UNIVERSIDADE CATÓLICA PORTUGUESA

Exploring AI Adoption in the European Automotive Industry

Drivers and Barriers

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Católica Porto Business School
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Abstract

The European automotive industry faces increased competitive pressure and the use of artificial intelligence emerges as a crucial factor to drive improvements and maintain competitiveness. This study explores how AI is being adopted within the automotive industry using the Technology-Organisation-Environment-Framework. Based on eleven interviews with managers, data scientists and AI experts, the study identifies key drivers and barriers in the adoption process. Findings indicate that AI adoption is frequently initiated with a bottom-up approach, in which functional departments identify potential applications that are then developed together with central AI or Data Analytics teams. Organisational barriers, including limited resources, lengthy approval processes, and data compliance challenges, emerged as particularly significant, while technical barriers stemmed from complex infrastructure, legacy systems, and data quality and accessibility issues. External barriers were mainly due to regulatory and policy constraints. Despite these challenges, strategic sponsorship, strong top management support, AI's business value, effective data management, and robust, updated IT infrastructure were identified as essential to enable AI adoption. Additionally, addressing barriers through organisation-wide, top-down initiatives appeared to be of importance. This study contributes to current literature by deepening the understanding of the adoption process, presenting influencing factors and revealing the interplay of organisational, technical and environmental aspects.

Keywords: artificial intelligence, AI adoption, automotive industry, TOE framework, exploratory research

Total number of words: 9998

Resumo

A indústria automóvel europeia enfrenta uma crescente pressão concorrencial, tornando essencial a adoção da inteligência artificial (IA) para manter a sua competitividade no mercado. Este estudo analisa a forma como a IA está a ser implementada no sector, considerando fatores tecnológicos, organizacionais e ambientais. A investigação baseou-se em 11 entrevistas a gestores e especialistas em dados e IA, permitindo identificar os principais fatores e obstáculos à adoção.

A introdução da IA ocorre frequentemente por iniciativa dos departamentos operacionais, sendo depois desenvolvida em colaboração com equipas especializadas. Os maiores desafios são de natureza organizacional, como a escassez de pessoal qualificado, a morosidade nos processos de decisão e as dificuldades na gestão de dados. Também foram identificadas barreiras técnicas, relacionados com infraestruturas complexas, limitações dos sistemas existentes e problemas de qualidade e acessibilidade dos dados. Adicionalmente, fatores externos, como regulamentos e políticas públicas, constituem barreiras relevantes. Apesar destes desafios, o sucesso na adoção da IA depende do investimento estratégico, do forte envolvimento da gestão, da clareza quanto ao valor comercial das aplicações, de uma gestão de dados eficaz e de uma infraestrutura tecnológica robusta. Iniciativas organizacionais de abordagem descendente (top-down) mostraram ser fundamentais para ultrapassar barreiras.

Este estudo aprofunda o conhecimento sobre a adoção da IA no sector automóvel, destacando interações entre fatores técnicos, organizacionais e ambientais.

Keywords: Inteligência artificial, adoção de IA, indústria automóvel, Quadro TOE, pesquisa exploratória

Total de palavras: 9998

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1. Introduction

Artificial Intelligence (AI) has emerged as a crucial factor in global economic growth with the potential of 7% gains over the next ten years (Acemoglu, 2025) with the biggest impacts in China and the US (PricewaterhouseCoopers, 2017). According to the annual AI Index report of 2024 by Nestor Maslej et al (2024) AI adoption efforts in companies are increasing and in 2023, 55% of survey companies were using AI in at least one business function already. The report also showed evidence that the adoption of AI can decrease costs and increase revenue. A recent McKinsey study revealed that especially larger companies are proactively adapting their processes and organisational frameworks to capture AI's full value. This underscores that these companies are not only integrating AI in multiple functions but try embedding AI into their overall operational strategy (Singla et al., 2025). While AI is driving global economic growth, its impact is especially valuable in sectors with complex networks that require accurate planning, manufacturing and logistics, like the automotive industry. Therefore this industry gains substantial benefits through AI implementation especially by improved quality control and process optimisation in manufacturing and accurate planning and prediction capabilities (G. Gupta, 2025; Plorin, 2022). Especially the German automotive industry has been under pressure due to various factors like slower productivity gains and competitive pressure coming from lower costs and extensive government support in the US and China. Experts are suggesting that German carmakers need to build and expand AI expertise, build data driven business models and further automate processes to remain competitive (Expert Group Transformation of the Automotive Industry, 2024). Despite significant progress in AI adoption, substantial gaps remain regarding which resources and organizational structures are essential for effective AI implementation (Loureiro et al., 2021; Mikalef & Gupta, 2021). While recent research in operations management has advanced the understanding of practical AI implementations, much of the focus has been on technical aspects, leaving organisational, strategic, and external factors underexplored (Fosso Wamba et al., 2022; Cannas et al., 2024; Helo & Hao, 2022). Addressing these gaps, this study aims to answer the research question: “How is artificial intelligence being adopted within the automotive industry?”. Specifically, it aims to identify the key drivers and barriers to AI adoption considering organisational, technical and environmental aspects of a company. The remaining study is organized as followed. In the next section, the theoretical background is set, and a literature review of existing AI adoption research is presented. Next, in Section 3 the qualitative methodology chosen for this study is presented and justified. Section 4 presents the findings and subsequently in section 5 the results are discussed, and conclusions are drawn.

