

A Work Project, presented as part of the requirements for the Award of a Master's degree in
Management from the Nova School of Business and Economics.

ARTIFICIAL INTELLIGENCE FOR PRODUCT DEVELOPMENT IN GERMANY'S
AUTOMOTIVE INDUSTRY

Nina Daniela Neumeier

Work project carried out under the supervision of:

Prof. João Castro

17/12/2024

ABSTRACT

The role of Artificial Intelligence (AI) for product development is becoming increasingly important for competitiveness. As integral parts of Germany's economy, this study focuses on exploring how the automotive and telecommunications industry can leverage AI in product development (PD) based on the Stage-Gate model. Influential adoption factors are then investigated by applying the TOE-framework to each industry. The results show that AI adoption focus does not yet lie on PD, despite outlined potential for competitiveness. Findings further reveal dominant influences of in-house expertise, industry dynamics, leadership, organizational culture and structure and existing prerequisites of PD practices for consideration across industries.

Keywords: Artificial Intelligence, AI Adoption, Technology Strategy, Digital Transformation, Innovation, Product Development, Automotive, Telecommunications, Stage-Gate Model, TOE Framework, Application Areas, Challenges, Success Factors

This work used infrastructure and resources funded by Fundação para a Ciência e a Tecnologia (UID/ECO/00124/2013, UID/ECO/00124/2019 and Social Sciences DataLab, Project 22209), POR Lisboa (LISBOA-01-0145-FEDER-007722 and Social Sciences DataLab, Project 22209) and POR Norte (Social Sciences DataLab, Project 22209).

Table of Contents

1. Introduction	3
2. Literature Review	6
2.1 Role of Innovation for Competitiveness	6
2.2 Industry Characteristics	7
3. Conceptualization – <i>Joint Section</i>	8
3.1 Stage-Gate Model	8
3.2 TOE Framework	9
4. Methodology – <i>Joint Section</i>	12
4.1 Selection and Conduction of Expert Interviews	12
4.2 Evaluation and Analysis	13
5. Results	14
6. Discussion – <i>Joint Section</i>	25
6.1 RQ1: Identified Use Case Potential and Technological Factors	25
6.2 RQ2: Organizational and Environmental Factors.....	28
7. Managerial Implications – <i>Joint Section</i>	33
8. Limitations and Future Research – <i>Joint Section</i>	34
9. References	35
Appendix	60

1. Introduction

Constituting a disruptive role for economic growths by potentially creating 4.4 trillion dollars in economic value worldwide, it does not come with surprise that a global race of nations striving for artificial intelligence (AI) leadership has taken off (Chakravorti, Bhalla, and Chaturvedi 2023). While the U.S. and China are competing to be the world's top AI economy, many European countries like Germany are trying to stay ahead (Chakravorti, Bhalla, and Chaturvedi 2023) with a planned expenditure for AI promotion of EUR 5 billion by 2025 (European Commission 2024). However, what hereby sets the current AI revolution apart from previous transformative periods, is its accelerated adoption rate (Makridakis 2017). While the Industrial Revolution unfolded over 85 years, the adoption of AI is expected to reach its peak within the next five years, pushing organizations to act quickly to stay competitive (Cooper 2024a). Companies that position themselves as front-runners in the adoption of AI by 2025 are projected to experience a 122 percent positive cash flow change (de Boer, Ellingrud, and Richter 2022). If Germany as a leader within the European Union with a national economy of €4.12 trillion (Eurostat 2023) wants to remain and expand its well-known position, it must focus on domestic companies with significant potential in AI to implement the technology as quickly as possible (Strategy& 2024).

Contrasting their physical nature, both the automotive and telecommunications industry are hereby integral to Germany's economic landscape. Being globally renowned for its automotive industry (Glunz 2024), Germany is housing some of the world's largest car manufacturers such as Volkswagen, BMW, and Daimler. With a contribution of around 5% to Germany's GDP, the automotive industry remains a vital driver of economic growth (Statistisches Bundesamt 2019) and is currently facing the biggest transformation of its history (Heuss and Cornet 2023). Thereby, experts agree that AI will impact and transform the industry with different areas of impact including operational efficiency in manufacturing, supply chain as well as R&D practices (Hejtmánek 2023). The telecommunication industry in turn is one of the most

innovative national sectors contributing above average to overall economic growth, accelerated by renown companies like Deutsche Telekom, 1&1 and Freenet. Further, it constitutes a key driver of the national digitalization strategy (BMWK 2020). Telecommunication companies are increasingly exploring new avenues to improve their bottom line through AI by making use of data science, enhancing the customer experience, and optimizing network operations (Candiani 2024; Jorge et al. 2022). However, for many companies AI based value realization remains a challenge (Fountaine, McCarthy, and Saleh 2019a; Holmström 2022). While research has comprehensively focused on the role of AI within different functions (Chowdhury et al. 2023; Hidayat, Defitri, and Hilman 2024), despite the recognized potential of product development (PD) for improvement (Akroush and Awwad 2018; Nepal, Yadav, and Solanki 2011; Wang et al. 2024) and its impact on competitive performance (Calantone, Vickery, and Dröge 1995; Puriwat and Hoonsopon 2022), the recognition of AI in this area remains relatively low. As of 2023 only about 13% of firms worldwide utilize AI for this purpose (Chheda et al. 2023; Cooper 2024c). Developing purposeful AI use cases can be a complex endeavor encompassing multiple steps (Hofmann et al. 2020) and current best practices are still evolving through external challenges such as faster market dynamics and technological advancements. Therefore, this research will explore comparative insights between the automotive and telecommunications industries to investigate potential application areas as well as reasonings behind low adoption rates in product development. This analysis is especially relevant given the unique prerequisites and characteristics of each sector, which may significantly influence adoption patterns (Lopez-Garcia and Rojas 2024; Dinmohammadi 2023). To emphasize the contrasts in the product nature between both industries and given the limited scope, this study will narrow its research to applications related to the development of traditional automotive products like combustion vehicles and digital telecommunications products and services. Since in addition, there has not yet been a study that considers the nature of the industry and thus comparatively illustrates the role of AI in product development and its adoption, the following research questions arise:

R1: How is the current perception of AI usage potential for PD within the German automotive and telecommunications industry?

This research will be assessed by identifying the most promising use cases based on feasibility and ability to deliver meaningful business outcomes (Maiworm 2024). Thereby, it will concentrate on how AI can enhance related processes and its business impact, rather than on AI-driven products like autonomous driving systems or IOT devices. It is further important to note that PD encompasses not only the development of new products but also the further development of existing ones (Fayomi et al. 2021; Gutterman 2023). Consequently, for the purposes of clarity and consistency within our research, we will use the term "*product development*" to collectively refer to both new product development and product enhancement. This approach allows us to maintain a unified understanding throughout our study. After investigating application areas and within the technological context, as well as realization potential, in the subsequent research we will focus on organizational factors and external ones influencing firm level widespread AI adoption in PD processes:

R2: What are the perceived main organizational and external factors influencing firm AI readiness in PD in Germany's automotive and telecommunications industry?

By addressing these research question for each industry, we aim to explore factors from both perspectives while further drawing lessons learned based on differences and similarities. This analysis thereby positively contributes to theoretical understanding as well as practical application.

2. Literature Review

The following chapter establishes a structured foundation, serving as a basis for further exploration of the research questions outlined earlier.

2.1 Role of Innovation for Competitiveness

As markets evolve, the speed of innovation is primarily reflected in the rapid development of new products and technologies (Jiyao, Reilly, and Lynn 2009). Companies across industries increasingly acknowledge that innovation, as the systematic development and marketing of new ideas, products, services, and processes, is essential for meeting evolving consumer demands (Caldwell and Anderson 2017; De Jong, Furstenthal, and Roth 2022). Innovation practices thereby not only enhance existing offerings but also potentially disrupt industries and reshape markets (Caldwell and Anderson 2017). Building on this foundation, Porter (1985) describes a sustainable competitive advantage to occur when a company achieves either higher profits through product differentiation or similar profits at lower costs compared to its competitors (Bogdan and Pavelescu 2015; Porter 1985). As outlined by several researchers, achieving competitive advantage through innovation in fast-paced markets however therefore requires a strong focus on reducing time-to-market (Clark and Fujimoto 1989; Datar et al. 1997; Mabert, Muth, and Schmenner 1992; Vesey 1991). Faster response times and delivery of high-quality customized products increase possible price premium, customer loyalty and market share, while accelerating operations reduces production and logistical costs, ultimately boosting profitability (Kumar and Motwani 1995). Realization of a firm's innovation and competitiveness is hereby driven by its accumulated technological capabilities (Schumpeter 1911). Going in hand, leading innovators consistently realize substantially better business outcomes from their AI investments compared to competitors that adopt AI at a slower pace (De Jong, Marston, and Roth 2015). Integrating this systematic approach as a growth catalyst is important for companies to remain

competitive in today's fast-changing markets and achieve a performance advantage over their competitors (Caldwell and Anderson 2017; De Jong, Furstenthal, and Roth 2022).

2.2 Industry Characteristics

The automotive industry is primarily distinguished by its industrial manufacturing focus, with original equipment manufacturers (OEMs) serving as the central players. These OEMs are at the heart of the industry, coordinating tightly structured and controlled supply chains around their core operations of manufacturing and assembly, whereby Germany represents a core location in automotive production (Pavlínek 2021). European automotive OEMs have traditionally relied on their engineering excellence, strong brand loyalty, and robust supply chains to maintain a competitive edge (Erickson, Johansson, and Chao 1984; Frieske and Stieler 2023; Meredith 2024; McKinsey 2014). However, these strengths could inadvertently create a sense of safety, while the volatile environment of rapid advancements in electrification, software integration, and intensifying competitive pressures pose significant challenges to traditional industry players (Cornet et al. 2023). Research indicates that vehicle purchase price is a primary factor influencing consumer decisions, whereby Chinese competitors leverage a significant cost advantage, with production costs approximately 20% to 30% lower than those of European OEMs (Cornet et al. 2023). Moreover, McKinsey analysis shows that European OEMs have a development cycle of almost double the length compared with competitors from other regions, allowing competitors to respond to market trends much more quickly (Cornet et al. 2023). As a result, German automotive manufacturers relentlessly set their focus on cost and speed through reinvention of different functions (Cornet et al. 2023). In this context, different technologies have been investigated intensively in their improvement potential in various functions, such as blockchain technology and 3D printing in supply chain and manufacturing (Feiler 2024; Lim et al. 2016). While traditionally not being data-driven, real-time data streams are also becoming increasingly prevalent for the industry with possible application to enhance speed and efficiency in these functions (Einabadi, Baboli, and Ebrahimi 2019). With focus on

AI, the greatest potential in advanced manufacturing industry, where operational performance is a key driver of business performance, is similarly identified in areas such as supply chain management and production (Chui et al. 2018).

3. Conceptualization – *Joint Section*

In this chapter, we review the conceptual framework that serves as a foundation of this research. The Stage-Gate model will be introduced, a well-established PD concept in academic literature (Cooper 1988). Further, the Technology-Organization-Environment (TOE) framework by Tornatzky and Fleischer (1990) was developed based on literature from previous research of technology adoption (Tornatzky and Fleischer 1990). This research employs the TOE framework as its theoretical foundation to create a structured framework for analysis. Together, these frameworks offer a comprehensive lens for understanding not only the potential of application for AI in PD but also influencing factors that can impede companies' AI readiness.

3.1 Stage-Gate Model

The product development process encompasses all essential stages involved in creating and launching new or enhanced products or services to fulfill customer needs (IBM 2023). The Stage-Gate (SG) model (*see Appendix, Figure 4*) serves as a conceptual framework, dividing the product innovation process into five sequential stages and decision gates (Cooper 1988) that managers use as an analytical tool to evaluate the procedure of the project (Trott et al. 2022). AI technologies may be integrated at each of these stage along the product development process (Cooper 2024) while the specific kind of usage of AI widely varies across the stages (Zhang, Zhang, and Song 2021).

The SG model starts with “*idea generation*” as the beginning of the product idea, leading to an initial scoping at which it is investigated and conceptualized. With easy-to-obtain information, the project team concludes whether the idea justifies more intense research (Schilling 2017). Stage two is dedicated to “*building the business case*”, where detailed market and technical

analyses are conducted to justify the project (Schilling 2017). In the third stage, “*development*”, AI generates product concepts according to research and user requirements while also exploring multiple possible variations (Takyar 2023). In stage four, “*testing & validation*”, the product undergoes extensive trials and market testing to ensure readiness (Schilling 2017). If approved, the project moves into stage five, launch, where it enters full-scale production and marketing. The process concludes with a “*post-launch review*” to analyze the product's performance and gather insights for future projects (Schilling 2017). Customizing the process allows companies to address their particular challenges while still benefiting from the structured approach of the SG model (Schilling 2017). Meanwhile, the exact terminology may vary for PD while the overall concept of its application remains the same. For simplification of our results demonstration, our research will continue to utilize SG terminology as the foundation for service development as well (Cowell 1988).

3.2 TOE Framework

The adoption of AI within firms as a significant strategic decision extends beyond purely technological considerations. As successful strategic decision making requires a 360-degree perspective on both internal as well as external factors (Shepherd and Rudd 2014), the TOE Framework emerges as a holistic model by encompassing three key dimensions: technological, organizational, and environmental contexts (Tornatzky and Fleischer 1990). Throughout research, varying factors have been applied for each dimension due to the framework's diverse applicability (Chatha et al. 2024; Gong et al. 2024; Y. Zhang, Jiang, and Shang 2024). We will therefore follow the model's main structure as a starting point to identify and assess the factors within each industry as outlined in the following. Thereby, we will focus on organizational readiness factors while considering both technological and external contexts as key influences on the organization.

Technological Context

To review organizational readiness in a technological context, the TOE framework includes an investigation of technological factors of influence. Factors such as complexity, referring to perceived relative difficulty to understand can be critical as the more complex a technology appears, the more effort and resources are required for successful integration (Chau and Tam 1997), constituting a potential barrier. The transition to new technological systems can often result in implementation complexity through disruption of ongoing operations (Besson and Rowe 2012). In addition, compatibility with existing systems can be critical for AI adaption in those processes (Cao et al., 2021; James & McGuire, 2016). Due to reported inaccuracy of AI results (Singla et al. 2024), the current capabilities and state of reliability can constitute another potential hindering factor. Therefore, the factors of capability, complexity as well as compatibility will be examined as a baseline for the technology's relative advantage.

Organizational Context

This construct emphasizes the internal factors within firms that influence their ability to adopt new technologies, particularly in the context of AI implementation in product development. Going in hand with the resource-based view (Wernerfelt 1984), past research addressed the question, which of a firm's resources is contributing most to product innovation performance, investigating financial, technological, human-based, and organizational factors (Julienti Abu Bakar and Ahmad 2010).

Looking into the organization, resource constrains appear as an important factor to consider, including human as well as financial ones (Jain and Grossmann 1999; Yoshimura et al. 2006; Ogura et al. 2019). Common major internal obstacles to a firm's AI implementation are the cost of adoption and cost of adapting operational processes (Kazakova et al. 2020). While financial investments can efficiently enable implementation (Zhang, Zhang, and Song 2021; Merhi 2023) lack of financial resources can constitute a hindering cause (Damanpour 1992). Moreover, current state of IT infrastructure as a resource has been outlined as another influencing factor

(Kazakova et al. 2020; Damanpour 1992). Since the performance of AI is largely depended on data availability and data quality (Budach et al. 2022) lack of it can be composed as a challenge for AI adoption. In our framework, data as a resource, will not be analyzed as a standalone factor, as we anticipate its significant relevance across multiple individual ones (Pumplun, Tauchert, and Heidt 2019). In addition, the presence human resources as in-house AI expertise is critical for successful AI integration (Margaryan 2023). Firms that lack skilled personnel may find it difficult to tailor AI tools to meet specific needs (Lajous et al. 2023) which can limit the potential benefits for the PD process (Hazan et al. 2024). Besides the firm's resources, top management (TM) support can be another vital factor. Senior executives must demonstrate strong organizational commitment by creating a clear AI vision and strategy, alongside investments and sufficient allocation of resources (Zhang, Zhang, and Song 2021; Merhi 2023). Strong endorsement from leaders not only ensures essential resources but also fosters a culture of adaptability and continuous learning (Odilov 2024). This has been outlined as biggest challenge in building an AI-powered organization (Fountain, McCarthy, and Saleh 2019a). Moreover, successful PD relies on the coordinated efforts across various functions and teams due to the interconnectedness of the process across organizational units (Felekoglu, Maier, and Moultrie 2013; A. K. Gupta, Raj, and Wilemon 1985; Kahn 1996). When departments work in isolation, it can lead to fragmented strategies and hinder the cohesive application of AI (Ramirez 2024). Thus, our research will examine the organizational factors of financial, technical, human resources, top management support, organizational structure and organizational culture.

Environmental Context

Next to in-house-development, existing pre-made AI solutions can constitute an alternative solution (Bickford et al. 2023; Gordon 2024). Limited availability of technology vendors can hinder companies from accessing specialized expertise necessary for effective AI implementation in PD (Jarvis 2020). As the complexity of vendor selection have been discussed

in various contexts (Parthiban, Zubar, and Katarak 2013; C. A. Weber, Current, and Benton 1991), the challenge of identifying external providers to meet specific needs can further apply to integration of vendor-based AI technologies. Externally, firms must further ensure that their AI initiatives comply with existing data security policies. If a holistic end-to-end AI governance framework is not ensured (Rulf et al. 2023), misalignment with compliance standards, can result in legal repercussions (European Parliament 2023). Uncertainty about changing political regulations and economic developments can then further impede the firm's capability for innovation (Courvisanos 2009), e.g. by negatively affecting public or external funding (Kazakova et al. 2020). As a result, external factors to be examined are external providers, governmental regulations as well as political and economic environment.

4. Methodology – *Joint Section*

Since the organizational introduction of AI is a complex topic that has not yet been fully investigated in PD, this qualitative study allows for a comprehensive exploration of AI integration in product development, ensuring a well-rounded understanding of both the industry specific potential use cases and contextual challenges.

4.1 Selection and Conduction of Expert Interviews

Semi-structured expert interviews were conducted, allowing researchers to collect in-depth information while balancing focus and flexibility, unlike unstructured interviews (Ruslin et al. 2022). This method was chosen to gain deep insights from professionals who are directly involved in the fields of AI, automotive, and telecommunications, that could not be captured through quantitative surveys. Moreover, we deliberately focused on selecting interview participants who held technical and managerial positions directly involved in product development, R&D or AI for obtaining responses grounded in specialized AI knowledge, rather than more general views on AI applications in support processes to avoid biased or uninformed opinions impacting the data (Patton 2014). No distinction was hereby made between AI

adopters and non-adopters, as our research focuses exclusively on the expert knowledge of practitioners, which might be detached from organizational influences on practical realization. The interview protocol was carefully designed to ensure that the questions were open-ended, allowing participants to provide detailed, nuanced responses.

In total, 108 individuals were contacted, of which 16 agreed to participate in the interviews (*see Appendix, Figure 8*). In total, seven automotive and six telecommunications industry experts with different professional backgrounds were interviewed, as well as two joint AI consultants and vendors providing their perspective for both industries. The participants were made up of c-level executives, senior-level executives, engineers, data scientists, R&D experts, consultants, and board members. As the quality of OEM product outcomes in terms of quality, costs and timing can significantly depend on suppliers' performance (Forker 1997; Quesada, Syamil, and Doll 2006; Ragatz, Handfield, and Scannell 1997), those were also integrated as suitable interview partners for research objectives. Interviewees hereby stem from top leading organizations within the German automotive and telecommunications industry supported by AI-specialized vendors.

To secure the reliability and validity of the results, first, a pilot test was conducted with a small group of industry professionals, allowing for adjustments to be made before conducting the official interview. Interviews lasted 45 to 90 minutes and were conducted virtually, allowing to minimize geographical limitations. To maximize the reliability of the qualitative data, the interviews were recorded with consensus of the interviewees and resulting 885 interview minutes were transcribed in the following.

4.2 Evaluation and Analysis

The qualitative study followed a systematic thematic analysis approach. The process started with transcription and familiarization. Here, the raw interview data was transcribed and reviewed to ensure a comprehensive understanding of the discussions. Additionally, we compiled and analyzed citation metrics to assess research engagement, narrowing 418 overall

citations to 229 key citations specifically relevant to our study's focus. As a following step, we assigned 182 codes that capture the core message of each quote. The 37 themes were developed thereafter by organizing related codes into broader patterns in context of each framework to show deeper insights and relationships in the data. Themes were then integrated into the Stage-Gate model and TOE framework, as well as triangulated with existing literature to interpretate the data accordingly (*see Appendix, Figure 7*) which allows for both the systematic categorization of responses and the discovery of deeper insights (Braun and Clarke 2006).

5. Results

This presentation of results provides a comprehensive overview, and highlights use case potential within each industry, as identified by industry experts along the Stage-Gate Model (*see Appendix, Figure 9*). When investigating influential factors on PD based on the TOE framework (*see Appendix, Figure 5*), a consensus emerged across industries that PD is too nascent to have established specific influencing factors. Firms must first establish a foundational base first to prepare for AI readiness (I2/7; I3/10, I7/8, I8/2, I11/5,7). Complementarily, cross-functional characteristic of product development and its embeddedness in the firm (Song, Thieme, and Xie 1998; Troy, Hirunyawipada, and Paswan 2008) require a certain AI readiness on firm level to extract value from the technology (I4/10, I1/11, I6/1; I9/10). Consequently, while some success factors can be directly tailored to PD, many factors mentioned by industry experts pertain more broadly to the organization's general AI readiness.

Identified AI Use Case Potentials and Technological Factors

As highlighted by industry experts, bridging the gap between theoretical use in the stringent and predefined PD processes (I1/2) and real scalable “*proof-of-concepts*” (POC) (I3/16) in organizational settings remains a considerable hurdle (I8/1; I5/13; I3/16). This disparity underscores the importance of focusing on use cases that are both practically realizable and

create valuable outcomes. Fulfilling this need, use cases perceived as having the most potential were identified.

Application Areas

Three main application areas were outlined, among which different sub use cases could be classified, presented in the following (*see Appendix, Figure 9*).

