Knowledge Graphs, experiencing a resurgence in research due to AI trends, currently find themselves in the Trough of Disillusionment and are projected to reach the desired plateau of productive utilization in two to five years.

In summary, it is evident that individual phenomena related to AI potentials exist and are adequately explored. However, a comprehensive understanding and utilization of these effects are still pending. Such a holistic perspective will serve as a guide for stakeholders, aiding in the initial integration of possibilities and the exploration of new avenues.

Conception of the Methodology

The following chapter introduces the conceptual foundations of the developed methodology, outlining its role in integrating AI into mechatronic product development. It discusses key requirements, classification approaches, and methodological considerations. The chapter is adapted from the author's licentiate thesis [1].

Following the presentation of the initial project outline and the underlying situations in theory and practice with associated deficits, the development of a methodology for successful potential analysis of robust AI along the development process is now underway. As a first step, the development of the necessary rough concept is based. For this purpose, the development of a corresponding request image is initially carried out, visualizing the utilization potentials of the approach in detail once again. Subsequently, a detailed analysis of the phases and handover points of the V-model takes place, aiming to identify suitable support options for AI applications and the associated requirements as well as the prospects for success. Following this, requirements for the methodology to be developed are elaborated to ensure alignment with the identified deficits and target criteria. Building on this, the actual rough concept is constructed with the associated methodological steps.

Utilization Potential of AI along Product Development

In the realm of product development, the integration of AI holds immense potential for enhancing efficiency, innovation, and competitiveness. However, harnessing this potential requires careful consideration of various requirements, particularly in terms of accuracy and reliability. Therefore, the goal is to present a request image that visualizes the evolving demands placed on AI throughout the product development process.

As products evolve from conceptualization to market launch, the requests placed on AI systems undergo a corresponding evolution. At each stage of development, specific requirements regarding accuracy and reliability become increasingly critical. Understanding this evolution is essential for effectively harnessing AI's potential in product development.

The request image serves as a representation of the evolving requirements for AI accuracy and reliability throughout the product development process. It provides a clear and concise overview of how the demands placed on AI systems change as products progress from conceptualization to deployment.

The horizontal axis delineates the various stages of product development, from conceptualization and design to production and deployment. Each stage represents a distinct phase in the lifecycle, characterized by specific activities, milestones, and objectives. By organizing the stages of development along the horizontal axis, the target image provides a chronological framework for understanding how the demands placed on AI systems evolve over time.

The vertical axis of the request image quantifies the level of requirements for AI accuracy and reliability at each stage of the product development. This axis serves as a metric for assessing the criticality of accuracy and reliability in AI applications. At the bottom of the vertical axis, the level of requirements is minimal, indicating that accuracy and reliability are of lesser importance. As the axis ascends, the level of requirements increases, reflecting the growing importance of accuracy and reliability in AI systems.

By examining the request image, stakeholders can gain valuable insights into the evolving demands placed on AI systems throughout the product development process. Trends and patterns in the image can highlight areas where AI capabilities need to be strengthened or where additional resources should be allocated to ensure the success of the product.

The resulting request image is shown in Figure 7. The individual phases are explained in more detail in the following.

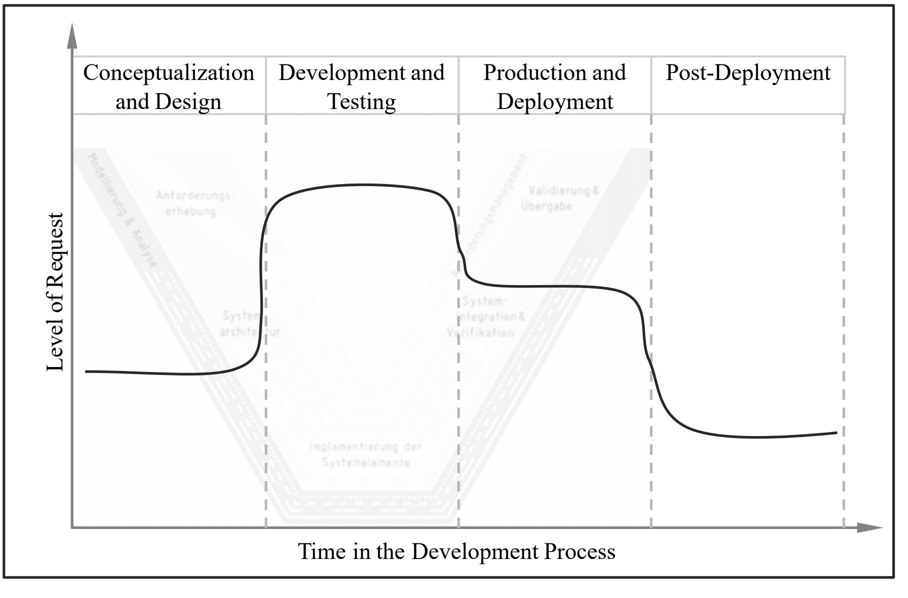


Figure 7: Request Image for Utilization Potential of AI along Product Development

During the **conceptualization and design phase**, AI is primarily utilized for ideation, prototyping, and feasibility analysis. At this stage, the emphasis is on creativity, exploration, and experimentation. While accuracy and reliability are important, they are not always paramount. The request image reflects a relatively low level of requirements for AI accuracy and reliability during this phase, as the focus is on generating diverse ideas and concepts.

As the product moves into the **development and testing phase**, the demands placed on AI systems reach their peak. Here, AI is used for tasks such as simulation, optimization, and validation. Accuracy and reliability become critical considerations, particularly as AI algorithms are deployed to predict performance, simulate behavior, and identify potential defects. The request image illustrates a significant increase in the requirements for AI accuracy and reliability during this phase, reflecting the need for robust and trustworthy AI.

In the final stages of **production and deployment**, AI is used for tasks such as quality control, predictive maintenance, and customer support. At this stage, the reliability is paramount, as it directly impacts product performance, safety, and customer satisfaction. The request image depicts a peak in the requirements for accuracy and reliability during this phase, reflecting the critical role in ensuring the success and longevity of the product in the market.

Even after the product is launched, in the so-called **post-deployment phase**, the demands placed on AI systems continue to evolve. As data accumulates and user feedback is collected, AI algorithms must adapt and improve over time. The request image represents this ongoing process of refinement, with the requirements for AI accuracy and reliability fluctuating as new challenges emerge and new opportunities arise.

The Linking Points of AI in the V-Model

As delineated earlier, the V-Model serves as a pivotal framework in software development and testing, offering a systematic approach to ensure the quality and dependability of software systems. Its distinctive "V" shape visually captures the interconnectedness of development and testing stages, with each development phase mirrored by a corresponding testing phase on the opposite side of the V. This model's applicability extends notably to mechatronic product development, providing a structured means to develop and validate all constituent components and their intricate interconnections. [8]

The overall aim is to bolster and enhance the effectiveness of all phases within this development process, as well as analogous or comparable processes, by adding meaningful value. Therefore, the subsequent phase involves the formulation of a dedicated process concept tailored for the context-sensitive and robust utilization of AI in V-Model-related product development. This seeks to leverage the capabilities of AI in a manner that aligns seamlessly with the specificities of the V-Model, as seen in Figure 8.

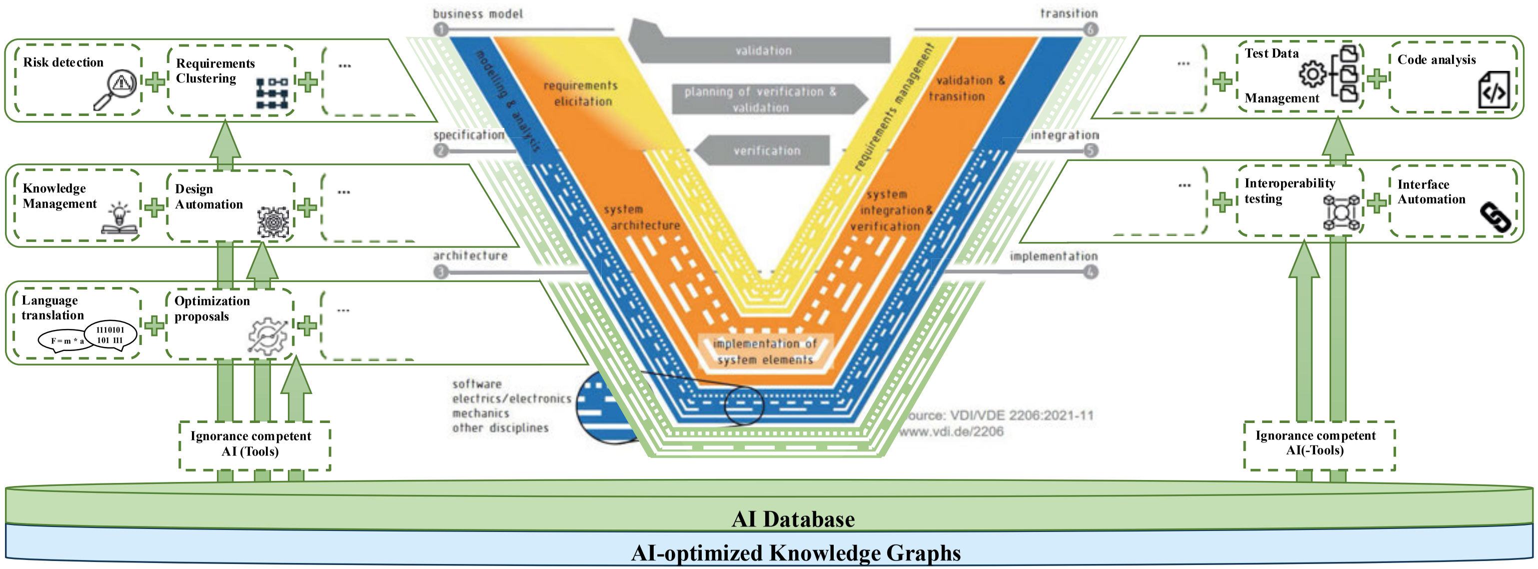


Figure 8: The process concept for holistic utilization of the potential of AI in the product development cycle

The concept addresses the nuances of integrating AI across diverse stages, ensuring not only contextual relevance but also resilience in the face of uncertainties and variations inherent in the product development lifecycle. By doing so, the proposed concept aims to advance the state-of-the-art in mechatronic product development, offering a roadmap for the effective incorporation of AI within the structured framework of the V-Model.

Initiating with an established business model (**Checkpoint 1**), the cycle transitions into the specification phase, where requirements for the mechatronic system are meticulously gathered and analyzed, spanning mechanical, electronic, and software aspects. These requirements form the foundation for the entire process. AI's utility extends to automated requirement capture, NLP, and early risk detection, among other capabilities. [46], [47], [48], [49]

Checkpoint 2 marks the conclusion of the specification phase, leading to the commencement of the system architecture phase. This stage involves integrating mechanical, electronic, and software components, ensuring alignment with requirements using the V-Model. The phase culminates in the establishment of architecture (**Checkpoint 3**). AI's support in this stage encompasses design automation, simulation models, error detection, collaboration, and knowledge management. [50], [51], [52], [53]

The implementation of system elements, the visually lengthiest phase, follows, encompassing the development of subsystems like mechanical structures, electronic components, and software modules. AI plays a pivotal role in translation, interpretation, and prediction approaches. The successful completion leads to **Checkpoint 4**, Implementation. [19], [54], [55]

System integration and verification come next, emphasizing seamless collaboration among mechanical, electronic, and software subsystems. The V-Model ensures proper functioning, concluding at **Checkpoint 5**. AI's support in this phase extends to interface automation and real-time monitoring, as highlighted in sources such as [56], [57], [58].

The final phase involves validation and transition, ensuring each component and subsystem meets requirements and functions correctly within the integrated mechatronic system. **Checkpoint 6** marks the completion, with AI contributing to intelligent test selection, test data management, and the generation or anonymization of synthetic data. [8], [59], [60]

Requirements for the Methodology

For a successful deployment of AI into the product development it essential to define the right requirements and generate the correct specific metrics. The task is therefore to examine how these processes can be designed to develop robust AI solutions that meet the requirements of product engineering. [61]

Requirement collection is the foundational stage in the process. It entails a detailed examination of the company's overarching goals and objectives, alongside a comprehensive understanding of the demands and preferences of end-users. To achieve this, various methodologies such as interviews, surveys, workshops, and focus groups are often employed, facilitating a holistic grasp of the intricate nuances and specificities. Additionally, stakeholder consultations and market research play pivotal roles in ensuring that the collected requirements are not only comprehensive but also align closely with market trends and emerging technological advancements. This phase serves as the bedrock upon which subsequent stages of AI implementation, such as design and development, are built, thereby laying a solid foundation for the creation of innovative and user-centric AI-driven products and services. [62], [63], [64]

Key questions to be addressed include:

- What problems are to be solved through the use of AI?
- What are the requirements of end-users for AI-powered products?
- What data is required for the development of the AI solution?
- What technical and regulatory requirements need to be met?

The next crucial step is developing specific metrics to gauge efficacy and success. These quantifiable benchmarks enable a structured evaluation of performance and impact, aligning seamlessly with the company's objectives and overarching goals.

Each metric should be clearly defined with precise parameters delineating its scope and measurement methodology. Moreover, these metrics ought to be dynamic, capable of adapting to evolving business needs and technological advancements. By closely aligning these metrics with the company's strategic vision and operational objectives, stakeholders can effectively monitor progress, identify areas for improvement, and make informed decisions to optimize the AI solution's functionality and impact. [65], [66], [67]

Possible metrics may include:

- **Precision and Dependability of AI Models:** This evaluates the accuracy and reliability, as well as consistency over time.
- **Effectiveness and Scalability:** This assesses the efficiency and ability to operate swiftly and utilize resources ideally, while also examining capability to scale with increasing data volume or complexity.
- **End-User Satisfaction:** This measures the level of satisfaction among end-users with the AI-powered product solution.
- **Regulatory Compliance and Security:** These metrics scrutinize whether the AI solution adheres to regulatory standards and if it provides robust security measures against potential threats.

Gathering requirements and defining precise metrics are crucial for developing resilient AI solutions. Thorough analysis and clear metrics ensure AI systems meet their objectives, delivering tangible value to products and customers.

General Concept and Classification

Below, the high-level concept for the robust and holistic AI support of mechatronic product development is presented. The methodology, depicted and explained in the following Figure 9, consists of three sub-models that converge in the actual support of the V-model using intelligent methods.

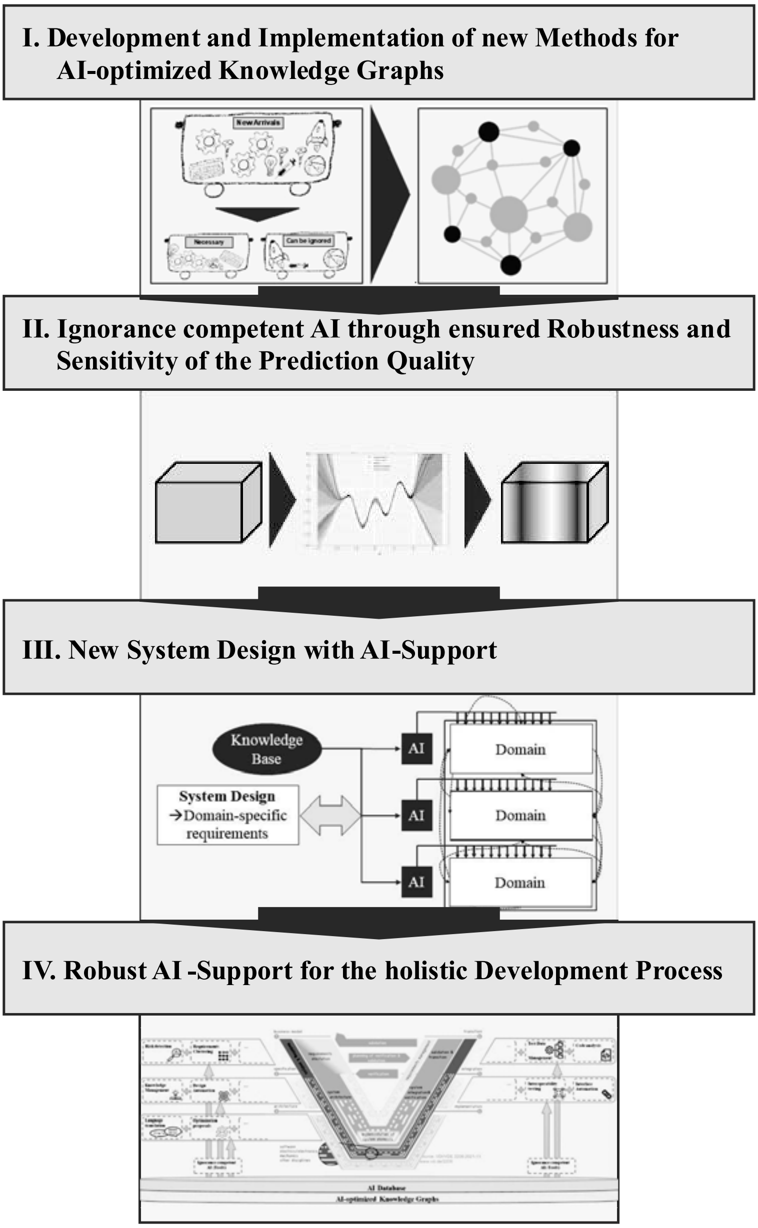


Figure 9: General concept for the robust and holistic AI support

In the initial phase, the focus is on the creation and enhancement of AI-optimized knowledge graphs. This involves the identification and integration of diverse data sources, ensuring comprehensive coverage of relevant information. The development process includes employing advanced machine learning algorithms to extract, classify, and link data points, resulting in a dynamic and evolving knowledge graph. The goal is to build a robust foundation that serves as the backbone for subsequent AI-driven processes.

