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# ARTIFICIAL INTELLIGENCE FOR PRODUCT DEVELOPMENT IN GERMANY'S AUTOMOTIVE INDUSTRY

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# ARTIFICIAL INTELLIGENCE FOR PRODUCT DEVELOPMENT IN GERMANY'S TELECOMMUNICATIONS INDUSTRY

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**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

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## 1. Introduction – *60158*

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.

# 1. 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 – *60158*

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-pasted 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 Challenges of Product Development – *58863*

Product development plays a critical role in maintaining competitiveness, as it enables companies to innovate, meet evolving customer needs, and differentiate themselves in an increasingly dynamic and fast-paced market environment (Egen 2024). However, various challenges can hinder these efforts, ultimately impacting a company’s ability to sustain its competitive edge. From the external perspective, competitive dynamics are a relevant influencing factor, as analyzing competitor strategies is essential to identify gaps in the market and differentiate products. Moreover, successfully developing a product that launches on time and at a competitive price is a complex challenge (Eppinger and Chitkara 2006; Schilling and Hill 1998). Product development is often carried out under tight schedules, as pace of technology development has led to tougher market dynamics and shorter product life cycles (Minderhoud and Fraser 2005). As products are only successful when they meet the expectations and preferences of the target group, understanding markets and changing customer needs is essential (van Kleef, van Trijp, and Luning 2005). Therefore, findings from market data analyses should be integrated along all stages of the development process (Kärkkäinen, Piippo, and Tuominen 2001). Complexity of specification activities within the PD process increases rapidly and further impedes the product development process due to requirements driven by highly regulated markets, complex products, and various product nuances (Weber and Weisbrod 2003). Thereby, requirements management as “*a set of techniques for documenting, analyzing, prioritizing and agreeing on requirements*“(IBM 2021), constitutes an additional challenge to be considered in the development process (Weber and Weisbrod 2003). Other obstacles arise from prior research indicating that environmental considerations have become a critical issue from both customer and regulatory perspectives. As a result, these concerns have increasingly influenced the field of product development (Chen and Chang 2013;

Böhler, Duwe, and Gackstatter 2023). According to Böhler et al. (2023), 80% of global CTOs and R&D executives consider sustainability to be from high importance for their company's strategy (Böhler, Duwe, and Gackstatter 2023). The challenge can be addressed via design of greener products (Le Mouëllic et al. 2023) and rethinking the development process (Böhler, Duwe, and Gackstatter 2023). From the contrasting internal perspective, financial as well as human resources constrains appear as a decisive factor to consider within the product development process (Jain and Grossmann 1999; Yoshimura et al. 2006; Ogura et al. 2019). Meanwhile the interconnectedness of PD with other firm functions can create further obstacles for the process as integrating activities across organizational units poses challenges for smooth collaboration (A. K. Gupta, Raj, and Wilemon 1985; Kahn 1996).

Overcoming these challenges is crucial for innovation and product development to drive transformation through AI (Aldoseri, Al-Khalifa, and Hamouda 2024). AI enhances innovation and product development by supporting traditional processes, enabling a wide range of applications (Scheidegger 2024). Within such use cases, AI technology regularly outperforms human capabilities which therefore has a significant effect on the various business performance dimensions (Aljuhmani and Neiroukh 2024; Wamba-Taguimdje et al. 2020).

### 2.3 AI and the Adaption Curve in Product Development – *58863*

Artificial Intelligence (AI) first emerged in 1956 during a research project that is widely regarded as the beginning of the field (BMBF 2024). It is often defined as "*the ability of a machine to perform cognitive functions associated with human minds*" (Chui and Malhotra 2018) which can play a significant role in the innovation process of a firm (Kakatkar, Bilgram, and Füller 2020). According to Brem et al. (2023), AI can act as an "*originator*" and as an "*facilitator*". Within the "*originator role*", AI can be leveraged as a creative model for PD, while the "*facilitator role*" enables AI to improve existing processes in efficiency and efficacy (Brem, Giones, and Werle 2021). The successful adoption of AI in processes and tools can then often be recognized by the label “*AI-enabled*” or “*AI-powered*” (Zhang, Zhang, and Song 2021). The most commonly adopted types of AI technologies in PD are analytical, functional, interactive, text, visual and robotic AI. Potential applications vary based on these different utilities and can encompass demand forecasting, smart personal assistants, computer vision and robotic process automation (Zhang, Zhang, and Song 2021). Besides these possible classifications, AI can also be characterized by levels of technology. The underlying technology that supports many AI applications is machine learning. It transforms vast datasets into algorithms that analyze information and repeatedly improve their performance through ongoing learning and adaptation. Deep learning is subset of this technology that enables the algorithm to learn from unstructured data (Chui et al. 2023). Generative AI can further transform this data into output of different forms such as text, images, and audio (SAP 2024) and is expected to generate one of the greatest values within product and service development (Singla et al. 2024). AI has continuously advanced in recent years, largely driven by the development of powerful hardware and increased availability of large datasets (BMBF 2024).

With the currently still relatively low adoption rate of 13%, AI in product development (Chheda et al. 2023) can be contextualized within the technology adoption curve (Rogers 1983). The technology adoption curve is a sociological model that tracks the acceptance and use of new technologies within a population. Each of the five segments *(see Appendix, Figure 3)* represent a distinct attitude and approach toward embracing new technologies (Rogers 1983). As of 2024, AI technology in product development is still categorized within the “*early adopter*” stage where some companies are beginning to realize its benefits. Early adopters acknowledge the potential of the new technology and invest while further spreading initial awareness (Bartley 2023). Meanwhile, the gradual transition into the “*early majority”* phase has begun, where larger-scale adoption and more consistent integration into business models occur (Rogers 1983; Cooper 2024a; Cooper2024c; Rogers, Singhal, and Quinlan 2008). This group embraces the innovation shortly after it has been validated and endorsed by the early adopters (Bartley 2023).

Many businesses are still exploring how to effectively integrate AI into their operations, with some sectors advancing more quickly (OECD 2024b). The hesitancy to fully commit to AI indicates that there is still a long way to go (PwC 2023) before the technology fully enters the "*early majority*" phase.

## 2.4 Industry Characteristics

The automotive and telecommunications industries each present unique characteristics that influence the adoption of AI in product development. These differences are mainly due to the varying importance of the value drivers in individual sectors, indicating that the potential for value creation varies depending on the industry and specific business use case (Chui et al. 2018). To better understand these dynamics, the following subsections will explore the distinct prerequisites of each industry.

### 2.4.1 Automotive Industry – *60158*

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).

#### 2.4.2 Telecommunications Industry – *58863*

The global telecommunications industry is a consumer-centered and data-driven service industry (Fernandes, Chow, and Dr. Gröne 2023) that is constantly growing while also facing ongoing strategic challenges in recent years such as decreasing revenues (Abraham et al. 2023) and costly investments to satisfy demand (Fernandes, Chow, and Dr. Gröne 2023). This results in strong competition while consumer benefit from a variety of options (Deutsche Telekom 2024b). Its product portfolio contains products and services such as mobile communications, fixed-network, and Internet Protocol Television (IPTV) products and services for B2C and B2B customers (Deutsche Telekom 2024a). The growing demand for connectivity has resulted in digitalization becoming a driving force (Deutsche Telekom 2024a). Telecommunications has established as a frontrunner in AI adoption (Chui and Malhotra 2018) with one of the highest share of AI usage in 2023 (OECD 2024a) and has further revolutionizing its industry landscape through technologies such as 5G, IoT and Cloud Computing (Wood 2024). The shorter life cycle of such technologies and intense competition drive telecommunication firm to accelerate the product development process to deliver results more rapidly (Kosaroglu and Hunt 2007). The industry is characterized by generating vast volumes of structured, unstructured as well as semi-structures data (Efimova 2024). This may include consumer-related information, network-related data as well as operational data, thus providing a range of quantity and variety (Hateley 2023), commonly referred to as "*big data*" (Efimova 2024). AI combined with these data sources enables telecommunication firms to deliver critical infrastructure for communication and online services to its customers more efficiently, thereby becoming an integral part of its technological roadmap (NVIDIA 2024). Meanwhile, the telecommunication industry is urged to transform into a fully software-driven business by leveraging AI to stay relevant in its competitive landscape (Mishra 2024). Due to rapidly evolving technological advancements accompanied by a growing importance of such products, it is vital for such firms to adopt innovation, especially in product development (Rutitis and Volkova 2019). For telecommunication firms, the current focus of AI technology adoption primarily lies on service operations (Rutitis and Volkova 2019) as the "*most valuable business area*" for the industry (Chui and Malhotra 2018), e.g. through applications such as virtual assistance to enhance the customer experience and improve customer engagement (NVIDIA 2024).

## 2. 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 (Fountaine, 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 Katakar 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.

## 3. 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.

## 5.1 Automotive Industry – *60158*

### 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).*

<u>Market Analysis & Requirements Engineering:</u> 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 optimize designs in relation to requirements 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-Sybolic 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.

<u>Compatibility:</u> 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).

<u>Complexity:</u> 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 trough 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).

<u>Top-Management Support:</u> 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).

<u>Organizational Culture:</u> Interviewees outlined hat 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).

<u>Organizational Structure:</u> 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 extend 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).

### 5.2 Telecommunications Industry - *58863*

#### Identified AI Use Case Potential and Technological Factors

Industry experts emphasized the requirement to evaluate AI use cases for PD by first determining the specific business need and conducting a "*proof-of-concept*" (I10/7; I13/5). The process includes establishing clear expectations, assessing practical feasibility, and determining the added value or ROI (I13/5; I15/6b). After these elements are thoroughly addressed, telecommunication firms proceed with adoption (I10/7; I11/7,17). However, even after initial adoption, certain applications are discontinued due to technological challenges or outcomes falling short of expectations (I11/22).

**Application Areas**

The following section illustrates the most promising application areas and use cases *(see Appendix, Figure 9)* for the telecommunications industry as derived from expert interviews.

Software Development Automation: Software development automation emerged as one of the most frequently mentioned use case areas within the telecommunications industry (I9/2,6; I11/1; I12/1; I13/5). Acting as a proxy for human intelligence, specifically generative AI enables automation along the software development process (I9/5,6). Externally provided generative AI tools, such as "*GitHub Code Assistant*", "*Tabnine*", and "*Microsoft CoPilot*", are transforming the development process by assisting developers with tasks like predicting code snippets, suggesting improvements, and completing code based on the given context (I9/2; I11/1; I13/5). These tools are revolutionizing the management of repetitive tasks by significantly reducing the need for manual coding. This can increase efficiency by 30 to 40% and thereby development speed (I9/2; I11/14,20). Code assistance further enhances the onboarding process for beginners by simplifying code explanation and generation (I13/5). While these tools are mostly used in the development stage (I11/2), the testing of code in the "*testing & validation*" stage can be automated through machine learning (I11/1; I15/2b), e.g. as traditional pass-fail criteria are often not capable of capturing error indications within data. This can identify irregularities in test cases that are otherwise overseen by developers (I11/17). Moreover, generative AI can enhance and accelerate the software development process by automating the creation of tailored user stories as a practice of requirements management. AI-driven tools ensure that user stories maintain a consistent format, making them easier to apply across various channels and ensuring clarity and comprehensibility for diverse development teams (I9/1). In the further software development process, automated regression testing through machine learning algorithms repeatedly run tests in diverse environments with varying conditions to validate the code (I9/3). These automations enable firms to accelerate development processes and thus increase time-to-market which further positively affects profitability metrics (I11/20; I14/1,2).