Market Analysis & Requirements Engineering: An expert noted that innovations perceived as promising may lack the necessary focus on detailed market analysis, leading to potential misalignments with market needs (I2/1). The use of AI not only offers considerable time savings, but also fast and direct access to relevant information, saving multiple thousands of euros for alternative external sources (I2/1,2). Interviewees agreed that these advances make it easier for companies to make informed decisions and significantly increase their ability to innovate, e.g. by identifying competitors and products in the same segment (I2/1), ensuring right market positioning for USP effectiveness (I1/3,4), and identifying market and customer characteristics and needs (I1/1). Especially in the global export industry, those vary a lot, as exemplified by strong differences in Chinese customer preferences, whereby AI enables identification of potential market deviations (I1/1). Participants emphasized that product development in the automotive industry is a complex process due to compliance with a vast array of national and international requirements it must address. Those stem from various sources, including regulatory standards, technical specifications, and market demands which can vary across regions (I7/; I2/4; I3/5; I5/3). These regulations provide detailed specifications, ensuring that products meet stringent safety and quality measures (I3/3) such as battery standards and ISO requirements (II3/5; I7/1). The challenge is further compounded by the need to integrate and balance external demands with internal requirements from departments such as Marketing, Sales, and Production (I3/5). Moreover, those are oftentimes very abstract rather than measurable and must be dealt with already at early stages of the process (I3/5). AI can

significantly improve components of requirements engineering by firstly analyzing and extracting relevant information and categorizing it based on specific product areas, breaking down abstract, high-level goals into actionable tasks and technical specifications and identify inconsistencies, ambiguities, or missing details (I3/3,19). In this context, the additional use of Retrieval Augmented Generation (RAG) was stressed as promising, by complementarily reducing “*hallucination errors*”, a common issue with LLM (I5/2). Since moreover, the process of manually translating and structuring these requirements is labor-intensive (I2/4), strong AI potential is recognized due to this area being prone to errors (I5/3). Documentation and creation of industry typical and mandatory documents for development purposes, such as specification sheet, CAD data, and test reports is highly facilitated (I5/2; I7/10). Overall, therefrom deriving AI-based improvements in time, costs and quality were regarded as increasingly essential for staying competitive (I3,19).

Design Optimization: AI is increasingly being used as a tool in product development to analyze and at an early stage (I4/1,3,5; I3/1). Advancements in AI have enabled the generation of CAD data from simple sketches, facilitating the creation of CAD models based on initial drawings. This capability is particularly beneficial early design phase (I3/1). In the later stages of PD, detailed design becomes critical, requiring precision and efficiency. Currently, AI-aided design tools are employed to enhance this phase supporting designer brainstorming and enabling more efficient and precise design processes (I3/1). Consequently, with help of 3D CAD systems, geometric details can be analyzed, the optimum for maximal durability and functionality be identified (I4/1), and material selection be improved (I1/5). In this context, besides defining specific individual details, another interviewee further stresses the AI potential in the use of AI for “*Design of Experiments*” (DoE) (I15/1a). Traditionally, design experiments have been conducted manually, requiring significant time and effort. The integration of AI into the design process can substantially accelerate this workflow by automatically generating and evaluating various design options (I15/1a), seeking to balance multiple co-influencing development

objectives such as exemplary fuel consumption and emissions (I8/4) within given regulatory boundaries (I8/5).

Product Testing: Following the sequence of the development process, each identified requirement must later be checked to ensure that it is fulfilled (I3/4). AI application potential is outlined here, as it can automatically derive test specifications by analyzing the requirements and suggesting test methods and develop complete test plans deriving therefrom which define the order and priority of the tests (I3/4). An expert underscored the idea that AI's value extends beyond operational efficiency in accelerating processes but also in eliminating unnecessary steps or tests that cover unlikely scenarios (I1/9), enabling more targeted resource deployment (I1/9). Another dominating theme within simulation use cases was the “*shift-left paradigm*”, which entails to carry out testing & validation in the PD process instead of after physical production (I1/8). The concept of digital twins and simulations is emphasized as beneficial key strategy, applied across various levels, such as individual components and whole systems, thereby incorporating different types of AI aiming to test, simulate, and virtualize processes and conditions extensively (I1/8; I4/2; I8/6). Focus here lies on physical modeling, which is based less on deep learning and more on rule-based AI systems, since physical modeling relies on deterministic and interpretable rules, making it suitable for accurately testing and validating (I1/8). Complementarily, the “*first wave of AI*” which was mainly rule based (I5/1) now further progresses into combination with neural networks, “*Neuro-Symbolic AI*”. This enables more exact simulations by combining explicit knowledge of physical laws with the ability of neural networks to fill in gaps or model complex phenomena that are hard to define purely with rules of physical laws for creating realistic simulations (I5/1), enhancing application feasibility. Hereby, implementing a “*shift-left*” testing approach presents a compelling business case for the automotive industry. Traditionally, 70–80% of PD efforts focus on testing & validation, often requiring costly prototypes reaching €50–70 million (I1/8; I4/2). Integrating testing earlier in the development cycle allows companies to identify issues sooner, reducing time and

expenses associated with extensive prototyping. Late-stage errors, such a brake recall, can be particularly expensive and thereby avoided (I1/8).

Technological Context

When asking participants for the technological maturity and readiness for daily operations, three main themes emerged, along which current technological success factors for scalability were assessed.

Compatibility: Lacking success of prior use cases has been traced back to the great effort of data generation and cleansing to ensure its continuous quality (I5/9). Furthermore, one participant added ensuring quality of data in terms of actuality is a fundamental endeavor, as in a dynamic industry as automotive, data can be quickly outdated, and its generated benefit limited (I1/14). One expert added that current AI systems often deliver results that are not clear, defined, or standardized (I1/25). This makes it difficult to link the data directly with other tools or processes (I1/25). It is also emphasized that without clear and compatible interfaces between the data generated by the AI and existing company systems, the benefits of AI remain limited, as this makes automation and further processing of the data more difficult (I1/25). In some cases, existing software infrastructure already supports AI integration as an additional feature or extension with beneficial outcomes particularly within CAD systems, which minimizes the need for substantial investments (I4/5). In contrast, especially where AI must be deeply embedded in an application system in highly automated or partially automated process chains, integration into such systems often requires considerable technical adjustments and customization effort (I3/6). It is therefore summarized that complexity of an AI use case largely depends on whether it operates independently or is integrated into highly interconnected systems, as fewer dependencies simplify implementation (I1/7; I4/12).

Complexity: Transparency of large models containing multiple layers was further stated as an obstacle (I5/8,14), which does not relate to the technology's maturity but its foundation element

(I5/14). While those models are very efficient, to some degree they constitute a “*black box*” regarding their decision making (I5/8) as the complexity of these models makes their internal processes opaque (I5/14), generating correct result but not necessarily through correct processes (I5/7). Here, potential use of “*short-cuts*” due to limited physical understanding was further highlighted to increase difficulty in reverse-engineering (I5/7,8). Moreover, data quality of training sets including potential biases which cannot be detected or corrected easily was mentioned as another concern to affect transparency (I5/10). Researchers therefore often must rely on observing outputs and adjusting training data or inputs to influence behavior (I5/14). Further, an expert noted the “*No-Free-Lunch-Theorem*” trade-off in AI context: as AI capabilities increase, output quality can decline, since the most effective AI is highly task-specific but tends to do over-fitting when having to draw conclusions for new data (I5/15).

Capability: Further critical opinions emerged towards the necessity of creativity and human intuition especially in the early stages of PD, where AI lacks the ability to replace these uniquely human qualities like expertise knowledge appropriately (I5/4,6; I1/13). Further, the limitations of current technology in “*first principles*” (I1/6), such as accurately modeling physical interactions (I1/6; I5/16) does not only affect technology understanding but output quality, outlined via the central issue of “*Sim-to-Real Gap*”, which refers to the discrepancy between simulated data and real-world scenarios.

Organizational and Environmental Factors

The findings from the qualitative study shed light on the importance and challenges of organizational and environmental factors influencing AI adoption.

Organizational Context

Resources: Resources overall emerged as a central influence on technology integration, such as the cost of AI implementation (I8/3). While the financial capacity was mentioned as one concern (I6/3), participants especially highlighted that companies are hesitant to allocate

substantial budgets without clear evidence of return on investment and that the benefits need to be clear and demonstrable (I4/8; I7/2,7).

Technological infrastructure further constituted a critical success factor for AI integration. Experts highlighted that existing tools and platforms in product design and development are already equipped to incorporate AI as an enhancement, allowing seamless integration as an additional function or extension without requiring major system overhauls. Examples include applications in design processes and efficient information sourcing, where AI can enhance performance and streamline workflows (I1/10; I4/5).

Given the cross-departmental nature of PD processes, one interviewee stressed whole cross-functional AI teams rather than present single experts as essential to leverage AI in PD (I4/10). Further, the generational gap in technical skills was another prominent theme (I7/3). Younger professionals were seen as more comfortable with AI technologies (I7/3), while decision-makers in traditional industries like the automotive sector, were outlined to be in comparably higher in age and therefore often lacking familiarity with the technology (I1/21). Many firms lacking clear guidelines and workforce development initiatives were stressed to hinder benefit leverage potential. In addition, hiring and training qualified employees has been marked as a complex endeavor which must be integrated as a pro-active long-term rather than short-term solution approach to address the traditional rigidity of the industry (I2/9,10,14; I4/7). At the same time, employees facing negative usage experience prior to training initiatives and therefore building a negative attitude towards AI based solutions beforehand seems to regularly occur on individual level of traditional firms (I2/9). In contradiction, analyzing the level of knowledge and attitude of employees, clearing up possible misunderstandings and creation of a positive basic attitude was thereby named as the critical foundation to implement AI strategies (I2/9,13).

Increasing productivity through automation was described as inevitable for maintaining competitive market positioning (I3/8). However, concerns about workforce replacement and

the perception of automation by workers' unions were emphasized as critical factors influencing adoption—an issue that has surfaced during previous industrial revolutions (I2,13; I3,8). Additionally, the interviewee highlighted the difficulty of fostering a mindset shift among employees, particularly in large, traditional companies. He further noted that employees in this country tend to prioritize personal job security, whereas in other countries, people are generally more open to change (I2/14).

Top-Management Support: Interviewees agreed that top-down support and a clear vision for AI initiatives are critical success factors for ensuring financial feasibility and enabling company-wide adoption, rather than limiting AI efforts to isolated use cases (I2/11,12; I8/7). However, instead of a clear AI strategy, an established “*learning by doing*” principle was outlined to be followed by one expert (I2/19). AI adoption in automotive firms however appears to be primarily driven by instance-level management (I1/16), as many decision-makers lack sufficient hands-on experience with AI (I1/17; I2/11), sometimes holding rather negative than neutral attitudes (I2/17). Complementarily, other experts pointed out that the industry is taking a cautious and slow approach to the integration of AI, mainly due to two co-influencing factors: limited understanding of the technology and hesitance from executives, as there is a high level of sensitivity (I4/9; I7/4,6). While even simple but clear improvements were mentioned as a starting point to present to TM (I1/16), still many managers are reluctant to use AI on a large scale until the technology is fully transparent and its reliability has been clearly proven (I4/4,8) to provide significant value (I7/9). Instead, requesting TM support has been stated to constitute a thoughtful approach considering the timing and way how to successfully present the business need (I6/2).

While experts perceived management teams to recognize the need to further explore AI-based solutions at the current stage (I7/5; I6/4), they also stressed volatile and challenging industry dynamics to further pressure the industry via strong competition and the market shift to electric vehicles (I6/3; I4/11). Those in turn force strategic focus on ensuring a stable core business and

don't leave much capacity for other topics and an explorative approach is hindered by management of day-to-day operations (I6/2,3; I4/11). Going in hand, further a lack of dedication to put discussion into practice, such as by representation in assigned teams, crucial for the definition of opportunities, needs and rules, was mentioned to slow adaption progress (I2/10, 17).

Organizational Culture: Interviewees outlined that the German automotive industry is strongly characterized by its historical orientation, which was outlined as one reason for its current lean period (I2/6; I3/15). Germany has a strong history of technological innovation, particularly in automotive engineering. However, compared to other countries, it faces challenges in practical implementation. When changes occur, there is a tendency to look back and analyze past successes, whereas other countries focus on forward-looking strategies and necessity for change for adaptability (I3/15). One interviewee exhibited that data is the central element for the successful use of AI as it is "*the origin of all value*" in a company (I3/7). Therefore, coherent understanding along all levels from production to management of data as one of the most valuable resources for the future of the company is essential (I3/7). As participants explained, historically, the automotive industry has been production-centric rather than It-centric, often perceiving data as a secondary by-product rather than a strategic asset. This perspective has led to data being undervalued and underutilized, making this mindset shift more complex (I3/13; I8/8) and differentiates traditional from new emerging industry players (I3/12; I7/11). For AI to reach its full potential however, data must not only be available, but also accessible. This awareness must be embedded throughout the organization, as data should not be seen as a minor technical detail, but as a strategic resource and every action and every capture contributes to the generation of consistent and reliable data that can later be used by AI (I3/7).

Organizational Structure: A prominent key issue included interfacing AI solutions with existing workflows and overcoming departmental silos (I8/10). The industry's hierarchical structures

and siloed operations rather than along the customer journey were stressed to lead to fragmented workflows and reduced efficiency in cross-functional AI projects (I3/14). One participant acknowledged that the challenging factor is not the organization of those processes only, but the interface, as AI yet cannot be easily employed along all stages that AI cannot be universally applied across all business functions (I2/8). The longstanding focus of established automotive companies on traditional products, such as combustion vehicles, has led to specialized expertise in these areas. However, the product architectures developed over decades for combustion engines and mechanical precision often entail a long "*rat's tail*" of complex systems and processes, increasing complexity in transitioning to data-based, flexible systems (I3/11). In contrary, emerging competitors in countries such as China were explained to have a structural advantage as they can start on a greenfield site without historical burden enabling to work in a data-driven way right from the start, which even becomes easier through the switch to electric vehicles, since complex mechanics of combustion engines are no longer required (I3/9).

Environmental Context

Regulations and Compliance: The regulatory environment and data compliance constituted an overarching relevant theme (I1/12,19,20; I5/11; I3/18). The Volkswagen emissions scandal, commonly referred to as "*Dieselgate*", has profoundly influenced the German automotive industry's approach to legal compliance as an expert explained that the industry adopted a more dominating heightened awareness and stringent compliance culture (I6/5), regarding adherence to legal standards as a core organizational value (I1/20). GDPR therefore seems to significantly influence data handling practices within the automotive industry while its impact on various use cases is relatively minimal when data is properly anonymized (I5/11). Since new regulations are introduced every few years, ongoing constant adaption does not significantly restrict innovation (I5/11; I7/7), whereby ability to develop solution for those changes was attributed to company size and resources and not stated as a matter of principle specific to AI (I3/18). Congruently, practitioners of the industry seem to prepare and explore the boundaries and future

opportunities within regulatory compliance through knowledge-sharing within present AI teams and other initiatives (I6/5). However, interviewees agreed that every action is accompanied and guided by large overarching organizational specifications and regulatory data requirements are stated to lead to increased effort and preparation through time-consuming, extensive backup checks with legal teams (I6/6). This cautious approach is even accelerated through internal Non-Disclosure Agreements for sensitive work topics, ensuring strict control over information accessibility, even within the organization (I1/33). While thereby including all-encompassing data is recognized as essential for generating optimal insights, it is stressed to also create a tension between leveraging AI usage and safeguarding against risks (I1/33).

External Providers: The degree of AI solution usage in the company to some extent depends on whether those are developed in-house or provided by external vendors, whereby this question arises during every stage of a process (I4/6). On the one hand, AI vendors were perceived as an efficient solution to eliminate the internal learning process covering lack of internal resources (I1/18,24; I2/15; I7/3). Benefits of in-house-solutions contain flexibility and customization, as it requires extensive-knowhow such as in data connection, monitoring and model management, which becomes especially challenging when processing large volumes of data with the need to ensure an overview (I4/6). On the other hand, costs and knowledge protection concerns were contrasted issues to influence the leverage of those benefits (I2/15,16; I8/3).

Political and Economic Environment: The political environment in Germany was described as a limiting factor for long-term investments such as in AI solutions. Uncertainties through unstable framework conditions and a high tax burden were mentioned to mainly relate to investments with high costs in AI solutions, where amortization extends over a long period of time (I2/18). Moreover, high energy costs, levies in the healthcare and pension system were outlined as additional burdens that weigh on companies (I2/18). These disadvantages were

concluded to reduce the competitiveness of the German automotive industry compared to countries such as the USA or China, which enjoy advantages through government subsidies or deregulation (I2/20; I5/12).

6. Discussion – Joint Section

6.1 RQ1: Identified Use Case Potential and Technological Factors

By identifying potential application areas for use cases and conducting a thorough investigation of technological factors, several key findings have emerged, as outlined in the following.

AI Usage in Product Development in Automotive and Telecommunications Industries Differs in Potential Application Areas in a Pre-Mature Phase for Both: The focus of prior research on AI's transformative role of line-oriented operational functions (Chui et al. 2018) was supported by experts as potential applications in production, such as quality control, automation, and predictive maintenance (I1/15,22; I5/17; I3/2; I16/1; I2/5,8; I8/9) were emphasized without particular prompts. At the same time, the results reveal specific PD use cases perceived as having high potential by practitioners, corroborating earlier potential outlined in this area (Chui et al. 2023). Particularly in the stages of “*building the business case*”, “*development*”, “*testing & validation*” (Cooper 1988), AI has been identified as a tool to enhance development processes and outcomes for the automotive industry. In contrast, telecommunication firms are advancing rapidly in their digitization efforts (Sfondrini 2024), leveraging AI in fast-paced innovation cycles with an indicated business focus on the “*development*”, “*testing & validation*” as well as “*post-launch review*” stage (Cooper 1988). Existing literature further highlights identified applications as significant profitability drivers, not only for the telecommunications sector but also across industries (Creasy et al. 2024; Viswanathan 2024; Takyar 2023; Cooper 2023), confirming their value contribution. Moreover, and as anticipated by literature (Creasy et al. 2024), additional relevant use cases beyond PD were linked to service and network operations including virtual assistance, predictive

maintenance and anomaly detection (I9/4; I10/3; I11/5,6). Interview findings therefore imply that AI adoption in both industries is not primarily focused on PD and still appears to be in a premature phase of AI use in PD applications.

Gap Between Theoretical Potential and Realization Hinders Firms of Both Industries

from Transitioning to the *Adopters*” Phase: Insights from experts in both industries reveal a significant disparity between the theoretical potential of AI use cases and “*proof of concept*” projects (I8/1; I5/13; I3/16; I5/5; I10/9; I11/7,22). Given diverse influences of technological factors on feasibility, implementations in both industries often fail to meet expectations regarding desired outcomes and required efforts. As shown by results, unclear or initially misjudged business needs obstruct necessary endorsement of investments and integration efforts for AI adoption in PD and can ultimately lead to abandoned AI projects. This discrepancy could therefore provide one factor contributing to the stated failure rate exceeding 80% for AI-related projects (Weiner 2021). Congruently, based on Rogers (1983), firms are more likely to adopt technologies that offer a clear advantage over existing processes when they perceive these benefits as clear and impactful, leading to improved performance or competitive positioning (Gangwar, Date, and Ramaswamy 2015). If firms instead react to lack of clearness by adopting a passive approach (Huisman and Kort 2000), significant opportunities for the “*early majority*” may be missed (Rogers 1983). Instead, acknowledging project failures as learning opportunities could facilitate future adoption processes and improve the accuracy of further potential estimations (Argyris and Schon 1978).

Overlooking AI Potential Can Limit Positive Business Impact in Both Industries:

Our results indicate that derived use cases from both industries align with the “*originators*” and “*facilitators*” role characteristics (Brem, Giones, and Werle 2021). The influence of these roles contributes to achieving business outcomes, encompassing improved process efficiency, cost reduction, and, consequently, increased product profitability as based on our findings. Such

outcomes then directly address common challenges for PD, e.g. by improving resource efficiency (Ogura et al. 2019), streamlining requirements management (Weber and Weisbrod 2002), and accelerating time-to-market (Datar et al. 1997). However, despite these examined business outcomes, our findings indicate that the potential of AI is not being fully leveraged yet. Although resource efficiency is a central component of sustainable innovation strategies (Schaltegger and Wagner 2011), sustainability unexpectedly appears underemphasized as a positive business outcome. This contrasts Böhler et al. (2023), finding sustainability as a high priority for executives. An automotive interviewee attributes this disparity to the strategic emphasis on reducing development cycles and enhancing efficiency (I4/2), while literature finds higher sustainability potential in the manufacturing processes and in the features of the product (Lukin, Krajnović, and Bosna 2022; Mildenberger and Khare 2000). Similarly, for telecommunication firms, AI-enabled optimization of network capacity results in reduced CO2 emissions, while, as confirmed by literature (Gómez et al. 2024), the positive financial impact constitutes the main driver (I10/5; I15/5b). Overall, this suggests that by lacking acknowledgement of the potentially positive impacts of AI in PD practices, companies risk missing opportunities to enhance their competitiveness (Cornet et al. 2023; Friedrich et al. 2021).

Prioritizing Easy-to-Implement AI Use Cases Fosters Confidence Within Both Industries for Further Future AI Deployment: Given the influences of various technological obstacles, achieving full-scale implementation or even a fully automated development process (I3/17) therefore remains a significant challenge for both industries. However, our findings also reveal that certain use cases within each industry are not only easier to implement but also mature enough to deliver measurable value, making them ideal entry points for integrating AI into PD (Davenport 2018; Cooper 2024). Congruent with generative AI in product development being confirmed as one of the greatest opportunities to deliver significant value to businesses (Chui et al. 2023), our findings indicate that “*easy-to-implement*” use cases most often involve

generative AI application. Outlined examples included software code generation in telecommunication firms and CAD design optimization in automotive firms. Due to the technologies simplified usability (Chui, Robinson, and Alex Singla 2023), generative AI simultaneously creates AI learning and experimentation opportunities for employees (Booth et al. 2024) which enables fostering an innovative organizational culture for AI adoption. Such straightforward applications can allow companies to quickly showcase AI's benefits like efficiency and cost savings with manageable effort (Davenport 2018). Additionally, these can act as pilot projects for “*proof of concept*”, demonstrating AI's value and establishing a foundation for more extensive and complex implementations (Sagodi et al. 2022).

6.2 RQ2: Organizational and Environmental Factors

After exploring both internal organizational dynamics and firms' ability to react to the external environment, we were able to derive the following key findings.