To ensure the effectiveness and reliability of the AI system, the second step emphasizes the implementation of robustness and sensitivity measures. This involves thorough testing under diverse conditions and scenarios to identify potential biases, weaknesses, and vulnerabilities in the AI model. Addressing these issues ensures that the AI system is competent enough to handle uncertainties and ignorance in real-world situations, enhancing its reliability and usability.

With the AI-optimized knowledge graphs and a robust AI model in place, the next step involves integrating AI support into the overall system design. This includes identifying key decision points, processes, and interactions within the development lifecycle where AI can provide valuable insights, predictions, or automation. The goal is to create a symbiotic relationship between human expertise and AI capabilities, enhancing overall efficiency and decision-making.

The final step encompasses the seamless integration of AI throughout the holistic development process. This involves continuous monitoring, learning, and adaptation of the AI system to evolving requirements and challenges. The AI support is designed to complement human expertise, offering insights, predictions, and automation that contribute to a more efficient, informed, and adaptive development process. Regular updates and refinements to the knowledge graph and AI model ensure that the system remains at the forefront of technological advancements.

In summary, the proposed methodology follows a systematic approach, starting with the development of AI-optimized knowledge graphs and ensuring the robustness and sensitivity of the AI model. It then integrates AI support into the overall system design, culminating in a robust AI-supported development process that enhances decision-making and efficiency across the board.

Detailing the Methodology

The following chapter provides an in-depth elaboration of the developed methodology, detailing its structure, components, and application in the context of AI-driven mechatronic product development. It refines the conceptual framework introduced earlier and expands upon specific methodological elements. Parts of this chapter are adapted from the author's licentiate thesis [1].

Building upon the developed rough concept, the subsequent step involves the four-step detailing of the method for the holistic potential analysis and utilization of AI possibilities in the development of mechatronic systems.

The initial phase involves creating and improving the knowledge base for AI-optimized Knowledge Graphs by identifying and integrating diverse data sources, utilizing advanced machine learning algorithms to extract, classify, and link data points, with the aim of establishing a dynamic foundation supporting subsequent AI-driven processes. The second step emphasizes implementing robustness and sensitivity measures through thorough testing under diverse conditions to enhance the AI system's reliability and usability.

The third step involves integrating AI support into the system design, identifying key decision points and processes where AI can provide insights or automation, aiming for symbiosis between human expertise and AI capabilities to enhance efficiency and decision-making. In the final step, integration into the development cycle will occur, along with an examination of the resulting outcomes and phenomena.

AI and Knowledge

In the initial phase, the focus is on creating and refining AI-optimized methods for knowledge mining. This entails identifying and integrating diverse data sources to ensure comprehensive coverage. Using advanced machine learning algorithms, the extraction, classification and linking of the data points takes place, resulting in a dynamic knowledge graph. The objective is to establish a robust foundation, serving as the backbone for subsequent AI-driven processes. From this arises the first research question, visualized in Figure 10.

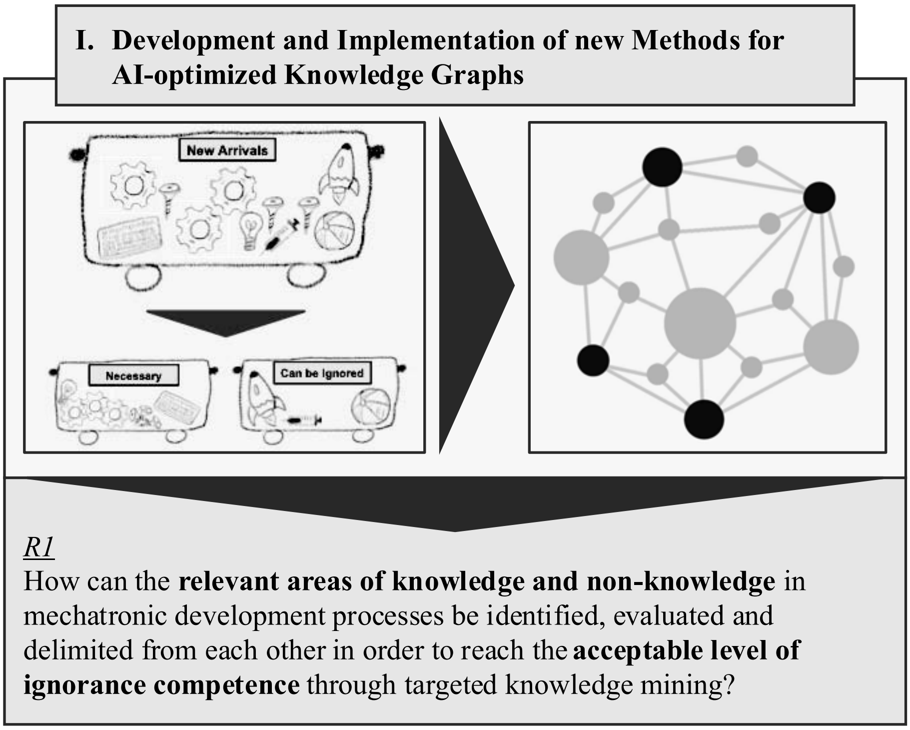


Figure 10: Development and Implementation of new Methods for AI-optimized Knowledge Graphs

AI plays a crucial role in mechatronic product development, particularly as a robust database. Leveraging AI methodologies like machine learning and knowledge representation, it efficiently manages extensive volumes of information, ensuring organized storage and retrieval. This AI-driven database serves as a valuable asset, granting engineers rapid and comprehensive access to a wealth of knowledge, including past designs, simulations, test results, and best practices. The centralized repository not only expedites the design process but also fosters collaboration among interdisciplinary teams by offering a shared platform for exchanging information. [68]

The basis for this is, in any case, an appropriate database. In this context, the quantity of the necessary information is not even the actual problem but the identification of the selection relevant for the purpose - keyword Knowledge Explosion. This phenomenon refers to the rapid proliferation of information and data, particularly in the fields of science and technology. This surge in knowledge is driven by technological advancements, especially the internet and powerful computers, combined with increased global interconnectedness and collaboration. These factors have greatly facilitated the accessibility, storage, and sharing of information. [69]

The Knowledge Explosion has brought numerous advantages, including widespread access to extensive information, the capacity to exchange ideas, and collaborative efforts in research and development. However, it has also presented challenges, such as grappling with information overload and the necessity for advanced techniques and tools to navigate and derive meaning from the data. Therefore, the objective is to adeptly navigate and harness the abundance of available information, but individual experts often hold essential knowledge within companies, limiting its availability. This may result in unnecessary redundancies and hinder further development. [70], [71]

To overcome this challenge and effectively utilize existing knowledge, processes of identifying, evaluating, and organizing information are crucial. Techniques like data mining, statistical analysis, and machine learning analyze data from various sources to extract meaningful insights. The goal is to convert data into actionable knowledge for informed decision-making, applicable across fields like engineering, finance, and sustainability. The knowledge analysis process involves data cleaning, visualization, as well as interpretation and therefore is an iterative approach that may lead to new questions. [72], [73], [74], [75]

But what happens in cases where this knowledge cannot be fully captured, and thus there is no uniform information base for the use of intelligent methods? At this point, AI can provide significant added value. AI databases can identify such gaps and assist in addressing them. As a result, a more comprehensive understanding of the system is achieved, enabling better prediction. [76]

Knowledge Graphs and Data Imputation

To appropriately assess the situation and evaluate the knowledge base, Knowledge Graphs can be employed as a technique. While the methodology is not new, initial publications date back at least to the 70s, they have experienced a kind of renaissance following the AI boom. [77], [78]

At its core, a Knowledge Graph is a graph-based data structure that captures entities, their attributes, and the relationships between them. Unlike traditional databases that store information in tables, Knowledge Graphs embrace a graph-oriented approach, where nodes represent entities and edges denote the relationships between them. This interconnected structure enables the representation of complex, real-world knowledge in a highly expressive and flexible manner. [79]

The concept of semantic enrichment lies at the heart of Knowledge Graphs, where raw data undergoes augmentation with semantic annotations to imbue it with significance. They achieve this by harnessing ontologies, taxonomies, and schemes, enabling them to encode not just the data, but also the underlying semantics. This semantic layer facilitates robust inferencing and reasoning capabilities, empowering AI systems to extract deeper insights and make more informed decisions. [80]

The construction of a Knowledge Graph comprises multiple stages, commencing with data acquisition and preprocessing. Raw data sourced from a variety of outlets, including structured databases, unstructured text, and online content, is initially ingested and then standardized. This transformation process often includes entity recognition, relationship extraction, and disambiguation techniques aimed at guaranteeing data quality and coherence. After preprocessing, the data is translated into a graph-based representation, where entities are mapped to nodes and relationships to edges. This mapping process entails establishing ontologies, schemes, and vocabularies that dictate the structure and semantics of the Knowledge Graph. Utilizing graph-based algorithms, patterns can be uncovered, related entities clustered, and missing relationships inferred, thereby enhancing the graph with supplementary knowledge. The four steps for the so called extraction pipeline can be found in Figure 11. [81], [82], [83]

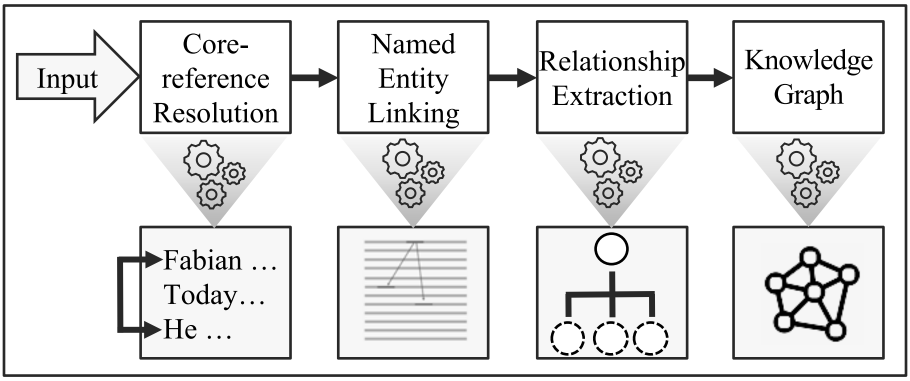


Figure 11: The four process steps for creating Knowledge Graphs

In NLP, knowledge graphs facilitate entity linking, semantic parsing, and question answering by providing a structured representation of knowledge that can be leveraged to interpret and generate natural language text. Moreover, in machine learning, Knowledge Graphs serve as a source of structured data for training and inference, enabling models to exploit rich relational information and generalize more effectively. This integration into the intelligent systems has profound implications for the field, unlocking new possibilities for knowledge representation, reasoning, and decision-making. By encapsulating domain knowledge in a graph-based format, AI systems gain a deeper understanding of the underlying semantics, enabling them to perform more sophisticated tasks with greater accuracy and efficiency. Furthermore, Knowledge Graphs facilitate interoperability and integration across disparate AI systems and data sources, fostering collaboration and knowledge sharing in complex AI ecosystems - as a parallel representation of the real situation, as already explained in the Introduction. [84], [85]

But despite their promise, knowledge graphs are not without challenges. Scaling them to handle large-scale, dynamic datasets poses scalability and performance issues. Additionally, ensuring the quality, completeness, and consistency of knowledge graphs remains a persistent challenge, requiring ongoing efforts in data curation, validation, and maintenance which is similar to the situation of AI use in product development with resilient deployment. [86]

Subsequently, it is possible to fill in incomplete knowledge areas using Machine Learning methods. These methods can infer missing information, detecting implicit relationships, predicting new connections, and filling gaps based on existing data. This process is referred to as data imputation. Further details can be found in, among other sources, **Paper IV**. [87]

Following that, there is an opportunity to validate the data incorporated into the knowledge Graph, ensuring its accuracy and reliability. More details on this can be found in the Chapter AI and Ignorance Competence and again **Paper IV**. It is essential to establish quality assurance processes for consistently reviewing and updating the data. [68], [88], [89], [90]

Below are two approaches for applying intelligent methods for both knowledge generation and early analysis through simulated expert knowledge, supporting the creation of corresponding Knowledge Graphs as well as the next steps in using the actual intelligent methods.

Intelligent Analysis of Components

The presented method, visualized in Figure 12, serves the intelligent analysis of components with the goal of consolidating them into a feature table.

The process creates data structured in a suitable way to apply a knowledge graph representation, which enhances AI-driven inference and decision-making. Consider a multi-inference knowledge graph: a construction knowledge graph can be built directly from extracted data, where an entity such as part contains attributes like length, width, and depth, and connects to entities such as hole 1, hole 2, etc. via relationships defining relative angle or relative position. Further refinement occurs when interfacing with standardization knowledge graphs, which introduce standard specifications such as M3 or M12, including attributes like tool type and cost per hole. This layered approach facilitates automated reasoning, enabling AI-driven optimization of component manufacturability based on cross-domain data.

With this structured representation in place, the next step is to localize and extract relevant geometric and topological features from components, supporting AI-based manufacturability assessments.

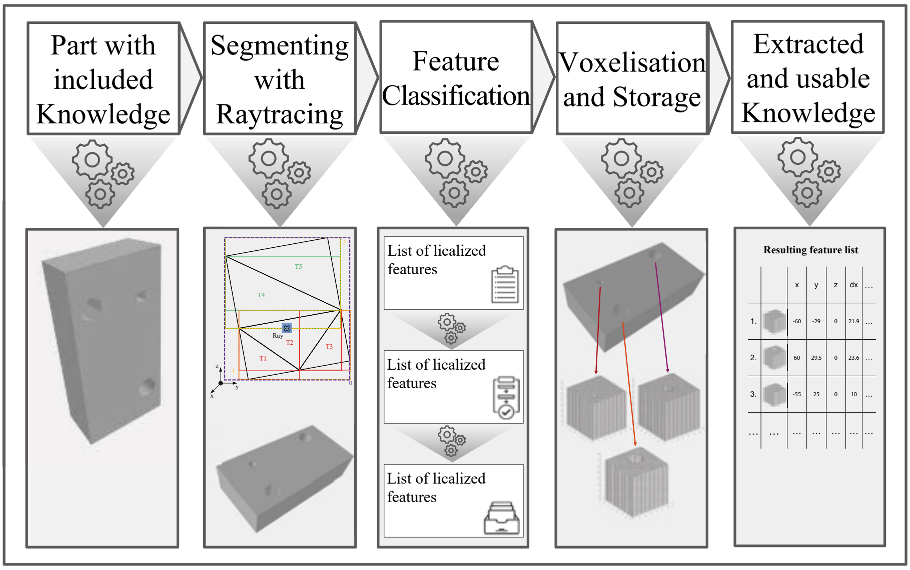


Figure 12: The process steps for the intelligent analysis of components and features leading to the extracted knowledge, developed in Paper II

Initially, an approach is devised to swiftly localize features while also determining their origin and dimensions using raytracing techniques. This approach offers the advantage of enabling precise segmentation of features and their immediate surroundings. Regions devoid of features are disregarded, streamlining subsequent analysis.

The selected approach provides resolution advantages for the subsequent voxelization, which serves as a crucial preparatory step for supplementary analysis utilizing techniques like ANNs for automated recognition of trained phenomena. By avoiding a uniform resolution in favor of individual segments with sufficiently high resolution, the examination of features attains necessary detail. Opting for a uniform resolution would render such detailed examination impractical due to increased computational demands.

Following segmentation, the next phase involves classifying the segmented areas based on known feature classes. A method is developed to assign features to defined classes using rule-based catalogs and associated examination procedures. Incorporating precise dimensional data and contextual placement within the component facilitates cataloging and further processing.

An example of a special feature could be an existing hole drilled in the component. If a ray starts outside the component and exits on the opposite end, it must intersect the hole at least two times. If the number of intersections is greater, it could indicate another feature or multiple instances of the same feature type being examined. Further querying procedures are then required to investigate these possibilities and provide a conclusive determination. Figure 13 illustrates the querying procedure for the selected example of boreholes.

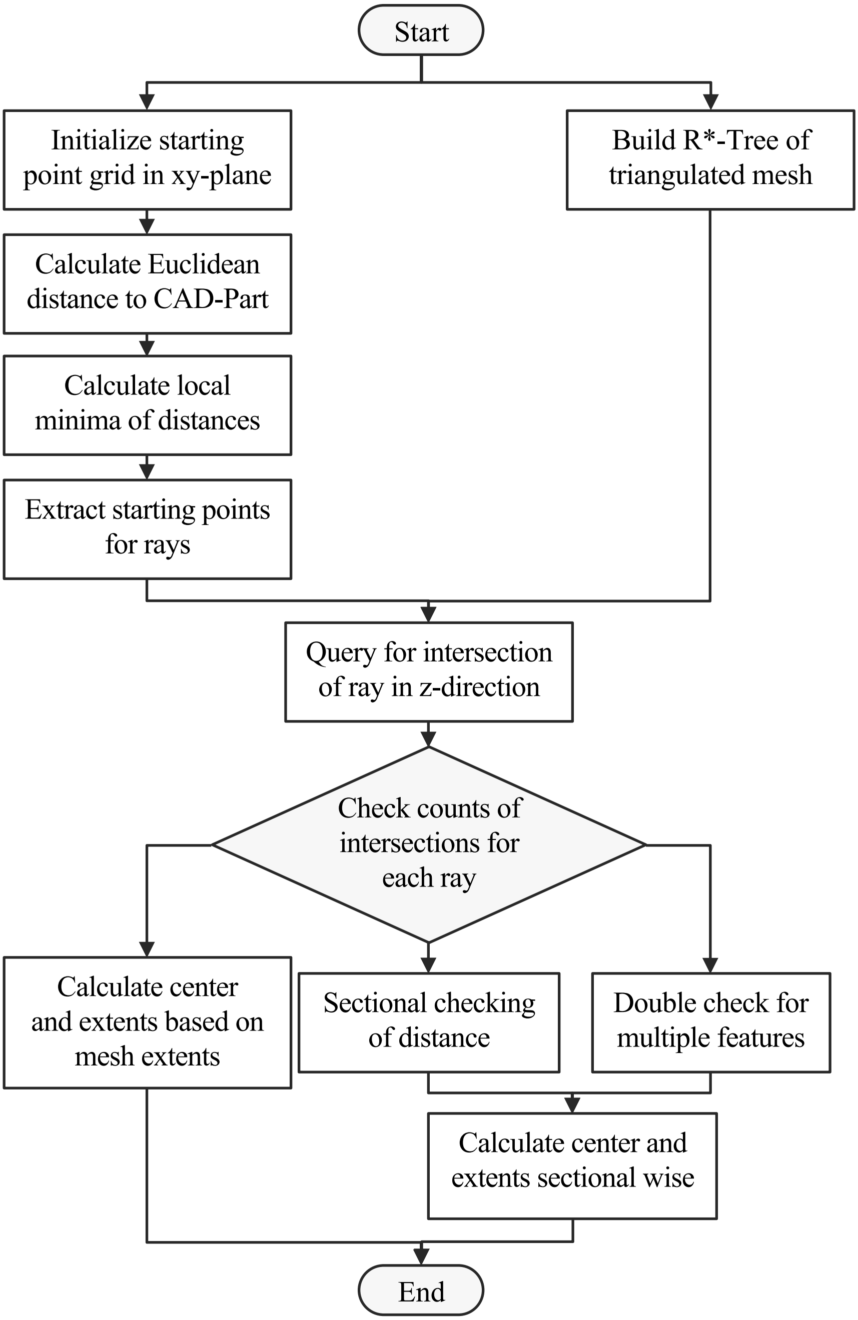


Figure 13: Sequence procedure for the detection of boreholes, developed in Paper II

Finally, the component segments are converted into a format conducive to mathematical analysis and subsequent processing, utilizing the ongoing voxelization approach. Leveraging the segmentation accomplished earlier, an appropriate resolution is chosen to maintain computational efficiency without sacrificing detail. Thus, this approach not only facilitates the extraction of knowledge but also adheres to sustainable practices throughout the development process. An exemplary result can be found in Figure 14. In this case, all 38 features in the xy-plane were automatically detected.