Simulations: Simulations enable firms to replicate and analyze how products perform in realistic and complex environments, e.g. through "*digital twin*" technology (I13/6). These simulations leverage both historical and real-time consumer behavior data (I10/2,4; I13/6) to provide critical insights into performance and functionality. This capability supports the development and testing of networks by enhancing coverage, optimizing performance, and generating actionable insights. Derived insights play a key role in strategic decision-making, helping firms allocate investments effectively, plan network capacity, and reduce resource consumption (I10/2; I13/9). Another use case is the generation of automatic proposals for technical teams to support the development process (I10/2). The concept of streaming telemetry is a key enabler for AI-driven simulations since this approach enables efficient and centralized analysis through real-time data transmission. The transmission is performed directly from devices to central collection points and is reliably compatible with automated data analysis tools based on machine learning (I11/19). An expert highlighted that while human intervention is still necessary for overall decision-making, which limits the full realization of efficiency gains (I10/6), simulations nonetheless play a critical role in significantly reducing the manual labor required by the team (I9/3).

Feedback Data Analysis: Feedback data analysis enables companies to extract actionable insights for PD from the market launch phase (I10/3) and thereby respond to customer needs more effectively (I9/7; I13/6). By processing vast amounts of data, sentiment analysis, for example, illustrates a powerful AI use case application for extracting valuable insights into customer opinions and behaviors. As explained by an interviewee, sentiment analysis captures the meaning of this feedback at scale which empowers telecommunication providers to identify trends, measure customer satisfaction, and make data-driven improvements to their services (I9/4). This capability is particularly valuable in a sector where millions of customers provide feedback with diverse contexts (I9/4). Through AI, companies can detect patterns in user sentiments that influence PD, ensuring tailored product and service improvements (I9/4). AI-powered tools based on customer feedback can structure and present large sets of data while advanced systems can then further retrieve information based on NLP (I11/3,4). These systems arrange unstructured data and increase data quality by enabling simplified access to information (I11/3). The information based on user behavior and customer feedback data can then be used as insights for PD and facilitate the continues improvement of products and services. It can further be used for advancing next-generation technologies such as 6G mobile networks to meet evolving user needs of the future (I10/3).

**Technological Context**

Building on insights from industry experts, the following section will demonstrate the influence of technological factors on AI usage potential based on three influences.

<u>Compatibility</u>: Based on our expert interviews, the factors of system and data compatibility are decisive and often challenging for AI adoption, particularly in the telecommunications industry (I11/18; I12/4; I14/6; I16/3b). As one expert pointed out, the creation of an integrated platform is a basic prerequisite to establish an infrastructure where AI models can be effectively trained which, however, requires intense efforts (I14/6). Harmonizing AI with existing systems in a complex process is essential to enable the efficient processing of data streams while minimizing disruptions during integration (I15/1b; I14/6). As traditional system was not originally designed to handle large volumes of data, telecommunication firms increasingly transition to external cloud solutions which allow for more flexibility and scalability (I11/18). Externally provided

infrastructure is further easier to maintain as its often based on a service offering (I13/8). Equally critical for the compatibility of AI with existing systems is the availability and quality of data as AI relies on high-quality datasets for training and accuracy (I12/4). An interviewee suggested that data standardization and distribution is not yet mature for an appropriate level of compatibility in the telecommunications industry (I12/4). Even though data is vastly available due to its software-focus (I9/7,8,9), data quality is affected by fragmentation and poorly defined data requirements that have not been aligned with business needs (I9/7; I10/7). Further, interviewees stressed the need for structured and cleaned data and thereby the establishment of a common data structure (I10/7,12).

Complexity*:* An interviewee stressed the need for simplification to enable broader usage and widespread scalability of AI in PD processes, especially for more specific solutions (I12/2). AI algorithms are highly sophisticated and demand deep technical expertise, not only for monitoring and maintaining their applications but also for selecting the most suitable algorithms for specific use cases and tasks. Choosing the wrong algorithm can lead to inefficient performance, reduced accuracy, and unnecessary resource consumption (I14/9). Complexity is further increased by lacking transparency and ambiguous interpretability as current AI applications often still act as a "*black box*" which is why developers often cannot fully understand automatically generated code (I11/20,22). For example, developers struggle to determine the origin of the code's failure, in case of errors or unexpected behavior, which complicates debugging processes (I11/12,20). This decreases positive efficiency effects, hinders adoption rates through perceived increased complexity of adoption and leads to a decline in code maintainability and quality (I11/20).

Capability: Based on an expert's insights, the adoption of such industry-relevant use cases is not specifically hindered by the technology's reliability and capability (I10/9). AI is still improving by continuously increasing its capabilities as they keep on "*getting better every* *month*" (I9/18). Generative AI tools have already reached a level of technological advancement that enables consistent deployment in product development processes (I10/7). An expert further highlighted the expectation that generative AI will soon have the capability to automate more complex processes, extending beyond repetitive routine tasks to encompass more creative and sophisticated processes (I11/21). Moreover, there are machine learning algorithms within telecommunication firms that have already been reliably established and implemented into PD processes with proven capability and reliability for an extended time (I13/4). Sufficient maturity of AI's capabilities has been proven even in scenarios with limited data availability, e.g. for running simulations to derive new trends and products (I10/7). Nevertheless, an expert emphasized that despite diverse use cases of AI in product development, the technology has not yet reached full maturity to independently create entirely new products. (I10/1,8).

**Organizational and Environmental Factors**

As previously outlined in chapter five and further confirmed by industry experts (I9/10; I12/7) general AI readiness factors will be demonstrated to assess the perception of organizational and environmental factors on AI adoption in PD, given its early-stage adoption level.

**Organizational Context**

The dimension of organizational challenges includes several factors that determine how hindering firms perceive internal structures and prerequisites for AI adoption in PD processes within the telecommunications industry.

<u>Resources</u>: Holistic AI adoption can require significant financial investments, especially for developing proprietary solutions and licenses (I11/13; I14/7,8). However, several interviewees stated that financial resources are not considered a significant challenge their firms (I10/4; I11/13; I12/5). Instead, it was further emphasized that the strategic focus primarily lies on operational constraints to maintain customer commitments rather than prioritizing AI adoption which requires compromises in resource allocation (I10/4; I12/5). It was also noted that IT

infrastructure is still generally not perceived as a challenge since telecommunication firms continuously adapt IT systems to keep them up-to-date and enable compatibility, further extended by externally provided cloud-based infrastructure (I11/13,18; I13/8).

Human resources in the form of in-house expertise, however, were confirmed as a common challenge for technology adoption in telecommunication firms. In-house expertise is critical for identifying at which PD stages, AI adds value, e.g. for optimizing designs, conducting simulations, or validating results (I14/5) as well as for efficiently adopting it into specific processes. It is important for firms to build enduring AI in-house expertise, e.g. through trainings and skill-enhancing initiatives as the technology continuous to increase in relevance (I9/16; I11/16). Here, mastering in-house expertise can increase the chances of staying competitive (I14/13) which requires having the talents inside the company (I9/16).

While hiring external consultants can address some expertise gaps, many specialized solutions require internal development, as external tools and libraries often fail to meet the industry's unique needs (I10/10; I14/4). Teams must therefore also have the skills and resources to independently develop and tailor AI models (I10/10; I14/3; I16/5b). However, attracting talent with relevant AI expertise is a significant challenge to German telecommunication firms. One expert highlighted that this is particularly problematic for telecommunication firms because skilled and highly demanded professionals often prefer more recognized and prestigious industries (I9/11).

<u>Top Management Support</u>: Top management (TM) support was stated as providing *"the right tools and resources*" to enable employees effective integration of AI into existing workflows. German telecommunication leaders further apply approaches such as communicating concrete goals by highlighting success stories and sharing those within their teams. TM support can also include the promotion of AI trainings and skill-enhancing initiatives (I11/16). AI trainings can deliver necessary know-how and increase efficiency for using AI-based tools (I11/1). Moreover, specific KPI targets can be determined to create engagement in employees, e.g. by

establishing the requirement to write a specific proportion of code through AI assistance (I11/16). Actively communicating the benefits and business value of integrating AI in processes further promotes its success as most employees are regularly under too much pressure to complete PD within the given schedule and therefore deprioritize experimentation with new technologies (I11/15).

Here, however, effective communication between top, middle, and lower management is often impeded because TM communication tends to be too "*high-level*." This approach leads to differing perspectives and priorities across management levels, which frequently obstruct the development of a shared understanding (I10/15). Nevertheless, another interviewee highlighted that necessary TM support is frequently confirmed within their firm by repeatedly demonstrated board-level interest as well as direct involvement through regular progress reviews. The engagement by the executives in this firm ensures that AI remain a strategic priority and give departments flexibility to hire skilled employees (I9/10,13). This holistic approach not only set clear expectations but also signaled the importance of AI to all organizational levels (I11/15).

Organizational Culture: An interviewee highlighted that an open mindset for innovation and the integration of AI in daily workflows are expected from telecommunication employees which is actively supported by the firm's TM (I10/17,18; I11/16). One interviewee further mentioned that their PD software engineers are generally enthusiastic about adopting new technologies, actively driving AI adoption (I12/8). However, while most developers in product departments practice an innovation-oriented culture and integrate AI into their routines (I12/8; I13/5), some employees still prefer proven alternative processes (I13/5). Especially less digitally progressive parts of their organization are less easy to adjust (I9/19). Some employees may even perceive the confronted amount of innovation as overwhelming, which can result in a "*wait-and-see*" approach which delays action until the outcomes of ongoing innovations such as AI become clearer (I10/10).

These attitudes complicate the adoption process and risk missing out on significant development steps towards AI adoption (I10/10), however, are actively challenged through the encouragement to experiment and learn (I9/19). According to an industry expert, this includes a "*forward perspective*" which is crucial to continuously meet customer expectations in the dynamic telecommunications markets. Here, the actively communicated question in mind is "*what can we do now to improve our competitive standing later*" (I13/7). Such practices empower telecommunication firms to establish a sustainable ground for driving technological progress and fostering continuous innovation (I10/17).

<u>Organizational Structure</u>: As industry experts mentioned, organizational structure affects AI adoption in different aspects (I9/12; I10/12,14). Existing vertical structures in some telecommunication firms are not only misaligned with customer needs but also obstruct the effective deployment of technologies (I10/14). As the German telecommunications industry is characterized by rapidly changing innovations with short innovation cycles, this fast pace is embedded in most organizational structures and processes (I10/11). To ensure this specialized AI initiatives or "*center of excellence*" with employees from data science, engineering, and product backgrounds support departments to incorporate AI across all functions (I9/12). These initiatives are integrated in all organizational dimensions with clearly defined business goals to avoid misalignments (I10/16). The interviewee further highlighted that horizontal collaboration is enabled through cross-functional teams (I10/14). Cross-functional teams can bring together various departments to collaborate and provide diverse expertise that directly aligns PD with the customer journey (I10/14). Nevertheless, while data is abundantly available, it is still often fragmented across departments and unstructured due to different department "*languages*". Without data harmonization across the organization, this fragmentation reduces data quality (I10/12).