While Telecommunication and Automotive Firms Hold a Solid Position in Physical Resources, Human Factor Constitutes a Challenge for Both: While the literature highlights the importance of AI expertise as a foundation for building capabilities (Margaryan 2023), human resources related activities, e.g. attracting and retaining skilled employees, constitute a functional and strategic challenge in automotive and telecommunication firms. Since the “*tech-skill gap*” in the German economy continues to grow (Durth, Kalinna, and Soller 2023) hiring might not only be an industry and firms specific but domestic barricade in Germany. While the automotive industry is impacted by the generational gap, for the telecommunications industry's its perception as a less attractive employer became evident. This observation is supported by literature indicating that telecommunication employees express a negative perception concerning the industry's future (Barkway and Gröne 2024). While vendors are perceived as a potential capability solution by both industry experts, the conflict between internal and external AI solutions has been addressed in literature as “*Make-or-Buy decision*” which presents a complex choice (Stratman 2024) for both types of firms. However, interviews let derive that

hereby, automotive firms' might be more driven by cost and speed influences, while telecommunication firms might be more influenced by its realistic business value compared to previous solutions. Since overall, results however indicated a solid resource-based position of both industries, resources (Julianti Abu Bakar and Ahmad 2010) alone might not be sufficient to explain success in AI solution exploitation in PD.

Balancing Short-Term Operational Priorities with Long-Term Innovation Strategies

Makes AI Integration a Common Business Challenge in Both Industries: Although our findings across both industries and literature affirm that organizational resources are critical success factors, our results complement the concept of dynamic capabilities as an extension of the Resource-Based View (RBV), focusing on the firm's ability to modify and leverage their resources over time (Teece 1994). This perspective has previously been taken in literature to address digital transformation and its impact on PD (Schneider et al. 2023). As interviewed automotive experts acknowledged the necessity of exploring AI-based solutions as an opportunity to threats of competitor pressure, this indicates German automotive firms' competence in terms of opportunity sensing to address changing market circumstances (Moore 2021; Teece 1994). However, volatile, and demanding industry dynamics similarly compel German automotive companies to prioritize maintaining a stable core business in times of highly competitive pressure and product shifts. Similarly, telecommunication firms view the urgency of AI adoption as less critical since their primary focus remains on maintaining operational stability, reflecting commitment to customer value delivery by continuously meeting changing customer expectations (Zakir Gaibi et al. 2021). In conclusion, insights from both industries reveal that despite differing market demands, both industries therefore face a shared challenge: balancing short-term operational needs with long-term innovation strategies to effectively integrate AI (Dhairyawar, Stoop, and Kock 2024; West, Koller, and Bhargava 2024; Staack and Cole 2017).

Leadership Support in Telecommunication Firms Provides Remarkable Benefits in AI Integration due to Enhanced Dynamic Capabilities: Results further revealed that the automotive industry exhibits caution in integrating AI, primarily due to concerns about transparency and reliability as well as limited technology understanding in the c-level to even increase uncertainty. Therefore, especially in such volatile industry dynamics, executives may be reluctant to implement AI on a large scale until its effectiveness is conclusively demonstrated. As prior research has shown the negative influence of perceived risk on CEO's technology adoption decisions (Ferri et al. 2020), successful integration of AI solutions in German automotive firms in turn requires a balance between the pursuit of opportunities and the management of risks which constitutes a significant challenge (Todd and McCurry 2023). Coherent with related literature findings (Zhang, Zhang, and Song 2021; Merhi 2023) without a clear strategic vision from TM however, AI projects could be viewed as isolated experiments rather than integral components of the company's long-term goals. Within the context of dynamic capabilities, this restricted leadership perception in turn can hinder the allocation of necessary resources and transforming initiatives for structural and cultural change (Teece 1994). Nevertheless, those are necessary for complete depletion of AI solutions (Ellström et al. 2021). In telecommunication firms, TM is generally not perceived as a barrier. Managers mostly not only acknowledge the necessity for innovation but actively encourage the adoption of new technologies through organizational efforts. This seems due to inherently dynamic and innovation-driven characteristics (Mishra 2024; Rutitis and Volkova 2019; Wood 2024) requiring progressive decision-making and adaptability by its leadership. Since these findings have been outlined as the biggest challenge in building an AI-powered organization (Fountaine, McCarthy, and Saleh 2019), the significance of TM support and the resulting benefit of telecommunication firms becomes evident.

Cultural Data-Driven Prerequisites and Foresight of Telecommunications Benefit AI Integration: Closely related, organizational culture's crucial role was highlighted by our

results. Hereby, the dependence of AI adoption on effectively managing attitudes and understanding across the workforce, including unions constitutes a potential obstacle to AI integration in several practices. While openness to technological innovation is predominantly evident among employees for whom technology is particularly job relevant (Opitz et al. 2012), this challenge appears more widespread in automotive firms, whereas it is more limited to non-technical departments for the telecommunications industry. Still, interviews therefore especially underscored that, even in innovation-driven firms, it is essential to engage all employees in technological change.

Similar to existing literature, interviewees of both industries additionally suggest that organizations must recognize data as a strategic asset for AI to reach its full potential (J. Gupta 2024), hereby constituting a current challenge especially in automotive firms. The industry's production-centric identity led to a neglect of data's operational and strategic importance, which telecommunication firms in contrary are forced to acknowledge through its nature of business operations, effectively leveraging their diverse data sources to address the increasing demand for data-driven connectivity (Cloudera 2022). Central to this is a highlighted forward-looking mindset, not only on addressing current challenges but also on anticipating future opportunities and trends which is key for adapting effectively to evolving market demands (Estendorfer 2024). In contrary, AI integration and exploration in the German automotive industry appear to be hindered by two key factors: a historically retrospective approach to addressing changes, and the lasting impact of critical industry events, even when individual firms were not directly involved. Unwritten rules of conduct, shaped in part by heightened public scrutiny and stricter regulatory oversight following incidents like the "*Dieseldgate*," further exacerbate these challenges. While interviews showed that the resulting necessity for extensive legal reviews does not hinder innovation in automotive PD itself, adherence to organizational protocols can still slow down AI initiatives in automotive firms in general. Meanwhile, the collection of PII poses certain limitations for telecommunication firms, as it

restricts the range of data that can be freely utilized. While anonymization techniques can address privacy concerns, the information value for AI is partly reduced. Therefore, both industries are to some extent limited in the capacity for experimental growth (Keller 2024) despite different routes.

Despite Advanced Digital Transformation in Telecommunication Firms, Both Industries Face Structure-Related Challenges That Compromise Data Quality: Organizational structure was stressed as a major influencing factor by interviewed automotive experts, underscored to impede the effective deployment of AI solutions, as the firms' focus on vertical silos hinders the seamless integration of AI across various business processes. The complexity seems to be further compounded by established product architectures developed over decades for combustion engines and mechanical precision. These legacy systems introduce additional layers of complexity when transitioning to data-driven, flexible AI systems. Interviews with automotive experts let derive that the issue of interfacing AI solutions with existing workflows is both a technical and organizational challenge. Adapting organizational structure can function as an essential transforming capability in AI adoption, whereby in hand with our findings, literature has found organizational structural inertia a common phenomenon, depending on firm size, age and history (Colombo and Delmastro 2002; Teece and Pisano 1994). Overcoming these structural barriers however is essential to fully leverage AI's potential (Felekoglu, Maier, and Moultrie 2013; Moore and Woodcock 2021). The German telecommunications industry, on the other hand, demonstrates an advanced organizational transformation progress (Sfondrini 2024; Mishra 2024) through already implemented specialized AI initiatives and systematic cross-departmental collaboration. However, despite the industry's advantage of data-centricity and horizontal workflows (Singla et al. 2024; Mori, Richardson, and Saleh 2023; Cloudera 2022), the tangible value for AI adoption is weakened as unstructured datasets are fragmented across its business functions (Dhasarathy et al. 2020; Cloudera 2022). Our findings therefore

highlight structure-related organizational challenges as a shared business obstacle to AI adoption in both types of firms.

Companies Successful in PD Practices Might Benefit from Prerequisites for AI Adoption:

Overall, interviews results revealed that influencing factors and challenges along the TOE framework show a strong interconnectedness (*see Appendix, Figure 5*). Moreover, although we started with a conceptual model for technology adoption, crystalizing success factors interestingly relate to studies that identify organizational level factors to differentiate successful PD practices from failure (Cooper and Kleinschmidt 1995). This implies that those firms which demonstrate general success in PD already possess favorable prerequisites for implementing AI success factors, as many of the necessary conditions are inherently fulfilled, enabling the organization to seamlessly adapt to technology-specific requirements. While automotive and telecommunication firms face similar success factors despite differing industry characteristics, the telecommunications industry appears comparably well prepared for AI adoption in PD processes as our findings suggest that firms already successfully meet several critical success factors described by Cooper and Kleinschmidt (1995).

7. Managerial Implications – Joint Section

When assessing organizational AI readiness and associated challenges, our analysis across the two sectors reveals key insights for successful AI Adoption in PD that can also serve as benchmarks for other industries. Therefore, the following managerial implications should be considered by any type of firms before starting the adoption process.

Firstly, organizations should assess existing PD practices to identify strengths that align with AI success factors, such as organizational agility, cross-functional collaboration, and a data-driven culture of innovation as a foundation to be able to identify where prerequisites are sufficient and where an active change is necessary. Then, practitioners need to define clearly which specific opportunities or challenges are targeted within PD practices to align with

business goals. The guiding principle should therefore always be an assessment whether AI offers a superior solution and whether there is a measurable business impact using tangible metrics. An explicit business need facilitates setting priorities in allocation of resources. Complementarily following a reciprocal bottom-up and top-down approach is vital. TM should be trained with technological foundations and the specific potential of AI in PD. This equips leaders to independently identify opportunities for AI adoption and ensures readiness to evaluate and respond effectively to adoption proposals from lower-level departments. Moreover, it is decisive to evaluate existing organizational structures to determine whether they meet the necessary conditions for AI adoption. In cases where structures are too rigid for immediate changes, AI initiatives can act as a flexible and dynamic starting point. These should promote an innovative forward-looking culture and cross-departmental collaboration, while training and engaging employees at all levels. As a final prerequisite, establishing a standardized and unified data structure is essential to enable AI systems to operate effectively across departments to support cross-functional PD processes.

8. Limitations and Future Research – *Joint Section*

Despite these advances, our research has limitations that provide promising base for future research. The sample so far has consisted mostly of large firms with a reduced number of interviewees providing qualitative expert insights primarily stemming from higher management and no quantitative data. Moreover, no distinction was made between AI adopters and non-adopters. This could affect the generalizability of our findings across different sizes and types of organizations as well as across positions. Expanding the research scope to encompass a broader base of companies and potentially increasing the number of participants and variations of hierarchy level could enrich the data to weigh the influences of possible interconnectedness as well as the strength of the perceived challenges, so that outlined success factors can be addressed in an even more prioritized manner. Future research should delve deeper into

quantitatively assessing the perceived level of challenge associated with each factor and explore the quantitative interconnectedness across examined dimensions.

9. References

- Abraham, Joshan, Miguel Frade, Thomás Lajous, Jorge Amar, and Yuval Atsmon. 2023. "The AI-Native Telco: Radical Transformation to Thrive in Turbulent Times." McKinsey. Accessed December 1, 2024. <https://www.mckinsey.com/industries/technology-media-and-telecommunications/our-insights/the-ai-native-telco-radical-transformation-to-thrive-in-turbulent-times>.
- Akroush, Mamoun N., and Abdulkareem Salameh Awwad. 2018. "Enablers of NPD Financial Performance." In *International Journal of Quality & Reliability Management* 35 (1): 163–86. <https://doi.org/10.1108/IJQRM-08-2016-0122>.
- AltexSoft. 2023. "Unstructured Data, Explained." AltexSoft. Accessed December 8, 2024. <https://www.altexsoft.com/blog/unstructured-data/>.
- Argyris, Chris, and Donald A. Schon. 1978. *Organizational Learning: A Theory of Action Perspective*. Vol. Reading, MA: Addison-Wesley.
- Arnaboldi, Michela, Giovanni Azzone, and Marco Giorgino. 2015. "Long- and Short-Term Decision Making." *Performance Measurement and Management for Engineers*, 107–15. Elsevier. <https://doi.org/10.1016/B978-0-12-801902-3.00007-4>.
- Barkway, Will, and Florian Gröne. 2024. "The Key to Telcos' Survival? Talent." PwC. Accessed December 1, 2024. <https://www.pwc.com/gx/en/industries/tmt/the-future-of-telcos-relies-upon-talent.html>.
- Basu Mallick, Chiradeep. 2023. "What Is a 6G Network? Working and Benefits - Spiceworks." Spiceworks Inc (blog). Accessed December 2, 2024. <https://www.spiceworks.com/tech/networking/articles/what-is-6g/>.
- BBC News. 2015. "Volkswagen: The Scandal Explained." BBC News sec. Business. Accessed December 7, 2024. <https://www.bbc.com/news/business-34324772>.

- Bekker, Alex. 2019. "5 Types of Artificial Intelligence That Bring Value to Business." ScienceSoft. Accessed December 5, 2024. <https://www.scnsoft.com/blog/artificial-intelligence-types>.
- Besson, Patrick, and Frantz Rowe. 2012. "Strategizing Information Systems-Enabled Organizational Transformation: A Transdisciplinary Review and New Directions." *The Journal of Strategic Information Systems*, 20th Anniversary Special Issue, 21 (2): 103–24. <https://doi.org/10.1016/j.jsis.2012.05.001>.
- Bickford, Jeanne Kwong, Abhishek Gupta, Steven Mills, and Tad Roselund. 2023. "Emerging AI Risks Underscore Urgent Need for Responsible AI; More than 70% of Organizations Are Struggling to Keep Up." BCG Global. Accessed December 4, 2024. <https://www.bcg.com/press/20june2023-emerging-ai-risks-need-for-responsible-ai>.
- Blumberg, Sven, Michael Chui, Lareina Yee, and Kia Javanmardian. 2024. "What Is AI (Artificial Intelligence)?" McKinsey. Accessed December 3, 2024. <https://www.mckinsey.com/featured-insights/mckinsey-explainers/whats-the-future-of-ai>.
- BMWK. 2020. "IKT-Branchenbild 2020." Berlin: Bundesministerium für Wirtschaft und Energie. https://www.bmwk.de/Redaktion/DE/Publikationen/Digitale-Welt/ikt-branchenbild.pdf?__blob=publicationFile
- Boer, Enno de, Kweilin Ellingrud, and Gérard Richter. 2022. "What Is Industry 4.0 and the Fourth Industrial Revolution?." McKinsey. Accessed December 7, 2024. <https://www.mckinsey.com/featured-insights/mckinsey-explainers/what-are-industry-4-0-the-fourth-industrial-revolution-and-4ir>.
- Bogdan, Ciocănel, and Florin Marius Pavelescu. 2015. "Innovation and Competitiveness in European Context." *Procedia Economics and Finance* 32 (December):728–37. [https://doi.org/10.1016/S2212-5671\(15\)01455-0](https://doi.org/10.1016/S2212-5671(15)01455-0).

- Bower, Keith M. 2024. "What Is Design of Experiments (DOE)?" ASQ. Accessed December 7, 2024. <https://asq.org/quality-resources/design-of-experiments?srsId=AfmBOoq6WX3qxb87Pn4ntaIbHc>
- cO3pKmgRRPgqdLgHdJCmIXejThYWBöhler, Christian, Julia Duwe, and Steffen Gackstatter. 2023. "How Product Development Can Drive Sustainability." Roland Berger. Accessed December 4, 2024. <https://www.rolandberger.com/en/Insights/Publications/How-product-development-can-drive-sustainability.html>.
- Booth, Bryce, Jack Donohew, Chris Wlezien, and Wu Winnie. 2024. "How to Use Generative AI in Product Design" McKinsey. Accessed December 1, 2024. <https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/generative-ai-fuels-creative-physical-product-design-but-is-no-magic-wand>.
- Bousmalis, Konstantinos, and Sergey Levine. 2017. "Closing the Simulation-to-Reality Gap for Deep Robotic Learning." Google Research. Accessed December 8, 2024. <https://research.google/blog/closing-the-simulation-to-reality-gap-for-deep-robotic-learning/>.
- Braun, Virginia, and Victoria Clarke. 2006. "Using Thematic Analysis in Psychology." In *Qualitative Research in Psychology* 3 (2): 77–101. <https://doi.org/10.1191/1478088706qp063oa>.
- Brem, Alexander, Ferran Giones, and Marcel Werle. 2021. "The AI Digital Revolution in Innovation: A Conceptual Framework of Artificial Intelligence Technologies for the Management of Innovation." *IEEE Transactions on Engineering Management*, 1–7. <https://doi.org/10.1109/TEM.2021.3109983>
- Budach, Lukas, Moritz Feuerpfel, Nina Ihde, Andrea Nathansen, Nele Sina Noack, Hendrik Patzlaff, Hazar Harmouch and Felix Naumann. 2022. "The Effects of Data Quality on

- Machine Learning Performance.” Hasso Plattner Institute, University of Potsdam.
<http://dx.doi.org/10.48550/arXiv.2207.14529>
- Burkacky, Ondrej, Miklós Gábor Dietz, Dieter Kiewell, Jared Moon, Alexandre Ménard, Mark Patel, and Rodney Zemmell. 2024. “What Is Quantum Computing?.” McKinsey. Accessed December 1, 2024. <https://www.mckinsey.com/featured-insights/mckinsey-explainers/what-is-quantum-computing>.
- Calantone, Roger J., Shawnee K. Vickery, and Cornelia Dröge. 1995. “Business Performance and Strategic New Product Development Activities: An Empirical Investigation.” *Journal of Product Innovation Management* 12 (3): 214–23.
<https://doi.org/10.1111/1540-5885.1230214>.
- Caldwell, Cam, and Verl Anderson. 2017. “Competitive Advantage: Strategies, Management and Performance” EconBiz. Accessed December 8, 2024.
<https://www.econbiz.de/Record/competitive-advantage-strategies-management-and-performance-caldwell-cam/10011711935>.
- Cambridge Dictionary. 2024. “Simulation.” Cambridge Dictionary. Accessed December 2, 2024. <https://dictionary.cambridge.org/de/worterbuch/englisch/simulation>.
- Candiani, Silvia. 2024. “Transforming Telecoms with AI.” Microsoft Industry Blogs. Accessed December 9, 2024. <https://www.microsoft.com/en-us/industry/blog/telecommunications/2024/10/01/transforming-telecoms-with-ai/>.
- CFI Team. 2024. “Original Equipment Manufacturer (OEM).” Corporate Finance Institute. Accessed November 24, 2024.
<https://corporatefinanceinstitute.com/resources/valuation/original-equipment-manufacturer-oem/>.
- Chakravorti, Bhaskar, Ajay Bhalla, and Ravi Shankar Chaturvedi. 2023. “Charting the Emerging Geography of AI.” Harvard Business Review. Accessed December 1, 2024.
<https://hbr.org/2023/12/charting-the-emerging-geography-of-ai>.

Chatha, Kamran Ali, Muhammad Shakeel Sadiq Jajja, Fatima Gillani, and Sami Farooq.

2024. “Examining the Effects of Technology–Organization–Environment Framework on Operational Performance through Supply Chain Integration of the Firm.”

Benchmarking: An International Journal 31 (5): 1797–1825.

<https://doi.org/10.1108/BIJ-10-2022-0665>.

Chau, Patrick Y. K., and Kar Yan Tam. 1997. “Factors Affecting the Adoption of Open

Systems: An Exploratory Study.” *MIS Quarterly* 21 (1): 1–24.

<https://doi.org/10.2307/249740>.

Chheda, Shital, Vincent Genest, Eric Lamarre, Ahmed Nizam, Marti Riba. 2023. “The Value of Digital Transformation.” *Harvard Business Review*. Accessed December 2, 2024.

<https://hbr.org/2023/07/the-value-of-digital-transformation>.

Chowdhury, Soumyadeb, Prasanta Dey, Sian Joel-Edgar, Sudeshna Bhattacharya, Oscar

Rodriguez-Espindola, Amelie Abadie, and Linh Truong. 2023. “Unlocking the Value of Artificial Intelligence in Human Resource Management through AI Capability

Framework.” *Human Resource Management Review* 33 (1): 100899.

<https://doi.org/10.1016/j.hrmr.2022.100899>.

Chui, Michael, James Manyika, Medhi Miremadi, Nicolaus Henke, Rita Chung, Pieter Nel,

and Sankalp Malhotra. 2018. “Notes from the AI Frontier-Insights from Hundreds of Use Cases.” McKinsey Global Institute. Accessed December 10, 2024.

<https://www.mckinsey.com/~/media/mckinsey/featured%20insights/artificial%20intelligence/notes%20from%20the%20ai%20frontier%20applications%20and%20value%20of%20deep%20learning/notes-from-the-ai-frontier-insights-from-hundreds-of-use-cases-discussion-paper.ashx>.

Chui, Michael, Roger Roberts, Lareina Yee, Eric Hazan, Alex Singla, Kate Smaje, Alex

Sukharevsky, and Rodney Zemmel. 2023. “The Economic Potential of Generative AI:

The next Productivity Frontier.” McKinsey. Accessed December 8, 2024.

- <https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/the-economic-potential-of-generative-ai-the-next-productivity-frontier#introduction>.
- Chui, Michael, Kelsey Robinson, and Alex Singla. 2023. "The Benefits of Generative AI for Business." McKinsey. Accessed December 10, 2024.
- <https://www.mckinsey.com/mgi/our-research/dont-wait-create-with-generative-ai>.
- Clark, Kim B., and Takahiro Fujimoto. 1989. "Lead Time in Automobile Product Development Explaining the Japanese Advantage." *Journal of Engineering and Technology Management* 6 (1): 25–58. [https://doi.org/10.1016/0923-4748\(89\)90013-1](https://doi.org/10.1016/0923-4748(89)90013-1).
- Cloudera. 2022. "Being Data Driven In The Telecommunications Industry—A Global View." Cloudera Resource Library. Accessed December 8, 2024.
- <https://www.cloudera.com/content/dam/www/marketing/resources/solution-briefs/being-data-driven-in-the-telecommunications-industry.pdf.landing.html>.
- CloudFlare. 2024. "Large Language Models." CloudFlare. Accessed December 11, 2024.
- <https://www.cloudflare.com/de-de/learning/ai/what-is-large-language-model/>.
- Collins Dictionary. 2024. "CAD SYSTEM Definition and Meaning." Collins English Dictionary. Accessed December 13, 2024.
- <https://www.collinsdictionary.com/dictionary/english/cad-system>.
- Colombo, Massimo G., and Marco Delmastro. 2002. "How Effective Are Technology Incubators?" *Research Policy* 31 (7): 1103–22. [https://doi.org/10.1016/S0048-7333\(01\)00178-0](https://doi.org/10.1016/S0048-7333(01)00178-0).
- Cooper, Robert. 1988. "The New Product Process: A Decision Guide for Management." *Journal of Marketing Management* 3 (January):238–55.
- <https://doi.org/10.1080/0267257X.1988.9964044>.