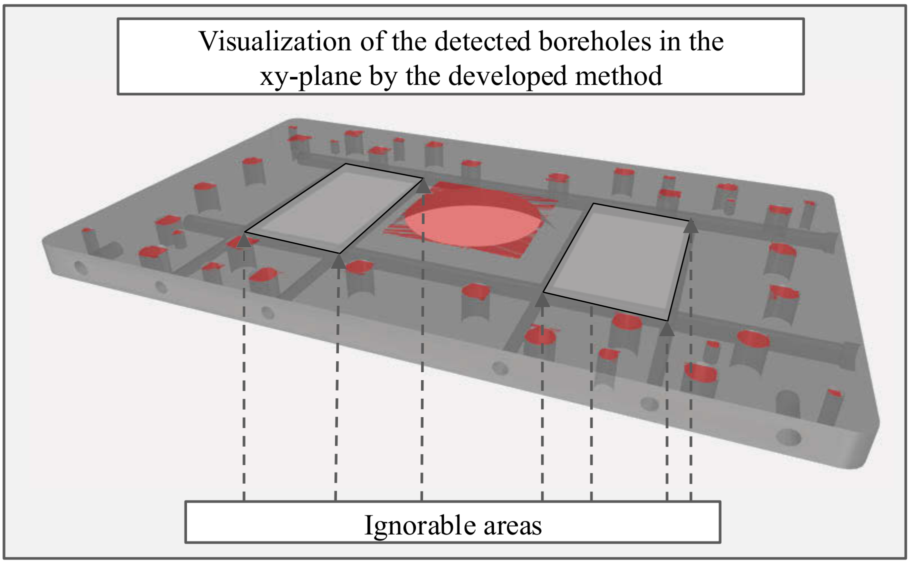


Figure 14: Visualization of the detected features by the developed method in the xy-plane, developed in Paper II

In conclusion, the detailed process established serves as a valuable tool to effectively manage existing masses of information. Existing projects are thoroughly examined and labeled, while new components are appropriately addressed. This process also establishes essential precautions for future AI utilization. Completed projects become valuable content rather than cluttering storage space. This method was developed in collaboration with a manufacturing company for exactly this purpose. Their projects served as a corresponding proof of concept. More details on the used techniques as well as the process steps can be found in **Paper II**.

With regard to the development process, the developed methodology is particularly beneficial for creating the knowledge base - as evident in Figure 15.

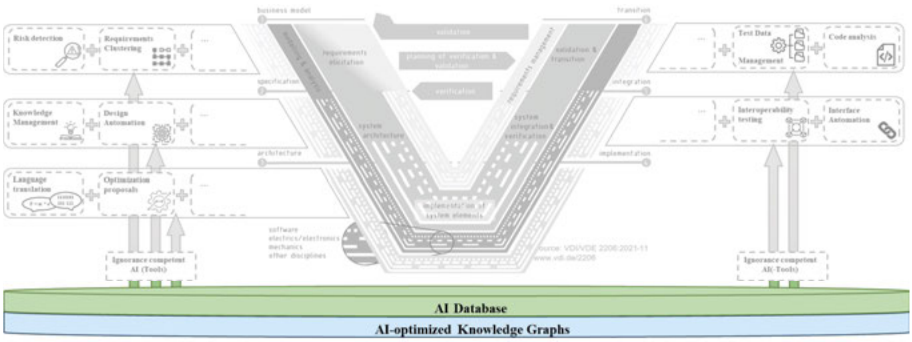


Figure 15: The placement of the Intelligent Analysis of Components method within the development process

Intelligent Component Manufacturability Testing

AI can make certain statements, focusing on the feasibility and success potential of projects or components. By utilizing knowledge resources and suitable algorithms, AI assesses the likelihood of achieving desired outcomes and identifies potential obstacles or challenges during the development process. This enables companies to make informed decisions regarding resource allocation, time management, and overall project feasibility.

In this context, an AI-based approach, visualized in Figure 16, combined with preprocessing to address the knowledge explosion, was developed in **Paper III**. This involves selectively ignoring irrelevant information within a CAD model to effectively support and secure production-oriented design in virtual product development. The specific case discussed is the feasibility of holes in components for milling processing. 37 different wells were successfully analyzed in Figure 16. The outcomes match those of commercial tools, yet the efficient and assured management of irrelevant data provides a time advantage, facilitating targeted analysis concerning producibility.

The workflow in Figure 16 illustrates the intelligent assessment of manufacturing feasibility in virtual product development. In the preprocessing step, relevant areas are initially extracted from the examined product. Subsequently, these voxelized regions enter the 3D-Convolutional Neural Network (CNN), enabling the analysis of individual construction elements. The final step involves visualizing the results. Any identified manufacturing deficiencies can be rectified using a CAD program.

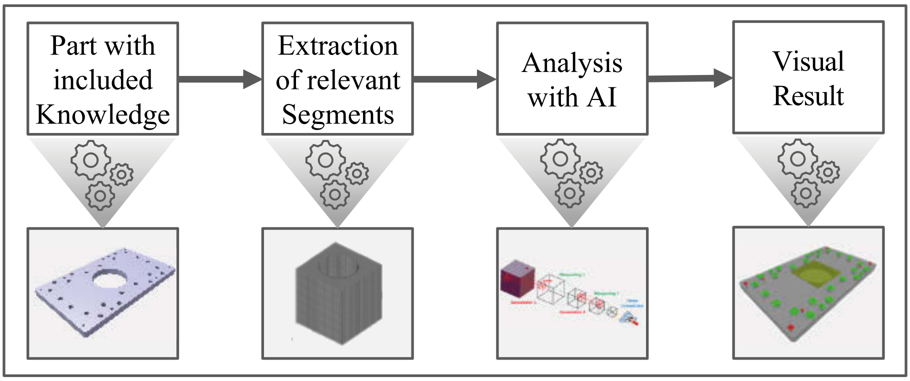


Figure 16: Exemplary visualization of the AI-supported method for the detection of manufacturability, developed in Paper III

The process follows an iterative development approach. Employing a bottom-up strategy, it begins with task formulation (feasibility analysis of drillings) and then generates the required dataset. The approach is clearly influenced by CRISP-ML(Q) and QUA3CK methodologies. CRISP-ML(Q) is a machine learning methodology adapted from CRISP-DM, focusing on iterative data analysis and model development. QUA3CK integrates quality management into agile product development, emphasizing continuous improvement and customer satisfaction. Unlike traditional linear processes, both methodologies are iterative and prioritize adaptability and quality, aligning with modern agile practices. [91], [92], [93]

For a comprehensive understanding of the developed 3D-CNN and the intricacies of the completed training processes, refer to **Paper III**. This document provides a detailed exploration of the architecture, configurations, and outcomes of the 3D-CNN, shedding light on the methodologies employed in its development and training.

In summary, it can be concluded that while the basic feasibility check can also be performed with conventional tools, the developed methodology significantly increases speed due to the quick decision-making capability of AI methods. Furthermore, the AI enables feasibility checks that do not follow conventional logic and only allow for an assessment as a whole. Here, the AI recognizes corresponding patterns and implements them in the future. Particularly when combined with the methods from **Paper II**, AI can ignore irrelevant areas and thus analyze only the relevant areas quickly.

This method was developed in collaboration with a manufacturing company whose projects served as corresponding proof of concepts and aimed to improve interaction with customers in the early phases of development.

With regard to the development process, the developed methodology is particularly beneficial for the phase between Checkpoints 1 and 2 - as evident in Figure 17.

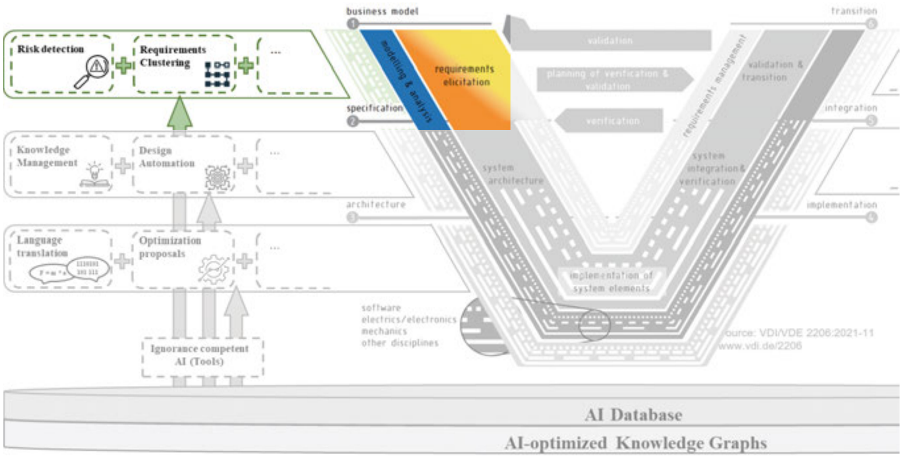


Figure 17: The placement of the Intelligent Component Manufacturability Testing method within the development process

Addressing the 1st Research Question

The first research question, developed in the Introduction, concerns

R1	How can the **relevant areas of knowledge and non-knowledge** in mechatronic development processes be identified, evaluated and delimited from each other in order to reach the **acceptable level of ignorance competence** through targeted knowledge mining?

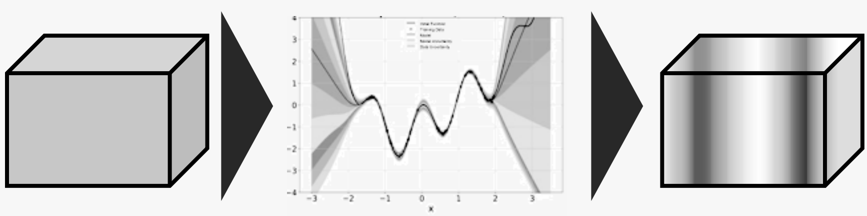
and was methodically addressed.

In the course of the previous chapter, existing methods for the knowledge base in the form of Knowledge Graphs were presented and the specially developed methods for the targeted differentiation between relevant and ignorable information as well as for fast and intelligence-supported manufacturability checks were introduced. Consequently, the first research question can be regarded as successfully answered, as the methods function reliably, and existing information becomes usable knowledge in this way.

AI and Ignorance Competence

As the second step in the presented general concept, ensuring the effectiveness and reliability of the AI system is emphasized through the implementation of robustness and sensitivity measures. Addressing the potential issues enhances the AI system's competency in handling uncertainties and ignorance in real-world situations, boosting its reliability and usability. This condition is referred to in the following as ignorance competence. The term refers to the recognition and acknowledgment of one's lack of knowledge or understanding in a particular subject or field. Rather than being a state of complete ignorance, it entails being aware of the boundaries of one's expertise and being open to learning and seeking further knowledge. In essence, ignorance competence involves understanding what one doesn't know and being willing to engage in the process of acquiring new knowledge and skills to bridge those gaps. This mindset promotes humility, curiosity, and continuous growth, as individuals who possess ignorance competence are more likely to seek out opportunities for learning and development, leading to personal and professional advancement. From this arises the second research question, visualized in Figure 18. [94], [95]

II. Ignorance competent AI through ensured Robustness and Sensitivity of the Prediction Quality



R2
How can the critical **analysis parameters for success** and the **ideally suitable segments of the development process** for the use of robust and context-sensitive artificial intelligence be identified?

Figure 18: Ignorance competent AI through ensured Robustness and Sensitivity of the Prediction Quality

In the context of the V-Model or comparable development processes, it becomes evident that the robustness of the forecasting model plays a fundamental role. From a temporal perspective, it may be sufficient in early development phases to obtain a rough estimate. For example, to acquire an initial metric for further work or to obtain a general forecast of the temperature ranges in which the application operates, thereby considering materials that can be taken into account. In subsequent stages, it might become imperative for the predictions to demonstrate either a heightened level of precision or a minimal margin of error, particularly in contexts like autonomous driving or other safety-sensitive domains. To ensure the suitability of the model for each phase and, for economic reasons, to train the model to a sufficient extent for its intended use, the consideration of robustness and sensitivity is indispensable, as [96] and [97] also examine in their work.

Within the method, the concept of ignorance competence emerges as a compelling area of inquiry. As one navigates through the intricate seas of information, the aim is to uncover the delicate equilibrium between the robustness and sensitivity inherent in intelligent systems. These systems not only possess the prowess to sift through overwhelming data volumes but also exhibit a remarkable sensitivity to contextual nuances. [98]

The robustness of AI systems becomes evident as they grapple with the challenges posed by vast and diverse datasets. Therefore AI systems have to fortify themselves against noise, uncertainties, and adversarial inputs, ensuring resilience in the face of complex information landscapes, as [99] also clarifies. Understanding the robust nature of AI is integral to appreciating its adaptability and reliability in diverse decision-making scenarios, which also plays a major role in the medical sector, for example, as [100] shows.

Conversely, the sensitivity of AI systems is another aspect that contributes to their nuanced decision-making processes. These intelligent systems have the capability to selectively ignore irrelevant information, honing in on the salient features that are critical for informed decision-making. The exploration of sensitivity in AI involves understanding how these systems discern patterns, recognize context, and navigate the delicate balance between information retention and intentional ignorance.

With this intersection between AI and ignorance competence, it is crucial to dissect the dual nature of these systems - robust in their ability to handle complexity and sensitive in their capacity to discern and prioritize information. Through this exploration, the aim is to illuminate the evolving landscape of AI, shedding light on the dynamic interplay between robustness and sensitivity as essential attributes in shaping the future of intelligent decision-making.

Understanding Uncertainty and Sensitivity

Utilizing ANNs for predictions necessitates a thorough assessment of their reliability and addressing potential undesired consequences related to AI.

Quantifying uncertainties within ANNs is crucial for computing an additional output value reflecting prediction certainty, thereby informing users about potential deviations. [101], [102]

Before delving into uncertainty analysis in ANNs, it's essential to grasp the underlying sources. Aiding in comprehension, these uncertainties can be categorized into data and model uncertainties. [103]

1. **Data Uncertainty:** Data uncertainty stems from inherent inaccuracies due to noise or imperfect structuring, such as sensor-recorded data. Collecting more data doesn't fully mitigate this uncertainty, which can manifest as homoscedastic (constant variance) or heteroscedastic (variance dependent on input data). [104]
2. **Model Uncertainty:** Conversely, model uncertainty arises from insufficient training data, impacting the model's accuracy, especially in regions with limited reference data. This limitation hinders the model's generalization capability, affecting its representation of patterns and relationships in the data. [105]

A secured **robustness** is crucial for ensuring reliable predictions within the dynamic landscape of ANNs. Robustness assessment involves gauging both training success and prediction quality. ANNs learn from data during training to capture patterns, while the prediction phase tests their adaptability to novel inputs. Deviations from expected values indicate low robustness, whereas accurate predictions for unknown data signify high robustness. Extending this evaluation to Out-of-Distribution (OOD) data enhances understanding of the network's robustness. [106], [107]

Modern development processes prioritize robustness, especially in early stages with limited data. This necessitates the incorporation of model uncertainty considerations. Model uncertainty, influenced by training data and accentuated in regions with scarce reference data, is integral to comprehensively assessing robustness. The analysis strategically focuses on areas involving new and unknown input data, offering a holistic perspective by integrating considerations of model uncertainty. [108]

Sensitivity analysis is crucial for understanding how ANNs respond to variations in parameters. The influences of hyperparameters, such as neuron count and learning rate, are evaluated for their impact on training outcomes. Assessing sensitivity becomes vital when predictions are required for previously measured inputs, as high sensitivity can lead to diverse effects and potential additional costs in real development processes. [109], [110]

In sensitivity analysis, data uncertainty is a crucial metric for evaluating how predictions respond to variations in training and input data. This approach provides key insights into model robustness and reliability.

The next section presents a method from **Paper IV** that leverages these techniques to enable ignorance-competent AI, ensuring appropriate application at each development phase.