**Environmental Context**

Regulations and Compliance: Regulations like the GDPR can be perceived as both challenge and opportunity in the German telecommunications industry (I10/19,21). Firms must assure the protection of customer data, confidential information, and ethical standards (I10/19). As there is a tendency to be confronted by heavy external regulations in Germany, compliance may create operational hurdles to its telecommunication firms (I14/9). Meanwhile, frameworks also provide clear guidelines about data usage for new technologies such as AI. This signals a security and responsibility, especially for innovative solutions focused on high levels of protection for consumers (I10/19,20). However, balancing the need to foster innovation with strict regulatory compliance is especially challenging in such an industry, where handling personally identifiable information (PII) is a central concern (I9/14; I14/9; I16/1b). Its classification as "*critical infrastructure*," in Germany adds further complexity due to an additional layer of intense regulatory burden (I13/3) as working with personal data in such regulated environments requires "*careful attention to many rules*" (I16/4b) The high occurrence of PII thereby also reduces data quality as personal data must often be anonymized before firms are permitted to utilize it for AI in PD processes (I13/3; I16/4).

Moreover, sensitive company data must be safeguarded to prevent competitive risks by ensuring that proprietary data remains internal and is not utilized to train external models (I15/3b). To address such concerns, tool providers like Microsoft have created tailored solutions to ensure that user-generated data is not reused for model training (I11/9,11; I14/11). Data security concerns and the compliance to various regulations thereby reduce the speed and efficiency of AI adoption for telecommunication firms (I12/3). Despite significant regulations and compliance standards, an interviewee expressed optimism about their firm's ability to adapt to even stricter AI-specific regulations, noting that there is still time to prepare before the AI Act takes effect in 2026 (I9/15).

External Providers: As stated by interviewees, certain basic problem statements within the telecommunications industry can be effectively resolved by leveraging generic or customized vendor solutions (I9/17,18; I14/17; I16/5b). Here, external consultants and experts may provide additional knowledge to guide the internal adoption process (I10/10). Most firms within the German telecommunications industry are vastly powered by such external partnerships, e.g. with cloud services and other telecommunication providers (I13/2,8). These collaborations can provide firms with tools and interfaces that enable the efficient application of different types of use cases, e.g. for data analysis (I11/19). However, it was highlighted that complex industry-specific challenges for AI use cases demand tailored solutions, which generic vendor tools mostly cannot address (I11/8; I14/17; I16/2b; I16/5b).

Political and Economic Environment: An industry expert stated that while governmental funding is highly relevant to their firm, this has often been hindered Germany's slow-paced administration (I14/15,16). While Germany has various skills and resources to offer (I10/20), its governments was criticized as broad and unfocused due to a lack of clear priorities which is needed to drive progress (I10/20). While countries like China set explicit strategic goals such as AI leadership by 2030, Germany often struggles with indecisiveness and frequently shifting strategy. It was further added that Europe's tendency to regulate rapidly often prioritizes strict compliance over innovation (I10/20) This concern is further amplified by the fact that those drafting relevant regulations often lack a clear understanding of the technology itself and thereby create ambiguous policies (I9/14). On the other hand, Germany as economic environment can enable a competitive advantage to telecommunication firms by providing significant interdisciplinary expertise and resources in areas such as mathematics and informatics to leverage AI for key technologies such as 6G and quantum computing (I10/21).

# 7. Discussion – *Joint Section*

## 7.1 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 "*Early 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).

### 7.2 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 (Julienti 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 (Dhairyawan, 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 neglection 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 "*Dieselgate*," 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).

## 8. 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.

## 9. 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.

## 10. Conclusion – *58863*

By conducting the first cross-industry exploratory study focused on factors that influence AI adoption in PD not only in specific industries but also in the geographical German context, we identified specific differences in the impact and challenges of AI integration in PD. Further we derived overarching decisive success factors for firms to consider beyond the industries in investigation focus. Automotive and telecommunications industry both face competitive pressure, compelling them to exhibit awareness about AI in PD for sustained advantage. Yet, adoption remains limited and AI adoption efforts in both industries are not primarily dedicated to PD and focused on the currently most value-adding business areas instead. In telecommunications, AI potential is mainly found in automated software development, simulations, and feedback data analysis, while the automotive sector emphasizes market analysis & requirements engineering, design optimization, and product testing. As AI adoption in PD can facilitate differentiation, the automotive industry should therefore consider its prioritization. The interview analysis enabled us to identify potential barriers for the implementation of AI in PD and uncover interconnections among various factors across key dimensions. Common technological challenges include complexity, data quality, and system integration. Findings further revealed dominant influences of in-house expertise, industry dynamics, leadership support, organizational culture, and structure as well as existing prerequisites of PD practices to consider across industries. Despite differing origins, the challenges in AI adoption across the two sectors are to some extend aligned, enabling the development of generalized recommendations. Our research provides actionable guidance via "*easy-to-implement*" use cases and via addressing AI readiness factors even for organizations across other industries to enter the "*early majority*" phase (Rogers 1983) in this near-future technological shift for PD.

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# 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-Sybolic 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

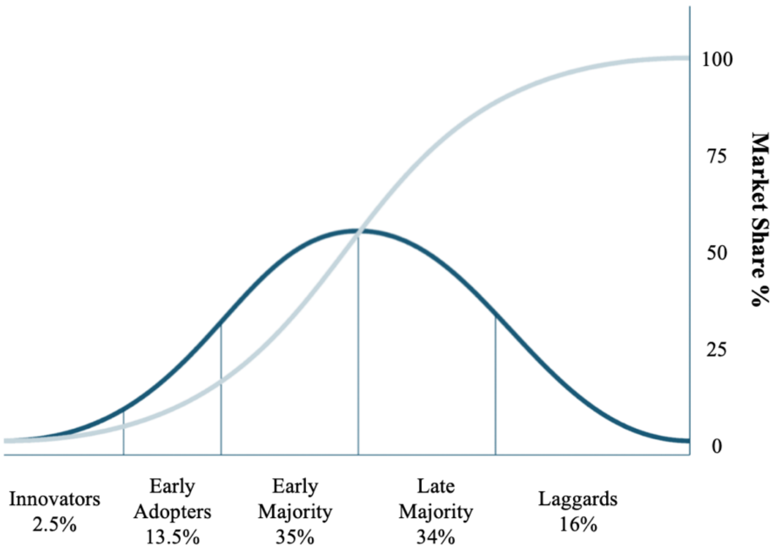


*Figure 3: Innovation Adoption Curve by Rogers (1983)*

## 4. Stage-Gate Model

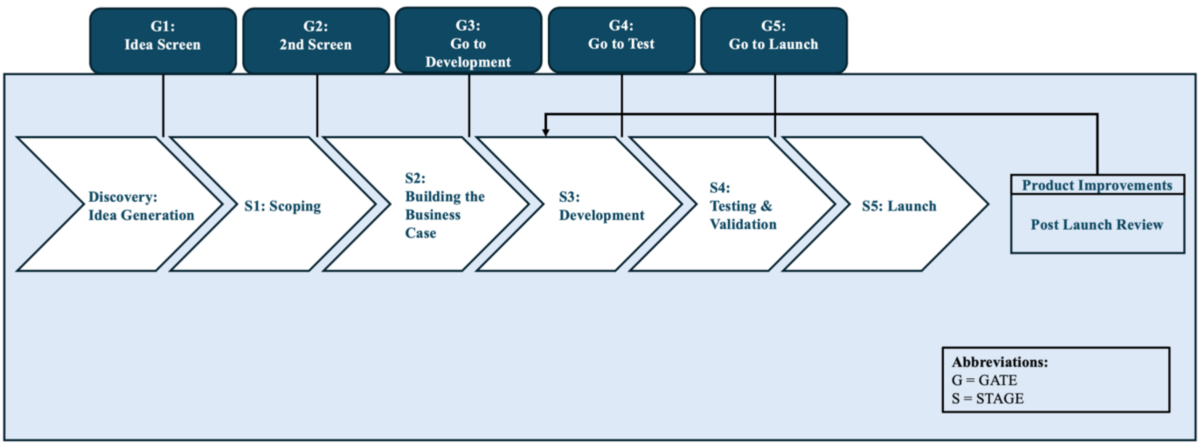


*Figure 4: Modified Stage-Gate Model based on Cooper (1988)*

## 5. TOE Framework

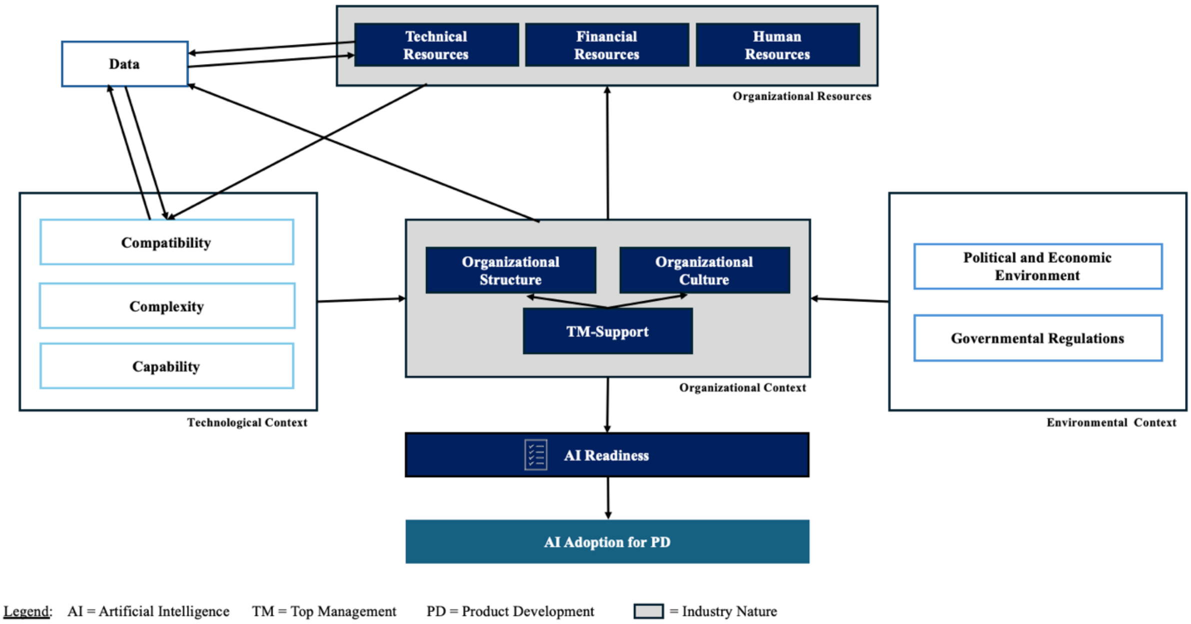


*Figure 5: Modified TOE Framework based on Tornatzky and Fleischer (1990)*

## 6. Qualitative Interview Questionnaire

| Interview Outline |
|---|
| **Format:** Semi-structured, open-ended interviews with industry practitioners.<br><br>**Time Frame:** 45-90 min.<br><br>**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).<br>• Interviewee briefing regarding research aims, interview focus and scope.<br>• Brief explanation of understanding towards "AI", "product development", "usage potential" and introduction to the Stage-Gate model.<br>• 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?
  - *Optional add on, depending on given interviewee answers:*
  - 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?
    - *Optional add on, depending on given interviewee answers:*
    - 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?
    - *Optional add on, depending on given interviewee answers:*
    - 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?
    - *Optional add on, depending on given interviewee answers:*
    - 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