2. Literature Review

Attention to AI in society, in the business context and in research has increased rapidly in recent years. Businesses integrate it into operations and decision making to improve efficiency and enhance strategic decisions by incorporating internal and external information (Baabdullah, 2024; Dissanayake et al., 2024). The cognitive capabilities of AI models have led to significant impact on diverse business areas, including marketing, customer relationship management, supply chain management, product design, manufacturing and logistics and research on this topic has sharply increased since 2018 (Dissanayake et al., 2024). Loureiro et al. (2021) reviewed AI applications in business and identified four clusters: societal impact, organizational impact, AI systems, and methodologies. Within the organizational cluster, studies emphasize AI's transformative role by reshaping employee interactions, enhancing problem solving, and improving knowledge management in areas like lean supply chains. AI also supports strategic decision-making by integrating technical data, organizational context, and human insights, while transforming manufacturing through improved efficiency, quality, and customization (Loureiro et al., 2021). Key operations management applications include intelligent decision making, demand forecasting, predictive maintenance, quality control, inventory optimization and prediction of delivery times (Choi et al., 2022; Lenin, 2023). Nucci et al. (2023) further showed that AI adoption significantly boosts productivity and revenue and increases overall performance by business process improvements (Zebec & Indihar Štemberger, 2024). These findings position AI as a critical success factor for European car manufacturers and suppliers, who face higher operating costs and fierce competition from their Asian counterparts (Expert Group

Transformation of the Automotive Industry, 2024). European companies have increasingly integrated AI into various business areas to maintain a competitive edge through achieving gains in accuracy, robustness and reliability (Mueller & Mezhuyev, 2022). However they are struggling with the adoption of AI due to a lack of digital readiness, organizational barriers, regulatory hurdles, complex environmental conditions and technological challenges, including insufficient data availability, poor data quality and system integrations (Cooper & Brem, 2024; Kovic et al., 2024; Mueller & Mezhuyev, 2022).

2.1. Technology Adoption Frameworks

Various theoretical frameworks, often referred to as technology adoption frameworks, have been developed for understanding and analysing the technology adoption process (Emon, 2023). Originating from social psychology or organisational disciplines, these models provide a structure to analyse and identify key influencing factors to technology adoption. Despite the common purpose, they differ in their individual focus, some focusing on the adoption on an individual level while others focus on a society or organisational level. Widely used frameworks include the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), the Technology-Organization-Environment Framework (TOE) and the Innovation Diffusion Theory (IDT) (Emon, 2023).

The TAM, introduced by Davis in 1986 examines the behavioural intention of individuals by measuring the perceived usefulness and the perceived ease of use as predictors to technology adoption (Davis, 1985; Emon, 2023). Building on the TAM, the UTAUT, developed by Venkatesh et al. (2003), includes performance expectancy, effort expectancy, social influence and facilitating conditions as influencing factors to the intention of technology adoption (M. D. Williams et al., 2015). Both the TAM and UTAUT explore the adoption process on an individual level. In contrast, Roger’s Diffusion of Innovation Theory (DIT), published in his seminal book Diffusion of Theory in 1962, is used to analyse how innovations are spreading within a social system over time, emphasizing the innovation itself, communication channels, the time of diffusion, which he describes as various stages from early to late adoption, and the social system as key elements of adoption (Emon, 2023; Miller, 2018). These frameworks focus on the individual and societal level, however none of it explores the adoption at an organisational level. The TOE framework investigates these organisational factors and is applied in several studies to analyse the adoption of information technologies or information systems at an organisational level (Alsheibani et al., 2018; Ganguly, 2024; Seethamraju & Hecimovic, 2023). It is also considered as the most suitable technology adoption framework to explain the adoption process of AI in organizations (Chatterjee et al., 2021). Therefore, the TOE framework is chosen for this research.