Ignorance Competence through ensured Robustness and Sensitivity

In the realm of uncertainty analysis for network predictions, diverse techniques with unique strengths and drawbacks exist. Evaluating the performance characteristics of these procedures is crucial to discern their suitability for specific applications. Within **Paper IV**, a method was therefore developed to counter this situation with a suitable process, the aim of which is to enable proficient handling with AI. This can be seen in Figure 19. The details for the techniques can be read for example in [111], [112], [113] as well as in **Paper IV**.

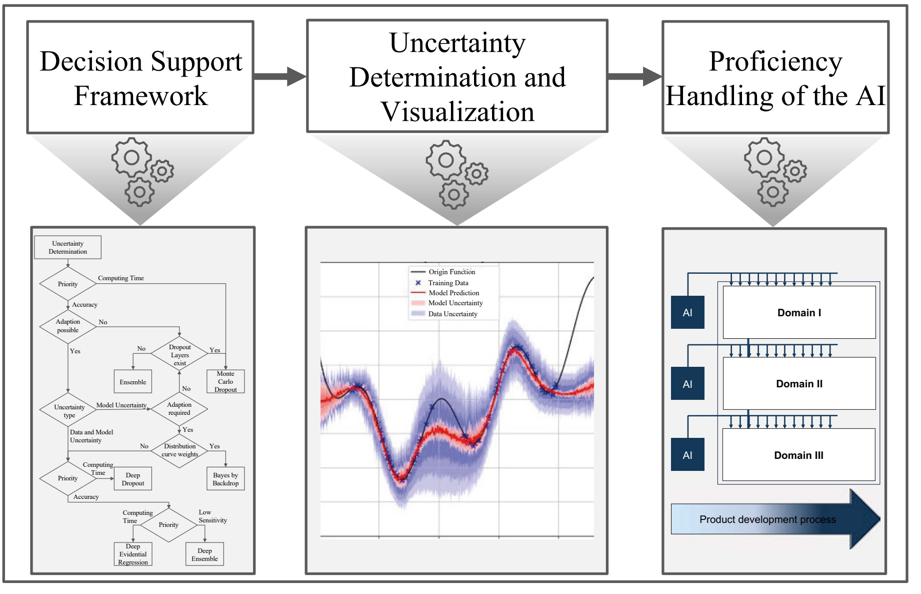


Figure 19: The method for the use of Robustness- and Sensitivity-checked AI, developed in Paper IV

Employing a decision tree approach, visualized in Figure 20, facilitates this assessment, guiding users to choose a routine aligning with their specific needs and situational requirements.

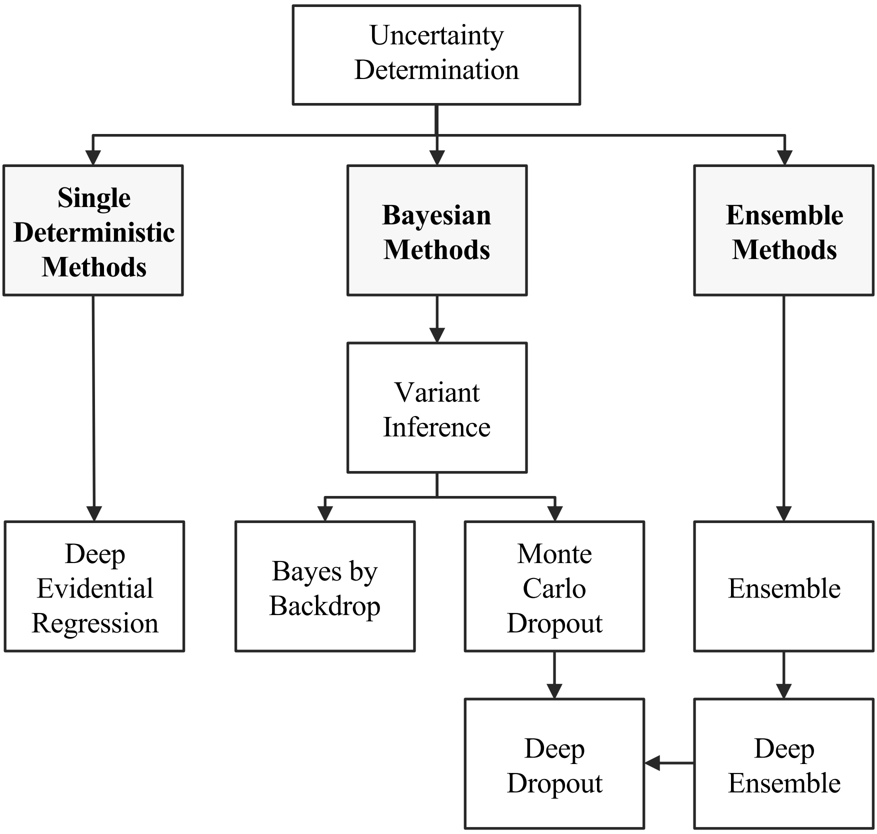


Figure 20: Overview of the techniques for determining uncertainty, developed in Paper IV

In order to gauge the suitability of these techniques for particular applications, it becomes imperative to thoroughly evaluate and analyze their performance characteristics. This comprehensive assessment is essential for making informed decisions about the most fitting approach based on the specific requirements and intricacies of the given application.

In the subsequent analysis, the goal is to subject the previously mentioned methods to testing, comparing their outcomes while considering their distinct underlying approaches. The evaluation focuses on assessing two crucial types of uncertainty: data uncertainty and model uncertainty.

For the performance test, a function that incorporates both a cosine and an exponential component is chosen. Additionally, a gap within the training data is introduced to scrutinize the behavior within the interpolation range.

In Figure 21, the left side visually represents the predictions of the methods post-training. The original function is depicted in black, and the training data is represented by the x-symbols. The network prediction is shown in red, accompanied by the variance displayed in pink. This diagram includes divisions into various variance ranges, based on the probabilities of the Gaussian normal distribution. Notably, some of the presented methods possess the capability to distinguish between uncertainties and provide them based on their respective types, as illustrated on the right side. Here, the model uncertainty is represented in red, while the data uncertainty is displayed in blue.

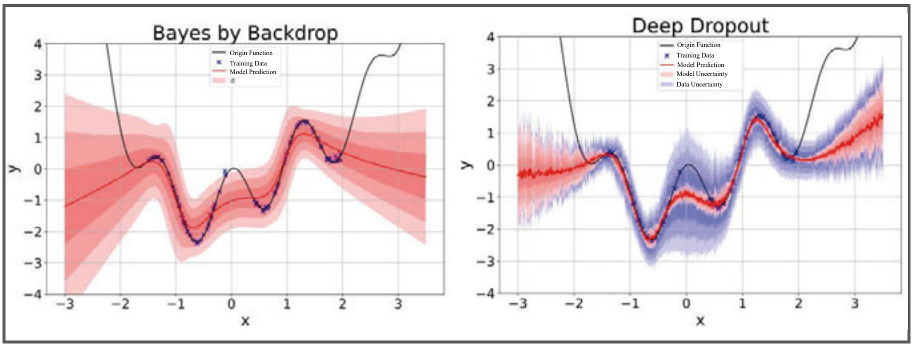


Figure 21: Exemplary results of the uncertainty determination, on the right with distinction between model (red) and data uncertainty (blue)

Following the analysis of the process results, the subsequent step involves the creation of a performance spectrum for each method. The outcomes are then assessed and visually represented in the form of a structured tree, serving as a decision-making aid. When employing uncertainty analysis for predicting ANNs, users can choose the most suitable method based on the available data and framework conditions. The decision tree offers users a navigational tool through different branches, allowing them to determine the most appropriate procedure tailored to their specific circumstances.

Given that each method comes with its own set of advantages and disadvantages, there is no universally preferred solution. Specific use cases create conditions where one method may excel, while another may yield different outcomes. Ultimately, the selection of the method hinges on the user and the application at hand.

The resulting decision tree from **Paper IV** is depicted in Figure 22. It allows the identification of the most suitable procedure, enabling users to interpret procedures and AI results effectively. This approach shifts away from perceiving them as black boxes, fostering proficiency in handling them. Consequently, AI-based prediction models can serve as effective communicators between domains in modern product development, fostering trust. More details can be found in **Paper IV**.

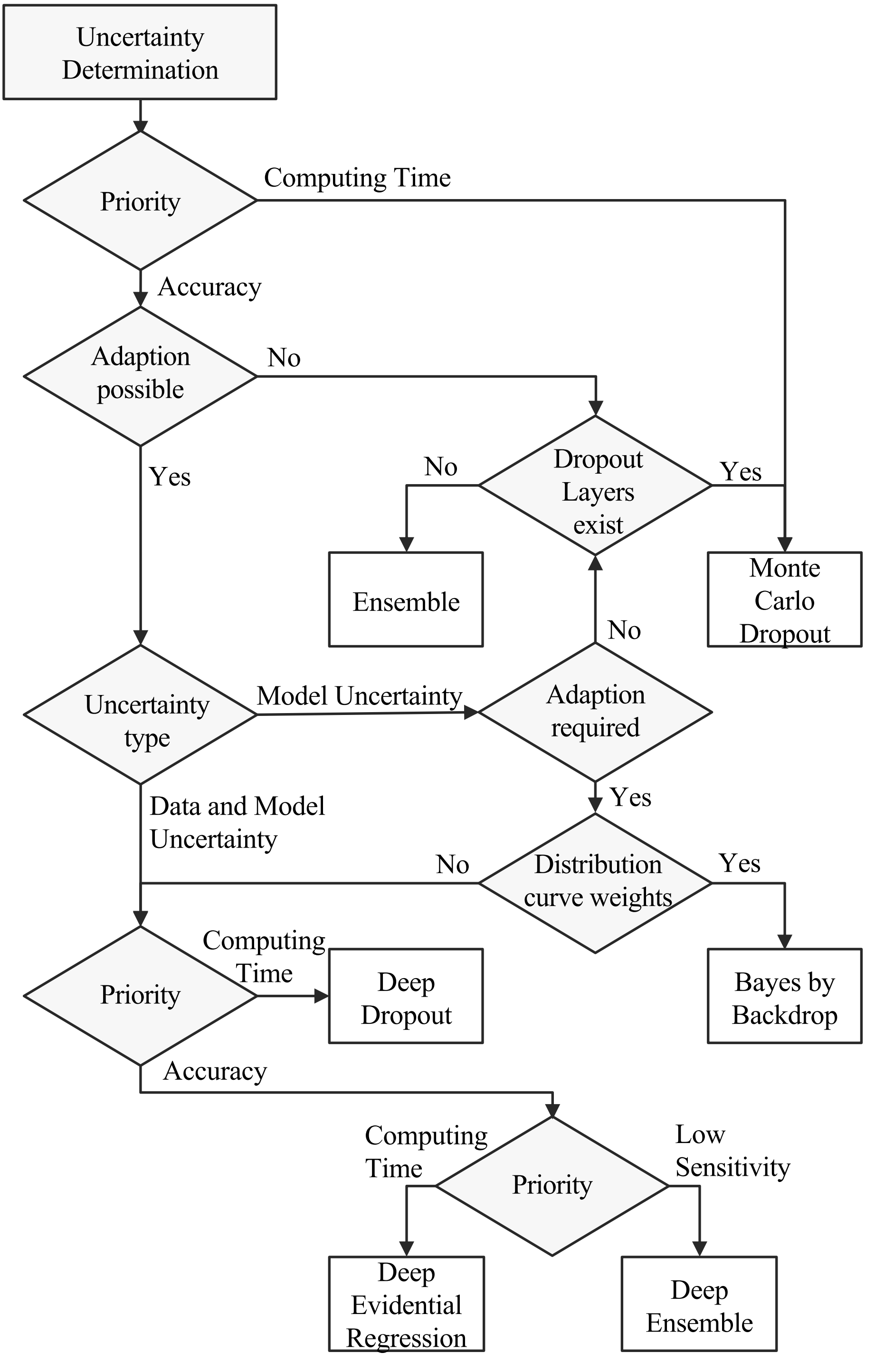


Figure 22: The resulting decision tree for practical applications

With regard to the development process, the developed methodology is particularly beneficial for the phase between Checkpoints 2 and 4 - as evident in Figure 23. Here, the robustness of AI predictions, optimization suggestions, and translations must be known as precisely as possible. It is crucial to determine whether it is merely an early estimation or a reliable and safety-critical statement.

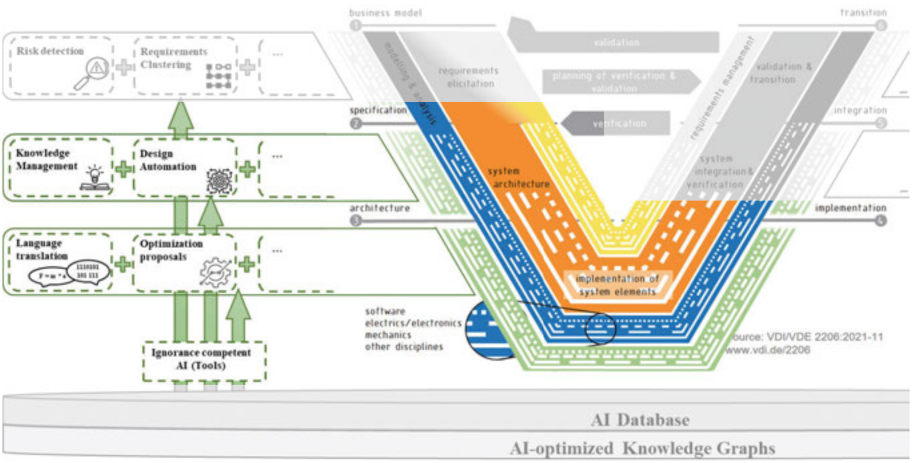


Figure 23: The placement of the Ignorance Competence through ensured Robustness and Sensitivity method within the development process

Addressing the 2nd Research Question

The second research question, developed in the Introduction, concerns

R2	How can the critical **analysis parameters for success** and the **ideally suitable segments of the development process** for the use of robust and context-sensitive artificial intelligence be identified?

and was methodically addressed.

Relevant requirement questions and corresponding metrics were proposed that could lead to the investigation with the aim of answering the stated question. The specially developed methods for the best possible use of robustness tests for AI were also presented to ensure application potential and requirements, as shown in Figure 7. The findings also show that AI can provide support in all phases, the conditions are just different. As a result, and based on the progress made, it is possible to use AI safely and in line with requirements in mechatronic product development. At the same time, this means that the research question has been addressed and answered accordingly.

New System Design

Given the imperative to harmonize multifaceted requirements and disciplines throughout the process of mechatronic product development, the necessity for seamless integration across various domains becomes progressively apparent. Co-simulation frameworks offer a promising avenue for achieving this integration by allowing different components of a mechatronic system to interact in a simulated environment. [114], [115], [116]

However, ensuring effective communication and coordination among these disparate domains remains a significant challenge. The goal therefore is to explore the role of AI in facilitating the linking of diverse mechatronic domains within a co-simulation framework, as the process concept in Figure 24 demonstrates. Specifically, the focus is on three key aspects: translation, interpretation, and prediction.

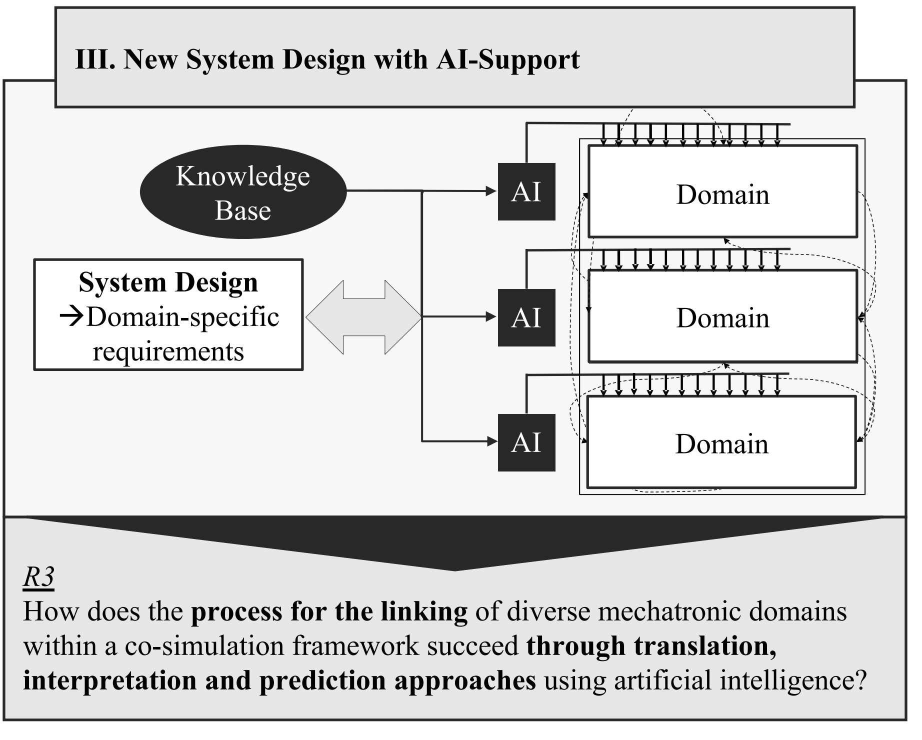


Figure 24: New System Design with AI-Support

Bridging the Gap Between Domains by Translation

In a co-simulation environment, multiple simulation tools interact with one another, generating virtual measurement data that is exchanged between tools or stored for later analysis. These simulated datasets provide critical input for machine learning models, enabling AI to identify hidden patterns, optimize simulation workflows, and enhance predictive accuracy. For example, structural simulations may produce stress distribution data, which can inform thermal simulations by predicting material expansion effects. Similarly, control system simulations can generate real-time feedback data, which can be used to train adaptive AI models for system optimization.

By structuring these exchanges, AI-driven translation approaches help standardize and contextualize simulation outputs, making them interoperable across domains while preserving semantic integrity.