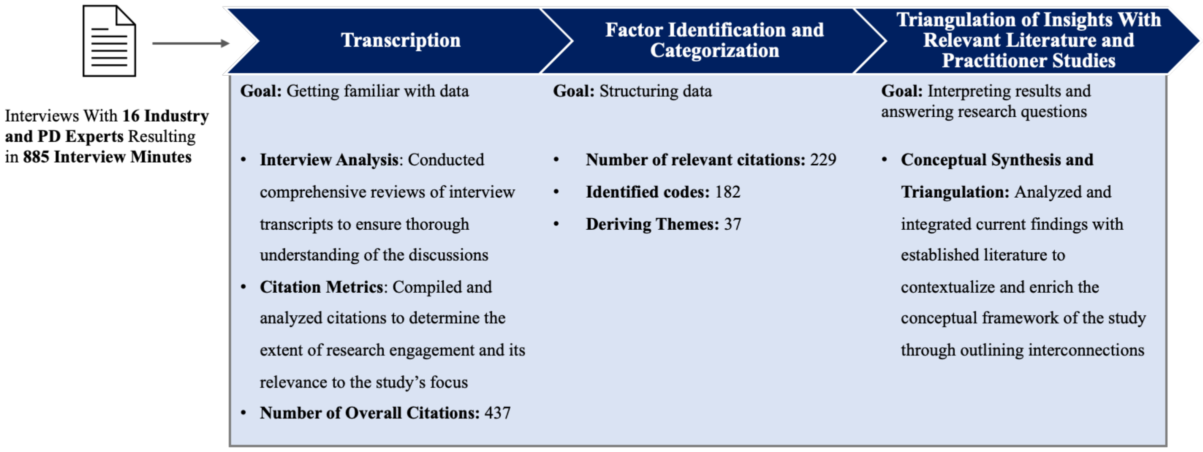


*Figure 7: Methodology based on Braun and Clarke (2006)*

## 8. List and Profiles of Interviewees

| | Last Name, Name | Interview Method | Duration | Current/ Prior Position | Industry Sector | Company/ Prior Company |
|---|---|---|---|---|---|---|
| I1 | Geiger, Elmar | Microsoft Teams | 60min | Product Planning Manager | Automotive | Ford Motor Company |
| I2 | Goertler, Thomas | Zoom | 90min | CEO/Senior Vice President Product Management | Automotive | Vision2Product/ Huber Automotive/ Al-Ko Vehicle Technology |
| I3 | Lorenz, Sven | Microsoft Teams | 45min | Head of Data & AI / Head of Digital Program and Data Governance | Automotive | Volkswagen AG / Porsche AG |
| I4 | Motati, Kesava | Microsoft Teams | 45min | Product Manager - Design and Release- Body Engineering | Automotive | Ford Motor Company |
| I5 | Dr. Seiberth, Gabriel | Microsoft Teams | 60min | President Europe & Member of the Executive Board/ Managing Director | Automotive | KPIT/ Accenture |
| I6 | Schmidt, Sebastian | Microsoft Teams | 60min | Business Owner Audi Commerce Plattform | Automotive | Audi AG |
| I7 | *Anonymized* | Microsoft Teams | 30min | Senior Vice President R&D and Product Management | Automotive | Al-Ko Vehicle Technology |
| I8 | *Anonymized* | Microsoft Teams | 60min | Head of Drive/Electronics Development | Automotive | *Leading OEM Supplier in Germany* |
| I9 | Abrahamson, Jonathan | Microsoft Teams | 45min | Chief Product & Digital Officer | Telco | Deutsche Telekom |

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|---|---|---|---|---|---|---|
| I10 | Irnich, Ulrich | Microsoft Teams | 45min | CTO | Telco | Vodafone |
| I11 | Junke, Thomas | Microsoft Teams | 60min | Vice President Engineering, Architecture | Telco | Infinera |
| I12 | *Anonymized* | Telephone | 30min | Head of Technology and Innovation | Telco | *Leading Telco Firm in German Market* |
| I13 | *Anonymized* | Microsoft Teams | 60min | Data Scientist | Telco | *Leading Telco Firm in German Market* |
| I14 | *Anonymized* | Microsoft Teams | 45min | Head of Product Management | Telco | Nokia Siemens Networks |
| I15 | Krieg, Daniel | Microsoft Teams | 90min | Senior Consultant - ML & ML-Plattformen | AI Vendor | Synvert |
| I16 | Fommhold, Carsten | Microsoft Teams | 60min | Teamlead Data Science & AI | AI Vendor | Synvert |

*Figure 8: List and Profiles of Interviewees*

## 9. Identified Use Cases

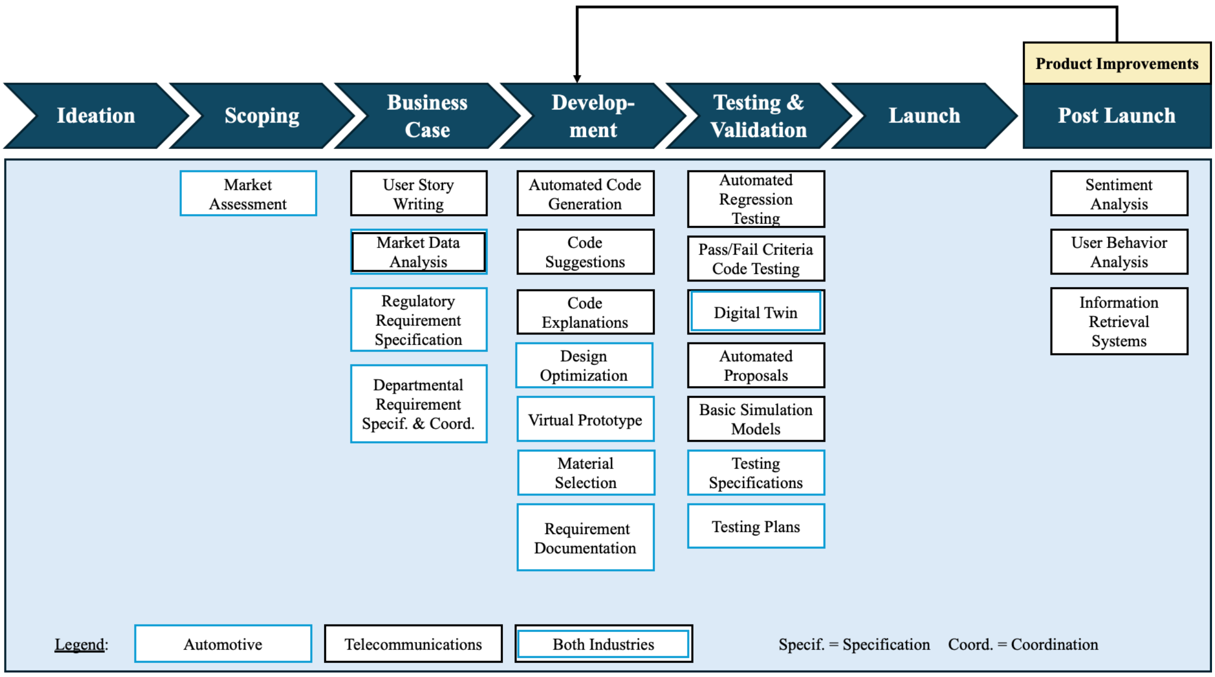


*Figure 9: Identified Use Cases Along the Stage-Gate Process Model based on Cooper (1988)*

## 10. Citations List of Automotive Industry

| ID | Nr | Quotation |
|---|---|---|
| I1 | 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. |
| I1 | 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. |
| I1 | 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. |
| I1 | 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. |
| I1 | 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. |
| I1 | 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. |
| I1 | 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. |
| I1 | 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 |

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| | | 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. |
| **I1** | **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. |
| **I1** | **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. |
| **I1** | **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. |
| **I1** | **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. |
| **I1** | **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. |
| **I1** | **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. |
| **I1** | **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. |
| **I1** | **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. |
| **I1** | **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. |
| **I1** | **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. |
| **I1** | **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. |
| **I1** | **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. |
| **I1** | **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. |
| **I1** | **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 |

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| | | 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 |

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| | | 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 |

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| | | 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. |
| **I3** | **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. |
| **I3** | **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. |
| **I3** | **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. |
| **I3** | **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. |
| **I3** | **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. |

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| **I3** | **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. |
| **I3** | **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. |
| **I3** | **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. |
| **I3** | **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. |
| **I3** | **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. |
| **I3** | **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. |
| **I3** | **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. |
| **I3** | **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. |
| **I3** | **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. |
| **I3** | **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 |

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| | | 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 |

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| | | phase and it will probably take some time before AI is intensively and comprehensively integrated into production processes. |
| **I4** | **12** | The complexity of an AI use case depends on whether it operates independently or within highly interconnected systems. |
| **I5** | **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. |
| **I5** | **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. |
| **I5** | **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. |
| **I5** | **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. |
| **I5** | **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. |
| **I5** | **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. |
| **I5** | **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. |
| **I5** | **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. |
| **I5** | **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. |
| **I5** | **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. |
| **I5** | **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 |

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| | | 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. |
| **I5** | **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. |
| **I5** | **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. |
| **I5** | **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. |
| **I5** | **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. |
| **I5** | **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. |
| **I5** | **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. |
| **I6** | **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. |
| **I6** | **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. |
| **I6** | **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. |
| **I6** | **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. |
| **I6** | **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 |

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| | | Experience Days, and so on, to constantly discuss where things are headed and what possibilities exist for us under this regulatory framework. |
| **I6** | **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. |
| **I7** | **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. |
| **I7** | **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. |
| **I7** | **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. |
| **I7** | **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. |
| **I7** | **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. |
| **I7** | **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. |
| **I7** | **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. |
| **I7** | **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. |
| **I7** | **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. |
| **I7** | **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. |
| **I7** | **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. |
| **I8** | **1** | In theory, everything works perfectly; in practice, bridging that gap is something different. |
| **I8** | **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. |
| **I8** | **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 |

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| | | 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*