- Cooper, Robert G. 2024a. "The AI Transformation of Product Innovation." *Industrial Marketing Management* 119 (May):62–74.
<https://doi.org/10.1016/j.indmarman.2024.03.008>.
- Cooper, Robert G. 2024b. "The Artificial Intelligence Revolution in New-Product Development." *IEEE Engineering Management Review* 52 (1): 195–211.
<https://doi.org/10.1109/EMR.2023.3336834>.
- Cooper, Robert. 2024c. "How to Transform Your New-Product Development with AI: From Vision to Deployment." Business Publication of ISBM at Pennsylvania State University Smeal College of Business. https://isbm.org/b2b-pulse/content-library/?_sft_category=business-readings.
- Cooper, Robert G., and Elko J. Kleinschmidt. 1995. "Benchmarking the Firm's Critical Success Factors in New Product Development." *Journal of Product Innovation Management* 12 (5): 374–91. <https://doi.org/10.1111/1540-5885.1250374>.
- Cornet, Andreas, Ruth Heuss, Patrick Schaufuss, and Andreas Tschiesner. 2023. "A Road Map for the Automotive Industry in Europe." Accessed December 1, 2024.
<https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/a-road-map-for-europes-automotive-industry?>
- Courvisanos, Jerry. 2009. "Political Aspects of Innovation." *Research Policy* 38 (7): 1117–24.
<https://doi.org/10.1016/j.respol.2009.04.001>.
- Cowell, Donald W. 1988. "New Service Development." *Journal of Marketing Management* 3 (3): 296–312. <https://doi.org/10.1080/0267257X.1988.9964048>.
- Damanpour, Fariborz. 1992. "Organizational Size and Innovation." *Organization Studies* 13 (3): 375–402. <https://doi.org/10.1177/017084069201300304>.
- Datar, Srikant, Clark Jordan, Sunder Kekre, Surendra Rajiv, and Kannan Srinivasan. 1997. "New Product Development Structures and Time-to-Market." *Management Science* 43 (4): 452–64. <https://doi.org/10.1287/mnsc.43.4.452>.

- Davenport, Thomas H. 2018. "The AI Advantage: How to Put the Artificial Intelligence Revolution to Work." The MIT Press.
<https://doi.org/10.7551/mitpress/11781.001.0001>.
- De Jong, Marc, Laura Furstenthal, and Erik Roth. 2022. "What Is Innovation?" 2022.
Accessed December 1, 2024. <https://www.mckinsey.com/featured-insights/mckinsey-explainers/what-is-innovation>.
- De Jong, Marc, Nathan Marston, and Erik Roth. 2015. "The Eight Essentials of Innovation".
Accessed December 8, 2024. <https://www.mckinsey.com/capabilities/strategy-and-corporate-finance/our-insights/the-eight-essentials-of-innovation>.
- Deepgram. 2024. "Rule-Based AI" Deepgram. Accessed December 2, 2024.
<https://deepgram.com/ai-glossary/rule-based-ai>.
- Dhairyawar, Shreyas, Jasper Stoop, and Sigmar Kock. 2024. "Striking the Balance: Innovation vs. Business Continuity." Deloitte Netherlands. Accessed December 2, 2024. <https://www.deloitte.com/nl/en/services/consulting/perspectives/striking-the-balance--innovation-vs--business-continuity.html>.
- Dhasarathy, Anusha, Ankur Ghia, Sian Griffiths, and Rob Wavra. 2020. "Accelerating AI Impact by Taming the Data Beast". McKinsey. Accessed December 4, 2024.
<https://www.mckinsey.com/industries/public-sector/our-insights/accelerating-ai-impact-by-taming-the-data-beast>.
- Durth, Sandra, Anna Lena Kalinna, and Henning Soller. 2023. "Closing the Tech Talent Gap: Adopting the Right Mindset." McKinsey. Accessed December 5, 2024.
<https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/tech-forward/closing-the-tech-talent-gap-adopting-the-right-mindset>.
- Einabadi, B., Ali Baboli, and Mohammad Ebrahimi. 2019. „Dynamic Predictive Maintenance in industry 4.0 based on real time information: Case study in automotive industries". IFAC-PapersOnLine, 52(13), 1069-1074. <https://doi.org/10.1016/j.ifacol.2019.11.337>

- Ellström, Daniel, Johan Holtström, Emma Berg, and Cecilia Josefsson. 2021. “Dynamic Capabilities for Digital Transformation.” *Journal of Strategy and Management* 15 (2): 272–86. <https://doi.org/10.1108/JSMA-04-2021-0089>.
- Erickson, Gary M., Johny K. Johansson, and Paul Chao. 1984. “Image Variables in Multi-Attribute Product Evaluations: Country-of-Origin Effects.” *Journal of Consumer Research* 11 (2): 694–99. <https://doi.org/10.1086/209005>.
- Estendorfer, Florian. 2024. “The Importance of Innovation in the Telecommunications Sector.” Telefónica. Accessed December 5, 2024. <https://www.telefonica.com/en/communication-room/blog/the-importance-of-innovation-in-telecommunications-sector/>.
- European Commission. 2024. “*Germany AI Strategy Report*.” Brussel: European Commission. https://ai-watch.ec.europa.eu/countries/germany/germany-ai-strategy-report_en.
- European Parliament. 2023. “*EU AI Act: First Regulation on Artificial Intelligence*.” Brussel: European Parliament. <https://www.europarl.europa.eu/topics/en/article/20230601STO93804/eu-ai-act-first-regulation-on-artificial-intelligence>.
- Eurostat. 2023. “*Database-Eurostat*.” Luxemburg: Eurostat. https://ec.europa.eu/eurostat/data/database?node_code=nama_10_gdp.
- Fayomi, Ojo Sunday Isaac, Isaac Gbenga Akande, Sunday Olayinka Oyedepo, Ikechukwu Dunmade, and Desmond Esegoghene Ighravwe. 2021. “Prospective of Product Development and Improved Production Processes.” *IOP Conference Series: Materials Science and Engineering* 1107 (1): 012003. <https://doi.org/10.1088/1757-899X/1107/1/012003>.
- Feiler, Hugo. 2024. “Council Post: Driving The Future: How The Blockchain Is Revolutionizing The Automotive Industry.” Forbes. Accessed December 7, 2024.

- <https://www.forbes.com/councils/forbestechcouncil/2024/08/09/driving-the-future-how-the-blockchain-is-revolutionizing-the-automotive-industry/>.
- Felekoglu, Burcu, Anja M. Maier, and James Moultrie. 2013. "Interactions in New Product Development: How the Nature of the NPD Process Influences Interaction between Teams and Management." *Journal of Engineering and Technology Management* 30 (4): 384–401. <https://doi.org/10.1016/j.jengtecman.2013.08.004>.
- Ferri, Luca, Rosanna Spanò, Marco Maffei, and Clelia Fiondella. 2020. "How Risk Perception Influences CEOs' Technological Decisions: Extending the Technology Acceptance Model to Small and Medium-Sized Enterprises' Technology Decision Makers." *European Journal of Innovation Management* 24 (3): 777–98. <https://doi.org/10.1108/EJIM-09-2019-0253>.
- Forker, Laura B. 1997. "Factors Affecting Supplier Quality Performance." *Journal of Operations Management* 15 (4): 243–69. [https://doi.org/10.1016/S0272-6963\(97\)00001-6](https://doi.org/10.1016/S0272-6963(97)00001-6).
- Fountaine, Tim, Brian McCarthy, and Tamim Saleh. 2019. "Building the AI-Powered Organization." Harvard Business Review.
- Friedrich, Roman, Stefan Hoffmann, Tobias Lampe, and Sebastian Ullrich. 2021. "Putting Sustainability at the Top of the Telco Agenda." BCG Global. Accessed December 8, 2024. <https://www.bcg.com/publications/2021/building-sustainable-telecommunications-companies>.
- Frieske, Benjamin, and Sylvia Stieler. 2023. "Resilient Supply Chains and Robust Strategies for the Transformation of the Automotive Industry." In *Antriebe und Energiesysteme von morgen*, 64–81. Wiesbaden: Springer Fachmedien. https://doi.org/10.1007/978-3-658-41439-9_6.
- Froehlich, Andrew. 2024. "What Is Streaming Network Telemetry?" TechTarget. Accessed December 1, 2024.

<https://www.techtarget.com/searchnetworking/definition/streaming-network-telemetry>.

Gangwar, Hemlata, Hema Date, and Richard Ramaswamy. 2015. "Understanding Determinants of Cloud Computing Adoption Using an Integrated TAM-TOE Model." *Journal of Enterprise Information Management* 28 (February):107–30.
<https://doi.org/10.1108/JEIM-08-2013-0065>.

Gartner. 2024. "Definition of Neuro Symbolic AI - IT Glossary." Gartner. Accessed December 13, 2024. <https://www.gartner.com/en/information-technology/glossary/neuro-symbolic-ai>.

GitHub. 2024. "Regression Testing: Definition, Types, and Tools." GitHub. Accessed December 5, 2024. <https://github.com/resources/articles/software-development/regression-testing-definition-types-and-tools>.

GlobalSuite Solutions. 2020. "What Are ISO Standards?" GlobalSuite Solutions (blog). Accessed December 12, 2024. <https://www.globalsuitesolutions.com/what-are-iso-standards/>.

Glunz, Andreas. 2024. "Economic Key Facts Germany" KPMG Germany. Accessed December 4, 2024. <https://kpmg.com/de/en/home/insights/overview/economic-key-facts-germany.html>.

Gnanasambandam, Chandra, Harrysson, Martin, and Singh, Rikki. 2024. "How Generative AI Could Accelerate Software Product Time to Market." Accessed December 5, 2024. <https://www.mckinsey.com/industries/technology-media-and-telecommunications/our-insights/how-generative-ai-could-accelerate-software-product-time-to-market>.

Gómez, Javier Gil, Aleksander Matlok, Tiago Silveira, and Lieven Verboven. 2024. "The Growing Imperative of Energy Optimization for Telco Networks". Accessed December 8, 2024. [https://www.mckinsey.com/industries/technology-media-and-](https://www.mckinsey.com/industries/technology-media-and-telecommunications/our-insights/how-generative-ai-could-accelerate-software-product-time-to-market)

telecommunications/our-insights/the-growing-imperative-of-energy-optimization-for-telco-networks.

Gong, Xiuyuan, Lu Li, Nengzhi Yao, and Qiaozhe Guo. 2024. "Configurational Paths of Entrepreneurial Activity: An Analysis Based on the Technology–Organization–Environment Framework." *The American Journal of Economics and Sociology* 83 (4): 831–54. <https://doi.org/10.1111/ajes.12595>.

Gordon, Leon. 2024. "Best Practices For Leaders Integrating AI Into The Workplace." *Forbes*. Accessed December 1, 2024. <https://www.forbes.com/councils/forbestechcouncil/2024/08/16/best-practices-for-leaders-integrating-ai-into-the-workplace/>.

Grover, Varun. 2007. "An Empirically Derived Model for the Adoption of Customer-Based Interorganizational Systems." *Decision Sciences* 24 (June):603–40. <https://doi.org/10.1111/j.1540-5915.1993.tb01295.x>.

Gupta, Ashok K., Subramanian P. Raj, and David Wilemon. 1985. "The R&D-Marketing Interface in High-Technology Firms." *Journal of Product Innovation Management* 2 (1): 12–24. [https://doi.org/10.1016/0737-6782\(85\)90012-8](https://doi.org/10.1016/0737-6782(85)90012-8).

Gupta, Jay. 2024. "Data Analytics in Telecommunications." *Quantexa*. Accessed December 7, 2024. <https://www.quantexa.com/resources/data-analytics-in-telecommunications/>.

Gutterman, Alan. 2023. "Product Development: A Guide for Sustainable Entrepreneurs." *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.4577742>.

Hazan, Eric, Anu Madgavkar, Michael Chui, Sven Smit, Dana Maor, Gurneet Singh Dandona, and Roland Huyghuenes-Despointes. 2024. "The Race to Deploy Generative AI and Raise Skills" *McKinsey*. Accessed December 6, 2024. <https://www.mckinsey.com/mgi/our-research/a-new-future-of-work-the-race-to-deploy-ai-and-raise-skills-in-europe-and-beyond>.

- Hejtmánek, Jan. 2023. "Early Generative AI and Its Impact on Automotive Industry, 2023 Summary." Deloitte. Accessed December 1, 2024.
<https://www2.deloitte.com/cz/en/pages/technology/articles/early-generative-ai-and-its-impact-on-automotive-industry.html>.
- Heuss, Ruth, and Andreas Cornet. 2023. "McKinsey: Europäische Autoindustrie in Größter Transformation Ihrer Geschichte." McKinsey. Accessed December 5, 2024.
<https://www.mckinsey.de/news/presse/2023-30-08-automotive-masterplan>.
- Hidayat, Muhammad, Siska Yulia Defitri, and Haim Hilman. 2024. "The Impact of Artificial Intelligence (AI) on Financial Management." *Management Studies and Business Journal* 1 (1): 123–29. <https://doi.org/10.62207/s298rx18>.
- Hofmann, Peter, Jan Jöhnk, Nils Urbach, and Dominik Protschky. 2020. "Developing Purposeful AI Use Cases - A Structured Method and Its Application in Project Management." *15th International Conference on Wirtschaftsinformatik (WI)*.
<https://www.fim-rc.de/Paperbibliothek/Veroeffentlicht/1025/wi-1025.pdf>
- Holmström, Jonny. 2022. "From AI to Digital Transformation: The AI Readiness Framework." *Business Horizons* 65 (3): 329–39.
<https://doi.org/10.1016/j.bushor.2021.03.006>.
- Huisman, Klaas J.M., and Peter M. Kort. 2000. "Strategic Technology Adoption Taking Into Account Future Technological Improvements: A Real Options Approach." *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.246980>.
- IBM. 2021. "What Is Requirements Management?" IBM. Accessed December 7, 2024.
<https://www.ibm.com/topics/what-is-requirements-management>.
- IBM. 2022. "What Is Data Quality?" IBM. Accessed December 4, 2024.
<https://www.ibm.com/topics/data-quality>.
- IBM. 2023. "What Is Product Development?" IBM. Accessed December 7, 2024.
<https://www.ibm.com/topics/product-development>.

- IBM. 2024a. “What Is Requirements Management?” IBM. Accessed December 3, 2024.
<https://www.ibm.com/topics/what-is-requirements-management>.
- IBM. 2024b. “What Is Sentiment Analysis?” IBM. Accessed December 6, 2024.
<https://www.ibm.com/topics/sentiment-analysis>.
- IBM. 2024c. “What Is Shift-Left Testing?” IBM. Accessed December 3, 2024.
<https://www.ibm.com/topics/shift-left-testing#>.
- IBM. 2024d. “What Is the Internet of Things (IoT)?” IBM. Accessed December 5, 2024.
<https://www.ibm.com/topics/internet-of-things>.
- Jain, Vipul, and Ignacio E. Grossmann. 1999. “Resource-Constrained Scheduling of Tests in New Product Development.” *Industrial & Engineering Chemistry Research* 38 (8): 3013–26. <https://doi.org/10.1021/ie9807809>.
- Jarvis, David. 2020. “The AI Talent Shortage Isn’t over yet.” Deloitte. Accessed December 5, 2024. <https://www2.deloitte.com/us/en/insights/industry/technology/ai-talent-challenges-shortage.html>.
- Jiyao, Chen, Richard R. Reilly, and Gary Lynn. 2009. “New Product Development Speed: Too Much of a Good Thing?” *Journal of Product Innovation Management* 29(2): 288–303. <http://dx.doi.org/10.1111/j.1540-5885.2011.00896.x>
- Jorge, Amar, Tomás Lajous, Shreya Majumder, and Zachary Surak. 2022. “How AI Is Helping Revolutionize Telco Service Operations.” McKinsey. Accessed December 5, 2024. <https://www.mckinsey.com/industries/technology-media-and-telecommunications/our-insights/how-ai-is-helping-revolutionize-telco-service-operations>.
- Julianti Abu Bakar, Lily, and Hartini Ahmad. 2010. “Assessing the Relationship between Firm Resources and Product Innovation Performance.” *Business Process Management Journal* 16 (3): 420–35. <https://doi.org/10.1108/14637151011049430>.

- Kahn, Kenneth B. 1996. “Interdepartmental Integration: A Definition with Implications for Product Development Performance.” *Journal of Product Innovation Management* 13 (2): 137–51. [https://doi.org/10.1016/0737-6782\(95\)00110-7](https://doi.org/10.1016/0737-6782(95)00110-7).
- Karri, Ruehie Jaiya. 2022. “Technology Skills Gap: Definition, Analysis and Steps to Close.” HackerEarth Blog (blog). Accessed December 2, 2024. <https://www.hackerearth.com/blog/talent-assessment/skill-gaps-in-software-development/>.
- Kazakova, Snezha, Allison Dunne, Daan Bijwaard, Julien Gossé, Charles Hoffreumon, and Nicolas van Zeebroeck. 2020. “*European Enterprise Survey on the Use of Technologies Based on Artificial Intelligence: Final Report*.” In. LU: Publications Office. <https://data.europa.eu/doi/10.2759/759368>.
- Keller, Daniel. 2024. “Council Post: AI Regulation, Global Governance And Challenges.” Forbes. Accessed December 6, 2024. <https://www.forbes.com/councils/forbestechcouncil/2024/11/12/ai-regulation-global-governance-and-challenges/>.
- Kosinski, Matthew. 2024a. “What Is Black Box AI and How Does It Work?” IBM. Accessed December 1, 2024. <https://www.ibm.com/think/topics/black-box-ai>.
- Kumar, Ashok, and Jaideep Motwani. 1995. “A Methodology for Assessing Time-based Competitive Advantage of Manufacturing Firms.” *International Journal of Operations & Production Management* 15 (2): 36–53. <https://doi.org/10.1108/01443579510080409>.
- Lajous, Tomás, Stephanie Madner, Carlo Palermo, and Rens van den Broek. 2023. “The Seven Biggest Telecom Industry Trends.” McKinsey. Accessed December 4, 2024. <https://www.mckinsey.com/industries/technology-media-and-telecommunications/our-insights/tech-talent-in-transition-seven-technology-trends-reshaping-telcos>.

- Lenovo. 2024a. “Interactive AI: Transforming User Experiences Globally”. Lenovo US. Accessed December 4, 2024. <https://www.lenovo.com/us/en/glossary/interactive-ai/>.
- Lenovo. 2024b. “Visual AI: Innovation in Image Recognition ” Lenovo US. Accessed December 6, 2024. <https://www.lenovo.com/us/en/glossary/visual-ai/>.
- Lim, Choon Wee Joel, Kim Quy Le, Qingyang Lu, and Chee How Wong. 2016. “An Overview of 3-D Printing in Manufacturing, Aerospace, and Automotive Industries.” *IEEE Potentials* 35 (4): 18–22. <https://doi.org/10.1109/MPOT.2016.2540098>.
- Lukin, Edi, Aleksandra Krajnović, and Jurica Bosna. 2022. “Sustainability Strategies and Achieving SDGs: A Comparative Analysis of Leading Companies in the Automotive Industry.” *Sustainability* 14 (7): 4000. <https://doi.org/10.3390/su14074000>.
- Mabert, Vincent A., John F. Muth, and Roger W. Schmenner. 1992. “Collapsing New Product Development Times: Six Case Studies.” *Journal of Product Innovation Management* 9 (3): 200–212. [https://doi.org/10.1016/0737-6782\(92\)90030-G](https://doi.org/10.1016/0737-6782(92)90030-G).
- Maiworm, Bastian. 2024. “Identifying and Prioritising AI Use Cases in Companies.” *amberSearch* (blog). Accessed December 6, 2024. <https://ambersearch.de/identifying-prioritising-ai-use-cases/>.
- Makridakis, Spyros. 2017. “The Forthcoming Artificial Intelligence (AI) Revolution: Its Impact on Society and Firms.” *Futures* 90 (June):46–60. <https://doi.org/10.1016/j.futures.2017.03.006>.
- Margaryan, Anoush. 2023. “Artificial Intelligence and Skills in the Workplace: An Integrative Research Agenda.” *Big Data & Society* 10 (2): 20539517231206804. <https://doi.org/10.1177/20539517231206804>.
- Martin, Alan. 2021. “Robotics and Artificial Intelligence: The Role of AI in Robots” *AI Business*. Accessed December 3, 2024. <https://aibusiness.com/verticals/robotics-and-artificial-intelligence-the-role-of-ai-in-robots>.