One of the fundamental challenges in co-simulation is the disparity in representation and semantics across different domains. For example, mechanical and electrical systems often employ different modeling techniques and notations, making it difficult to establish meaningful connections between them. AI techniques, particularly NLP and machine learning, can play a crucial role in bridging this gap. [117], [118], [119]

NLP algorithms play a pivotal role in the integration process by scrutinizing textual descriptions, specifications, and documentation linked with each domain. They extract pertinent details and transform them into a standardized format, streamlining the mapping of variables, parameters, and interfaces across various components. This harmonization facilitates smooth communication within the co-simulation framework. Furthermore, machine learning algorithms enhance this process by discerning patterns and relationships from historical data, progressively refining the accuracy and efficiency of the translation process. [120], [121], [122]

Interpretation: Extracting Meaning from Interactions

Once the various domains are linked within the co-simulation framework, the next challenge is to interpret the interactions and exchanges that occur between them and the associated players. This involves understanding the cause-and-effect relationships, identifying anomalies or deviations from expected behavior, and making real-time decisions to ensure the stability and performance of the overall system.

Incorporating AI techniques such as pattern recognition, anomaly detection, and decision-making algorithms significantly enhances the integration process. These algorithms analyze the data streams generated by each domain during simulation, enabling them to discern patterns of interaction and identify any unusual or unexpected behaviors.

Subsequently, appropriate corrective actions can be taken. For example, a decision tree algorithm trained on historical data can analyze the current state and inputs of a mechatronic system to predict potential future paths. By identifying critical decision points and their likely outcomes, the system can proactively adjust its parameters or configurations, thereby mitigating the risk of undesirable outcomes before they occur. [123], [124]

Prediction: Anticipating Future States

In addition to interpreting the present interactions within the co-simulation framework, AI can also be used to predict future states and behaviors of the integrated mechatronic system. This proactive approach enables preemptive decision-making and optimization, leading to improved performance, reliability, and efficiency.

Machine learning techniques such as regression, time series analysis, and reinforcement learning (RL) can be employed to forecast the evolution of system variables and parameters. By learning from historical data and incorporating real-time feedback from the simulation environment, these algorithms can generate accurate predictions of future states, enabling advanced control strategies and optimization algorithms to be applied. [125], [126], [127]

Beyond conventional machine learning techniques, RL provides an adaptive approach to optimizing system behavior by continuously learning from real-time feedback. **Paper V** demonstrates how RL can be applied to enhance DC motor control, ensuring dynamic adaptation to changing conditions while maximizing efficiency. This case study underscores how RL-based strategies can complement structured AI methodologies by introducing self-optimizing mechanisms that refine control logic over time. By integrating such learning-based frameworks, predictive AI models can evolve beyond static optimization, achieving higher levels of adaptability and resilience.

More details on this topic can be found in Paper V.

AI beyond the Algorithm

Integrating AI into mechatronic product development requires broader considerations than purely technical aspects. Beyond algorithms and data models, organizations face transformations in their structures, leadership philosophies, and workforce competencies. Four key dimensions are particularly relevant, which can be seen in Figure 25.

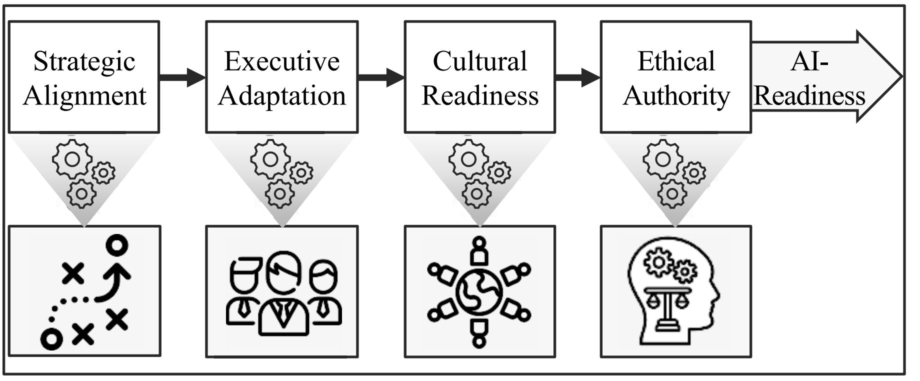


Figure 25: AI-Readiness: Four steps are necessary regarding structure, people, and ethics.

First, strategic alignment with AI ensures any new solution reinforces the company's overall objectives rather than functioning as an isolated tool. Clarity in data governance and well-defined ethical frameworks form the basis, promoting consistency in data usage and paving the way for sound risk management. [128]

Second, organizational readiness goes beyond simply adopting new systems. To harness "AI as a co-pilot," companies often need to revise existing processes and consider more agile structures, potentially challenging traditional hierarchies. Realizing AI's full potential typically demands the development of "critical AI competencies" throughout the workforce - enabling engineers, managers, and operators to interpret algorithmic suggestions, recognize model limits, and maintain ultimate control of outcomes. [129]

Third, cultural transformation is paramount for fostering employee trust and ensuring their engagement in AI-driven processes. Transparent communication strategies and dedicated upskilling help overcome initial skepticism. By encouraging iterative feedback loops, the organization both refines AI solutions continuously and empowers staff to identify blind spots and flag unintended consequences, thereby increasing adoption and effectiveness. This assertion is reinforced by the findings of the 2023 Future of Jobs Report, published by the World Economic Forum. According to the report, a significant majority of companies (77 %) have identified the enhancement of existing employees' skills through upskilling and reskilling as a top priority. This strategic initiative aims to equip workers with the necessary competencies to transition seamlessly into roles that are increasingly automated or driven by artificial intelligence. [130]

Finally, ethical and societal considerations guide responsible AI deployment. Companies must articulate clear guidelines to prevent discriminatory outcomes or hidden biases, reflecting accountability and transparency. Providing dedicated channels for employees to raise potential ethical dilemmas or negative job impacts further strengthens trust. Organizations that address ethical matters proactively not only mitigate risks but also enhance user acceptance, allowing AI to serve as a catalyst for legitimate innovation rather than a source of uncertainty. The EU's Ethics Guidelines for Trustworthy AI (2019) define Trustworthy AI in this context as being threefold: lawful, ethical and robust. The key requirements which underpin this definition are as follows: human oversight, privacy, transparency, fairness and accountability. In order to facilitate implementation of these guidelines, the EU developed ALTAI, a self-assessment framework for organizations. [131]

Incorporating these societal and structural perspectives, alongside the technical and methodological insights discussed earlier, can greatly improve the chances of meaningful, sustainable AI adoption. By uniting strategic vision, organizational alignment, cultural readiness, and ethical diligence, organizations create an environment in which AI can excel as a collaborative partner across mechatronic development processes.

More details on this topic can be found in Paper VI.

Generalizing the Methodology

The following chapter presents the generalization of the developed methodology, providing a structured framework for implementing and assessing AI in mechatronic product development. By extending the previously established approach, this generalization ensures that AI applications can be systematically identified, effectively utilized, and comprehensively evaluated within different engineering contexts.

The integration of AI into mechatronic product development holds significant potential for improving efficiency, quality, and competitiveness. However, realizing these benefits requires a structured approach that objectively assesses AI's real impact, considering both technical aspects as well as organizational and procedural implications. To address this need, the methodology has been expanded into a generalized framework, which enables the targeted identification of AI potentials, feasibility analysis, and ultimately, a structured assessment of AI effectiveness within development processes.

To provide a structured approach to this generalization, a five-step framework has been developed. This framework systematically guides organizations through the identification, analysis, and evaluation of AI applications within mechatronic product development. Each stage serves as a key pillar in assessing AI's role, impact, and feasibility. The final step incorporates a quantitative assessment, allowing for structured potential measurement. A visualization of the complete concept can be found in Figure 26.

In the following section, the individual steps of the structured approach are described in detail.

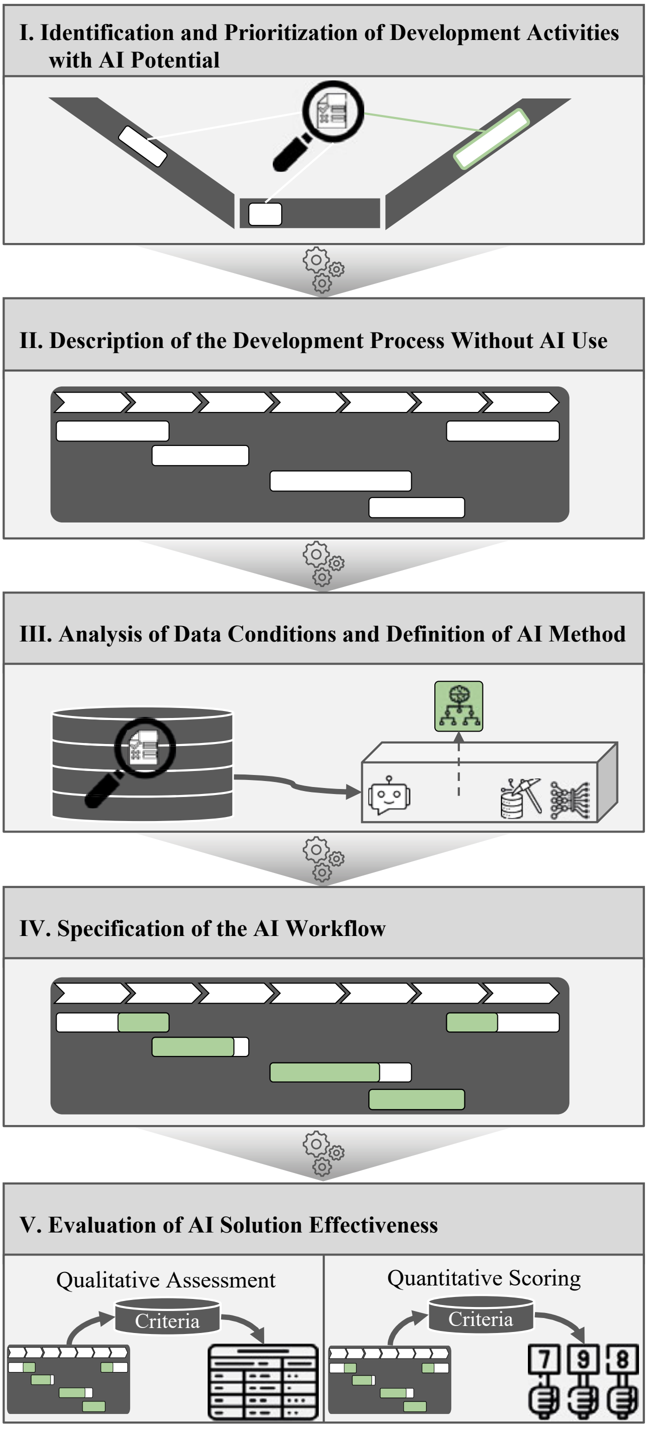


Figure 26: The five-step based generalization framework for identifying and evaluating AI potential.

1. Identification and Prioritization of Development Activities with AI Potential

The first step focuses on systematically identifying all activities in the mechatronic development process that could potentially benefit from AI support. Since not every activity can equally benefit from AI, careful classification is essential for targeted resource allocation. Activities are analyzed throughout the entire V-model, from requirements definition and system design to testing and validation. Activities are captured in detail, classified based on their significance within the overall process, and prioritized for potential AI support. This thorough identification and prioritization step provides a solid pre-selection of processes to focus on.

Prioritization Criteria:

- **Complexity of the Activity:** Highly complex tasks involving many variables and challenging human decisions often have significant AI potential. Activities that require complex analytical skills are thoroughly evaluated.
- **Scope and Quality of Available Data:** AI models require high-quality, rich data to operate effectively. Activities with a robust data base are prime candidates for AI solutions. Data structure and availability are assessed in detail.
- **Time and Cost of Manual Execution:** Higher manual effort indicates greater potential benefit from AI automation. Actual time and costs are thoroughly assessed.
- **Error Susceptibility and Quality Requirements:** Processes in which errors have a significant impact benefit particularly from AI systems that provide consistent, accurate decisions. Error statistics and quality requirements are systematically collected.

2. Description of the Development Process Without AI Use

In the second step, the existing development process without AI support is comprehensively documented and analyzed. This step is crucial as it forms the foundation for all subsequent optimizations and provides a reliable reference for later comparisons. To comprehensively capture the status quo, all relevant process steps are documented in detail, including execution, required resources, involved roles and responsibilities, and communication and information flows.

Special emphasis is placed on identifying and documenting necessary decisions and underlying decision-making processes, including involved stakeholders and utilized information. Challenges and obstacles in the current process are explicitly addressed. These can be technical, such as system incompatibilities or data fragmentation, or organizational, such as unclear responsibilities or inefficient coordination processes.

Alongside qualitative process documentation, an extensive quantitative analysis is performed. This involves systematically capturing and analyzing key figures such as process duration, cycle times, number of process steps, and error rates. Bottlenecks, delays, and recurring error sources are identified, evaluating their impacts on overall process performance. Additionally, resource consumption, including personnel effort, material use, and technical infrastructure utilization, is thoroughly examined.

This detailed and comprehensive process description and analysis serves as a fundamental basis for later clearly measuring and showcasing improvements achieved through AI integration. It enables defining concrete targets for AI integration and objectively and transparently evaluating implementation successes.

3. Analysis of Data Conditions and Definition of AI Method

After analyzing the current process, the third step involves a detailed examination of available data. Data quality, structure, and availability are critical for successful AI implementation. Data sources are identified, integration possibilities are examined, and measures to improve the data foundation are recommended. Data storage and processing requirements are also analyzed. Based on the data analysis, the most suitable AI method is selected. Selection criteria include problem definition, data volume, and required accuracy. Possible methods include regression analysis, classification, or clustering.

4. Specification of the AI Workflow

In the fourth step, the AI-supported workflow is detailed. This step is critical as it defines how AI will be integrated into the existing development process. First, all relevant sub-processes suitable for AI support or automation are identified. Detailed descriptions of each process step involving AI are provided, starting with initial data preprocessing to ensure data quality and integrity. Measures such as data cleaning, normalization, and transformation are detailed to optimally prepare data for the AI model.

Next, suitable AI algorithms are selected and rated. Selection is based on thorough analysis of specific application requirements. Different algorithms such as decision trees, neural networks, or ensemble methods are compared and assessed. The training process of the selected model is planned in detail, involving iterative steps of model adjustment, validation, and optimization. Validation techniques like cross-validation ensure the robustness and generalizability of the model.

Technical implementation of the AI solution into the existing IT infrastructure follows, involving development of interfaces, definition of data flows, and ensuring seamless integration. Scalability and maintainability are also considered. Finally, organizational and personnel aspects of AI integration are addressed, including employee training, adjustment of internal processes, and managing the transition from manual to AI-supported execution.

5. Evaluation of AI Solution Effectiveness

The concluding stage of the methodology systematically evaluates the effectiveness of the AI solution. To provide a comprehensive assessment, two complementary perspectives are introduced:

1. **Qualitative Assessment**
   A descriptive evaluation, drawing on potential and investment criteria, highlights each solution's key successes, challenges, and overall outcomes.
2. **Quantitative Scoring**
   Building on the same set of criteria, a weighted multi-criteria scoring approach is applied. By translating the descriptive insights into numerical ratings and summing these according to custom weights, stakeholders gain an at-a-glance comparison of AI solutions and how well they align with the organization's strategic priorities.

To address both the prospective benefits and the necessary resource commitments, the evaluation distinguishes between Potential Criteria, which focus on gains and impact, and Investment Criteria, which address costs, dependencies, and regulatory considerations.

Potential Criteria

- **Precision and Reliability of AI Models**: Assesses performance metrics like precision, recall and accuracy.
- **Effectiveness and Scalability**: Examines measurable process improvements such as reduced cycle times, resource optimization, and ability to transfer the AI solution to related challenges.
- **End-User Satisfaction**: Evaluates user acceptance and usability through structured feedback sessions or surveys.

Investment Criteria

- **Effort for Model Creation and Data Generation/Maintenance**: Estimates personnel hours, time frames, and budgetary needs.
- **Dependency on Process Experts**: Gauges reliance on specialists for periodic validation and system upkeep.
- **Regulatory Compliance and Security**: Checks adherence to data protection laws and security standards.

A dualistic approach, incorporating both a narrative account of successes and a numerical rating, has been employed to provide a pragmatic foundation for decision-making regarding further investments in AI or the ongoing optimization of daily operations.

Measuring Effectiveness through a weighted multi-criteria Evaluation

The fifth step initially provides descriptive judgments of AI effectiveness, but weighted scoring refines this analysis and allows for direct comparisons. Each of the above criteria (e.g. accuracy, user satisfaction, compliance) can be assigned a score (typically 1 to 5) multiplied by a weight that reflects the organization's strategic focus. The key steps are:

1. **Criteria Definition**
   Specific metrics from the potential and investment categories are translated into measurable factors (in this case a 1-5 scale).
2. **Assigning Weights**
   Each criterion is given a relative weight that adds up to 100 %. For example, a safety-critical company may place a higher priority on compliance.
3. **Scoring Each Scenario**
   A scenario's subscore is the product of a criterion's score and its weight. These subscores are summed to produce an overall score.
4. **Interpreting the Scores**
   Higher overall scores indicate better alignment with company priorities. However, as some ratings are subjective, the final number should be read in context.

This approach provides a flexible, transparent framework that allows organizations to adjust weights in response to changing objectives or regulatory conditions. Descriptive insights from the five-step methodology are combined with numerical indicators to provide a robust, two-tiered assessment of AI solutions within mechatronic product development.

Validating the Methodology through Real-World AI Applications

The following chapter demonstrates how the developed methodology is applied in real-world AI applications within mechatronic product development. By examining three distinct industrial scenarios, this chapter validates the methodology's practical relevance and its ability to systematically structure AI adoption. Each case study highlights different capabilities in terms of translation, interpretation, and prediction and demonstrates their impact on engineering processes.