## 11. Citations List of Telecommunications Industry

| ID | Nr | Quotation |
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| I9 | 1 | How the problem statements are written and how the user stories are written, and we use now AI specifically in this case Genitive AI to help our product managers write user stories in a way which is consolidated um omni-channel, which means that they when they write things that should be up it should be written in a way which can solve in multiple different channels uh and in a consistent way um and previously that would be a process that could take a long time to write a good user story could take and it' s like writing a book right |
| I9 | 2 | Software development process, um, we use off-the- shelf tools there, so you would have heard of things like GitHub Copilot, um, which are tools that come from Microsoft, which the developers use to help them write the code, again, super useful, and we see something, you know, between sort of 30 and 40 percent efficiency gains coming from software developers using those tools because now they' re writing maybe what 30 to 40 percent less code than they were before because the the models are able to help them with that. |
| I9 | 3 | Automatic regression testing; testing is super important in this industry because when you're putting products in front of millions of customer they have to work very well, and you have to test them in lots of different environments with different handsets, um, with different on different networks in different parts of the country and different conditions. And all of those things are super hard to do if you don' t have, automated testing for this. It repeatedly runs tests with machine learning algorithms. Artificial intelligence plays a role in creating those environments where you can test your code to make sure they work properly, because otherwise you have people doing it, um, and then that would be super hard to have a testing team of people manually doing all those tests |
| I9 | 4 | Obviously, the responses you get from customers the feedback you get from customers if you getting hundreds of thousands or tens of thousands of feedback, um, getting sentiment analysis at scale rather than having someone manually reading thousands of comments. Not only this but AI can then also be used for advancing our customer service for example through chatbots or any other kind of virtual assistant. |
| I9 | 5 | I mean ultimately AI is a proxy for human intelligence so it has applications wherever human intelligence is applicable which is basically everywhere within software product development so it' s it' s about sort of finding efficient ways of doing things at scale and not having humans having to do it manually so wherever you can wherever you can think you can broadly apply it |
| I9 | 6 | That' s more efficiency that will come, that' s more speed that will come and that' s certainly changing the way the software developers, even product managers, do and write their work, um, but fundamentally means a lot less people and a lot more code, so yeah, I think that we' re still very much at the start of what this, what this will be, and I think the way that we think about product development in the future will be fundamentally different from how we do today |
| I9 | 7 | I think the thing about ICT and the thing about telecommunications as we are quite customer-driven is um if I compare it to other industries like um sort of manufacturing or those sorts of areas um if we the thing about ours is we have intangible products but they' re software-based products um and software um and AI as a general rule relies on data um and good data and large amounts of data, so AI is the author of our home; bites are lost, robots are inaccessible, the current issue of AI is the nation' s greatest destiny in government history. That' s the training data that we use to change the models. The feedback data that streams that we use to run analytics for product development insights. And that' s all super available for us within a software-based industry. |
| I9 | 8 | In the manufacturing industry or the like, because I think their data is available, but it' s not as readily available. |
| I9 | 9 | I think the other thing that would be different in this industry is the production of what we do. Again, we have intangible products. Software is broadly intangible which is highly valuable for AI adoption due to increased data availability. And there' s automation that can happen. And there' s an efficiency that can come, but I think it' s probably to a lesser degree, I would think, than in a software-based industry where you can sort of automate a lot with computers. You will always need people topping tomatoes in a hamburger restaurant. The need for sort of human intervention and sort of, I guess, the blue-collar work here is going to be still much higher within that context. |
| I9 | 10 | There aren’t really specific factors that only apply to product development yet but rather overall organizational readiness factors. But I think we could always be more ready as a firm to adopt AI in business areas like product development. And I think the good thing about this part of the business is it' s a newer part of the business and we' re able to sort of be flexible and hire the right talent. And from our board level down, there' s a lot of interest in the work that we do here. |
| I9 | 11 | The big challenge there is getting the talent because, you know, people like you guys who are sort of in the tech, who understand the tech and want to sort of join a company, don' t always think about telecom in the first instance. They might think about you know people with this sort of talent moving into a more sort of product or well-known technology. So finding talent is always a bit more a challenge. |
| I9 | 12 | In my view, AI should not be a department, it should be embedded in everything. But whilst we' re still on this longer term journey and we' re not quite at the stage where everybody’s a digital native and an AI native, then we have this center of excellence of people who data science, engineering and product backgrounds who are who are able to sort of evangelize this work on behalf of the broader company and provide help and support to the people in finance or the people in legal teams who don' t know how to use this. And need some support. And so that' s one of the ways that we' re happening. We' re handling this. |

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| **I9** | **13** | My boss is super interested in the work that' s happening here. And we meet once a month on the progress that' s happening in the AI domain specifically. So, yeah, it' s important that you have sort of top- level stewardship of from the CEO down saying this is what I expect and this is what we need |
| **I9** | **14** | Specifically in telecommunications where we have lots of PII, personally identifiable information, this is something which and we' re heavily regulated as an industry. We' ve got to be super careful with how we use this data. And the thing about Europe, as you guys would know, is we' re usually very quick to regulate something before we think about growing something or understanding something. And unfortunately, sometimes we have a situation where the people. People writing the regulations don' t understand the technology. And what that causes is back to our earlier point, sometimes the fact that people who have an interest in the technology and want to build it don' t want to work in an environment where it' s super restricted to do it |
| **I9** | **15** | Regulations and lack of clarity on how to understand the regulations is something which is which is something we have to keep in mind. Happily, the regulations don' t come into effect until 2026 on the AI Act. So we still have some time to understand and formulate that. |
| **I9** | **16** | And its difficult to sort of make predictions too far into the future, other than to say that making the investments now in in in the application of it, rather than the development of it. I think that' s for others now for when it comes to our industry, but certainly the application of it now, finding ways of having the talent inside the company. |
| **I9** | **17** | Some problem statements are generic enough where you can get you can use a vendor for it. There' s other problem statements, which you can' t get a vendor to do because it' s just so specific to our industry. Or a company where you need to go and build it yourself. So we have to do both. |
| **I9** | **18** | They' re the foundational models are so generic in their world knowledge that they provide applications in so many different places. And they keep on getting better every month. So I think that when it comes. To sort of generically applying parts of this technology, large language models are a good example of they can work in customer service or finance or HR, they can work in multiple different industries as well. |
| **I9** | **19** | And I think there' s other parts of the business that I mentioned as well, which are not as sort of progressive or digitally native, which take more time to come to terms with the idea of using technology like this. There' s also I guess a fear in some parts of the company around maybe having their job reduced or removed because the technology replaces them. And these are all the things we have to sort of come, you know, deal with when we think about wanting to. Use the technology more. |
| **I10** | **1** | Fundamentally, AI is already being used extensively in product development, particularly when it comes to network expansion and similar tasks. However, saying that we're starting with a blank slate and using AI to develop an entirely new product—well, I haven't really seen that happen yet |
| **I10** | **2** | In network expansion projects, we use so-called digital twins, for example. These allow us to simulate various models, particularly in the network environment. This enables us to analyze how consumer behavior changes and how investments can be optimally allocated to achieve optimal network coverage. A simple example of using this technology is when we aim to increase network coverage for users by five percent. The model simulates, based on the digital twin, which measures would be required to achieve this. It shows us where new radio masts would need to be built to reach this goal. The system can simulate where mobile radio stations need to be deployed to ensure sufficient network coverage in the affected areas. The AI generates proposals, which are then directly forwarded to the technical teams so that mobile antennas can be set up in time. Through these simulations, we gain valuable insights that we use for strategic decisions in network expansion. Investments in this area are particularly significant, which further highlights the importance of this technology. |
| **I10** | **3** | In the area of customer service, we are increasingly investing in AI solutions, such as the advancement of chatbots and digital agents. Further, we continuously analyze user behavior and the feedback we receive. These insights are directly integrated into product development, enabling us to derive targeted improvement suggestions to continually optimize customer interaction and the experience with our products.This primarily involves analytical AI, which is used at the end of the funnel, during the market launch phase. At the same time, it continuously generates new feedback and data, serving as input to restart the development process. These insights also contribute to the development of the next generation of mobile networks. Currently, projects are focusing on 6G, using data collected from previous user behavior to simulate new models. These simulations help test and optimize the capabilities of the upcoming generation of mobile technology, ensuring it is as user-friendly as possible for end customers. |
| **I10** | **4** | Essentially, our goal is to offer our customers as many options as possible while ensuring the best possible network experience. Although we invest over two billion euros annually in Germany alone, these resources are limited. This means we must make compromises in terms of both financial means and available resources. To achieve the greatest benefit for our customers, we rely on our digital twin model. This allows us to efficiently simulate various scenarios. What used to take weeks can now be simulated and analyzed within a few hours. This enables us to quickly identify the best scenarios and the most significant differences (deltas) to optimally manage our investments and strategically improve network coverage. |
| **I10** | **5** | Another important aspect is sustainability. We are already using AI-driven systems to optimize the energy consumption of our network infrastructure. For example, we reduce the power output of our network infrastructure at night when network load is low due to minimal user activity. This saves up to 35–80% of energy costs. As activity picks up again in the morning, the system automatically scales the network capacities back up. Such dynamic adjustments would hardly be possible manually, as network load changes often occur quickly and locally. This is where AI comes into play, reacting to these fluctuations in real-time and efficiently adjusting network performance without requiring human intervention. These measures result |

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| | | in significant $CO_2$ and energy cost savings. The energy savings are in the range of megawatts, which makes a substantial difference for both the environment and our company's costs. |
| **I10** | **6** | The digital twin enables us to simulate and analyze all possible scenarios, but the actual decision-making logic remains largely a human process. Humans decide which scenarios are relevant and which investments should be prioritized, based on specific commitments and objectives. This means that in investment decisions, we have not yet reached the same level of autonomy as in energy optimization. |
| **I10** | **7** | For me, the business need always comes first in any AI application. Often, this gets pushed to the background because many people simply say, 'We need AI for the sake of AI.' But for me, the first question is always: What is the actual business need behind it? If I can't answer that, then there's no reason to use AI. It must be clear what the AI is supposed to do and what specific value it brings.<br>The next step is directly connected to this: Do I have the right data to even address this business need? A good data model is crucial because without the right data, AI can hardly deliver useful results. Only once I understand what I want to achieve and whether the data is available does it make sense to move on to selecting the AI. The current hype around generative AI in areas such as image recognition and language translation includes technologies that are now so advanced they can be consistently deployed. However, if you look at processes like product development or market analysis, it's already possible to run simulations with relatively little data and derive new trends and products from them. That is feasible, but in our board discussions so far, we haven't identified a real need to apply AI specifically in those areas. |
| **I10** | **8** | In our digital journey, we are already using AI in areas such as accessibility, data analysis, and optimizing our existing digital services. We are also continuously exploring how these applications can be meaningfully expanded. However, I currently do not see AI-driven product development creating entirely new concepts or products outside of our current core area. |
| **I10** | **9** | What I often observe, however, is that the technology itself is rarely the obstacle. Over the past few years, technology has advanced significantly and given a solid data foundation, now offers excellent possibilities. The bottleneck often lies more in the data or the organizational structure.<br>Many companies struggle to adapt their existing structures to the rapid pace of innovation. There is often a mismatch between the rapid technological developments and the slower processes of change within organizations. Only a few companies manaIge to keep up with this speed and successfully integrate the innovations. In most cases, the adaptation ultimately fails because the organization is not yet ready to fully embrace and implement the innovations. |
| **I10** | **10** | The lack of expertise in dealing with AI is undoubtedly an issue, but it is relatively straightforward to address. External consultants or experts can be brought in to provide the necessary knowledge and support the implementation process. However, what I observe more often is that the real challenge lies in the overwhelming number of innovations people are faced with, leading to a sense of overload. In such an environment, many tend to revert to what has worked well in the past—in other words, they adopt a wait-and-see approach. This hesitation, however, can be detrimental, particularly in the current dynamic phase. By not acting proactively, there is a risk of missing out on critical developmental steps. |
| **I10** | **11** | The ICT industry is heavily characterized by regular innovations, whether at the network or product level. This rapid pace of innovation is already embedded in the organizational structures and processes of the sector. In contrast, if I'm working in traditional manufacturing with a fixed machinery setup and clearly defined development cycles, transitioning to an innovative, digital world is naturally much more challenging. This is logical because, in the digital environment, innovation cycles are shorter, and new solutions can be brought to market more quickly, whereas production facilities often require lengthy development and approval processes before they can be operational.<br>This is particularly evident in the telecommunications market. The shift from 2G to 3G, then 4G, and now 5G has already adopted an accelerated rhythm, with 6G already on the horizon. The innovation cycles are becoming increasingly shorter, enabling developments that were previously unthinkable. With 5G, we now have a technology that combines high bandwidth with low latency, which is particularly beneficial for industrial control systems.<br>The entire industry is advancing, and we are currently in a sort of "perfect storm." Computing power has massively increased—an enormous advantage for AI—and, at the same time, vast amounts of data are available, which can also be optimally utilized by AI. This combination of data and computing power enables the creation of new innovations in a very short period. |
| **I10** | **12** | Data is generally available in sufficient quantities, but it is often organized in the same way as the structure of the organization itself. This means that each department—be it Sales, Marketing, Operations, IT, or Customer Service—works with its own 'language' and data structures. Sales speaks differently than Marketing, and Marketing speaks differently than Operations, and this pattern continues throughout the organization. This is precisely where the challenge for AI applications lies: AI operates horizontally and requires data that is comprehensible and compatible across departments. Even if the data is moved to the cloud, the issues persist as long as the data remains in its original structures and is not harmonized. For AI, structured and cleaned data is crucial because only then can it effectively work with various information sources. In large companies, this is often a challenge, as each department thinks and works in its own 'language.' This is evident even in meetings: even when departments talk to each other, there are often communication issues. The same applies to the data. A thorough cleanup and the establishment of a common structure are therefore necessary to make AI truly productive." |
| **I10** | **13** | Yes, IT infrastructure definitely plays a role. If the IT is outdated and scalable cloud solutions are not available, it becomes challenging to efficiently implement new technologies like AI. With traditional IT, I have to provision physical servers and storage resources, which is time-consuming and costly. In contrast, |