- McKinsey. 2014. “The Future of German Mechanical Engineering.” McKinsey. Accessed December 2, 2024. <https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/the-future-of-german-mechanical-engineering-operating-successfully-in-a-dynamic-environment>.
- Meredith, Sam. 2024. “Germany’s Auto Giants Are Struggling to Stay Relevant.” CNBC. Accessed December 7, 2024. <https://www.cnbc.com/2024/10/18/vw-bmw-mbg-germanys-top-car-brands-are-struggling-in-the-ev-era.html>.
- Merhi, Mohammad I. 2023. “An Evaluation of the Critical Success Factors Impacting Artificial Intelligence Implementation.” *International Journal of Information Management* 69 (April):102545. <https://doi.org/10.1016/j.ijinfomgt.2022.102545>.
- Merritt, Rick. 2024. “What Is Retrieval-Augmented Generation Aka RAG?” NVIDIA Blog. Accessed December 4, 2024. <https://blogs.nvidia.com/blog/what-is-retrieval-augmented-generation/>.
- Mildenberger, Udo, and Anshuman Khare. 2000. “Planning for an Environment-Friendly Car.” *Technovation* 20 (4): 205–14. [https://doi.org/10.1016/S0166-4972\(99\)00111-X](https://doi.org/10.1016/S0166-4972(99)00111-X).
- Milliou, Chrysovalantou, and Emmanuel Petrakis. 2011. “Timing of Technology Adoption and Product Market Competition.” *International Journal of Industrial Organization* 29 (5): 513–23. <https://doi.org/10.1016/j.ijindorg.2010.10.003>.
- Mishra, Shamik. 2024. “From Telco to Tech Co.: How the Shift to Software-Driven Business Is Unlocking a New Era of Innovation in Telecoms.” Capgemini. Accessed December 1, 2024. <https://www.capgemini.com/insights/expert-perspectives/from-telco-to-tech-co-how-the-shift-to-software-driven-business-is-unlocking-a-new-era-of-innovation-in-telecoms/>.
- Moore, Phoebe V., and Jamie Woodcock. 2021. “*Augmented Exploitation: Artificial Intelligence, Automation, and Work*.” Edited by Phoebe V. Moore and Jamie

- Woodcock. London: Pluto Press.
- <https://www.plutobooks.com/9780745343495/augmented-exploitation/>.
- Graham, Kenneth, and Robert Moore. 2021. "The Role of Dynamic Capabilities in Firm-Level Technology Adoption Processes: A Qualitative Investigation." *Journal of Innovation Management* 9 (1): 25–50. https://doi.org/10.24840/2183-0606_009.001_0004.
- Mori, Lapo, Bryon Richardson, and Tamim Saleh. 2023. "Improving AI Data Quality in Manufacturing" McKinsey. Accessed December 6, 2024.
- <https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/clearing-data-quality-roadblocks-unlocking-ai-in-manufacturing>.
- Nepal, Bimal P., Om Prakash Yadav, and Rajesh Solanki. 2011. "Improving the NPD Process by Applying Lean Principles: A Case Study." *Engineering Management Journal* 23 (3): 65–81. <https://doi.org/10.1080/10429247.2011.11431910>.
- Odilov, Jamshid. 2024. "Digital Use of Artificial Intelligence in Public Administration." *International Journal of Law and Policy* 2 (3): 7–15. <https://doi.org/10.59022/ijlp.161>.
- Odilov, Sherzod. 2024. "AI Leadership: Why AI Is Every Leader's Responsibility." Forbes. Accessed December 13, 2024.
- <https://www.forbes.com/sites/sherzododilov/2024/07/14/ai-leadership-why-ai-is-every-leaders-responsibility/>.
- Ogura, Masaki, Junichi Harada, Masako Kishida, and Ali Yassine. 2019. "Resource Optimization of Product Development Projects with Time-Varying Dependency Structure." *Research in Engineering Design* 30 (3): 435–52.
- <https://doi.org/10.1007/s00163-019-00316-6>.
- Opitz, Nicky, Tobias F. Langkau, Nils H. Schmidt, and Lutz M. Kolbe. 2012. "Technology Acceptance of Cloud Computing: Empirical Evidence from German IT Departments."

- 45th Hawaii International Conference on System Sciences, January, 1593–1602.
<https://doi.org/10.1109/HICSS.2012.557>.
- Parthiban, Privna., Hameed Abdul Zubar, and Pravin Katarak. 2013. “Vendor Selection Problem: A Multi-Criteria Approach Based on Strategic Decisions.” *International Journal of Production Research* 51 (5): 1535–48.
<https://doi.org/10.1080/00207543.2012.709644>.
- Patton, Michael Quinn. 2014. *Qualitative research & evaluation methods: Integrating theory and practice* (4th ed.). SAGE Publications, Inc.
- Pavlínek, Petr. 2022. Relative positions of countries in the core-periphery structure of the European automotive industry. *European Urban and Regional Studies*, 29(1), 59-84.
<https://doi.org/10.1177/09697764211021882>.
- Porter, Michael E. 1985. *Competitive Advantage: Creating and Sustaining Superior Performance*. Free Press. NY.
- Pumplun, Luisa, Christoph Tauchert, and Margareta Heidt. 2019. “A New Organizational Chassis for Artificial Intelligence - Exploring Organizational Readiness Factors.” Publications of Darmstadt Technical University, Institute for Business Studies (BWL). Darmstadt Technical University, Department of Business Administration, Economics and Law. <https://econpapers.repec.org/paper/darwpaper/112582.htm>.
- Puriwat, Wilert, and Danupol Hoonsopon. 2022. “Cultivating Product Innovation Performance through Creativity: The Impact of Organizational Agility and Flexibility under Technological Turbulence.” *Journal of Manufacturing Technology Management* 33 (4): 741–62. <https://doi.org/10.1108/JMTM-10-2020-0420>.
- Qlik. 2024. “AI Analytics: What It Is, Why It Matters, & Use Cases.” Qlik. Accessed December 5, 2024. <https://www.qlik.com/us/augmented-analytics/ai-analytics>.

- Quesada, Gioconda, Ahmad Syamil, and William J. Doll. 2006. "OEM New Product Development Practices: The Case of the Automotive Industry." *Journal of Supply Chain Management* 42 (3): 30–40. <https://doi.org/10.1111/j.1745-493X.2006.00015.x>.
- Ragatz, Gary L., Robert B. Handfield, and Thomas V. Scannell. 1997. "Success Factors for Integrating Suppliers into New Product Development." *Journal of Product Innovation Management* 14 (3): 190–202. <https://doi.org/10.1111/1540-5885.1430190>.
- Ramirez, Omar. 2024. "Overcoming Data Silos: Strategies for Integrating AI Across Organizational Functions." Trebellar. Accessed December 4, 2024. <https://blog.trebellar.com/overcoming-data-silos-strategies-for-integrating-ai-across-orgs/>.
- RedHat. 2023. "What Are Foundation Models for AI?" RedHat. Accessed December 2, 2024. <https://www.redhat.com/en/topics/ai/what-are-foundation-models>.
- Rogers, Everett M., Arvind Singhal, and Margaret M. Quinlan. 2014. *Diffusion of Innovations. In An Integrated Approach to Communication Theory and Research* (pp. 432–448). Routledge.
- Rowshankish, Kayvaun, Rodney W. Zimmel, Tomás Lajous, and Kimberly Borden. 2024. "What Is Digital-Twin Technology?" McKinsey. Accessed December 4, 2024. <https://www.mckinsey.com/featured-insights/mckinsey-explainers/what-is-digital-twin-technology>.
- Rulf, Kirsten, Francois Candelon, Gaurav Jha, Clement Dumas, and Max Männig. 2023. "Why AI Regulation Is an Opportunity for CEOs." BCG. Accessed December 11, 2024. <https://www.bcg.com/publications/2023/why-ai-regulation-is-an-opportunity-for-ceos>.
- Ruslin, Ruslin, Saepudin Mashuri, Muhammad Sarib, Firdiansyah Alhabsyi, and Hijrah Syam. 2022. *Semi-Structured Interview: A Methodological Reflection on the*

- Development of a Qualitative Research Instrument in Educational Studies Ruslin*. Vol. 12 (February): 22–29. <https://doi.org/10.9790/7388-1201052229>.
- Rutitis, Didzis, and Tatjana Volkova. 2019. “Product Development Methods Within The Ict Industry Of Latvia.” *Management / Vadyba* (16487974) 34 (1): 15–23.
https://openurl.ebsco.com/EPDB%3Aagcd%3A13%3A19831789/detailv2?sid=ebsco%3Aplink%3Ascholar&id=ebsco%3Aagcd%3A138362469&crl=c&link_origin=www.google.com.
- Sagodi, André, Christian Engel, Johannes Schniertshauer, and Benjamin Van Giffen. 2022. “Becoming Certain About the Uncertain: How AI Changes Proof-of-Concept Activities in Manufacturing – Insights from a Global Automotive Leader.” *Hawaii International Conference on System Sciences*.
<https://doi.org/10.24251/HICSS.2022.828>.
- Schaltegger, Stefan, and Markus Wagner. 2011. “Sustainable Entrepreneurship and Sustainability Innovation: Categories and Interactions.” *Bus. Strat. Env.*, 20: 222-237.
<https://doi.org/10.1002/bse.682>.
- Schilling, Melissa A. 2017. *Strategic Management of Technological Innovation*. Fifth edition. New York, NY: McGraw-Hill Education.
- Schneider, Malte H. G., Dominik K. Kanbach, Sascha Kraus, and Marina Dabic. 2023. “Transform Me If You Can: Leveraging Dynamic Capabilities to Manage Digital Transformation.” *IEEE Transactions on Engineering Management*, vol. 71, pp. 9094-9108. <https://doi.org/10.1109/TEM.2023.3319406>.
- Schumpeter, Joseph A. 1911. *The Theory of Economic Development*. Harvard University Press. Cambridge.
- Sfondrini, Nicola. 2024. “Council Post: The Telco-To-Techco Evolution: Paving The Way For Digital Transformation.” *Forbes*. Accessed December 1, 2024.

- <https://www.forbes.com/councils/forbestechcouncil/2024/05/17/the-telco-to-techco-evolution-paving-the-way-for-digital-transformation/>.
- Shepherd, Neil Gareth, and John Maynard Rudd. 2014. "The Influence of Context on the Strategic Decision-Making Process: A Review of the Literature." *International Journal of Management Reviews* 16 (3): 340–64. <https://doi.org/10.1111/ijmr.12023>.
- Singla, Alex, Alexander Sukharevsky, Lareina Yee, and Michael Chui. 2024. "The State of AI in Early 2024." McKinsey. Accessed December 5, 2024. <https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai>.
- Singla, Alex, Asin Tavakoli, Holger Harreis, and Klemes Hjatar. 2024. "The Gen AI Operating Model: A Leader's Guide." McKinsey. Accessed December 2, 2024. <https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/a-data-leaders-operating-guide-to-scaling-gen-ai>.
- Song, Xiaowei Michael, Richard Jeffrey Thieme, and Jinhong Xie. 1998. "The Impact of Cross-Functional Joint Involvement Across Product Development Stages: An Exploratory Study." *Journal of Product Innovation Management* 15 (4): 289–303. <https://doi.org/10.1111/1540-5885.1540289>.
- Spence, Mike. 2024. "AI Adoption Isn't a Choice Anymore - It's a Competitive Advantage." TrellisPoint. Accessed December 4, 2024. <https://trellispoint.com/blog/ai-adoption-is-not-a-choice-anymore-it-is-a-competitive-advantage>.
- Staack, Volker, and Branton Cole. 2017. "Innovation Benchmark Report." PwC. Accessed December 4, 2024. <https://www.pwc.com/gr/en/publications/specific-to-all-industries-index/innovation-benchmark-report.html>.
- Statistisches Bundesamt. 2019. "Automobilindustrie: Deutschlands wichtigster Industriezweig mit Produktionsrückgang um 7,1 % im 2. Halbjahr 2018." Statistisches Bundesamt. Accessed December 3, 2024. https://www.destatis.de/DE/Presse/Pressemitteilungen/2019/04/PD19_139_811.html.

- Strategy&. 2024. “Generative KI könnte BIP-Boost von bis zu 220 Mrd. Euro auslösen.”
Strategy&. Accessed December 6, 2024.
<https://www.strategyand.pwc.com/de/de/presse/generative-ki-kann-bip-heben.html>.
- Stratman, Kelly. 2024. “The AI-Powered Skills Gap.” AI Business. Accessed December 1, 2024. <https://aibusiness.com/generative-ai/the-ai-powered-skills-gap>.
- Susnjara, Stephanie, and Ian Smalley. 2024. “What Is Cloud Computing?” IBM. Accessed December 5, 2024. <https://www.ibm.com/topics/cloud-computing>.
- Tableau. 2024. “Artificial Intelligence (AI) Algorithms: A Complete Overview.” Accessed December 2, 2024. <https://www.tableau.com/data-insights/ai/algorithms>.
- Takyar, Akash. 2023. “AI in Product Development: Use Cases, Benefits, Solution and Implementation.” LeewayHertz. Accessed December 11, 2024.
<https://www.leewayhertz.com/ai-in-product-development/>.
- Teece, David, and Gary Pisano. 1994. “The Dynamic Capabilities of Firms: An Introduction.” *Industrial and Corporate Change* 3 (3): 537–56. <https://doi.org/10.1093/icc/3.3.537-a>.
- TIBCO. 2024. “What Is Data Availability?” TIBCO. Accessed December 2, 2024.
<http://www.tibco.com/glossary/what-is-data-availability>.
- Todd, Marlin, and Jim McCurry. 2023. “How to Balance Opportunity and Risk in Adopting Disruptive Technologies.” Accessed December 2, 2024.
https://www.ey.com/en_gl/insights/forensic-integrity-services/how-to-balance-opportunity-and-risk-in-adopting-disruptive-technologies.
- Tornatzky, Louis G., and Mitchell Fleischer. 1990. *The Process of Technology Innovation*. Vol. Lexington Books. Lexington, MA.
- Trott, Paul, David Baxter, Paul Ellwood, and Patrick Duin. 2022. “The Changing Context of Innovation Management: A Critique of the Relevance of the Stage-Gate Approach to Current Organizations.” *Prometheus* 38 (2).
<https://doi.org/10.13169/prometheus.38.2.0207>.

- Troy, Lisa C., Tanawat Hirunyawipada, and Audhesh K. Paswan. 2008. "Cross-Functional Integration and New Product Success: An Empirical Investigation of the Findings." *Journal of Marketing* 72 (6): 132–46. <https://doi.org/10.1509/jmkg.72.6.132>.
- Vesey, Joseph T. 1991. "The New Competitors: They Think in Terms of 'Speed-to-Market'." *Academy of Management Perspectives* 5 (2): 23–33. <https://doi.org/10.5465/ame.1991.4274671>.
- Wang, Xiaozhen, Hanna Lee, Kihyun Park, and Gukseong Lee. 2024. "The Strategic Role of R&D Outsourcing Practices and Partners in the Relationship between Product Modularization and New Product Development Efficiency." *Journal of Manufacturing Technology Management* 35 (1): 185–202. <https://doi.org/10.1108/JMTM-03-2023-0098>.
- Weber, Charles A., John R. Current, and William. C. Benton. 1991. "Vendor Selection Criteria and Methods." *European Journal of Operational Research* 50 (1): 2–18. [https://doi.org/10.1016/0377-2217\(91\)90033-R](https://doi.org/10.1016/0377-2217(91)90033-R).
- Weber, Matthias, and Joachim Weisbrod. 2002. "Requirements Engineering in Automotive Development: Experiences and Challenges." *IEEE Software* 20(1):331-340<http://dx.doi.org/10.1109/MS.2003.1159025>.
- Weiner, Joyce. 2021. *Why AI/Data Science Projects Fail: How to Avoid Project Pitfalls*. Synthesis Lectures on Computation and Analytics. Cham: Springer International Publishing. <https://doi.org/10.1007/978-3-031-01685-1>.
- Wernerfelt, Birger. 1984. "A Resource-Based View of the Firm." *Strategic Management Journal* 5 (2): 171–80. <https://doi.org/10.1002/smj.4250050207>.
- West, Andy, Tim Koller, and Rishabh Bhargava. 2024. "Resource Allocation for Long-Term Value Creation." McKinsey. Accessed December 1, 2024. <https://www.mckinsey.com/capabilities/strategy-and-corporate-finance/our-insights/tying-short-term-decisions-to-long-term-strategy>.

- Westbrook, Johanna, Michael M. Luck, and Diane Kelly. 2019. "Information Retrieval Systems - an Overview." Sciencedirect. Accessed December 5, 2024.
<https://www.sciencedirect.com/topics/computer-science/information-retrieval-systems#>.
- Yang, Xin-She, Xing-Shi He, and Qin-Wei Fan. 2020. "Mathematical Framework for Algorithm Analysis." *In Nature-Inspired Computation and Swarm Intelligence*, 89–108. Elsevier. <https://doi.org/10.1016/B978-0-12-819714-1.00017-8>.
- Yoshimura, Masayuki, Yasuhiro Fujimi, Kunio Izui, and Shunji Nishiwaki. 2006. "Decision-Making Support System for Human Resource Allocation in Product Development Projects." *International Journal of Production Research* 44 (5): 831–48.
<https://doi.org/10.1080/00207540500272519>.
- Zakir Gaibi, Gareth Jones, Pierre Pont, and Mihir Vaidya. 2021. "A Blueprint for Telco Transformation." McKinsey. Accessed December 4, 2024.
<https://www.mckinsey.com/industries/technology-media-and-telecommunications/our-insights/a-blueprint-for-telecoms-critical-reinvention>.
- Zhang, Haili, Xiaotang Zhang, and Michael Song. 2021. "Deploying AI for New Product Development Success." *Research-Technology Management* Vol 64 (5).
<https://www.tandfonline.com/doi/full/10.1080/08956308.2021.1942646>.
- Zhang, Yamin, Junfeng Jiang, and Yanying Shang. 2024. "Business Model Platformization Drives Social Value—A Configuration Research Based on the Technology-Organization-Environment Framework." *Managerial and Decision Economics* 45 (7): 4450–63. <https://doi.org/10.1002/mde.4277>.

Appendix

1. Glossary

Term	Definition
Artificial intelligence	Artificial intelligence is the machine's capability to perform specific cognitive functions that are typically linked with the human mind. (Blumberg et al. 2024)
Analytical AI	AI analytics means the application of AI techniques and algorithms that automate analysis processes, analyze and interpret data, derive insights, and also make predictions or recommendations. (Qlik 2024)
Algorithm	Instructions that must be followed in calculations or other operations. (Tableau 2024)
Automated Regression Testing	A process that ensures that software continues to function as expected even after changes were made to it. (GitHub 2024)
Black Box Phenomenon	Refers to AI systems where the internal processes are not visible or understandable for users as they can only observe the inputs and outputs. (Kosinski 2024)
CAD systems	Computer systems that are used to design parts or products before manufacturing them (Collins Dictionary 2024)
Cloud Computing	The provision of computing resources, such as servers, storage, or software, over the internet with a pay-as-you-go paying. (Susnjara and Smalley 2024)
Data Availability	The assurance that an organization's business data is accessible to relevant parties when needed.(TIBCO 2024)
Data Quality	A measure of how well a dataset adheres to criteria such as accuracy, consistency, completeness, and relevance, playing a key role in successful data governance.(IBM 2022)
Digital twin	A digital twin is a virtual representation of a physical object, person, system, or process, modeled within a digital version of its environment. (Rowshankish et al. 2024)
Dieselgate / Diesel Scandal	A scandal involving Volkswagen's manipulation of emissions tests to misrepresent pollution levels. (BBC News 2015)
Deep learning	Deep learning is an advanced subset of machine learning, highly skilled at handling diverse data types, including text and unstructured data like images. It requires minimal human intervention and often delivers more accurate results compared to traditional machine learning methods. (Blumberg et al. 2024)
Foundation models	A foundation model is a machine learning (ML) model that is pretrained to handle a variety of tasks. (RedHat 2023)
Functional AI	Functional AI is closely related to analytic AI in that it also processes vast amounts of data to identify patterns and dependencies. However, unlike analytic AI, which provides recommendations, functional AI actively takes actions based on its analyses (Bekker 2019)
Generative AI	Generative AI (Gen AI) is a type of artificial intelligence model designed to create content based on a given prompt. (Blumberg et al. 2024).
Information Retrieval System	Systems for managing, retrieving, and filtering information, with particular emphasis on real-time responses, often applied in areas like healthcare emergencies. (Westbrook, Luck, and Kelly 2019)
Interactive AI	AI systems designed to enable real-time, two-way communication with users, providing personalized and interactive experiences.(Lenovo 2024)
Internet of Things	A network of interconnected devices, vehicles, and appliances embedded with sensors and software, enabling data exchange and connectivity (IBM 2024d)
ISO Standards	Internationally recognized frameworks that target to establish uniformity and consistency across organizational processes. (GlobalSuite Solutions 2020)
Large language models	A large language model (LLM) is an artificial intelligence (AI) program capable of understanding and generating text, along with performing other tasks. (CloudFlare 2024)
Machine learning	Machine learning is a type of artificial intelligence that adapts to various inputs, including extensive historical data, synthesized data, or human-provided inputs. (Blumberg et al. 2024)
Make-or-Buy Decision	The process of deciding whether to produce goods or services internally or procure them externally, based on cost, resources, and strategy. (Arnaboldi, Azzone, and Giorgino 2015)
No-Free-Lunch-Theorem	A concept in computer science asserting that no single optimization algorithm is universally superior across all problem types. (Yang, He, and Fan 2020)
Original Equipment Manufacturer	A company that manufactures products or components, which are then rebranded or used by another company. (CFI Team 2024)
Requirements Management	A process involving the documentation, analysis, prioritization, and agreement on requirements to ensure alignment with project goals. (IBM 2024a)
Robotic AI	The creation and programming of robots to carry out highly specific tasks. (Martin 2021)
Use cases	Specific applications of generative AI designed to address distinct business problems, delivering measurable results. (McKinsey, 2023)

Unstructured data	Unstructured data refers to information that lacks a predefined structure or organization. (AltexSoft 2023)
Quantum Computing	A computing paradigm using quantum mechanics to solve complex problems at unprecedented speeds. (Burkacky et al. 2024)
Retrieval Augmented Generation	A method to improve generative AI accuracy by incorporating facts retrieved from external data sources. (Merritt 2024)
Rule based AI	AI systems governed by pre-established "if-then" rules to process data and make decisions. (Deepgram 2024)
Shift-Left Paradigm	An approach in software development that involves testing earlier in the lifecycle to speed up feedback and reduce the cost of bug fixes (IBM 2024c)
Simulation	A representation of real-world activities designed for training or problem-solving purposes. (Cambridge Dictionary 2024)
Sim-To-Real Gap	The challenge of transferring knowledge and performance from simulated environments to real-world applications. (Bousmalis and Levine 2017)
Sentiment Analysis	The process of analyzing text to determine emotional tone, categorizing it as positive, neutral, or negative. (IBM 2024b)
Streaming Telemetry	A continuous data collection mechanism where devices like routers or switches push data in real time. (Froehlich 2024)
Tech-Skill-Gap	A technology skills gap occurs when the skills required for a job exceed those possessed by the current workforce (Karri 2022)
Neuro-Symbolic AI	A hybrid AI approach combining machine learning and symbolic reasoning systems like knowledge graphs for more robust and explainable outcomes (Gartner 2024)
Design of Experiments	Design of Experiments is a field of applied statistics focused on the systematic planning, execution, analysis, and interpretation of controlled tests (Bower 2024)
Visual AI	AI focused on interpreting and analyzing visual data such as images and videos.(Lenovo 2024)
5G / 6G Mobile Network	The next evolution of mobile networks, leveraging untapped radio frequencies and AI to enable ultra-fast, low-latency communications (BasuMallick 2023)
Requirements Specification Sheet/ Data Sheet	A document detailing the required functionalities, constraints, and dependencies of a project based on stakeholder demands. (Eisenbart et al., 2011)
Reverse-Engineering	A process of deconstructing an object to understand its design, structure, or functionality, often for replication or analysis (GitHub, 2024).