The chapter is structured in two main parts. First, the three scenarios are introduced individually, outlining the initial situation, key challenges, and the proposed AI-based solution. Once the scenarios have been described, the methodology's five-step generalization framework is applied collectively to evaluate the AI implementations, assessing their feasibility, impact, and overall effectiveness. This structured approach ensures a comprehensive validation of the methodology while enabling direct comparisons between the different AI applications.

As established in the preceding sections, mechatronic product development encompasses multiple domains, ranging from mechanical design and electronics to manufacturing and quality assurance. This complexity necessitates structured approaches to identifying AI potential, defining workflows, and evaluating AI-driven impact. The newly developed five-step generalization framework provides precisely this structure, ensuring that AI adoption is methodically assessed and strategically deployed.

In this chapter, three real-world industrial scenarios are presented, following the steps shown in Figure 27.

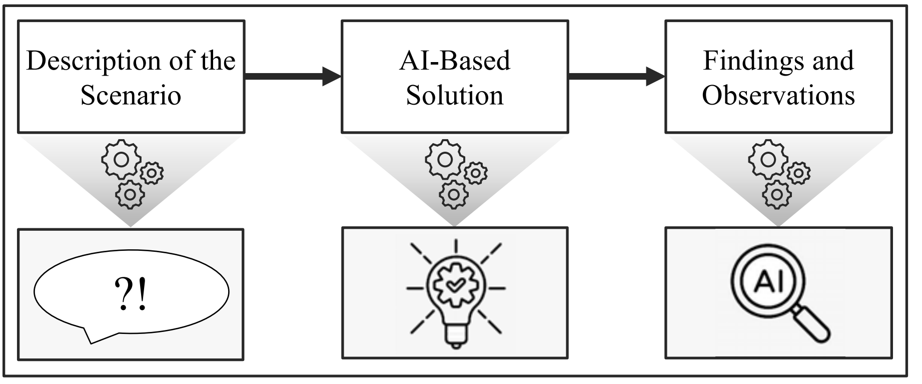


Figure 27: The three steps for the scenario presentations.

The chosen scenarios exemplify how AI can address the challenges of mechatronic development. Each scenario focuses on a different core theme:

1. **Translation - Bridging the Gap Between Domains (Scenario A)**
   Highlights the role of AI in unifying fragmented information and enabling rapid, cross-disciplinary communication.
2. **Interpretation - Extracting Meaning from Interactions (Scenario B)**
   Demonstrates how AI-powered data analytics can uncover deeper insights from sensor-rich production processes, reducing error rates and optimizing decisions.
3. **Prediction - Anticipating Future States (Scenario C)**
   Explores the use of time-series forecasting and predictive modeling to anticipate system behavior, thereby preventing failures and improving efficiency in safety-critical applications.

Each scenario is derived from authentic industrial applications within large and medium-sized companies. While the organizational contexts differ, all three share a common objective: the application of AI to enhance mechatronic product development processes. By outlining the initial situation, key challenges, and AI-based solutions, these scenarios illustrate the methodology's practical applicability and its structured approach to AI adoption.

Following these scenario descriptions, a dedicated evaluation chapter will apply the multi-step framework to systematically assess and compare their outcomes. This structured approach enables an objective measurement of AI-driven efficiency gains, cost factors, end-user satisfaction, regulatory compliance, and other key metrics.

Collectively, these scenarios validate the breadth of AI applications in mechatronic development, demonstrating the methodology's effectiveness and its potential for broader adoption in industrial contexts.

Case A: Translation: Bridging the Gap between Domains

Silver Automotive (an anonymized representation of a major automotive manufacturer) is a large, globally active company. Its product development cycle spans multiple domains - mechanical design, electronics, production, and more - each with specialized processes and data sources. Historically, communication and knowledge exchange among these domains have depended on manual document reviews, extensive email chains, and sporadic face-to-face meetings.

Goal of the Scenario: Enhance interdisciplinary communication by implementing an AI-based system (in this case, a chatbot) that offers rapid, reliable access to technical information across departments. This solution aims to reduce redundant queries, manual searches, and the time-intensive need to bridge knowledge gaps among various experts.

Relevance: By delivering critical information promptly, the AI solution fosters more agile workflows and improves collaboration among domain specialists. It alleviates fragmentation caused by separate data silos and harmonizes knowledge for faster, more consistent decision-making in automotive R&D projects.

1. Description of the Scenario

Current Development Process: Team members from various engineering disciplines, including powertrain, chassis, and electronics, primarily exchange information through spreadsheets, extensive reports, or spontaneous meetings. Each department maintains its own data repositories, resulting in limited visibility and restricted access to information across teams. The existing process at Silver Automotive can be seen in Figure 28.

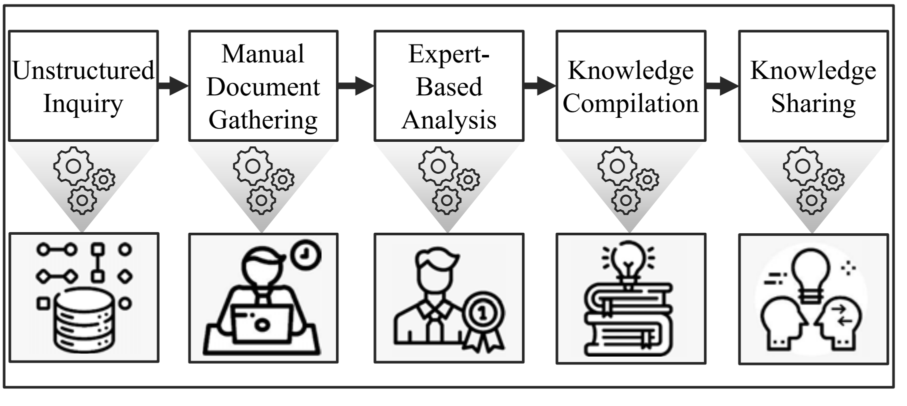


Figure 28: The current scenario at Silver Automotive.

Key Challenges:

- **Fragmented Knowledge:** Essential insights remain locked in departmental archives, causing duplicated efforts or incomplete understanding.
- **Long Search Times:** Engineers often spend hours digging through documents or awaiting peer responses.
- **Frequent Updates:** Rapid changes to project requirements may not reach all departments equally, risking misalignment or version-control problems.

2. AI-Based Solution

Employed Methods: An AI-powered chatbot using natural language processing is proposed to facilitate rapid retrieval of cross-domain knowledge. It consolidates data sources and domain expertise into a centralized repository. When employees inquire about topics such as design parameters or production constraints, the chatbot provides concise and contextually relevant answers. The new process idea for Silver Automotive can be seen in Figure 29.

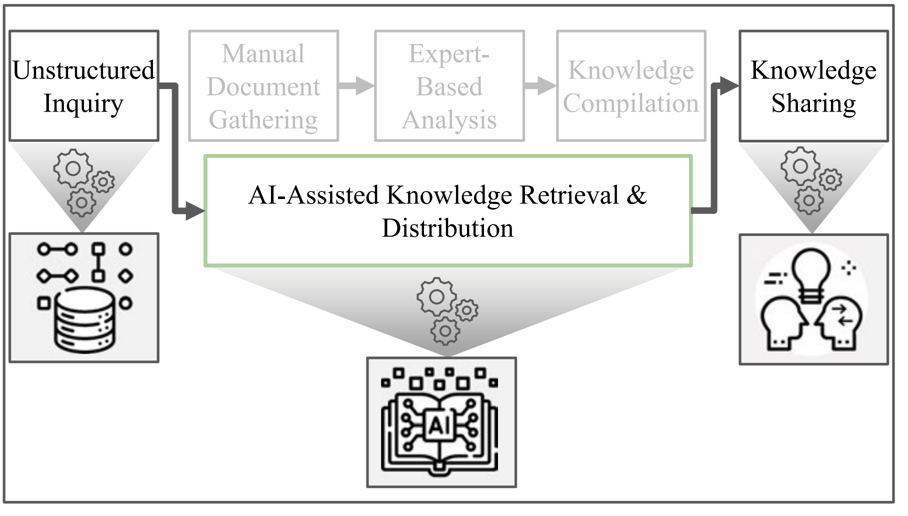


Figure 29: The process flow idea for Silver Automotive by using AI.

Implementation:

1. **Data Integration:** Existing documents, wikis, and department-specific repositories are consolidated into a unified, searchable knowledge base. Domain experts help structure and tag critical content.
2. **Chatbot Development:** The AI system is trained to understand automotive-related terminology (e.g., part numbers, system specifications) and manage context-based queries involving mechanical, electronic, or production topics by accessing the knowledge base.

3. **System Deployment:** A user-friendly interface enables staff to ask questions in plain language. The chatbot provides relevant documentation excerpts or direct links, accelerating routine tasks.

Anticipated Benefits:

- **Faster Turnaround:** Users get near-instant answers, substantially reducing waiting times and updating all stakeholders if possible.
- **Improved Consistency:** Uniform responses to common inquiries help minimize interpretation differences across departments.
- **Less Reliance on Meetings/Emails:** Fewer repetitive email chains or alignment meetings for everyday questions, freeing up engineering capacity.

3. Findings and Observations

Early internal feedback suggests that the chatbot is significantly reducing response times for cross-domain enquiries, improving day-to-day development efficiency. Employees report that recurring questions, such as the use of standard parts or specific design constraints, are now answered instantly, eliminating the need to consult multiple departments. Although the initial setup required some data curation and staff training, the long-term benefits for cross-functional collaboration have been significant.

The methodological approach in this scenario aligns with existing research on AI-driven organizational transformation and intelligent knowledge extraction. **Paper VI** explores the structural and cultural prerequisites that enable companies to effectively integrate AI into their workflows, emphasizing the importance of aligning human expertise with AI-assisted processes. Furthermore, **Paper II** examines methods for identifying and extracting significant features from complex data structures, a key aspect of ensuring AI-driven knowledge retrieval is both relevant and precise. Together, these studies provide complementary perspectives on the challenges and opportunities of AI-powered cross-domain knowledge management in mechatronic product development.

Case B: Interpretation: Extracting Meaning from Interactions

ProWeld Solutions is an anonymized medium-sized enterprise specializing in welding-based manufacturing processes for automotive components. A pivotal sub-process involves high-speed capacitor discharge welding, which is essential for producing safety-critical assemblies. The welding process demands consistent, fault-free results. Historically, however, welding quality has depended on rigid tolerance settings for parameters such as force and current, leading to an overreliance on simplistic binary assessments that often declare parts as “not OK” (n.OK), even when they could pass a metallographic examination.

Goal of the Scenario: Enhance the interpretative power of the welding quality assessment through AI, in order to reduce false rejections and optimize production. By integrating a data-driven system that interprets multi-sensor signals (force, current, discharge times, etc.), the aim is to handle the complexity and variability of the process more effectively.

Relevance: Accurate interpretation of real-time welding data not only reduces unnecessary scrapping of parts but also improves overall process reliability and lowers costs. In a broader sense, it fosters deeper insights into the physics of welding, enabling continual refinement of production parameters.

1. Description of the Scenario

Current Process: Operators rely on a fixed-tolerance system that labels parts as “OK” or “n.OK” based solely on narrow parameter windows for force and current. This approach leads to a high rate of n.OK classifications, many of which are later found to be acceptable. The fragmented storage of test data across Excel sheets and machine logs complicates a holistic analysis. The existing process can be seen in Figure 30.

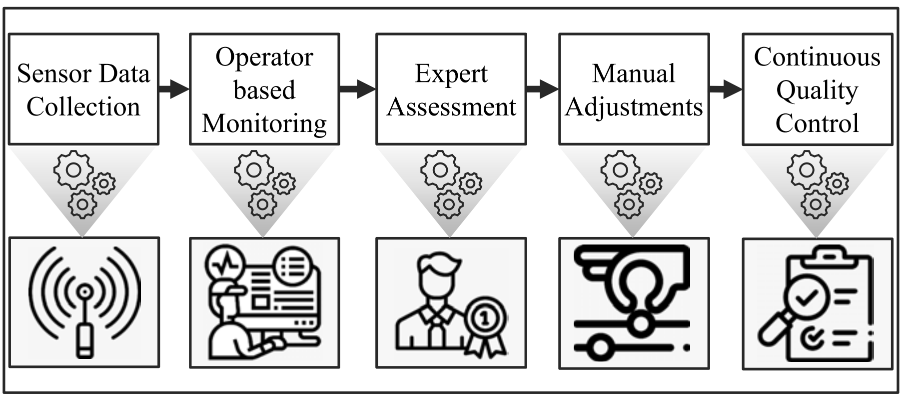


Figure 30: The existing scenario at ProWeld Solutions.

Key Challenges:

- False negative classification of parts, inflating material waste and production costs.
- Limited data analysis methods that fail to capture subtle correlations between parameters.
- Manual investigations and post-process metallographic checks, which delay corrective action.

2. AI-Based Solution

Selected Approach: An interpretative AI system is introduced to analyze multi-sensor welding data more holistically. By examining force, energy, current rise times, and mechanical parameters (e.g., plunge depth), the system can provide deeper insights into weld quality. The new process solution with AI can be seen in Figure 31.

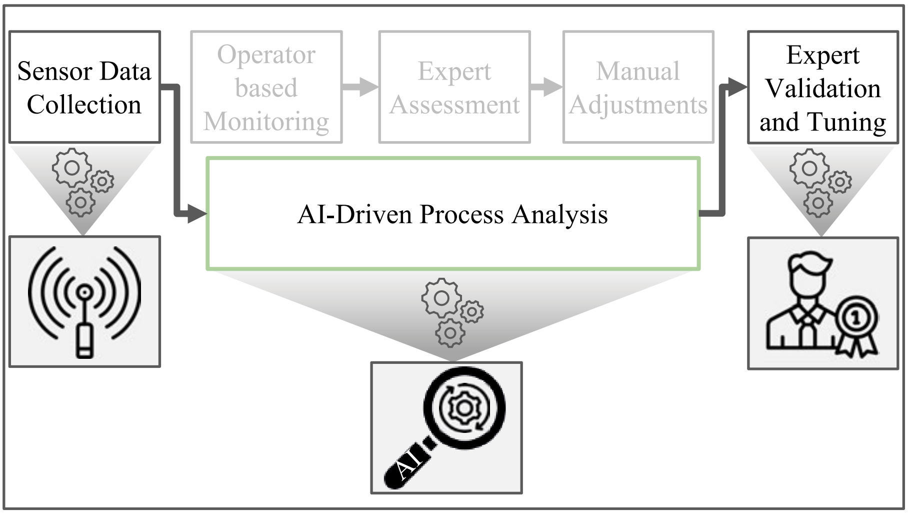


Figure 31: A new process design for ProWeld Solutions with the integration of AI.

Implementation:

1. **Data Acquisition and Preparation:** Historical machine measurements, along with "OK"/"n.OK" labels confirmed via metallographic analysis, are consolidated into a central database. Data cleaning, synchronization, and transformation steps ensure coherence.
2. **Model Selection and Training:** Various classification algorithms (e.g., random forests, neural networks) are evaluated. The training process focuses on interpreting complex parameter interactions instead of relying on single thresholds. Validation sets measure the system's precision, recall, and overall predictive power.
3. **System Integration:** The trained model is deployed at the welding station's monitoring interface. It interprets sensor data in real time, providing a nuanced quality assessment rather than a strict binary outcome. Operators can confirm or override suggestions, contributing feedback for continuous model improvement.

Anticipated Benefits:

- Significant reduction in false n.OK classifications.
- Real-time indications of weld anomalies, enabling faster intervention.

- Greater understanding of how parameter interactions affect weld outcomes.

3. Findings and Observations

Preliminary tests show a notable decrease in scrapped parts wrongly labeled as n.OK. Metallographic reviews confirm the integrity of parts reclassified as acceptable, highlighting the value of advanced data interpretation. By shifting from rigid parameter windows to a multi-parametric AI approach, ProWeld Solutions not only saves material and labor but also fosters a data-driven improvement culture. The new system encourages operators and engineers to explore deeper correlations between process parameters, fueling continuous optimization. Future enhancements may include refined feature engineering for current/force waveforms and broader deployment across ProWeld Solutions' additional welding lines.

The methodological approach in this scenario closely aligns with research on AI-driven interpretation of manufacturing data and ensuring the reliability of machine learning models. **Paper III** explores how AI can be leveraged to analyze complex relationships within virtual product development, enabling the extraction of meaningful insights from manufacturing processes. Additionally, **Paper IV** addresses the importance of maintaining accuracy and robustness in AI models, ensuring that their integration improves reliability rather than introducing new uncertainties. Together, these studies reinforce the significance of precise data interpretation and model stability in AI-assisted quality control and production optimization.

Case C: Prediction: Anticipating Future States

PredictX Systems (an anonymized mid-sized enterprise) specializes in industrial safety components, particularly rupture discs, which are single-use pressure relief devices that prevent catastrophic system failures in high-pressure environments. Traditionally, configuring an optimal rupture disc design requires extensive physical testing and expert-driven parameter selection, with engineers determining specifications based on prior experience and incremental adjustments. This manual approach leads to long development cycles, high material costs, and suboptimal parameter selections, as engineers rely on historical designs rather than data-driven predictions.

Goal of the Scenario: PredictX Systems aims to develop an AI-driven predictive modelling system that optimizes rupture disc configuration by analyzing past test results and material properties. Rather than selecting parameters through trial and error, the AI model recommends optimal configurations from the outset, reducing the number of physical test iterations required and accelerating product development. By using historical performance data, the system enables faster, more accurate decision-making, ultimately reducing costs and improving the reliability of bursting disc configurations.

Relevance: Effective configuration prediction is essential in industries where precision and reliability are critical. Manually selecting rupture disc parameters can result in overly conservative safety margins, increasing costs, or underestimated thresholds, compromising safety. AI-driven optimization ensures that each rupture disc design meets safety requirements while minimizing waste and unnecessary iterations. In addition, AI promotes standardization of engineering processes, reducing reliance on individual expertise and improving knowledge retention across design teams.