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| | | cloud infrastructures allow us for much more flexible and rapid scaling, which is often critical for modern technologies. However, IT infrastructure is just one factor. |
| **I10** | **14** | If I automate processes horizontally, then departments must also collaborate horizontally. This requires cross-functional teams in which various departments like Sales, Marketing, IT, and Customer Service work together on a common topic. In such cross-functional teams, you can see that it works because each area can directly contribute its input to achieve a shared goal. In contrast, traditional organizations often have structures that are still strongly siloed and not aligned with the customer journey. Departments often work in isolation and vertically rather than serving customer needs in a seamless line. This is where a fundamental prerequisite is missing: a structure that enables horizontal collaboration. When organizations begin to align more closely with the customer journey and dissolve these rigid boundaries, the path is also cleared for successful AI applications and automations. |
| **I10** | **15** | The restructuring is certainly a task for top management, but it's not just about changing structures. Equally important are language, communication, and effective change management. Often, top, middle, and lower management simply don't "speak the same language." The issue is less about a lack of willingness to communicate and more about the different levels having their own perspectives, which are not always clearly aligned. A good example was the rapid shift to remote work at the start of the COVID-19 pandemic. At that time, the objective was clear, and the urgency was evident, leading to all levels within the company pulling together — even in areas where remote work was previously considered impossible. It worked because there was no other option, and the goal was crystal clear to everyone. In other projects and changes, this clarity is often missing. Communication at the management level is frequently too "high-level" and leaves significant room for interpretation. While this room for interpretation can foster innovation, it also leads to teams understanding the direction differently and potentially pursuing conflicting goals. |
| **I10** | **16** | A central AI initiative that involves all levels of the organization and clearly defines the goal of AI implementation across the company, is an effective approach for us. The key to success lies in clearly articulating the business need. If the purpose and value are not evident to everyone, it requires further discussion and alignment. As long as there is no unified understanding across all levels, the success of the initiative remains uncertain. |
| **I10** | **17** | Absolutely. An open corporate culture is essential. It requires a mindset that focuses on opportunities rather than problems and the courage to try new things and learn from these experiments. Take, for example, the traditional machinery manufacturer that has relied on the same methods for decades—this approach will no longer suffice in the future. Only by embracing new strategies and committing to continuous learning can companies adapt to evolving developments. This experimentation and adjustment of plans must be actively encouraged. Leadership plays a critical role in driving this transformation and ensuring the organization remains future-ready. Leaders must foster an environment where innovation is not only welcomed but actively pursued, creating a foundation for sustainable progress and growth. |
| **I10** | **18** | It's fundamentally about expanding our capabilities and embedding this expansion deeply into the company culture. This isn't achieved through a few presentations alone—it requires active experimentation and integration into daily work routines. Employees need to truly experience the new possibilities and understand the value they bring, not only in solving problems but also in driving growth and progress. |
| **I10** | **19** | I believe that projects can absolutely be implemented under GDPR, provided the right experts are involved early on and care is taken to avoid mistakes from the outset that could later be difficult to correct. Of course, Europe has a certain level of overregulation, and less of it would certainly be helpful. However, this regulation is important because it also signifies responsibility, especially with new technologies. Companies must ensure that they neither jeopardize their customers' data nor violate confidential information or ethical standards. For example, if an AI tool suddenly makes problematic statements or behaves unethically, that is clearly not in the company's interest. Mechanisms are therefore necessary to control and mitigate such risks. However, this does not necessarily require a new "AI Act" — the responsibility already lies with the companies themselves. Everyone knows the values and boundaries they want to set within their organization, and these can also be applied to new technologies. |
| **I10** | **20** | Germany struggles to set clear priorities in its digital agenda. Instead of defining the five central topics that should be consistently advanced, much remains vague and broadly dispersed. Of course, projects like a nationwide railway network are sensible, but that alone does not constitute a strategic digital agenda. A clear focus would help provide direction and ensure that we are not just working on many different fronts but achieving real progress in critical areas. Germany undoubtedly has the skills and resources to compete internationally. However, the key difference lies in strategic focus and the courage to implement bold initiatives. For example, China has set clear digital goals—they aim to be the global leader in AI by 2030 and are pursuing this vision relentlessly. Similarly, in the United States, big tech companies like Meta, Google, and Amazon have been making strategic AI investments for years, creating platforms that provide them with a significant competitive advantage. To position Germany competitively on the global stage in the fields of AI and ICT, several critical factors must be considered. While Germany possesses many strengths, it also faces certain limitations compared to leading nations. |
| **I10** | **21** | One key aspect is focusing rather than scattering efforts. It is essential not to spread resources too thin but to concentrate on specific key technologies and application areas. A differentiated strategy that targets a few but strategically relevant topics can be far more effective. Moreover, Germany has the opportunity to leverage its strong data protection standards as an advantage. Its strict regulations can be seen as a competitive edge, offering consumers a high level of protection. This trust can be utilized to develop innovative solutions that place data protection at the forefront. Another essential aspect is the use of interdisciplinary approaches. Germany excels in fields such as medicine, mathematics, informatics and |

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| | | chemistry. By fostering interdisciplinary collaboration and integrating new AI-powered technologies such as 6G and quantum computing, innovative solutions can be developed that provide a competitive advantage. Finally, the development of a clear digital agenda is crucial. A well-defined digital agenda with five to six clearly identified priorities creates a unified direction for businesses, research institutions, and policymakers. Such an agenda could focus on key technologies and thereby accelerate progress. |
| **I11** | **1** | The software teams are encouraged to acquire the necessary know-how through targeted training, particularly in the area of prompt engineering, to use Tab9 effectively and efficiently. The goal of these measures is to enhance development efficiency, enabling developers to spend less time on code generation while simultaneously improving code quality. A similar approach could potentially be applied to test automation, although this area of application is currently less common. For now, our primary focus remains on these areas of implementation. |
| **I11** | **2** | Currently, AI is not directly used in the early stages of our development process. However, AI is increasingly being tested and promoted in the development process, particularly in software development, for tasks such as code generation and improving code quality through the use of generative AI. We are currently evaluating the product Tab9, though I am not familiar with its manufacturer. We are in the rollout phase, with a number of licenses already available. Software teams are encouraged to acquire the necessary expertise, particularly in prompt engineering, through targeted training to use Tab9 effectively and efficiently.<br>The goal of these initiatives is to increase development efficiency so that developers spend less time on code generation while simultaneously improving code quality. A similar approach could potentially be applied to test automation, although this application area is currently less widespread. For now, we are primarily focusing on these areas of application. |
| **I11** | **3** | After the product launch, there is an existing system that was not originally designed for generative AI—a so-called "information retrieval" system. This system processes unstructured data such as customer documents, service bulletins, or release notes to enable "intelligent" searches which can improve data quality and make the process much easier. The team can use it to retrieve specific information when issues arise in the field. There are currently considerations to further enhance this system using generative AI. However, I am not familiar with the current status of this development. |
| **I11** | **4** | There are also ideas about how generative AI could be used for further optimization. Specifically, there is consideration of whether the process for operators could be simplified through the use of generative AI, making it easier to retrieve and summarize information. Tools like Grafana already exist to structure and clearly present large data sets. A potential future step could involve conducting such queries using natural language, which would significantly improve user-friendliness and efficiency—although this remains a vision for the future at this point |
| **I11** | **5** | In this context, there are also considerations to integrate artificial intelligence into our products. Two main areas where AI could play a role are predictive maintenance and anomaly detection in network operations. Predictive maintenance is particularly relevant for customers with large networks, where it is challenging to manually identify potential issues within the flood of data. Technologies such as big data mining, machine learning, and neural networks could help efficiently detect anomalies without requiring manual rule or algorithm development. However, these approaches are still in the evaluation phase and are not yet available in a market-ready product. |
| **I11** | **6** | Failover capability requires capacity reserves to reroute traffic in the event of connection disruptions. For example, if it is possible to detect early that a component is nearing the end of its lifespan or experiencing gradual degradation, the replacement of that component could be planned during a maintenance window when traffic is lighter. Such proactive measures prevent potential failures |
| **I11** | **7** | The current state of development is characterized by the execution of proof-of-concept projects to determine whether the expectations can be met. At this stage, efforts are focused on evaluating practical feasibility and actual benefits before a broader market rollout can take place which can be difficult when also considering actual real-life implications that can be much different |
| **I11** | **8** | To ensure that critical situations are detected without generating too many false alarms, a well-thought-out approach is required. Traditional data analysis methods can identify anomalies, but not every anomaly represents a truly critical issue requiring immediate action. In many cases, significant human interaction is still needed to evaluate anomalies and draw the correct conclusions. This process could be improved through the use of neural networks or other machine learning systems trained on historical data. However, there are challenges, particularly in accessing relevant data. Operators are often unwilling to share their data due to concerns that competitors might infer insights about their operating costs or other sensitive information. These privacy concerns make it difficult to obtain suitable data for system training and limit the improvement of models to the data operators are willing to provide. Additionally, the diversity of network elements from providers like Infinera presents another obstacle. A universal solution that works across an operator's entire network would be ideal but is challenging to implement. While specific solutions for certain products could be helpful and serve as a selling point for manufacturers, operators tend to focus on cross-network solutions. This creates a discrepancy between expectations and the current reality. A step-by-step implementation approach, gradually reducing complexity and tailoring the solution to the operators' needs, could be an effective way to address this tension. |
| **I11** | **9** | The availability and handling of data indeed pose significant challenges, but less due to a lack of data and more because of concerns about privacy and security. Operators are often hesitant to share sensitive data—particularly about issues in their networks—because it could potentially provide valuable insights to competitors. These concerns also impact the use of AI, as data protection plays a central role. |