Figure 1: Glossary

2. List of Abbreviations

Abbreviation	Full Term
AI	Artificial Intelligence
B2B	Business to Business
B2C	Business to Consumer
CAD	Computer Aided Design
CTO	Chief Technology Officer
CIO	Chief Information Officer
CEO	Chief Executive Officer
CCO	Chief Customer Officer
C-Executives	Chief Executives
GDPR	General Data Protection Regulation
EU	European Union
FM	Foundational Model
IOT	Internet of Things
ISO	International Standard Organization
IPTV	Internet Protocol Television
KPI	Key Performance Indicator
LLM	Large Language Models
ML	Machine Learning
NLP	Natural Language Processing
OEM	Original Equipment Manufacturer
PD	Product Development
POC	Proof of Concept
PII	Personally Identifiable Information
RAG	Retrieved Augmented Generation
ROI	Return on Investment
R&D	Research and Development
SG	Stage-Gate

Telco	Telecommunication
TM	Top Management
TOE	Technology-Organization-Environment
VP	Vice President
3D	Three Dimensional

Figure 2: List of Abbreviations

3. Innovation Adoption Curve

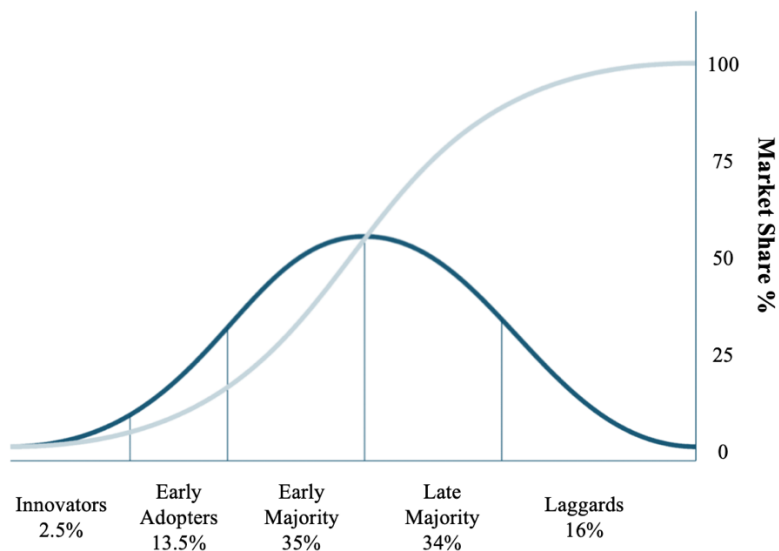


Figure 3: Innovation Adoption Curve by Rogers (1983)

4. Stage-Gate Model

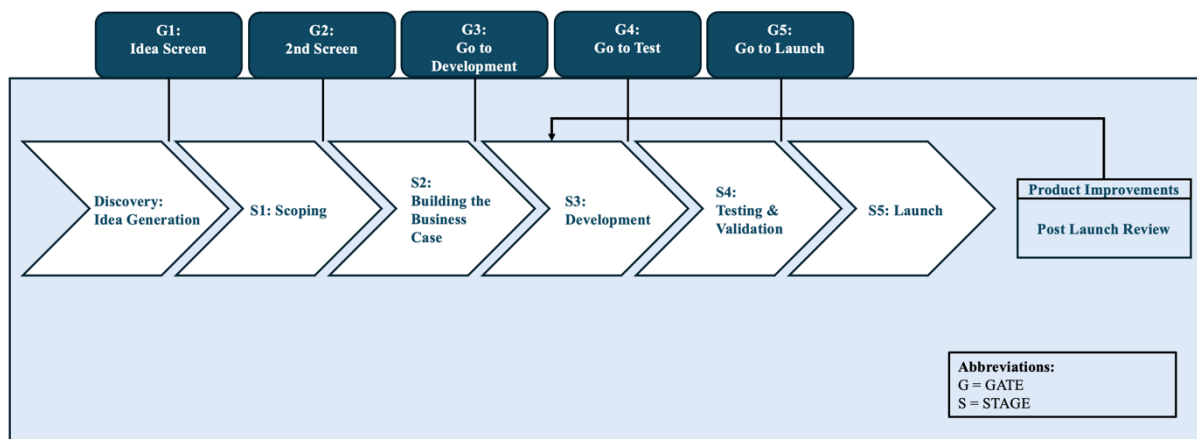
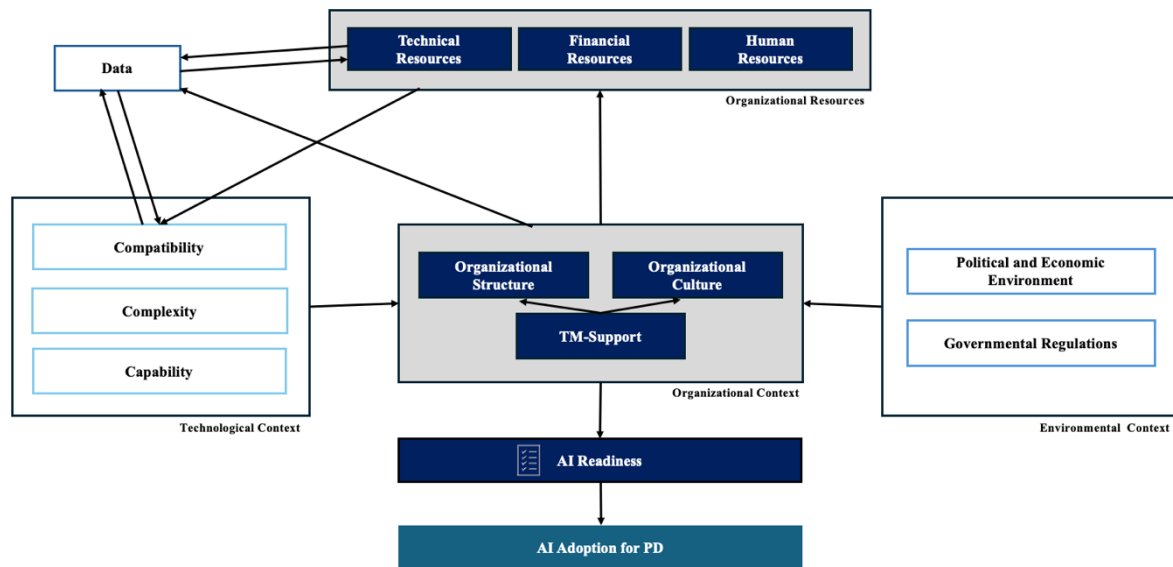


Figure 4: Modified Stage-Gate Model based on Cooper (1988)

5. TOE Framework



Legend: AI = Artificial Intelligence TM = Top Management PD = Product Development = Industry Nature

Figure 5: Modified TOE Framework based on Tornatzky and Fleischer (1990)

6. Qualitative Interview Questionnaire

Interview Outline
Format: Semi-structured, open-ended interviews with industry practitioners. Time Frame: 45-90 min. Goal: Investigation of AI usage and adoption in product development; examining and discussing internal and external factors as well as associated challenges through the lens of previously determined concepts from literature review.
Section 1: Interviewer Introduction
- Interviewer introduction (name and academic background). - Interviewee briefing regarding research aims, interview focus and scope. - Brief explanation of understanding towards “AI”, “product development”, “usage potential” and introduction to the Stage-Gate model. - Requesting consensus to record the interview and include results and personal data in research results.
Section 2: Interviewee Introduction
2.1 Please briefly introduce yourself, the company you are working for and your position.
Section 3: AI Integration in PD
3.1 In which phases of the PD process along the Stage-Gate model (e.g., idea generation, scoping, building business case, development, testing & validation, market launch, post-launch) do you perceive most potential for your company and industry? Can you provide specific examples of products and applications also regarding which type of AI used?

• 3.2 How would you thereby expect AI to impact the PD process and overall PD performance in your company or industry? ◦ <i>Optional add on, depending on given interviewee answers:</i> • Along which noticeable improvement dimensions (e.g., speed, innovation, cost, quality, accuracy, efficiency, sustainability, risk reduction) do you expect changes to occur?
Section 4: Influencing factors and challenges for adopting AI in PD
• Technological Context: • 4.1 Which technological factors do you think are most influential in AI integration in PD? Do they constitute a challenge for your firm and industry? ◦ <i>Optional add on, depending on given interviewee answers:</i> • To what extend do you perceive capability of the current state of AI to influence AI adoption and how? • To what extend do you perceive current technological complexity in terms of perceived as relatively difficult to understand and use to influence AI adoption and how? • To what extend do you perceive compatibility of the technology with existing systems and infrastructure to influence AI adoption and how?
• Organizational Context: • 4.2 Which organizational/internal factors do you think are most influential in AI integration in PD? Do they constitute a challenge for your firm and industry? ◦ <i>Optional add on, depending on given interviewee answers:</i> • To what extend do you perceive your organization's financial resources to influence the AI adoption and how? • To what do you perceive current IT infrastructure to influence the AI adoption and how? • To what extend do you perceive data availability and accessibility to influence the AI adoption and how? • To what extend do you perceive in-house expertise to influence the AI adoption and how? • To what extend do you perceive top management support to influence the AI adoption and how? • To what extend do you perceive organizational culture influencing the AI adoption and how? • To what extend do you perceive organizational structure and cross-departmental collaboration to influence the AI adoption and how?
• Environmental Context: • 4.3 Which environmental/external factors do you think are most influential in AI integration in PD? Do they constitute a challenge for your firm and industry? ◦ <i>Optional add on, depending on given interviewee answers:</i> • To what extend do you perceive external providers to influence the AI adoption and how? • To what extent do you perceive governmental regulations and compliance (e.g. data security, intellectual property) to influence AI adoption and how? • To what extent do you perceive political and economic environment to influence AI adoption and how?
Section 6: Additional Insights
• Is there anything else you would like to add or assume important for this research endeavor?

Conclusion
Thank you very much for your time and precious insights. Would you be willing to participate in future discussions or follow-up interviews as part of this research?

Figure 6: Qualitative Interview Questionnaire

7. Methodology

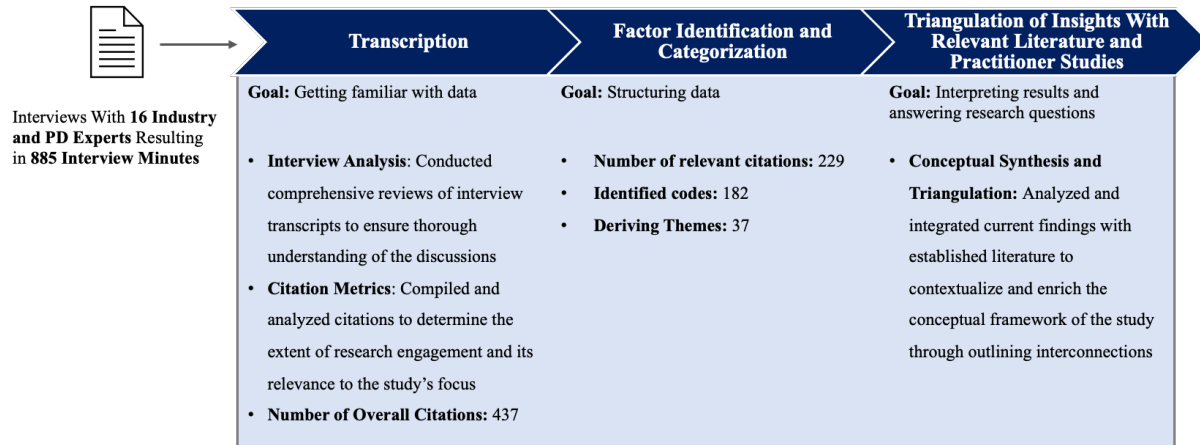


Figure 7: Methodology based on Braun and Clarke (2006)

8. List and Profiles of Interviewees

	Last Name, Name	Interview Method	Duration	Current/ Prior Position	Industry Sector	Company/ Prior Company
I1	Anonymized	Microsoft Teams	60min	Product Planning Manager	Automotive	Leading OEM in Germany
I2	Anonymized	Zoom	90min	CEO/Senior Vice President Product Management	Automotive	Leading Automotive Electronics Supplier in Germany/ Leading OEM Supplier in Germany
I3	Anonymized	Microsoft Teams	45min	Head of Data & AI / Head of Digital Program and Data Governance	Automotive	Leading OEM in Germany/ Leading OEM in Germany
I4	Anonymized	Microsoft Teams	45min	Product Manager - Design and Release- Body Engineering	Automotive	Leading OEM in Germany
I5	Anonymized	Microsoft Teams	60min	President Europe & Member of the Executive Board/ Managing Director	Automotive	Leading Software Development & Integration Partner for Mobility Solutions/ Leading International Consulting Company in Germany
I6	Anonymized	Microsoft Teams	60min	Business Owner	Automotive	Leading OEM in Germany

I7	Anonymized	Microsoft Teams	30min	Senior Vice President R&D and Product Management	Automotive	Leading OEM Supplier in Germany
I8	Anonymized	Microsoft Teams	60min	Head of Drive/Electronics Development	Automotive	Leading OEM Supplier in Germany
I15	Anonymized	Microsoft Teams	90min	Senior Consultant - ML & ML-Plattformen	AI Vendor	Leading AI Consulting Company in Germany
I16	Anonymized	Microsoft Teams	60min	Teamlead Data Science & AI	AI Vendor	Leading AI Consulting Company in Germany

Figure 8: List and Profiles of Interviewees

9. Identified Use Cases

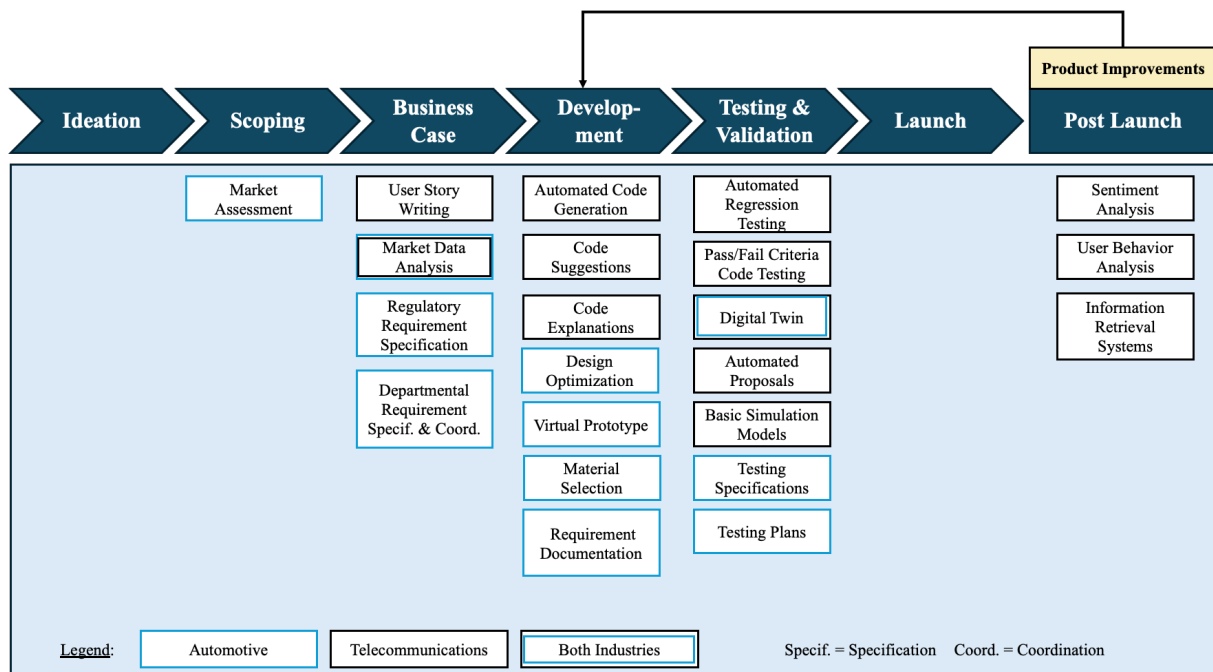


Figure 9: Identified Use Cases Along the Stage-Gate Process Model based on Cooper (1988)

10. Citations List of Automotive Industry

ID	Nr	Quotation
II	1	Does a customer want their charge port on an electric vehicle? Do they want it at the front or the rear? That sounds pretty simple, but it's quite complex because different countries have different parking attitudes. In China, for example, nobody parks forwards. Everyone parks backwards because the parking spaces are very narrow. Of course, AI could possibly help by telling you where, say, an Indian customer wants their charge port? Front or back? At the side or in the middle? Or somewhere else entirely? Or what, what does a customer use their center console for? Cooling? Heating? Should it be lockable? Does it even need one? Should it be movable? These are, of course, questions about the flexibility of vehicles in the future. For example, we have an incredible amount of discussion about door handles. Door handles on cars. Many of the newer vehicles have these, we call them flush, door handles that are more or less integrated into the body side. In an accident, if the electrics fail, you can no longer open the door because those stupid thorny hands can no longer get out. That is of course a safety concern. In winter, when it snows or when it's very cold, they can't get out. Then you can't open the door, which is of course stupid. Here you can use AI simply as another source of information. To find out what you might not be able to get otherwise. And you might be able to get the data relatively quickly.
II	2	Development in an automotive company is based on very, very stringent processes. We have development processes, of course. More or less every day in a three to four-year development cycle is more or less defined.
II	3	Because with vehicles, you always have to clearly define where I position the vehicle in the market and what is important at that moment for the vehicle to win. Where do I want to play and when I have decided that, i.e. where means at what price, in which market, against whom, against which competitor. That's the first point. The second point is what is my USP, so that I can somehow offer added value and perhaps the AI can help. But AI can also miss this point completely and offer innovations that are of no value at all in this position.
II	4	I think AI will increasingly be used in areas of the automotive industry where data, and in particular competitive data, is important. After all, you always develop a product in the context of its competition or a specific competitive environment. AI could be of great benefit here, for example to simulate certain scenarios or to access relevant data more quickly. We currently obtain competitive data via our competitive intelligence teams, internet research or external agencies and platforms that we purchase. These sources provide us with registration figures or insurance data from various countries, for example. However, this is often tedious, especially at a local level, or requires extensive coordination, for example via the purchasing department, in order to obtain information on large suppliers. AI, on the other hand, would make it possible to generate such information much faster. For example, AI could be used to create an overview of the top 10 automotive suppliers by turnover. Such information provides a good starting point for further steps and saves an enormous amount of time, as it would normally take days or weeks to research. AI is really helpful in such use cases. However, concerns about data quality often remain a major issue for us. The reliability of the data is still a problem at the moment. This could be due to the fact that AI models are not always fed with the most up-to-date data. This shortcoming needs to be addressed in order to exploit the full potential of AI in this area.
II	5	I see the main use cases for artificial intelligence (AI) mainly in the area of development and verification. Things are increasingly being simulated in the development process itself - this is a highly data-driven area in which AI can also be used. This is comparable to the CAD models we have known for many years, which are becoming increasingly complex during development and are being enriched with more and more product data. Rule-based AI, as we know it classically, can be very helpful here, for example in making certain recommendations when selecting materials or making other decisions. There are many factors that play a role here, and rule-based approaches can certainly provide support. From my point of view, the classic use cases mainly involve applying rules based on existing data, recognizing statistical clusters or segmenting and evaluating data. Here too, the aim is to model the product, especially if it is a physical product, and to take physical restrictions into account. This is particularly useful for rule-based AI approaches, such as those previously known as expert systems, as physical laws and similar rules can be incorporated.
II	6	When it comes to statistical AI, however, I take a more critical view. Such systems have no "understanding" of physical principles, as is often referred to in technology as first principles. They lack this direct access to physical knowledge, which is why I would be rather cautious about giving them too much credit.
II	7	So, in the area of idea generation, on the one hand, this is typically relatively easy to implement on a technical level, and on the other hand, I don't have to observe so many regulations. As I said, depending on the use case, where I am now, because as an example, if I were to use a language model now and ask it for ideas, well, so what, not much happens. Then in the area of risk and chance of success assessment, phew, I have to dig relatively deep into the adjacent systems. I would basically always say that, if I have to incorporate something without dependencies, it's easier than if I have dependencies on other specialist areas, whatever they are, or have to observe regulations. And in the area of scoping, if I want to make forecasts and evaluate the chances of success, I typically have to connect some kind of data from other departments, so that's more difficult than when generating ideas, but it's still okay in some cases.
II	8	A central point in the area of testing and validation is the increasingly widespread use of the digital twin concept. This involves creating virtual images of the real world that are as detailed as possible. These digital twins make it possible to simulate and test early on in the production process, which can significantly reduce the effort required for physical tests later on. Everything that is simulated in advance no longer needs to be tested after production, or only with less effort. This approach is known as "shift left". The shift-left approach offers a clear business case: around 70 to 80 percent of the effort involved in product