1. Description of the Scenario

Current Setup: PredictX Systems currently relies on an expert-driven, manual approach for designing rupture disc. Engineers select material, thickness, and burst pressure based on historical designs and experience. Each configuration undergoes multiple rounds of physical testing, requiring prototyping, analysis, and iterative adjustments. Testing results are stored in decentralized formats, making it difficult to systematically extract insights from past iterations. The existing process can be seen in Figure 32.

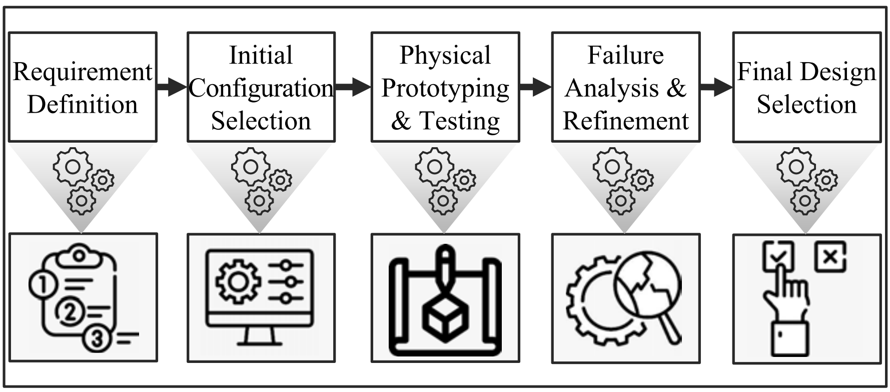


Figure 32: The present scenario for PredictX Systems.

Key Challenges:

- High material costs due to repeated prototyping and destructive tests.
- Inefficient trial-and-error approach, slowing down time-to-market.
- Lack of systematic optimization, as no predictive modeling exists to identify optimal configurations before testing

2. AI-Based Solution

Selected Approach: PredictX Systems introduces an AI-powered predictive modelling system that automates the rupture disc configuration process, replacing manual trial and error with data-driven optimization. The new designed process is shown in Figure 33.

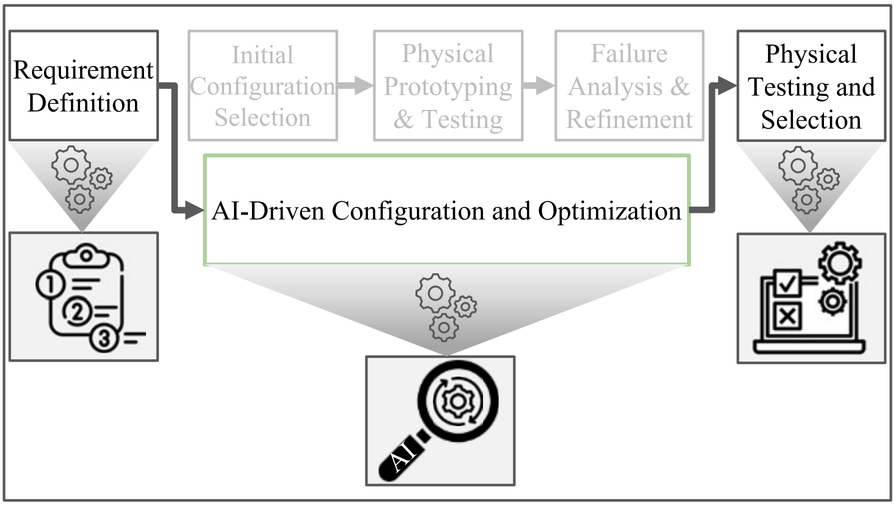


Figure 33: Redesigning the process by utilizing AI at PredictX Systems.

Implementation:

1. **Data Consolidation and Learning:** AI aggregates historical rupture disc test results, including material properties, pressure thresholds and failure patterns. The system learns how different parameters affect burst performance and identifies optimal design characteristics.
2. **AI-Driven Configuration Prediction:** Instead of engineers manually selecting specifications, AI analyzes historical data and suggests the most promising bursting disc configuration. Machine learning models (e.g. regression analysis, neural networks) predict how a given configuration will perform before physical testing.
3. **Simulation-Based Validation:** AI simulations replace early-stage physical prototyping, significantly reducing material waste. Engineers validate AI-generated designs with minimal manual iterations, focusing only on fine-tuning and safety validation.

Anticipated Benefits:

- Reduction in required physical tests, cutting material costs and accelerating development.
- More precise rupture disc configurations, improving both safety and cost efficiency.
- Systematic knowledge retention, as AI learns from every test iteration, improving future predictions.

3. Findings and Observations

Initial AI-assisted design iterations have shown that the number of required physical test cycles can be significantly reduced, therefore reducing costs and development time. Engineers report confidence in the AI, as the model systematically identifies optimal configurations that comply with known safety standards. Early trials also show that the predictions minimize excessive safety margins, achieving high reliability without unnecessary material usage.

In the future, PredictX Systems aims to refine the AI model by incorporating additional variables, such as manufacturing tolerances and environmental conditions, to further improve the system's predictive power and adaptability.

The methodological approach in this scenario aligns with research on AI-driven knowledge extraction and predictive modeling for optimized decision-making. **Paper II** examines methods for systematically identifying and structuring relevant data, ensuring that AI-driven predictions are based on well-defined and meaningful features. **Paper V** extends this by demonstrating how RL can be applied to optimize system behavior, leveraging predictive capabilities to derive new insights from available data. Together, these studies highlight the potential of AI in enhancing efficiency, reducing costs, and improving the quality of engineering decisions through advanced predictive analytics.

Evaluation of the Scenarios

The preceding sections introduced three real-world scenarios, Translation (A), Interpretation (B), and Prediction (C), each illustrating a distinct AI application. This chapter systematically evaluates them using the five-step framework, combining qualitative insights with a quantitative assessment.

A descriptive analysis in Table 1 first outlines key benefits, investments, and organizational impact, followed by a numerical scoring approach in Table 2 that allows structured comparisons using a 1-to-5 scale, where higher scores indicate better outcomes. For investment-related criteria, higher scores reflect lower resource demands, signaling more favorable conditions for adoption. This dual approach provides a detailed narrative and at-a-glance evaluation.

The following steps from the framework are analyzed for each scenario:

1. Identification and Prioritization of Development Activities
2. Description of the Process Without AI
3. Analysis of Data Conditions and Definition of the AI Method
4. Specification of the AI Workflow
5. Evaluation of AI Solution Effectiveness

The scoring weights are illustrative; companies may adjust them to reflect their strategic priorities or compliance needs.

Table 1: Qualitative Assessment of the Scenarios

Step	**Scenario A (Translation)**	**Scenario B (Interpretation)**	**Scenario C (Prediction)**
1. Identify & Evaluate Activities	High potential for bridging domain silos; fragmented data	High potential due to multi-sensor welding data & high rejection rate	High potential for optimizing rupture disc design, reducing test cycles & material costs
2. Process Without AI	Manual doc searches & email threads slow collaboration	Rigid tolerance checks, manual classification of welded parts	Manual, trial-and-error disc configuration, requiring multiple physical tests
3. Data & AI Method	Centralized knowledge base + chatbot (NLP approach)	Sensor fusion & classification (Random Forest, neural nets)	AI-driven rupture disc optimization using regression & neural networks
4. Specify AI Workflow	Chatbot integrates departmental docs, user Q&A	Model integrated at welding station, real-time classification	AI suggests optimal rupture disc parameters, reducing physical tests
5. Solution Effectiveness	Faster cross-domain queries, reduced overhead	Lower false rejection, deeper data insight, improved reliability	Lower test iterations, reduced material waste, faster development
Potential Criteria	**Precision:** Moderately high for text retrieval **Effectiveness:** High synergy **User Satisfaction:** Positive acceptance of AI chatbot	**Precision:** High in test phase **Effectiveness:** Notable cost savings **User Satisfaction:** Operators trust real-time feedback	**Precision:** High accuracy in rupture disc prediction **Effectiveness:** Cuts material costs & cycle time **User Satisfaction:** Engineers trust AI recommendations
Investment Criteria	**Model/Data**: Ongoing doc curation **Expert Dependency:** Some domain-specific expert involvement **Regulatory/Security:** Low risk, mainly internal data	**Model/Data:** Continual sensor expansions **Expert Dependency:** Weld experts to validate **Regulatory/Security:** Medium, stable industrial standards	**Model/Data:** Large test dataset needed **Expert Dependency:** Engineers validate but iterate less **Regulatory/Security:** Compliance via physical tests

Table 2: Quantitative Evaluation of Scenario Effectiveness

	Criterion	Weight	Scenario A		Scenario B		Scenario C	
			Rating	Score	Rating	Score	Rating	Score
POTENTIAL	**Precision & Reliability of AI Models**	0.20	4	0.80	5	1.00	5	1.00
	Effectiveness & Scalability	0.25	4	1.00	5	1.25	5	1.25
	End-User Satisfaction	0.15	4	0.60	4	0.60	4	0.60
INVEST	**Model/Data Maintenance Effort**	0.15	3	0.45	2	0.30	2	0.30
	Dependency on Process Experts	0.10	3	0.30	2	0.20	2	0.20
	Regulatory Compliance & Security	0.15	4	0.60	3	0.45	2	0.30
Total Score			**3.75**		**3.80**		**3.65**	

In **Scenario A**, the AI chatbot exhibited a high elevated level of precision in text retrieval, thereby markedly reducing wait times for cross-departmental queries. This efficacy was attained through enhanced domain alignment, and end-user satisfaction was found to be predominantly favorable. Employees reported a swift adoption of the chatbot following the completion of data curation. From an investment perspective, the maintenance of the document repository is an ongoing task, and a certain level of subject-matter expertise remains necessary to ensure data accuracy. Regulatory concerns are minimal, given that this scenario primarily handles internal data without extensive external compliance.

When translated into numeric scores, Scenario A achieves the second-highest ranking, reflecting its strong impact on knowledge integration and efficiency. While it requires continuous document maintenance and some expert involvement, its minimal regulatory constraints and broad usability contribute to its favorable positioning.

In **Scenario B**, the high precision demonstrated in real-time weld assessments was evident following comprehensive training with historical sensor data. The interpretation of complex parameter interactions resulted in a substantial reduction in false rejections and material wastage, thereby demonstrating notable effectiveness. Furthermore, the operators gained valuable insights into process variability, leading to a high level of user satisfaction. With regard to investment, the further expansion and calibration of sensors necessitates the continuous allocation of resources. However, the dependence on welding experts remains pertinent for the updating of classification thresholds and the evaluation of borderline cases. The regulatory and security aspects are moderate, governed by general industrial standards without direct consumer-facing constraints.

On the numeric scale, Scenario B attains the highest overall score due to its strong precision and cost-saving potential. Despite ongoing sensor calibration needs and moderate compliance demands, its ability to enhance process reliability and reduce material waste makes it a highly effective AI application.

In **Scenario C**, AI-driven predictive modelling was employed to optimize rupture disc configurations, thereby significantly reducing reliance on trial-and-error physical testing. The system demonstrated high precision in recommending optimal material and pressure parameters, thus enabling faster development cycles and reduced material costs. Engineers reported positive user satisfaction, as the AI-assisted design process allowed for quicker validation with fewer manual iterations. However, it is important to note that the investment requirements were notable, particularly in terms of building an extensive training dataset from historical test results and ensuring that AI-generated configurations meet stringent safety standards. While regulatory compliance remains a key consideration, the AI solution enhances standardization and traceability in the design process.

Quantitatively, Scenario C ranks third, demonstrating strong precision and effectiveness in optimizing configurations before testing. However, higher investment requirements, particularly in data collection and compliance, moderate its overall advantage. While long-term benefits include reduced material waste and faster development, initial costs remain significant.

These findings demonstrate how AI can be systematically evaluated in mechatronic product development, using both qualitative insights and a numeric summary of potential vs. investment criteria:

- **Translation (A)** unifies domain knowledge with moderate maintenance overhead and minimal compliance complexity.
- **Interpretation (B)** lowers error rates and uncovers deeper process insights, at the cost of ongoing sensor calibration and moderate compliance focus.
- **Prediction (C)** optimizes rupture disc configurations, significantly reducing physical testing and accelerating development cycles, while requiring substantial data infrastructure and regulatory validation.

In numerical terms, the three scenarios reveal distinct trade-offs, yet their weighted scores remain closely aligned, underscoring their comparable effectiveness. Scenario B achieves the highest score, largely due to its strong cost-saving potential and reliable classification accuracy. Scenario A follows closely, benefiting from its efficiency in knowledge integration with relatively low regulatory and infrastructure demands. Scenario C, while excelling in precision and optimization, ranks slightly lower due to its higher initial investment requirements. The small variations in scores emphasize that each approach offers substantial benefits, with differences driven primarily by specific implementation factors and investment considerations.

Ultimately, these evaluations confirm that AI solutions can effectively address major challenges in mechatronic product development, provided that adequate planning accounts for performance gains, resource demands, and compliance requirements. Combining descriptive analysis with numeric scoring offers a balanced approach, enabling decision-makers to identify where and how to invest in AI for maximum organizational benefit.

Addressing the 3rd Research Question

The third research question, developed in the Introduction, concerns

R3	How does the **process for the linking** of diverse mechatronic domains within a co-simulation framework succeed **through translation, interpretation and prediction approaches** using AI?

and was methodically addressed.

In modern mechatronic product development, multiple domains are closely interconnected while relying on different software tools, models, and data structures. Establishing a co-simulation framework that effectively integrates these domains remains a challenge, particularly when real-time collaboration and unified data management are necessary. The third research question therefore examines how translation, interpretation, and prediction, the three core AI approaches studied in the scenarios, can collectively facilitate the integration of diverse domains within a co-simulation context.

Translation (Scenario A)

- **Bridging Information Gaps**: The AI-enabled “translation” approach consolidates fragmented documents, engineering notes, and specification files across mechanical, electronic, and production teams. By providing near-instant retrieval of knowledge, it reduces the latency and misunderstandings often found in domain handovers.
- **Co-Simulation Relevance**: When multiple simulation tools such as structural analysis, fluid dynamics, or control system validation need to communicate, a translation-oriented AI can act as a central reference point, ensuring that domain-specific terminologies, data formats, and parameters remain consistently aligned.

Interpretation (Scenario B)

- **Deeper Data Insights**: The "interpretation" approach demonstrates how AI can parse complex sensor data (e.g., from welding or other manufacturing processes) to generate meaningful, context-rich feedback. This capacity is crucial when co-simulating multi-domain interactions, such as real-time adjustments in a mechanical structure's performance based on electronic or thermal feedback.
- **Shared Domain Understanding**: Advanced interpretation fosters a shared language of data. Instead of relying on rigid thresholds or separate analysis modules, co-simulation frameworks can feed interpreted sensor streams into multiple domain models, promoting cross-cutting optimizations and seamless domain interplay.

Prediction (Scenario C)

- **AI-Driven Design Optimization:** The prediction approach demonstrates AI's capability to forecast optimal configurations for rupture discs by considering material properties, thickness, and pressure thresholds. In a co-simulation environment, AI enhances cross-domain interactions by ensuring that mechanical, material, and safety constraints are optimized before physical testing takes place.
- **Proactive Domain Coupling:** By integrating AI-generated design insights into each domain's simulation environment, control logic, material selection, and mechanical constraints can be preemptively adapted. This proactive coupling fosters a more integrated, automated system-level simulation, where mechanical engineers can dynamically adjust stress models, manufacturing parameters, and failure thresholds based on AI-driven predictions, leading to fewer physical test iterations and enhanced design robustness.

These three AI approaches align with the generalized methodology and collectively support iterative co-simulation improvements. Initial translation solutions unify knowledge bases, while interpretation solutions refine cross-domain data synergy, and predictive solutions forecast interdependent domain behaviors. By applying these methods in tandem, consistent data models and informational flows are established, enabling more realistic simulations that incorporate mechanical, electronic, and control perspectives.

Thus, R3 is addressed by demonstrating how AI-based translation, interpretation, and prediction synchronize diverse mechatronic domains within a co-simulation framework. Each scenario highlights a key aspect of domain linkage, from bridging silos and interpreting signals to adapting system parameters. Combined with the generalized methodology, these approaches foster a robust, integrated environment for data-driven collaboration across mechatronic disciplines.

Summary and Conclusion

The integration of AI into mechatronic product development presents both significant opportunities and methodological challenges. This dissertation introduced a structured methodology to systematically implement and evaluate AI solutions across development activities, ensuring their potential benefits and necessary investments are holistically assessed. By following a rigorous research approach, the study combined conceptual methodology development with empirical validation through real-world industrial case studies.

The research was grounded in a structured four-stage approach, progressing from problem identification to methodological development, feasibility studies, and final validation. Initially, the study identified the fundamental challenges of AI adoption in mechatronic product development, particularly in interdisciplinary collaboration, process integration, and decision-making complexity. These challenges underscored the need for a generalizable framework that enables organizations to identify, utilize, and evaluate AI solutions in a structured manner.

To address these challenges, the dissertation introduced a generalized AI methodology, which was developed based on insights from the licentiate thesis and extended to form a structured, stepwise framework. The methodology provides a comprehensive approach for determining AI applicability in mechatronic development, systematically progressing from identifying relevant development activities to assessing AI-driven effectiveness. The five-step process ensures that AI potential is considered not only in terms of technical feasibility but also in its broader organizational and economic impact.

Through an interdisciplinary approach, the research examined AI's role in translation, interpretation, and prediction, highlighting how these dimensions influence mechatronic product development. Three real-world industrial case studies demonstrated how AI can bridge domain gaps, extract meaningful insights from manufacturing data, and anticipate system states to optimize engineering decisions. Each scenario provided empirical validation for the methodology, illustrating both its strengths and potential refinements.