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| | | An example from our own environment illustrates this: products designed to enhance efficiency in code development can only be utilized if it is ensured that the input data does not leak externally. For instance, it would be unthinkable to use a public generative AI model like ChatGPT if there were a risk that competitors might learn about the projects Infinera is currently working on. That would, of course, be unacceptable. Therefore, it is essential that AI products are designed to protect internal data and be used exclusively for company-specific purposes. Microsoft's Co-Pilot and Tab9, for example, offer solutions that align with this direction. At the same time, we have a Data Security Policy in place that prohibits the use of publicly available AI models for development purposes to safeguard sensitive company information. This demonstrates that the real bottleneck is not in the availability of data but in how data can be securely and compliantly used. |
| **I11** | **10** | Public models are essentially not an option in this regard because they must ensure that the input data is not used for training purposes. This is a critical point, as companies like ours need to protect sensitive information. For example, Microsoft offers a model called Co-Pilot, which is trained on publicly available data, but they guarantee that the data generated through user queries will not be used to further train the model. This assurance is of great importance to us because it ensures that no confidential information is leaked or ends up in a public model. |
| **I11** | **11** | In product development, data protection currently does not play a particularly significant role for us, as we primarily work with technical data that is not subject to strict data protection regulations like the GDPR. However, data protection could play a more significant role, especially in customer service. Here, it is important to ensure that customer data is handled carefully in accordance with legal requirements. A potential issue could arise if customer data is used to train AI models. In such cases, one loses some degree of control over the data, which could lead to problems, especially if this data later flows into public models or tools like generative AI. There is also concern that the use of public AI models, such as those provided by Microsoft Co-Pilot, could make our customers' sensitive data accessible to competitors, potentially leading to legal issues. Therefore, we must be very cautious about which data we feed into external models. Regarding the sharing of data with external providers, especially companies like Microsoft, which may be based outside the EU, we must exercise similar caution. Infinera has its headquarters in the U.S. and development locations in India, which means we often deal with international data flows. In the U.S., data protection regulations are not as stringent as in the EU, which could be problematic, particularly when it comes to internal data sharing. However, in development, where we primarily work with technical data, we are less affected by regulatory requirements since this data is generally not considered personal.<br>The primary concern in development lies in protecting intellectual property and preventing data leaks that could give competitors an advantage. This is less about legal regulations and more about competitive protection and safeguarding corporate secrets. |
| **I11** | **12** | This mirrors some lessons learned from open-source development. Modern development often involves selecting and integrating open-source packages. However, if the quality of the open-source code is poor or something does not work as expected, developers may end up spending significant time debugging code they did not write, which also diminishes the efficiency benefits. |
| **I11** | **13** | The implementation of AI in our case does not fail due to financial resources. Even though some licensing costs can be high, If the use of AI results in measurable efficiency gains, this investment is definitely worthwhile. As for other resources, most AI applications run in the cloud anyway, so the only essential requirement is a stable network connection, which is generally always available. Therefore, I don’t see any significant resource constraints in this regard. |
| **I11** | **14** | The use of artificial intelligence is perceived both as an opportunity and a necessity. In software development, AI is primarily driven by the desire for efficiency gains. Efficiency gains mean offering more features to customers at the same cost, which in turn provides a competitive advantage. Those who fail to leverage these advantages will face significant challenges in the long run. From a competitive perspective, foregoing these efficiency gains is simply not an option. The real question is how much efficiency can be achieved and how much investment is required to train employees. Currently, the technology is still in the hype phase, with numerous reports confirming the trend. For example, it was recently revealed that Google now relies on AI to generate a quarter of all newly produced code. Such figures are impressive and reinforce our own determination not to fall behind. |
| **I11** | **15** | Yes, the use of artificial intelligence is definitely perceived as a means to remain competitive, and this is largely a top-down driven decision. It is not just a matter of understanding or persuasion within the development teams but a holistic process that is heavily supported by management. Management makes the decision to allocate resources and licenses for AI systems, something that would not be possible without their approval. I. As a result, only about five to ten percent of employees are genuinely motivated to deeply adapt and experiment with new technologies like AI. |
| **I11** | **16** | When top management takes the initiative to implement AI across various departments, several measures can be taken to ensure and promote its success. First and foremost, it is essential to provide the right tools and resources so that employees can work effectively with AI. However, this alone is not enough—management must also play an active role in communicating the benefits and successes of AI. An effective approach is to highlight success stories and share them across the team to boost motivation and make the value of AI more tangible. Additionally, setting concrete goals can help drive AI integration. For instance, a certain percentage of employees could be required to complete AI training, or skill-enhancing initiatives could be introduced, such as training sessions on topics like prompt engineering or the efficient use of AI in code creation. Furthermore, specific targets could be established, such as ensuring that a certain proportion of code is developed using AI-assisted methods or encouraging teams to actively experiment with and |

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| | | integrate AI into their workflows. Another important measure is raising awareness among leadership and ensuring that all employees have access to AI tools and are encouraged to use them in their projects. This approach ensures that AI is not just seen as a technological possibility but also as a strategic goal actively promoted within the organization. |
| **I11** | **17** | Typically, product testing is structured so that pass-fail criteria are defined for each individual test case, which are then evaluated. However, it is possible that hints of issues exist within the data that are not captured by traditional pass-fail criteria. In such cases, machine learning could potentially help identify these anomalies. |
| **I11** | **18** | In the telecommunications industry, especially among traditional telecommunications customers, it is often challenging to make existing IT systems compatible with modern AI and data-mining applications. These systems were originally not designed with a focus on processing large volumes of data or integrating technologies like machine learning or data mining. Instead, they are tailored for regulated and conservative data handling, making it difficult to adapt them for these new applications. While it is often possible to find ways to extract data and use it for analysis, the underlying infrastructure is not optimally designed for this purpose. In contrast, Internet Content Providers such as Google and Amazon, which operate their own data networks and exchange large volumes of data between their data centers, have more experience in the automated collection and evaluation of data. These companies have a deeper understanding and better infrastructure for efficiently processing large datasets, including aspects like processor utilization, storage health, and other technical parameters. Their advanced expertise in data utilization serves as an incentive for companies like Infinera to design their products to be more compatible with the sophisticated systems used by these major internet companies. |
| **I11** | **19** | The concept of streaming telemetry plays a central role here. In the traditional telecommunications industry, data was often collected locally and then retrieved as needed, typically in the form of files. This approach makes efficient centralized analysis challenging, as data must first be manually gathered and prepared, delaying and complicating the analytical process. In contrast, streaming telemetry continuously transmits a data stream directly from devices to a central collection point. This allows for near-instantaneous and ongoing real-time data analysis. This method is significantly more compatible with modern automated data analysis tools, which rely on machine learning, data mining, and visualization. For telecommunications companies, this means they must adapt their systems to support continuous data transmission and processing to fully leverage the benefits of modern data analysis and automation. Customers, particularly large enterprises, increasingly demand real-time data transmission and analysis capabilities as they enable more precise and faster fault detection, optimization, and maintenance. Partnerships and collaborations with major data system or cloud infrastructure providers ensure that products and systems remain interoperable. Thus, it's not just about technological adjustments but also about providing customers with the tools and interfaces they need to efficiently utilize this type of data processing and analysis. |
| **I11** | **20** | The use of AI-generated code offers potential efficiency gains, particularly in terms of development speed. However, it also presents risks, especially concerning the quality and maintainability of the code. When code is automatically generated without developers fully understanding it, this can lead to issues, particularly in cases of errors or unexpected behavior. The lack of transparency and interpretability in AI-generated code, often referred to as the "black box" problem, complicates debugging since developers cannot determine why the code behaves in a certain way or why it fails. When such challenges arise, they can partially negate the efficiency advantages. The key question is how these factors will evolve over time with the use of AI-generated code. Will prolonged use lead to a decline in overall code maintainability? This remains uncertain and will need to be assessed through practical experience. |
| **I11** | **21** | The hope is that generative AI will increasingly be able to automate more complex processes, extending beyond mechanical or repetitive routine tasks to areas where creativity is required. If successful, this could have profound implications for the entire software and tech industry, as well as other sectors that rely on knowledge workers. On the positive side, significant efficiency gains are anticipated. However, on the negative side, there are concerns that the value of human labor may be increasingly called into question as AI takes on tasks traditionally performed by humans. |
| **I11** | **22** | Some colleagues experimented with this approach, but it did not gain significant traction and ultimately fizzled out. This means that while these ideas were considered, they were not pursued further. The reasons for this included the high effort involved and the lack of a clear added value. The machine learning methods employed did not lead to a significant improvement in the quality or quantity of detected issues. As a result, the approach did not gain the necessary support, and the initiatives were not expanded. A similar situation applies to concepts like predictive maintenance: not every project achieves the desired success, leading to a certain hesitation in further pursuing such approaches. |
| **I12** | **1** | We work on proofs of concepts in various aspects of our existing and new products, for e.g. 6G or APIs. In innovation practices AI is inevitable! In production still too seldomly used, and when, then for internal efficiency improvements, automation and similar. Currently mostly used as analytical AI in the validation phase. We use AI for verification of SW on different platforms. It is a "Must do" thing – we will need to adapt the usage of AI, and its role is very important to the SW companies, else everything is either too complex, or too slow. |
| **I12** | **2** | Simplification for broader usage and widespread scalability is still needed! |
| **I12** | **3** | The security aspects and the adherence to the many rules with regards to privacy are definitely slowing down the adoption, but maybe with a good reason. |

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| **I12** | **4** | Availability of correct data and its sharing plays huge role. The more high-quality data sets we have for training, the better models we can build/use. This is still in pre-mature phase in the telecom industry, except for commercials… |
| **I12** | **5** | We do need to continue delivering the commitments we have towards our customers, so we cannot work on AI with full force, but I do not regard the financials as a hinderer here. |
| **I12** | **6** | Security concerns might slow down the AI adoption, but I am not 100% sure. |
| **I12** | **7** | In large organizations often there are parallel similar projects ongoing, which is sub-optimal. Although we have steered process for selection of tools and environments to be used, the start of new AP projects and roofs of concepts is not coordinated and can be doubled. Good overall AI readiness and awareness is crucial. management and incorporation of ambitions for AI are instrumental to the adoption of the new technologies in the large companies. |
| **I12** | **8** | The engineers in our product department are in large extend very keen on adapting to new technology which facilitates the adoption of AI at our firm |
| **I13** | **1** | When you say, pure master data, like an address somewhere, that's master data. It's not that critical. Yes, you can anonymize it. Then it's checked to ensure it's properly anonymized, and you can work with it. The question is just how useful anonymized data always is. I see this with colleagues who run campaigns, and they say, what are we supposed to do with anonymized data? In the end, we have to address the customers. So, ultimately, we need to know, can we send person x a letter, or are we not allowed to send her one? In that case, the anonymized data doesn't really help. |
| **I13** | **2** | These are all complete systems that we purchase—no idea exactly what, you'd have to look it up online—Ericsson, Nokia, something like that. We buy the entire system and, of course, use it. It does provide value for us as a company, but we didn't develop it ourselves. |
| **I13** | **3** | What has been on my mind over the past weeks and months is that we say, yes, we buy or have licenses for cloud providers like Google something, AWS, and so on. Now we've reached a point where we're a telco. That means, first, we're critical infrastructure, which is something you ideally don't want because it comes with massive regulatory requirements. And many of our... I don't want to say it's not a problem, but it's something we've had under control for decades now. |
| **I13** | **4** | Let me put it this way. I'll say it in two parts. General machine learning is used up to that point, there's no question about it. That's, up to there, you don't really need to talk about it. That's, well, that's our daily bread, that's what keeps me busy all the time. Gen-AI, is the maturity there? I think the problem with Gen-AI for us is that you have to look very hard for the machine, the use case, because what is Gen-AI good at? |
| **I13** | **5** | Then it goes to the developer. Ideally, at this point, you align with them about what exactly you envision, what they plan to implement, and what problems they foresee. There's not much you can do at that stage. When they start working, though, they should have code support, like the typical Copilot tools. We're just starting to implement those now. We have the POCs (proofs of concept) for this, and people want them. Introducing such tools isn't entirely straightforward—it brings up topics like security, data protection, and so on. As for the developers' experiences in our product departments so far, they've been mixed. Most find it really cool; others don't want to use it. Still, others are uncertain about it. But it can definitely bring benefits. It's not the 30% efficiency gain that's often promised or showcased in glossy presentations, but it can help. Especially—and I think this is something companies don't yet fully realize—it can accelerate onboarding for people who aren't yet very skilled in programming. It helps with explaining and generating code. |
| **I13** | **6** | Another relevant use case in telecommunications is definitely creating simulations for testing purposes. Digital Twin as a technology is especially important as it helps to show how a product acts in a real environment. Such simulations are also used for performance testing of new networks and use it to plan capacities based on simulation. Those can even help to make predictions with real time data to deliver analytical insights for our development decisions. we can then use the collected data from different sources to further improve and optimize our products and services based on customer preferences |
| **I13** | **7** | Our culture actively promotes innovation with a "forward perspective" to the future. The question is always, what can we do now to secure a better position later? We need to constantly stay ahead to align our strategy accordingly and build a culture that enables us to learn and adapt to new technologies. Sometimes this is not easy but I'd say that there we generally successfully implement it in our daily work routines, at least from what I experience in our company and department. |
| **I13** | **8** | Often external solutions are used to extend our IT infrastructure since this is easier than maintaining it ourselves, cloud services for example |
| **I14** | **1** | The second approach aims to leverage AI to accelerate development processes. An accelerated development process has a direct impact on what is known as time to market – the period from the start of development to the launch of a product. The importance of time to market for business success can hardly be overstated. Analysis shows that an earlier market entry – even just 10% faster – has a significantly greater impact on profitability than changes in price or costs. This makes rapid market introduction a critical success factor. |
| **I14** | **2** | In the current trend, the use of AI is therefore primarily being explored to reduce time to market. AI can accelerate the development process in many areas, whether through automated testing, optimization of designs, or more efficient production planning. In total, the combination of partnerships and targeted AI application offers tremendous opportunities to achieve the required pace of innovation despite existing technical challenges. |
| **I14** | **3** | The business case for investing in AI in product development aims to accelerate product development and reduce time-to-market. Although AI is still in its early stages, it is expected to enhance efficiency and offer significant benefits in the long term. The use of AI could facilitate faster design decisions while |