		development is spent on testing and validation. If errors are only discovered after production or in the field, this can be extremely expensive. One example is a recent recall by BMW due to a brake error in the software. If such errors had been found in the early development phase, for example in a test fleet of a few hundred vehicles or even in simulation, this would have resulted in a fraction of the costs now incurred for the recall. For this reason, Shift Left is an extremely important approach to minimizing costs and ensuring quality. Especially in the automotive and manufacturing industries, it is about creating digital twins to test, simulate and virtualize as much as possible. This approach is being implemented at various levels and involves different types of AI. In this context, it is mainly about physical modeling, which is less based on deep learning and more on rule-based AI systems. This is an area that I would like to look at more closely.
II	9	Of course, it would be desirable if AI could always “think for itself” and continuously develop ideas to make processes more efficient, faster or more cost-effective. The focus does not always have to be on speed. Rather, AI could also recognize that certain steps or tests are unnecessary because they cover scenarios that do not occur in practice. This allows resources to be deployed in a targeted manner without investing time and effort in unnecessary tests.
II	10	I believe that the IT infrastructure would certainly be capable of using AI as a source of information. However, the implementation and integration with other systems such as the next step that utilizes the data remains an open question. Typically, we start from a blank sheet of paper, so to speak.
II	11	Product development already requires collaboration across so many departments, so adding AI into the mix demands a shared understanding of its role across the firm.
II	12	The handling of sensitive information is particularly challenging here. Data cannot simply be processed or exchanged without further ado, especially when legal or security-related aspects play a role.
II	13	In most cases, when you normally try to validate this information, you often find that either there are errors in the data or the AI has more or less made something up — essentially invented something itself. And, of course, this is not acceptable for us in our work because we cannot work with data that cannot be relied upon. That’s why we are usually not yet at a point where we can rely on it. This is an issue.
II	14	I always hear that the data is somehow one to two years old and that is of course kind of pointless for us, because so much changes so quickly in our industry, it should actually work almost in real time. If not, those solutions don’t provide much additional value.
II	15	Of course, it might be possible to use automation and AI to more or less physicalize this work. You could do it yourself, but you wouldn’t need anyone else to do it. That would of course be one such application. In other words, a machine can do the same process thousands of times and is less prone to errors than a human being, so to speak. Actually error-prone. Or AI helps you to anticipate errors or potential problems that could arise based on early indicators. And early on you say, oh, AI has more or less developed an algorithm from lots and lots of data that says if we carry on now, the machine will break down tomorrow. So let’s replace the part today.
II	16	Having simple moments of success, where you can clearly see that something works, is crucial. Perhaps this could encourage top management to push these initiatives, enabling such successes to occur. They might say, ‘Hey, give it a try, and let’s see what happens.’ However, I believe AI is not primarily driven by top management. Instead, it is more likely pushed by instance-level management, where someone says, ‘Look, we’ve discovered something or have an idea—can we show it to you?’ I don’t think top management will generally declare, ‘We are now using AI.’ It’s more about what that means in practice.
II	17	And perhaps some decision-makers lack real experience with AI. When I think about the people who make decisions in our company, I get the impression that, outside of the IT department, they don’t really know what AI is. A typical director or head of department seems to know little about it in my estimation. Even I have very limited knowledge of the subject.
II	18	I think that if you build very company-specific solutions, for example, directly with external partners, you can get around the problem quite well.
II	19	Everything that has to do with development and programs really requires a very careful approach. For example, let’s say I’m working on a project that could potentially be produced in Europe - or maybe not. Unions, plants and many other factors play a decisive role here. Such decisions have far-reaching implications, and if such data is published, it can cause considerable unrest in the workforce and the industry as a whole. It is therefore extremely important to handle such sensitive data with the utmost care.
II	20	Absolutely, it’s a big issue - for example in connection with vehicles from China. There are reports that certain governments, such as those in the USA, are taking a clear stance: There will be no vehicles in America that were developed in China. This applies not only to production, but also to development. This makes it all the more important to comply with the legal requirements, because if violations were to become known, this could have serious consequences for the entire company. Integrity plays a central role, especially after the major scandals such as the one we experienced at VW. Compliance with the law is not only a matter of course for us, but almost a fundamental definition of our company’s values.
II	21	But I think the problem is that people, especially older ones like me, are just not yet used to AI in a way that it feels intuitive to say, ‘Of course, I’ll use AI for that.’ We still tend to rely more on traditional search functions on the internet. AI still feels like an extra step, perhaps one that the next generation, maybe the one between us or perhaps your generation, will naturally adopt as a tool. This shift might eventually make its way into companies as well. So, it might partly be a generational issue, where decision-makers in traditional industries, like the automotive sector, are still often from the older generation.
II	22	Of course, there is already a lot of this now, but the aim is simply to improve quality in production to a certain extent via AI and, well, AI simply via automation, camera and sensor systems. That certain errors no longer exist. For example, there is a camera that takes an incredible number of images along the weld seam. And AI

		then evaluates them and says that there may be an error, that there is an injustice. Of course, there's no way a big eye can do that. And when it gets to the customer and the error is there, then of course it's too late. But it's more like production. So I don't know where automation is in development, I don't know, I don't know exactly. So I wouldn't say there.
I1	23	But, on the other hand, it also makes sense to include all the data, because otherwise, you don't get the best information out of it. So, it's a point of tension, I agree. And, uh, we have many topics where we even have to sign internal Non-Disclosure Agreements to be allowed to work on these topics at all. So, this is truly classified, even internally. And it's definitely important to be careful with how AI is used to ensure it doesn't make too much data accessible, right?
I1	24	I believe it is more efficient to work with external experts or agencies, as I mentioned earlier, because it eliminates the need to go through the learning process of developing those skills internally. The downside, of course, is the cost of paying for their services. However, when it comes to understanding and implementing AI, it might be more effective to collaborate with external specialists who have more expertise in the field. Traditionally, automotive companies are not IT-focused—they are more centered on engineering, physical components, and hardware. A balanced approach might be to start with external agencies or experts while simultaneously using the collaboration to build internal knowledge and skills.
I1	25	That this is not yet compatible. Exactly. That AI is not yet such that the data that comes out of it is in any way clear and defined, so that it can also be connected to other tools and processes. Without a compatible interface for further processing, it is difficult to make full use of the technology.
I2	1	Decision-making is often driven by enthusiasm for an idea or product without sufficient consideration of the necessary market research. In many cases, there is an idea or innovation that is perceived as promising, but the necessary focus on market research is neglected in the details. This is where Artificial Intelligence (AI) comes into play, helping significantly to find relevant information. For example, AI can help identify competitors in the same segment or discover similar products, which is particularly important when it comes to patents that may need to be considered. The use of AI not only saves time, but also enables faster access to necessary information.
I2	2	If I think back to 20 years ago, it was necessary to purchase expensive databases from institutes that often cost between 3,000 and 8,000 euros. Today, however, with tools such as ChatGPT, I can obtain comparable information in just half an hour, which helps me enough to take the next step. These developments make it easier for companies to make informed decisions and increase their innovative strength.
I2	4	However, when it comes to the actual implementation, the legal requirements and specifications that need to be met are often underestimated. AI can be very helpful here to check which approval criteria are required for the product. The requirements vary depending on the market, which makes researching the relevant standards and legal texts time-consuming. AI can help to quickly analyze these extensive documents.
I2	5	Another aspect is the use of AI for decision support. When developing a battery management system (a BMS), the ability to make decisions in real time is crucial. AI can help to analyze data and make predictions, for example about the service life of the battery or the efficiency of the charging process. By using machine learning, patterns in user behaviour or operating conditions can be identified that contribute to the further optimization of the BMS.
I2	6	The German automotive industry is deeply rooted in its history, which is seen as one reason for its current challenges.
I2	7	Right now, it's more about laying the groundwork, ensuring we have the right data, systems, and skills.
I2	8	The problem with interfaces is almost always due to the human factor, rarely because processes themselves do not match. AI can be used sensibly in companies, but not everywhere. In production, for example, it mainly helps with planning when orders with high quantities require scenarios that have an impact on the machinery.
I2	9	The challenge is to organize an in-house workshop to clarify the basics. That would be my preferred approach, because it allows me as a company to control what happens. I may need someone to organize the workshop, but I can coordinate the content with my provider. It is important to first assess the level of knowledge in my company. How do the employees feel about this topic? Are they open-minded? Have some had positive experiences, while others have had negative experiences? There are many who use AI like a toy and are then disappointed because they don't get any useful answers. It is often the case that the quality of the answers depends heavily on the question. If I know the level of knowledge, I can determine my status quo and decide whether I can develop further myself or whether I first need to bring the employees up to a common level. It is important that everyone is positively conditioned before I start with my strategy.
I2	10	So far, I have not encountered a company that implements Artificial Intelligence (AI) professionally and consistently. Often, it is only employees who have privately engaged with AI that use these technologies, while colleagues in similar roles continue to work traditionally. There is often a lack of clear guidelines and training provided by the company to effectively integrate AI. This discrepancy highlights that many companies are still not fully leveraging the potential of AI, missing valuable opportunities for increased efficiency and innovation.
I2	11	The pressure to use artificial intelligence is already palpable, and in some companies this is already being practiced, while top management is often not fully informed about it. While there is an opportunity to take a bottom-up approach, I think a clear involvement of top management is necessary for a successful use of AI. As I said earlier, AI is one of the most disruptive technologies since the invention of the smartphone, and it's frightening how few companies have recognized this. If AI is introduced strategically from the top down, the right decisions can be made to make processes effective. It's important to sit down with executives and discuss basic knowledge of AI. The question should be: In which areas can AI be put to good use? Where are there

		labor-intensive processes that follow a clear structure, or where do large volumes of data need to be processed? Paper documents also represent data in this context.
I2	12	Furthermore, support from management is crucial. Without a clear vision and commitment from senior management, AI integration will only be implemented selectively and less effectively. If management sees risks more than potential benefits, sustainable development will not take place.
I2	13	It is important to communicate the introduction of AI to employees transparently and at an early stage. The use of AI should not be seen as a means of reducing staff, but as an opportunity to increase efficiency and react more quickly to changes. In today's fast-moving world, it is crucial to remain flexible and adapt to new circumstances. The predictability that existed 20 years ago no longer exists.
I2	14	In Germany people often complain about the regulations. Although it may be more pronounced, similar regulations also exist in other countries. So I don't think this is a really hard criterion. Rather, it is a mindset issue. It's not the case that everyone in Germany works the same way; the differences are obvious. Especially in large and very traditional companies, many people in Germany find it particularly difficult to make the necessary mindset change. I think that employees in this country are very concerned about personal safety, which is also due to the upbringing of my generation. In other countries, however, people are much more open to change.
I2	15	In addition, there are specialized consulting companies that can support the implementation of AI. If internal resources are lacking, it makes sense to bring external expertise into the company and analyze the fundamental processes, especially in sensitive areas that make up the company's core expertise. The question here should be how this knowledge can be protected and how AI can be used sensibly at the same time.
I2	16	Another significant obstacle to the implementation of AI is the hesitant attitude of some companies towards new technologies. There are many cases where IT departments are concerned about the potential loss of data, especially if confidential information is uploaded to such systems. This caution often means that companies are unable to recognize or exploit the benefits of these technologies.
I2	17	I believe that many companies are at a crossroads when it comes to engaging with the topic of Artificial Intelligence (AI). The main issue, in my view, is that while there is often discussion about AI, there is frequently no dedicated AI team responsible for implementing and adapting AI solutions within the organization. It is crucial to define what is needed and how AI should be utilized. Equally important is determining what should explicitly not be used.
I2	18	Focus is crucial, even if transition phases always entail a certain degree of complexity. However, the industry must also be defended here, as the political environment in Germany is anything but ideal for long-term planning. In order to invest sensibly and cost-effectively, stable framework conditions are needed that extend beyond one legislative period. These uncertainties have a particular impact on investments with high costs that can only be amortized over long periods of time.
I2	19	Take Huber, for example, a small company with 300 employees. Even they don't have a proper AI strategy yet, it's more a case of 'learning by doing'. When I look around medium-sized companies, the situation is often even worse. There are managing directors who regard AI as the devil's plaything.
I2	20	At the moment, this is difficult to plan, which is particularly problematic in conjunction with pressure from international competition. In countries such as China, there are state subsidies and in the USA there is a strong focus on deregulation. Germany, on the other hand, has high energy costs, high levies in the healthcare and pension systems and additional burdens on companies. All of this reduces the competitiveness of German industry.
I3	1	CAD data can now be generated from simple sketches so that a CAD model can be created on the basis of sketches. This supports the earlier design phase in particular. At a later stage in the process, the model must then be designed in more detail, whereby AI-aided design is already being used today to increase ease and preciseness. There are modules that support our designers in brainstorming.
I3	2	The industrial use of AI began in the 2010s with the emergence of machine learning methods, in particular neural networks. Applications such as pattern recognition for quality control in production and predictive maintenance for monitoring machine condition were implemented quite early on. These developments mark significant progress in the integration of AI into industrial processes.
I3	3	And we, the systems that we use there, today's IT support, these are always authoring systems, we call them. In other words, a CAD tool. Or a requirements engineering tool where people type in. They understand what is fed to them from regulation, production, marketing and so on. And then they describe the requirements precisely. And these are jobs or activities that can now be increasingly automated using these generative processes. In other words, an area of application. Where we use AI methods in this process. It's called requirements specification generation or requirements assistant. And the aim of this is to systematically translate the early phases, when there are still abstract target formulations or abstract legal requirements, into realizable individual specifications, individual requirements. However, there are already ways to effectively support certain sub-processes in system engineering with AI. A good example is requirements engineering, where AI can already act as an assistant. In product development, tens of thousands of national and international regulations often have to be taken into account, which, for example, contain precise specifications for the design of safety-relevant systems such as brakes. These regulations lead to a plethora of requirements that are normally translated and processed manually by experts. This process can now be supported by AI and represents the current state of the art. AI can integrate legal and technical knowledge into the development process and thus provide designers with targeted support.
I3	4	Mechanical designs, such as spatial models and CAD models, can then be derived from the requirements. Test specifications can also be created automatically, as each requirement must ultimately be checked to ensure

		that it is fulfilled. This process leads to the creation of test method suggestions, priorities and overall test plans, which can also be supported by AI.
13	5	Generative AI capabilities became known to the whole world with chat GPT. That has a whole new evaluation of possible applications. And now I'm coming back to the process here. The process is very much characterized by the fact that a lot of content is generated. Or content is implemented. Let me give you an example. Idea generation and scoping are right at the front. But even during scoping, when you're thinking about a vehicle product, requirements come in from all directions. You have the idea of building a new sports car. Two plus two seats like a 911 or something like that. And that's how you start, with some kind of input from marketing and sales and product strategy. But then the production people immediately say, yes, hold on, we have so many Chinese competitors who can build the cars for half the price. We have to create completely different production concepts so that we can do this. Requirements come from production. Then regulation worldwide says that there are regulations for batteries, for what do I know, for everything. Hundreds of requirements are also generated. Or hundreds of specifications are made that are still very abstract. Must not contain this, must be able to do this and that. And then this is translated into specific technical requirements. And then the requirements are broken down, whether they relate to the chassis, the bodywork, the oil fillings or anything else. When it comes to chemical requirements, materials. And then at some point it gets to the point where a, let's call it a component manager, someone who actually designs a part, can actually draw a CAD model for his, for your component.
13	6	The degree to which the technology maturity level and the maturity level of the company systems influence each other depends heavily on the specific process that is to be automated using AI. There are processes in which the AI function is deeply embedded in a larger application system. In these cases, the process chain is often already highly automated or partially automated, and AI components are added to further optimize the process. This type of integration requires a great deal of effort and a high degree of technical customization. Although the technical challenges involved in implementation are greater, the investment in such tightly integrated systems is worthwhile if the benefits are correspondingly high. In addition, there are less deeply integrated applications that function in a more modular way and can easily be incorporated into existing work environments, which are directly embedded into office applications or development environments and can therefore be used without significant adaptation efforts. These assistants support individual work processes without the need for deep integration into existing company systems.
13	7	The central element for the successful use of AI is ultimately the right mindset regarding the importance of data. The topic is often described in very technocratic terms - whether data is organizationally, legally or technically available - but there is a fundamental conviction behind it: Data is the origin of all value in a company. Without access to data, AI cannot work, and the current AI revolution is so powerful primarily because we now have almost unlimited access to data, combined with enormous computing power in the smallest of spaces. These two factors, data and computing power, have made the AI wave possible in the first place. It is therefore crucial that everyone in the company - from the shop floor to the boardroom - understands that data is one of the most valuable resources for the future of the company. Implementing such a mindset on all levels constitutes a challenge for the industry. AI only unfolds its potential if data is available and accessible. Awareness of this and a willingness to treat data as a strategic resource are therefore fundamental prerequisites for fully exploiting the opportunities offered by AI. It must not be the case that employees who work directly in the processes only look at their immediate benefits and think that a few seconds of time saved here and there will suffice. Instead, it must be clear to everyone that every action, every scan and check-off must be carried out precisely and carefully in order to generate consistent data that can later be used.
13	8	Another important aspect related to the use of AI involves the perspective of employee representatives, such as works councils and unions, and the question of its impact on employment. This discussion is not new; during every wave of industrial automation, there has always been a fear that new technologies, such as robots, would lead to job losses. Tasks once performed by humans now seem to be taken over by machines, often raising concerns that many people could become unemployed. Historically, however, it has been shown that companies that resisted automation due to fears about employment eventually fell behind in terms of productivity and became less competitive. The long-term outcome was often that these companies lost their market position or were forced to shut down. Embracing productivity improvements through automation has therefore remained essential and this is as true for AI as it was for previous technologies. This issue naturally prompts reflection on the balance between automation and employment. AI is not fundamentally different from earlier waves of automation: it is still about how to effectively integrate productivity gains while managing their impact on the workforce. In this sense, the challenge remains relevant but is not unique to AI.
13	9	Compared to the traditional automotive industry in Europe or the USA, new companies in countries like China indeed have a certain advantage, as they were able to start on a 'greenfield'—unburdened by outdated structures and historical processes. This is less of a cultural advantage in the traditional sense and more of a structural one, allowing them to work in a data- and technology-driven manner from the outset. Many of these new automotive companies were founded by individuals originally from the tech sector, bringing with them a technology- and data-oriented perspective. These tech companies view vehicles less as purely mechanical products and more as digital platforms that can be continuously improved through software updates and data-driven functionalities. The integration of data and digital processes is central to their approach, with vehicles being seen as flexible and dynamic platforms. The shift to electric drivetrains further simplifies this transition, as the complex mechanics of internal combustion engines are eliminated. This opens up more room for software-based innovations and digital technologies. In contrast, traditional automakers have historically viewed cars primarily as mechanical constructs, where data has long played a secondary role.

13	10	The variables influencing success in AI-enhanced product development are still emerging—it's too early to pinpoint what will consistently work, but the firm has to be definitely prepared to extract value from the technology in several functions, not one isolated department to realize benefits in product development.
13	11	On the one hand, the tradition of established car manufacturers brings with it enormous expertise, especially when it comes to the construction of complex combustion vehicles. These manufacturers are able to build highly developed vehicles that offer exceptional driving performance and are leaders on the Nürburgring, for example - like Porsche. However, these competencies are also a burden when it comes to the transition to modern, data- and software-centered mobility. Today's customers are less interested in pure racetrack performance; instead, the focus is on the need for a "smart" integrated vehicle. This is where the challenge for the traditional automotive industry becomes apparent: the existing product architectures, which have been developed over decades for combustion engines and mechanical precision, often entail a long "rat's tail" of complex systems and processes. These make the transition to data-based, flexible systems more cumbersome and complicated.
13	12	Many of these new automotive companies were launched by founders who originally came from the tech sector and have a technology and data-oriented perspective.
13	13	It requires investment to ensure that data is of high quality and accessible to all relevant functions across the company. Tech giants such as Amazon and Google are already living this principle - their business models are data-driven from the ground up. For them, the value of data is self-evident and deeply embedded in their corporate culture. In the automotive industry, on the other hand, data was often seen as a necessary by-product with no strategic value. For a long time, this industry was production-oriented and data was seen more as an annoying by-product that had to "run along". The shift to a data-driven mindset is therefore a major hurdle that the automotive industry must first overcome. However, this change in mindset, seeing data as a valuable resource and understanding its benefits across all areas, is a key success factor for the future. Only in this way can companies in the automotive industry fully benefit from AI and the associated potential.
13	14	A major challenge the industry encounters is integrating AI solutions within our existing workflows and breaking down departmental barriers. The industry's hierarchical and compartmentalized operations often result in workflows that are disjointed rather than along the customer journey, which diminishes the efficiency of cross-functional AI initiatives.
13	15	I think that's one reason why the German automotive industry is going through a lean period at the moment. Historically, the German automotive industry has developed many technologies - which is positive, as many innovations come from Germany. However, other countries are often more successful when it comes to implementation. We are very history-oriented in Germany; we like to work on the basis of what has worked in the last ten years. This is seen as a proven basis. When changes occur, we tend to look back and analyze what was successful before. In contrast, other countries, such as the USA or increasingly Asian countries, have a different approach. They tend to look forward and ask themselves what they can do or how they need to do things differently. Only then do they look at what has worked in the past. In Germany, on the other hand, the approach to change is more conservative. We find it difficult to change things, and I believe that this is a central problem.
13	16	There are already many ideas and suggestions out there of theoretical use cases in the area of product development. However, we at management level have to differentiate between those and real scalable proof of concepts to implement those. These are still quite limited in number, at least as far as we know.
13	17	In addition, certain tests can be carried out automatically with the help of simulations and AI-supported simulation processes. This is a vision of how the entire system engineering process could work in ten years' time.
13	18	I think the small companies will wait and see, because they say it's a new law that doesn't even apply yet. Let's see, let the big ones solve it. And if there are solutions, then we'll do it that way, if it's put into focus. But I don't think it's an issue of principle. I think that some people simply don't have the opportunity - it's always the case when new innovative processes come up, it's no different with AI than in other segments - that smaller companies sometimes want to wait until such a mainstream has established itself because they don't have the resources to try out a lot. Larger companies have their own research and innovation departments and are more likely to do this.
13	19	The use of AI in system engineering is increasingly seen as a necessity in order to maintain competitiveness. The advantages lie primarily in three areas: Cost, time and quality. One major advantage is the reduction in costs. AI can be used to automate many manual and knowledge-based activities, which can significantly reduce labor costs. Particularly in view of the high wage costs in Germany and increasing international competitive pressure, it is crucial to keep industrial production in Germany by optimizing processes. The second advantage is the time savings. Time pressure plays a major role in international competition, especially in comparison to Chinese competitors, who are already able to bring vehicles from development to production readiness in just two to three years. European companies usually need another four years for this. This time discrepancy is not only due to technological differences, but also to different working models, such as three-shift work in development centers, which is still uncommon in Europe. However, AI support can speed up the development process, which could make the European automotive industry more competitive. Another significant advantage is the improvement in quality. AI can help to ensure that specifications are more complete and precise, so that important details are no longer overlooked. If requirements are missing or inaccurately specified, this can lead to expensive and late design changes, as certain specifications are only taken into account when they are found to be missing. These late corrections are expensive and can only be avoided by specifying the requirements precisely from the outset. AI can help in this area by systematically