A key contribution of this work was the introduction of a structured and generalized evaluation framework, extending beyond qualitative assessments by integrating a quantitative multi-criteria evaluation system. The weighted scoring model allows organizations to objectively compare AI solutions, balancing expected benefits against required investments. This structured evaluation enables decision-makers to prioritize AI implementations that align with their strategic and operational goals, ensuring an informed and scalable AI adoption strategy.

Beyond the technical perspective, the dissertation emphasized that AI adoption requires broader organizational adaptation. Sustainable AI integration depends not only on technical feasibility but also on factors such as AI governance, process adaptation, workforce readiness, and ethical considerations. The incorporation of a corporate and societal perspective further strengthened the methodology, acknowledging AI's evolving role in complex, cross-domain engineering environments.

The research followed a full validation cycle by applying the methodology across industrial case studies to refine and generalize its applicability. By completing this cycle, from conceptual development to real-world validation, the study confirms that structured AI methodologies provide a solid foundation for enhancing efficiency, fostering innovation, and improving decision-making in mechatronic product development.

Addressing the 4th Research Question

The fourth research question, developed in the Introduction, concerns

> R4 How can previous development sub-processes for cross-domain tasks evolve with respect to the **new mutual synchronization capabilities** made possible by the robust AI and how do these new requirements **influence the current methodology**?

and was methodically addressed.

The increasing use of AI in cross-domain engineering tasks is reshaping traditional development sub-processes by enabling real-time synchronization between disciplines that previously operated asynchronously. This synchronization eliminates process bottlenecks by ensuring that modifications made in one domain, such as mechanical design, are immediately reflected in other interdependent areas like electronic control systems. The ability to integrate data from multiple sources and domains allows for dynamic decision-making, reducing the reliance on rigid, pre-defined workflows and fostering an environment where adjustments can be made proactively rather than reactively.

One of the most significant transformations enabled by AI is the enhancement of co-simulation frameworks. By integrating real-time data and predictive analytics, AI facilitates more accurate multi-domain simulations, allowing engineers to evaluate complex interdependencies across mechanical, electronic, and software systems with greater precision. This shift not only improves validation processes but also enhances overall design robustness by identifying potential conflicts before physical prototyping begins.

These advancements introduce new methodological requirements for AI-integrated development. Transparency and explainability are crucial for maintaining engineer trust and usability. Quality assurance metrics tailored to AI-assisted workflows ensure that predictions and decisions align with product development objectives. As AI extends across engineering domains, the methodology must enable seamless, domain-agnostic integration.

Overall, these changes emphasize the necessity of an adaptable, AI-ready methodology that supports dynamic development cycles and real-time decision-making across interdisciplinary teams. The evolution of cross-domain processes through AI synchronization is not merely a technical enhancement but a fundamental shift in the way product development is structured, requiring continuous methodological refinement and alignment with emerging AI capabilities.

Future Work

This dissertation has established a structured methodology for implementing and evaluating AI in mechatronic product development and demonstrated its applicability through real-world case studies.

One key area for future work is enhancing the methodology. While the current framework provides a systematic approach, broader validation across industries would strengthen its applicability. Incorporating real-world performance metrics and adaptive weighting mechanisms could improve its predictive power, allowing organizations to tailor AI assessment criteria to their needs. Additionally, integrating real-time AI feedback loops would enable continuous monitoring and refinement of AI-driven processes.

Another avenue for exploration lies in AI-driven synchronization in cross-domain processes. AI's role in enhancing collaboration between engineering disciplines has been demonstrated, but further research should examine its scalability in complex ecosystems like automotive, aerospace, and medical technology. Investigating its role in virtualized environments, such as digital twins and real-time simulation frameworks, could provide deeper insights into AI's potential for optimizing multi-domain engineering. Additionally, AI transparency and explainability remain critical for trust and decision-making, warranting further study on their impact in AI-assisted workflows.

Beyond technical advancements, ethical, regulatory, and societal considerations remain central to responsible AI deployment. Future research should explore how evolving regulations, such as the EU AI Act, shape AI adoption and compliance strategies. AI's influence on workforce transformation also calls for studies on upskilling programs to ensure a smooth transition toward AI-augmented engineering. Establishing governance models will be essential for ensuring accountability, ethics, and transparency in AI-driven decision-making.

While this dissertation provides a structured foundation, the rapid evolution of AI necessitates ongoing refinement. Further research should focus on validating the methodology across industries, enhancing its predictive capabilities with real-world data, and addressing regulatory challenges to ensure AI remains a responsible and sustainable enabler of innovation.

Summary of Papers

This chapter summarizes the content of the papers on which this thesis is based upon and describes the author's contribution to each paper. The summaries of Papers I-IV and VII-XI are from the author's licentiate thesis [1].

Paper I

Leveraging Robust Artificial Intelligence for Mechatronic Product Development - A Literature Review

This paper explores the existing literature regarding the application of AI as a comprehensive database, decision support system, and modeling tool in mechatronic product development. It analyzes the benefits of AI in enabling domain linking, replacing human expert knowledge, improving prediction quality, and enhancing intelligent control systems. For this purpose, a consideration of the V-cycle takes place, a standard in mechatronic product development. Along this, an initial assessment of the AI potential is shown and important categories of AI support are formed. This is followed by an examination of the literature with regard to these aspects. As a result, the integration of AI in mechatronic product development opens new possibilities and transforms the way innovative mechatronic systems are conceived, designed, and deployed. However, the approaches are only taking place selectively, and a holistic view of the development processes and the potential for robust and context-sensitive AI along them is still needed.

The author was the main person responsible for selecting, analyzing and subsequently evaluating the literature. Moreover, the author wrote the paper.

Published in International Journal of Intelligence Science in January 2024.

Paper II

Intelligent analysis of components with regard to significant features for subsequent classification

This paper develops an intelligent method to analyze existing data appropriately and, at the same time, prepare it ideally for further applications, such as forecast models based on AI. To achieve this, several steps need to be taken. Firstly, a suitable segmentation of the component is performed. The aim is to detect areas in a component where features and form elements are found.

Other regions are ignored after the inspection by segmentation and voxelization. Subsequently, the voxelization of the component takes place, which results in the three-dimensional component or Computer- Aided-Design file being mathematically readable. This is done by rasterizing the component based on a previously selected resolution and other upcoming steps. Finally, the segmented and relevant areas are analyzed accordingly.

The author developed the concept and method regarding the Intelligent analysis of components. Moreover, the author wrote the paper.

Published in SAE Technical Paper, presented orally by the author in July 2023, Stuttgart, Germany.

Paper III

Intelligent Component Manufacturability Testing in Virtual Product Development

The paper implements a series of steps to address the increasing knowledge acquisition in the automotive industry. It emphasizes a targeted approach to information processing and evaluation, with AI playing a key role. AI is used to assess existing knowledge, assign attributes, and assist in the economic evaluation of new components or projects. The integration of intelligent methods enables companies to make informed decisions regarding resource allocation, time management, and project feasibility. Additionally, AI-based approaches are combined with preprocessing to handle the knowledge explosion and enable efficient analysis of product manufacturability.

The author developed the concept and method regarding the Intelligent Component Manufacturability Testing. Moreover, the author wrote the paper.

Published in Proceeding of Artificial Intelligence und Machine Learning in der CAE-basierten Simulation, presented orally by Fabian Richter in October 2023, Munich, Germany.

Paper IV

Robustness and Sensitivity of Artificial Neural Networks for Mechatronic Product Development

This paper aims to evaluate the performance characteristics of different uncertainty analysis methods and assess their applicability in agile automotive development processes. By considering the specific requirements and constraints of each method, a decision tree is proposed to recommend suitable and situation-appropriate methods for performing uncertainty analyses in network prediction. The goal is to enhance data exchange between departments, mitigate disruptions, and ensure informed decision-making throughout the development process.

The author developed the concept and method regarding the final decision tree for the efficient use of Robustness and Sensitivity. Moreover, the author wrote the paper.

Published in Proceedings of Automotive meets Electronics and presented orally by the author in June 2023, Dortmund, Germany.

Paper V

Reinforcement Learning in Mechatronic Systems: A Case Study on DC Motor Control

This paper investigates the application of RL as a control strategy in mechatronic product development, focusing on its deployment during critical stages between system architecture and system integration and verification. The study involves developing an RL-based controller and comparing its performance to traditional PI controllers in dynamic and fault-prone environments. The findings demonstrate the RL controller's superior adaptability, stability, and optimization potential, particularly in handling dynamic disturbances and ensuring robust performance. The research highlights how RL can facilitate the transition from conceptual design to implementation by automating optimization processes, enabling interface automation, and enhancing system-level testing. Future research directions include integrating domain-specific knowledge into the RL process and validating this approach in real-world environments.

The author contributed to the development of the RL-based controller, conducted performance evaluations against traditional PI controllers, and authored the paper.

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Paper VI

Künstliche Intelligenz als Co-Pilot – Warum Unternehmen im Fahrersitz bleiben müssen (Eng.: Artificial intelligence as a Co-Pilot - Why Companies need to stay in the Driver's Seat)

This paper examines the ongoing integration of AI into all areas of life and emphasises the need for companies to take an active role in shaping this transformation. It discusses how AI not only enables productivity and efficiency gains, but also serves as a foundation for innovations that can make everyday life easier. The authors emphasise the need for a well-thought-out AI strategy that includes both technological investment and employee training in order to fully exploit the potential of AI. They also emphasise the importance of lifelong learning and adapting educational institutions to the requirements of an AI-driven future. Finally, regulatory frameworks and ethical guidelines are discussed to ensure that the development and use of AI is in line with societal values.

The author was involved in the concept and methodology as well as writing the paper.

Published as IW Policy Paper No. 1 in April 2024.

Paper VII

Integration of Vulnerable Road Users Behavior into a Virtual Test Environment for Highly Automated Mobility Systems

This paper describes an approach to integrate real human traffic behavior into the approval and testing process of highly automated vehicle systems. It provides a safe and valid way to test critical traffic scenarios between vehicles and pedestrians. Basically, two different methodologies for the metrological detection of human movements are analyzed and experimentally examined for their suitability for this use case. Besides the general functionality, plausibility and real-time capability are further investigation criteria. The paper concludes with the integration of the proposed solution into a test bed for highly automated vehicle systems using a representative traffic scenario.

The author was involved in discussions, supported implementation and assisted in writing the paper.

Published in Proceedings of Kolloquium Future Mobility in June 2022, Ostfildern, Germany.

Paper VIII

Data Flow Management Requirements for Virtual Testing of Highly Automated Vehicles

This paper presents a virtual co-simulation approach for highly automated vehicle systems and uses it to demonstrate the data management requirements for a co-simulation platform such as AVL Model.CONNECTTM. The basis for this is a real urban driving cycle for modern hybrid vehicles to investigate emissions, consumption and range as well as the effects of highly automated driving functions on these parameters.

The author was involved in discussions, supported conducting the study and assisted in writing the paper.

Published in Proceedings of AVL German Simulation Conference and presented orally by René Degen in September 2022, Regensburg, Germany.

Paper IX

Development and Analysis of a Detail Model for Steer-by-Wire Systems

This paper presents an innovative nonlinear detailed model of a Steer-by-Wire system. The detailed model represents all characteristics of a real Steer-by-Wire system. In the context of a dominance analysis of the detailed model, all dominant characteristics of a Steer-by-Wire system, including parameter dependencies, are identified. Through model reduction, a reduced model of the Steer-by-Wire system is then developed, which can be used for a subsequent robust control design. Furthermore, this paper compares the Steer-by-Wire system with a conventional electromechanical power steering and shows similarities as well as differences.

The author was involved in discussions, assisted in writing the paper and supported implementation as well as evaluation.

Published in IEEE Access Journal in January 2023.

Paper X

Design of a Model-Based Optimal Multivariable Control for the Individual Wheel Slip of a Two-Track Vehicle

This paper presents a model-based multivariable control for wheel slip, enabling individual force control for each wheel. Using a linearized multibody two-track vehicle model, including tire, air resistance, and motor dynamics, a state-space controller with reference and disturbance feedforward is designed. Contact point velocities serve as controlled variables, directly influencing wheel slip and driving forces, while wheel torques act as control inputs. Stability and robustness analyses confirm high bandwidth and well-damped dynamics, while simulations, such as accelerated cornering and the Fishhook test, demonstrate effective force adaptation and strong performance under real-world conditions. Dominant transfer paths further reveal key input-state relationships influencing control behavior.

The author was involved in discussions, assisted in writing the paper and supported implementation as well as evaluation.

Published in SAE Technical Paper, presented orally by Robert Rosenthal in July 2023, Stuttgart, Germany.

Paper XI

Methodical Data Collection for Light Electric Vehicles to Validate Simu- lation Models and Fit AI-based Driver Assistance Systems

This paper presents an approach to collect vehicle dynamic parameters for the validation of simulation models. For this purpose, a measurement system is developed to capture and monitor driving dynamic information of the device under test in real time. This data is used to fit pre-developed simulation models and DAS. To investigate the vehicle dynamic behavior in critical driving situations, an extensive test study is conducted. Therefore, different ordinary driving situations in urban traffic scenarios are analyzed. Finally, the collected measured data is compared with the simulation results of a multi-body model for a multi-lane cargo vehicle.

The author developed the simulation model, the measurement setup and the verification study. Additionally, he supervised the realization of the study. Moreover, the author wrote most parts of the paper.

Published in Proceedings of Kolloquium Future Mobility in June 2022, Ostfildern, Germany.

Svensk Sammanfattning

Denna avhandling undersöker hur artificiell intelligens kan integreras i mekatronisk produktutveckling för att förbättra tvärvetenskapligt samarbete, effektivitet och beslutsfattande. Mekatroniska produkter kombinerar mekanik, elektronik och mjukvara, vilket leder till komplexa utvecklingsprocesser där flera ingenjörsdiscipliner måste samarbeta. Trots framsteg inom ingenjörsvetenskap och produktionssystem kvarstår utmaningar, särskilt kring synkronisering mellan discipliner, informationshantering och beslutsfattande. Traditionella utvecklingsmetoder bygger ofta på sekventiella processer där olika discipliner arbetar i isolerade faser, vilket kan skapa fragmenterad kommunikation, långa iterationer och ineffektiva arbetsflöden. Artificiell intelligens erbjuder möjligheter att förbättra dessa processer genom att automatisera dataanalys, generera djupare insikter och skapa en mer integrerad produktutvecklingsmiljö.

För att säkerställa en effektiv och strategisk användning av AI krävs en systematisk metodik som identifierar var AI kan ge störst nytta och samtidigt beaktar de organisatoriska och tekniska utmaningarna. I denna avhandling presenteras därför en strukturerad femstegsmetodik som fungerar som en vägledning för AI-integration inom produktutveckling. Metoden omfattar identifiering och prioritering av relevanta utvecklingsaktiviteter, analys av befintliga processer, insamling och utvärdering av data, specificering av AI-arbetsflöden och en slutlig bedömning av AI-lösningarnas effektivitet. Genom en iterativ forskningsprocess utvecklades metodiken först på konceptuell nivå och vidareutvecklades genom praktiska tillämpningar i tre industriella fallstudier.

De tre fallstudierna undersöker hur AI kan tillämpas inom produktutveckling genom tre centrala aspekter: översättning, tolkning och prediktion. I det första fallet används AI för att förbättra informationshantering och kunskapsutbyte mellan ingenjörsdiscipliner. Genom AI-drivna språkmodeller och kunskapshanteringssystem standardiseras och struktureras teknisk information, vilket förbättrar samarbete och minskar behovet av manuella förfrågningar mellan avdelningar. I det andra fallet används AI för att analysera sensordata i realtid och förbättra kvalitetskontrollen i tillverkningsprocesser. Maskininlärningsmodeller identifierar mönster och avvikelser, vilket möjliggör snabbare och mer precisa beslut, minskad kassationsgrad och förbättrad produktkvalitet. Det tredje fallet undersöker hur AI kan optimera konfigurationen av blästerplåtar genom att förutse deras prestanda innan fysiska tester

genomförs. Genom att använda AI-drivna simuleringsmodeller kan antalet nödvändiga tester reduceras, vilket minskar materialförbrukningen och förkortar produktutvecklingscykeln.

Genom att kombinera en kvalitativ metod med en kvantitativ bedömning av AI-potentialen möjliggör detta arbete en balanserad analys av AI-lösningarnas praktiska fördelar och investeringsbehov. Den föreslagna metodiken sträcker sig från identifiering och prioritering av AI-applikationer till en slutlig utvärdering av deras effektivitet, där en viktad flerkriterieanalys används för att skapa en numerisk jämförelse mellan olika AI-initiativ. Detta gör det möjligt för företag att fatta mer strategiska beslut och prioritera AI-projekt som ger högst värde. Utöver de tekniska aspekterna beaktar avhandlingen också organisatoriska och kulturella faktorer som påverkar AI-integration. AI-implementering kräver mer än bara teknisk kompetens eftersom det även handlar om anpassning av arbetsflöden, förändrade roller och nya kompetensbehov. Dessutom berörs frågor kring AI-styrning, transparens och regulatoriska krav, särskilt i säkerhetskritiska tillämpningar där AI måste uppfylla strikta efterlevnadsstandarder.

Forskningen har genomförts genom en iterativ valideringsprocess där metodiken först utvecklades på konceptuell nivå, sedan testades i verkliga industriella sammanhang och därefter justerades för att säkerställa dess generaliserbarhet. Genom att slutföra denna forskningscykel från konceptutveckling till praktisk validering bekräftas att en strukturerad AI-metodik kan fungera som en grund för förbättrad effektivitet, innovation och beslutsfattande inom mekatronisk produktutveckling. De insikter som presenteras i avhandlingen bidrar till både akademisk forskning och industriell praxis genom att erbjuda en metodik som kan tillämpas i bredare ingenjörsmiljöer. Genom att implementera denna metodik kan företag inte bara effektivisera sina utvecklingsprocesser utan också stärka sin innovationsförmåga och konkurrenskraft i en snabbt föränderlig industriell miljö.

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