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| | | simultaneously reducing manufacturing costs and power consumption of chips. Every reduction in development time has the potential to increase competitiveness by bringing products to market faster |
| **I14** | **4** | Since we operate in highly specialized developments, many processes must be developed internally. It is not possible to rely on external libraries or tools. This means the team must possess the necessary expertise and resources to develop and adapt AI models independently. |
| **I14** | **5** | A deep understanding of the existing design process is essential. The company must clearly identify where AI can add value, whether in optimizing design decisions, simulation, or validation of results. |
| **I14** | **6** | Creating an appropriate platform is a fundamental prerequisite. It must be decided whether to use a terminal or cloud-based solution, and it is crucial to establish the right environment where AI models can be trained and tested. At the same time, this platform must be integrated with existing systems as seamlessly as possible and be compatible with the available data. |
| **I14** | **7** | Developing a proprietary LLM is a complex and resource-intensive process. This requires not only financial resources but also skilled professionals with experience in training and validating such models. |
| **I14** | **8** | A key consideration is that the use of AI can come with significant costs, especially when closed licenses are involved. |
| **I14** | **9** | Protecting intellectual property is critical when developing new AI-driven processes and technologies. The company must devise strategies to safeguard its IP while simultaneously leveraging the benefits of AI. |
| **I14** | **10** | I don't see organizational culture as the main focus when it comes to implementing AI solutions. We view AI primarily as a means to an end. Companies face specific problems that need to be solved, and AI is just one of the options to address these challenges. It’s important to understand that not every approach involving AI is necessarily sensible or cost-effective. |
| **I14** | **11** | Using public platforms, such as those offered by Microsoft, could be risky because all information processed there might potentially be accessible publicly. This carries the risk of sensitive technical details falling into the hands of competitors. Therefore, it is crucial to create a closed environment to protect intellectual property (IP). The costs associated with AI optimizations should not be underestimated, particularly when factoring in energy consumption and various licensing models. As with any tool, the focus should be on selecting the tool best suited to solving the current problem. This requires a certain level of curiosity and willingness to continuously engage with new developments. Even if a technology is not yet mature today, it could become useful in the near future. |
| **I14** | **12** | Overall, continuous collaboration and monitoring across various areas are necessary to evaluate and strategically utilize the potential of AI. The central guiding principle remains: if AI can provide a better solution to a problem than alternative approaches, it should be considered. |
| **I14** | **13** | At the same time, it’s crucial for us as a company to build long-term expertise in AI because we cannot ignore this topic. Everyone else in the market is leveraging AI, and the better we can master this technology, the greater our chances of staying competitive. |
| **I14** | **14** | Nevertheless, I approach the matter rationally. It’s not about creating unnecessary hype around AI; instead, I ask the question: “Do I have a specific problem that AI can solve?” In some areas, the answer is yes; in others, it’s no. I’ve learned from the blockchain hype, where many believed blockchain had to be used everywhere, even when it didn’t make sense. That taught us the importance of staying level-headed. I want to ensure we apply AI where it genuinely helps us and not just because it’s currently a trend |
| **I14** | **15** | The implementation of AI in our company indeed depends heavily on external factors, particularly government funding and regulations. In Germany, there is a tendency for companies to be hindered by extensive regulations, whereas in the U.S., a more straightforward approach is often taken. |
| **I14** | **16** | By the time government funding reaches the companies, a lot of time has usually passed. The funding only really got underway after the pandemic, which was too late to remain relevant in the fast-paced tech industry. |
| **I14** | **17** | For some problems we can use external tools as our needs at some cases are quite generic and can easily be addressed externally. However, high Specialization–creates challenges in finding suitable technology providers and therefore requires a thoughtful balance. |
| **I14** | **18** | Many companies have not yet recognized the potential inherent in this new reality. |
| **I14** | **19** | Integrating AI requires extensive technical expertise to first of all choose the right algorithm for each use case which can be highly complex. Then its also necessary to monitor and maintain the code. When this is not given, it can easily lead to underwhelming performance outcomes of these applications as well as bad accuracy and wasted resource |
| **I15** | **1b** | First, the data needs to exist—it has to be available somewhere and properly stored. Some organizations simply don’t store their data, which is not ideal. Without stored data, you can’t do anything data-driven. The data also needs to be accessible, meaning you need people who can provide it and integrate it into other systems. Even if it’s just loading the data into a Python script, there has to be a way to connect to it. And, as you’ve probably heard in the context of AI, when training a model, the model is only as good as the quality of the data. For example, if I want to train a model to perform a certain task, and my input data is just a table, the quality of that table directly impacts the model’s performance. |
| **I15** | **2b** | One could imagine that. Another crucial area where AI is widely used is automation. In the context of product development, there is typically a process involved. For example, during product development, I imagine there is a development process where a product is created—whatever that may look like—and then it undergoes testing. |
| **I15** | **3b** | What many clients are already asking for is to have their own version of ChatGPT available. The reasoning behind this is straightforward. If you use the standard version and ask it general questions, that’s fine. But if you ask questions like, “Hey, you know…”—there are two main concerns. First, the model doesn’t know what’s happening internally within the company. Second, I wouldn’t want to reveal company secrets in my |

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| | | queries and send them externally, as they're sent to an endpoint, and who knows what happens to them? That's something you shouldn't do, and nobody wants that. This means you need to host it yourself, which isn't a problem—it's entirely doable. Additionally, you can now equip the model with tools. For instance, you can provide it with a knowledge database based on company documents, which is relatively straightforward. Or you can integrate it with analytical databases, for example, by providing an interface that allows the model to execute SQL queries on a master data database. |
| **I15** | **4b** | On the one hand, we often hear lately that machine learning is expensive, especially in terms of resources like electricity and hardware—after all, it has to run on something. And yes, that's true. But on the other hand, consider a scenario where I can achieve a goal using a model with just two queries, compared to the traditional approach where an employee might spend half a day working, conducting research, and thinking of solutions, which could be error-prone because the process isn't always consistent. While that might consume less electricity, it requires significantly more work hours, which isn't ideal from a sustainability perspective either. Generally, wherever I can automate tasks, I naturally create efficiency. It's clear that automation leads to more efficient processes, which in turn makes things more sustainable. I believe you mentioned another point, but I've forgotten it now. However, considerations like quality and financial costs are closely tied to automation. For example, predictive maintenance is a great case where both costs and efficiency align with automation |
| **I15** | **5b** | I could imagine that while top management is aware of the topic, there are other priorities that might take precedence. Honestly, AI isn't the most critical thing in the world, especially if existing processes are already working well. At the end of the day, the goal for everyone is for the business to run effectively and generate revenue, and ML or AI is simply a tool to assist with that. If it improves things, great—it's a fantastic addition. However, I'm not sure to what extent they are aware of just how many areas AI, ML, or even something as simple as an optimization algorithm—which is now often categorized under ML—can create efficiencies. These efficiencies, in turn, make processes cheaper, reduce expenses, and ultimately increase profits. |
| **I15** | **6b** | Simply put, it's about identifying how many areas can be supported and addressing a common challenge in such ML projects. One of the difficulties, which often leads to it being overlooked entirely, is defining KPIs before the project begins and then evaluating them afterward. This means the return on investment needs to be something tangible. Ideally, by the end of the project, you'd have a clear figure, such as, "Hey, machine efficiency increased by 30%, making it this much better," which can also be presented effectively. That's great, but determining such metrics is often not easy in AI projects. |
| **I16** | **1b** | A particular challenge lies in handling sensitive information, as data cannot be processed or exchanged freely, especially when legal or security-related aspects come into play. With large data sets, such as 10,000 database entries, the question arises of how to efficiently extract the right and relevant information. |
| **I16** | **2b** | The decision on how to use AI within a company largely depends on whether existing technologies are leveraged or custom solutions are developed. Often, this involves weighing the options between tailored in-house developments and ready-made platform solutions. While in-house developments offer flexibility, they are complex and require extensive expertise in areas such as data integration, data monitoring, and model management. This complexity increases when handling large amounts of data while trying to maintain a clear overview. There are numerous options for every step of the entire process—deciding whether to build in-house solutions, rely on existing ones, or opt for providers offering comprehensive solutions. For instance, some providers position themselves by offering machine learning platforms that claim to handle 80% of the workload right out of the box, and so on. The main challenge lies in carefully considering these options and determining the best approach. |
| **I16** | **3b** | In many cases, existing IT systems and infrastructure are not immediately compatible with modern AI applications, as traditional systems are often not designed for such purposes. Consequently, the infrastructure often needs to be transformed to enable the integration of AI technologies. |
| **I16** | **4b** | As long as internal data or synthetic datasets are used for training and testing, the privacy risk remains low. Once personal or sensitive data is processed, careful attention to many rules is required for data protection—both legally and ethically. To some extend this risk can be mitigated through the anonymization of data. |
| **I16** | **5b** | It is entirely conceivable that technology will advance in the future to the point where many of today's compatibility and integration challenges will become less significant or even completely obsolete. Currently, there is a wide range of providers working to create solutions that simplify these processes, with differing business models. On one hand, there are open-source projects that are freely available, essentially saying, "Here you go, have fun using it." On the other hand, there are commercial providers who further develop these technologies and optimize them for enterprise use—On one side, there are standardized use cases where pre-existing, publicly available software can be used. These are often straightforward, requiring little customization or consultation, and can be implemented independently. The real challenge and added value, however, often lie in industry-specific or company-specific use cases, which are more complex and rarely offer universal solutions. This is where our consulting and tailored support come into play. In these cases, the focus is on developing solutions that are specifically adapted to the unique needs of a company or industry. This becomes particularly critical in more intricate scenarios—such as integrating complex systems, addressing unique processes, or meeting specific data requirements. |

*Figure 11: Citation Lists of Quotes for Telecommunications Industry*