		recording requirements and ensuring that no important details are overlooked. This ultimately helps to improve process quality and ensure high product quality.
I4	1	Artificial intelligence is also increasingly being used in the early phase of product development. Here, AI-supported tools and programs help to optimize designs and improve the service life or strength of components as early as the design process. Using 3D CAD systems and computer-aided simulations, radii, holes or other geometric details can be analyzed and adjusted to maximize the durability and functionality of parts.
I4	2	In the development process, the cheapest thing is actually not to do any physical tests. So you should actually avoid building prototypes, because they are expensive and you usually build a lot of them and then one department needs one and the other department needs one. And then you end up with 100, 200 prototypes, which are all very, very expensive, and then you have nothing. In other words, if you can use AI to test things virtually without reducing the number of prototypes, that would be a great area of application, for example, to have an application that says AI can create a test plan for your prototypes that reduces the number of prototypes by half. Of course, that would be an incredible business for a company that could develop AI software like that. Well, because we're talking about a prototype. A new vehicle, that can easily cost 150, 200,000 euros, one. And when you're talking about 50, 60, 100 prototypes, you can quickly, well, in such large development programs, the prototype costs can easily be 50, 60, 70 million euros or dollars. And if you could somehow reduce that, of course, that would be great. Cost reduction, mainly investment reduction, to be honest, when it comes to development, most people don't think about sustainability, even if that would be an advantage. How can you reduce development costs and how can you shorten the development cycle are the guiding questions. Shortening it is of course, I mean, the Chinese, they get a vehicle out in two years, we somehow need three and a half to four or five.
I4	3	The use of AI in product development brings promising benefits, especially when it comes to optimizing the service life or strength of a component. The classic 3D design process, in which a designer creates CAD models, is supplemented by AI-supported tools that can perform complex calculations and analyses for specific requirements.
I4	4	Another factor is the lack of practical experience with fully AI-supported development processes. To date, there are hardly any examples of car manufacturers worldwide that have developed and successfully presented a vehicle entirely with the help of AI. As such real-life case studies are still lacking, many companies are cautious and reluctant to use AI on a large scale. Accordingly, the large-scale use of AI in the automotive industry is likely to take time until sufficient data and experience is available to justify the investment as profitable.
I4	5	The field of product development with AI offers the advantage that companies can enter relatively quickly and cost-effectively. Since the necessary software is often already available, AI can be integrated as an additional feature or extension without requiring significant investments. The additional AI option is an enhancement of the tools already in use and can accelerate and make the design process more efficient without major changes or high additional costs.
I4	6	The decision as to how AI is used in companies depends largely on whether existing technologies are used or in-house solutions are developed. There is often a trade-off between customized in-house developments and ready-made platform solutions. Although in-house developments offer flexibility, they are complex and require extensive expertise in areas such as data connection, data monitoring and model management. This becomes particularly challenging when large amounts of data are processed and an overview must be maintained. For each step in this process, there is basically a choice: develop it yourself, rely on existing solutions or use comprehensive platforms provided by vendors. Some providers promise to cover up to 80% of requirements directly with their machine learning platforms. The challenge is to decide strategically which approach is best suited to the company's specific needs.
I4	7	To successfully integrate AI, a company must not only invest in the technology itself but also hire and specifically train qualified employees. This process is complex and cannot be implemented in the short term. Especially in historical loaden industries with some traditional rigidity this is not only crucial but quite a challenge.
I4	8	For a company, such an investment is only worthwhile if the benefits are clear and demonstrable. Businesses therefore compare the expected savings and efficiency gains from AI with existing processes. If AI promises significant advantages, such as substantial cost savings, an investment becomes justified. However, many companies, not only Ford but also other OEMs, remain cautious, as the direct benefits of AI in product development are often not yet clearly proven.
I4	9	In the automotive industry, the hardware component also plays a major role, which makes it more difficult to switch to new, data-driven and AI-based systems. In comparison, telecommunications companies, for example, are often more software- and data-focused and therefore have more flexibility to integrate new technologies at management level and also to make rapid changes. The automotive industry is therefore moving more slowly and deliberately, especially as AI is not yet fully understood and managers are hesitant until the technology is fully transparent and proven. Trust in the technology is critical here and will take time and demonstrable success before widespread implementations take place.
I4	10	To use AI in product development effectively, we need cross-functional teams that understand both the technology and our business needs—it's not enough to just have a technical expert on hand.
I4	11	Although AI is not yet widespread in the automotive industry, there has been an increasing openness towards smart solutions and AI-based systems in recent years. Many companies see the potential for AI-supported quality control and optimization, especially in manufacturing. However, the automotive industry is currently under considerable pressure due to the transformation towards electromobility, which poses an additional challenge for the integration of new technologies such as AI. Currently, many companies are still in the testing

		phase and it will probably take some time before AI is intensively and comprehensively integrated into production processes.
14	12	The complexity of an AI use case depends on whether it operates independently or within highly interconnected systems.
15	1	The first wave of AI consisted of rule-based AI, where a lot of knowledge was encoded in rules, such as in expert systems. These approaches still have their place, and attempts are currently being made to combine rule-based AI with neural networks - this is called neuro-symbolic AI. There is a lot of effort involved in modeling, especially if you want to carry out precise simulations and modeling in the development process. Many physical laws have to be modeled precisely in order to generate realistic simulations.
15	2	There have already been many proof of concepts and pilot projects that show how AI can be used in the development process. The use of generative AI tools such as ChatGPT to support the documentation of requirements is particularly interesting. A lot has to be documented in the development process, and generative AI can take over part of this labor-intensive and error-prone task. One promising approach is the use of Retrieval Augmented Generation, in which generative AI models are enriched with company-specific data. This reduces the risk of hallucinations - i.e. errors that the model "hallucinates" - which is a well-known problem with large language models. Nevertheless, comprehensive quality control is required to ensure that the generated content is correct and reliable. This means that this automation cannot run completely without human control. Nevertheless, a significant part of the documentation work and requirements management can be made more efficient by AI-supported processes.
15	3	A very important use case for AI in product development is requirements documentation. This is an area that is often prone to errors and AI could be a great help here, especially if you have to manage huge documents and requirements. You can use AI to implement automation in the documentation so that humans only have to check the important points. Using AI for documentation and requirements management saves a huge amount of time and avoids human error. You can quickly record requirements and ensure traceability without having to write every single line yourself. Of course, AI is not perfect. Even if you use it for automation, a human must always check afterwards whether the results are correct. You can't leave AI completely in control because it can often draw the wrong conclusions, which are then incorrect in a large documentation process.
15	4	I take a rather critical view of the use of AI in the early phases of product development. Creativity and human intuition are indispensable, especially when generating ideas, and it is often sufficient to simply sketch a concept on a drawing board instead of using AI. In these early steps, the work is often still too unspecific to generate real added value through AI. In such cases, models such as ChatGPT, which are trained on average data from the internet, tend to deliver general ideas that are difficult to replace with real innovations.
15	5	I also see clear limits to the use of AI when it comes to scoping, i.e. defining and narrowing down project requirements. Scoping is a knowledge-intensive task that relies heavily on specific expertise, and it is precisely this expert knowledge that a machine cannot replace in my opinion. In the creation of business cases, AI can draw on templates and automate some process steps, but that does not make it a real "value driver". Business cases are often very specific and tied to individual framework conditions, which is why the benefits of AI remain limited here.
15	6	Overall, human creativity remains unbeatable for me in these early phases. AI can provide support later, in more clearly defined development phases, but it is only suitable to a limited extent for basic idea generation or the definition of specific requirements.
15	7	There is the term "transparent AI", but in practice it is extremely difficult to understand exactly what is happening in these complex models. You can see the inputs and outputs of the system, but the way in which the system arrives at a decision often remains opaque. These models are essentially highly complex equations that are executed in real time, and no one can say for sure how they arrive at certain results. Even though we are currently trying to reverse-engineer these processes, it remains difficult to understand the exact steps involved. Another problem is that these systems often take so-called "shortcuts", as they do not have a complete world model and do not take physical restrictions into account. This means that the system sometimes arrives at correct results, but not necessarily through the correct or traceable process. There are cases where the model performs incorrect or unreliable operations that lead to incorrect or unreliable conclusions.
15	8	One important aspect that should not be lost sight of, however, is the handling of large models. Even though these models are becoming increasingly efficient and smaller, they are still very complex, with billions of parameters. These networks are deep and distributed across multiple levels, which means that it is extremely difficult to understand exactly what is happening within these models. This "black box" problem remains a challenge that should not be ignored. Even though these models are very powerful, there is always a degree of ambiguity about how they make their decisions.
15	9	However, many of these use cases have not yet proven to be fully successful, which is often due to the high effort required for data preparation. This includes data generation, data cleansing and the ongoing monitoring of data quality. This is one of the reasons why the first big wave of AI applications in the industry has often not delivered the hoped-for results.
15	10	Another important aspect is the quality of the data on which the models are trained. These models are often based on data sets such as ImageNet, a large labeled database. However, even such data sets can contain massive biases that are not always easy to recognize or correct. These biases in the data set can lead to the model making biased decisions without this being immediately apparent.
15	11	When it comes to the regulatory environment, there are of course always complaints. The General Data Protection Regulation plays a role in this, especially when it comes to use cases in which personal data is processed. However, I think that the impact of the GDPR on many use cases is relatively small as long as the

		data is anonymized. As long as you can't link the data to a person or create patterns that allow subsequent attribution, I don't think there are any significant restrictions. Discussions about data autonomy and the like play a role in this context, but in my opinion they do not affect the core area of AI development. There is still regulation, particularly through the Data Governance Act, but that is more about general compliance and less about freedom to innovate in AI. I don't understand the idea that Europe is being held back by excessive regulation in the field of AI. Yes, there is a lot of regulation, but I don't believe that these regulations will significantly restrict innovation.
15	12	Germany is therefore not fundamentally in a bad position, and the automotive industry is often talked about as being worse than it is. However, the main problem with the automotive industry is its uncompetitive costs, especially in view of the highly subsidized industry in China. This is why the automotive industry is keen to use AI to reduce costs, especially by automating repetitive tasks. In the past, muscle power was automated, today they want to automate 'mind power'. But as already mentioned, this only works in certain areas, due to the inherent limitations of AI.
15	13	The gap between theoretical use cases and their implementation is not just a step but a giant leap in a real business environment, proof of concepts is what firms are interested in in the end.
15	14	I wouldn't say it has to do with the maturity of AI, but rather that it is a fundamental element of AI. Artificial intelligence uses enormous computing power to sift through huge amounts of data with large neural networks comprising billions of parameters. In the case of large language models, this is almost the entire internet. Statistical patterns are derived from this data. In most cases this works well, but not always. These models cannot accurately predict when and why a particular pattern will occur. You simply don't know exactly what happens in these models when they work with 100 billion parameters. You can only observe and try to influence the AI's behavior through training or targeted input. But ultimately it remains unclear how these models react in detail.
15	15	With ChatGPT, the generalization capability increases, as does the multimodality - different modalities such as image and text can be used. However, the more an AI can do, the worse the output can be. This is described by the no-free-lunch theorem, which states that the best AI is a very specific, task-based AI. As long as the AI is very specifically focused on one task, it requires a high training effort and great demands on the availability and variability of data as well as on data quality. Such networks tend to overfit - they adapt too strongly to the training data and are then unable to generalize well, i.e. make predictions for unknown data.
15	16	A central topic is the sim-to-real gap, i.e. the discrepancy between the simulation of data and the real world. This particularly affects the use of Generative AI when it is aimed at pixel-level data processing. You often see this with models such as transformers that try to complete image data. But the structures that are generated are often not identical to the real world structures. This is why there are often discrepancies between the simulation and reality. These models cannot use real physical laws or world models, which can lead to errors that are then discovered in the real world.
15	17	When it comes to the physical development process, it's also about automating quality checks, especially in conjunction with robots. A vehicle, especially an electric one, has its own power source and built-in high-performance computing. This allows a lot of AI to be used in the production process. For example, the car could recognize itself what it needs next, diagnose itself to a certain extent and optimize the production process in this way. If you compare these approaches between different industries, it could make sense. However, in the early stages you probably won't find much more than what has already been said. Telecommunications companies, especially network operators, may not integrate AI heavily into their core products, but rather into automation processes such as peak load measurements. This automation could come into play especially in areas such as marketing and customer interaction. In the automotive and manufacturing industries, however, AI is being integrated more into the production process, particularly in the validation and safeguarding of the product.
16	1	The interconnected nature of our development processes means that a weak link in one department's readiness for AI can undermine the whole effort.
16	2	While the priority is clear, the actual budget allocated for this in the coming year remains to be seen. It's still somewhat experimental, and given the many other pressing topics, the advantages and use cases would need to be very clearly defined. Investing budget requires demonstrating clear returns, which might not yet be fully evident. It often comes down to who is advocating for the initiative. If the person leading the topic can effectively present and sell the business cases behind it, they will secure the funding needed to drive the initiatives forward. This is always a consideration for us—how and when to pitch these topics to higher management. From what I can see, the individuals working in this area are highly capable of handling such tasks effectively. However, I don't currently have insight into whether the budget for this area will grow next year, remain constant, or be reduced.
16	3	That's an issue. On the other hand, in our current situation, we no longer have the time or budgetary capacity to focus on these topics, as we are primarily trying to secure our core business. Although, this might actually be the right time to do more and move in that direction. However, I believe that many employees currently lack the framework or fail to establish it for themselves, as they are heavily driven by day-to-day operations and focused on managing the current situation. I think it's more about organizational reasons.
16	4	It has certainly been over three years since we actually sat down to discuss AI data and AI strategy and developed a clear model of what is good for the organization.
16	5	For us the topic of the In-Data Act and the AI Act is always something that plays a leading role everywhere. As a company, especially after the diesel issue, we are extremely sensitive when it comes to all types of applications, implementations, and so on. We run everything through our legal departments three times before taking any first steps, and yet we still try as best as we can to foster exchange within our AI teams, AI

		Experience Days, and so on, to constantly discuss where things are headed and what possibilities exist for us under this regulatory framework.
16	6	And if we take something from there, then we have to make a very strong abstraction that it is anonymous, that it does not contain any personal data, that it is deleted accordingly and so on. currently, we have contracts, data protection tools and coordination with our data or legal teams, tax and data legal protection to protect us. We are very aware of what we are doing and tend to say that we are happy if we can remove a content checkbox somewhere or put it somewhere else. We're simply clearly driven by very large specifications.
17	1	We also have a lot of documents that we need to check. Drawings, for example. Is a drawing even correct? So are there errors in it? Are there rules that need to be followed? And then it's always the case that when a drawing is changed, you ask yourself what it is, for example ISO standards. They also contain rules that people have to follow during development. There are always new versions of such a standard. Then someone sits down and reads through the whole standard, the old one and the new one. So how do we get to the point where more and more of these question-and-answer games are no longer done by people? And that is a question we are asking ourselves.
17	2	At the moment, it's more about waiting and carefully weighing options to see how the technology evolves and becomes more accessible. There's a certain hesitation to take a step forward when the direction is still unclear, with many opting to wait for the next two or three years to see how things develop. However, this hesitation isn't driven by uncertainty about the future development of the technology itself. Instead, it stems from a lack of clear understanding of the practical benefits and value that the technology can provide.
17	3	I believe this is the only way: we need service providers to support us with implementation – that's a key aspect. The second point that has become clear to me is that we need to deliberately place young talent in various positions who have already worked extensively with AI during their studies. For this generation, working with AI is second nature; they have a completely different approach and perspective. I believe this is a fundamental prerequisite for success.
17	4	It's simply a lack of knowledge that needs to be addressed. This includes, particularly, an understanding of the differences within artificial intelligence. For example, generative AI, such as ChatGPT or similar technologies, might already be more accessible to non-experts in technical fields. However, when it comes to analytical AI, for instance, we would really need concrete case studies to develop a pathway forward. What we need first is clarity about the various disciplines within AI to understand what kinds of applications are possible within each. This foundational understanding is still missing.
17	5	I'm sure that most managers of automotive companies are concerned about this. So I would be surprised if you called managers, even at a certain level, and they said they didn't want to talk to you. So my expectation would be that most of them would want to talk to you, simply because they want to become involved in the topic themselves. Well, I'd say that Germans tend to plan for a long time to do something. Others prefer to try things out and see what comes of it, yes. And that may also be something that reminds us of the culture here.
17	6	Wherever we know how to use this technology and have a solution for its application, we implement it. However, at the moment, there are only a few such cases.
17	7	I don't think that's an obstacle either. The IT hurdles in Europe are already relatively high anyway and companies have generally taken precautions, either they do it themselves or, if they are too small, they do it externally. And I think they are used to the fact that new technologies are constantly emerging and that you then have to look again to see whether the regulations still fit, whether something needs to be added, because that also changes. As I said, we're getting to the same point, I mean, I've seen a lot of technologies come along and this technology is coming somewhere else. It's very different from other things that have come before because it has a different nature. And the nature, I think, is to some extent in the function of the technology. So the people who write these programs tell me, for example, that they can't do what is difficult to imagine.
17	8	Since AI applications in product development are so new, firms need to approach it with flexibility and a willingness to adapt as we uncover what works.
17	9	It is well known that implementing such solutions, whether internally or externally, is a highly investment-intensive endeavor. The key challenge lies in recognizing the potential value and benefits of these solutions to justify taking action and committing to the necessary investments. At its core, it's always a question of balancing cost versus benefit. However, at the moment, the focus of the discussion is not on the effort required but rather on determining what to use and what the use case is. In development, we have not yet identified use cases where we believe it would make sense or provide significant value.
17	10	Development is such a continuously documentation-heavy area, starting with the specifications sheet, technical drawing documents that have to be created and the test reports. The time it takes to create development documents could be significantly reduced by AI solutions with greater accuracy.
17	11	The traditional perspective differs from new, emerging industry players who view data more strategically and as an essential part of their processes. We are not completely there yet.
18	1	In theory, everything works perfectly; in practice, bridging that gap is something different.
18	2	It is challenging to distinguish between the factors influencing general AI readiness and those specific to AI integration in product development, as most companies are still far from achieving full readiness and are in the early stages of developing the necessary base.
18	3	Why isn't it being implemented more widely? One major factor is cost. AI solutions are still relatively expensive, and there is a certain 'gold rush' atmosphere at the moment, where manufacturers and providers charge a premium for their tools and services. That makes it challenging to adopt. We've even considered launching a thesis project to explore the development of a tool tailored for our specific

		needs in this area, particularly as a development aid. However, it's clear that implementing AI is not yet straightforward or easily accessible.
I8	4	AI offers a wide range of potential applications, but it always requires tailored solutions for specific use cases. The idea is generated based on what one aims to achieve, and within the framework of a development mandate, we primarily see the use of AI in data evaluation. This includes analyzing measurement data, identifying patterns, detecting anomalies, and ultimately enabling a more targeted and efficient development process, which can also accelerate workflows. Manual data analysis—where someone sits in front of a computer to evaluate measurements—is naturally time-consuming. AI, however, needs to be trained to focus on what matters for the specific development goal. For instance, whether it's fuel consumption, emissions, or other factors, these goals often conflict with one another. A low fuel consumption might negatively affect emissions and vice versa. In the past, approaches using neural networks already existed as an initial step. Development parameters were entered, engines were run on test benches, and the system iteratively optimized itself by aiming for the best results across different criteria. AI can certainly enhance this process further, especially with greater automation, allowing for better interplay between various development objectives. This level of automation could bring significant advantages in achieving optimal outcomes.
I8	5	I have boundaries set by the manufacturer, for example in engine control. These boundaries are also defined by legislation, where the law states that emissions must not exceed certain levels under specific conditions. If you enter this range, an error must be logged. Similarly, if emissions deteriorate, this error also needs to be recorded. These are the limitations we face, and we are not allowed to cross them. The challenge is figuring out how we can approach these limits without triggering an error.
I8	6	With the applications we create and layer on top, we often get close to these boundaries. This is what AI needs to learn, where the limits are. I drive within the characteristic range long enough until a balanced system is achieved. AI could calculate this in parallel and further influence these systems to ensure everything remains in a loop. Using real-world experience gained during operations or in simulations, such scenarios could already be tested in advance within a simulation. This is where AI would take over the work. Then, the test bench would only serve as a final verification step to confirm the results through physical tests. I can imagine this very well. It would mean less use of the test bench, fewer resource demands—whether fuel or test bench capacities. Humans would have less manual work, and ultimately, it would bring benefits to the product and the end customer.
I8	7	It always depends on the extent to which I want to integrate AI. If it's to be used as a development tool, the first step is ensuring that the development department sees the value in it. This means securing funding and, of course, getting approval from top management. That's the first step. But it also depends on the broader organizational vision for how AI could be implemented. This requires top-down support to spread AI adoption across the entire company.
I8	8	Traditionally, automotive companies are not IT-centric. The focus is more on technology, physical parts, and hardware. The automotive industry has always been very innovative, and to remain so, it will continue to rely on technical development. Just think back to when everything was still drawn on drafting boards, and the first CAD programs came into use. How quickly CAD was adopted across companies! Soon after, we had simulations like airflow modeling around vehicles or through air ducts, and so on. Companies quickly adopted these tools when the benefits became clear. I believe AI is another such tool where the advantages will quickly become apparent. For this reason, companies will likely adopt and use AI as much as they can within their structures and requirements. I don't see companies standing still in this area—they want to move forward. AI promises efficiency, cost savings, and these are always major priorities. In the end, it always comes down to costs, and AI has the potential to make a significant impact here. After all, AI is something that has only really emerged in recent years.
I8	9	That hasn't materialized yet, but we are actively working on taking the first steps toward using AI in a way that allows us to apply it as a development tool. The idea is to integrate AI as a practical tool within our processes. Another potential application would be to use AI to improve or enhance a product during its lifecycle with the end customer, making it smarter and more efficient as part of the process.
I8	10	The effective implementation of AI requires not only technological adaptation, but also the overcoming of isolated structures within the organization.
I15	1a	Another advantage lies in the use of AI for Design of Experiments, a method for finding optimal solutions for product requirements through targeted test series. In the past, such experiments were often carried out manually, which was time-consuming. However, AI can significantly speed up this process by automatically calculating different options and making design suggestions. This saves time and makes it possible to proceed more efficiently.
I16	1a	I also see great potential in the industrial sector, for example in the automotive industry, particularly in the area of predictive maintenance. With the help of AI, potential machine failures can be detected at an early stage and preventive maintenance measures can be taken. This reduces downtimes and optimizes the service life and productivity of systems. In general, there are similar approaches in many industries: AI can help to optimize resources and make business processes more effective overall.

Figure 10: Citation Lists of Quotes for Automotive Industry