2.2. Technology-Organisation-Environment Framework

The Technology-Organisation-Environment framework was developed by Tornatzky & Fleischer (1990) in their book The Process of Technological Innovation. The TOE is part of the process from the initial innovation and development phase to the decision of firms to adopt new technologies (Baker, 2011). The TOE covers different aspects that influence the adoption process, distinguishing itself from other frameworks by focusing on an organizational level. The TOE examines three different contexts of a firm that are shown in Figure 1.

The technological context is concerned with the relevant and available technologies both inside and outside of the organisation. The organisational context considers organizational characteristics like size, structure, management culture and resources. The environmental context includes external factors such as the competitive or institutional landscape of the organization (Oliveira & Martins, 2011).

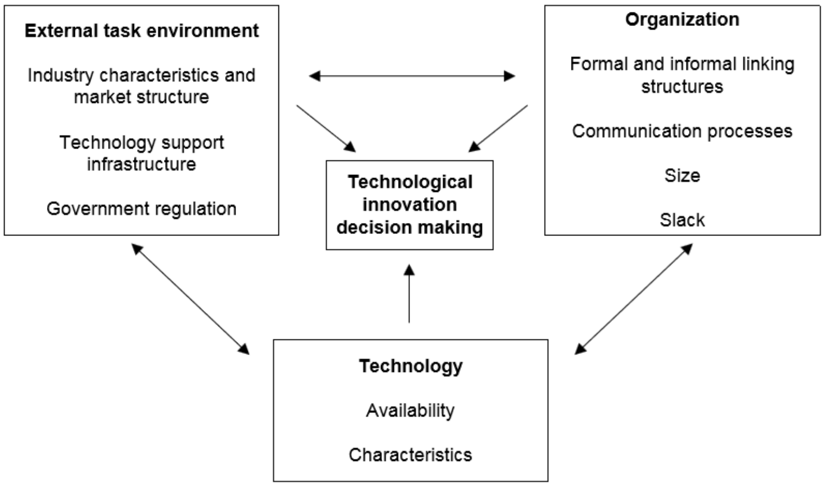

Figure 1: Technology, organisation, and environment framework (Tornatzky & Fleischer, 1990)

The interplay of these categories and broad scope of the framework enables exploratory research that also considers organisational and environmental factors in the adoption process of new technologies, moving beyond a pure focus on the innovation itself. However this means less focus on the influencing factors of end users (Emon, 2023). In the following part of the literature review these contexts are elaborated and a comprehensive literature search on AI adoption in organisations follows. Relevant factors are then mapped to each context. This aims to highlight key drivers and barriers of AI adoption in current literature.

2.2.1. The Technology Context

According to Tornatzky & Fleischer (1990), a firm's technological context involves both internal and external factors that influence technology adoption. Externally, the availability, characteristics, and pace of change of relevant technologies influence adoption. While some industries face rapid, radical innovations that increase risk and effort of adoption, others experience slower, incremental shifts. AI is a transformative technology with the potential to impact almost every industry and business function (Rao, 2022). Internally, the current available technological base of a firm, including IT infrastructure, data resources, the software and hardware, is pivotal in determining whether new technologies can be successfully integrated (Tornatzky & Fleischer, 1990; Wamba-Taguimdje et al., 2020). Building on Tornatzky & Fleischer (1990) notion of the technological context, the literature presents various internal technological factors that shape the adoption process of AI. For instance, studies emphasize that the perceived or actual benefit of AI technologies over traditional means, also referred to the relative advantage, and its ability to improve the efficiency and effectiveness of processes is driving firms to adopt AI (Dora et al., 2022; S. Gupta et al., 2022; Seethamraju & Hecimovic, 2023). However, the willingness to adopt AI is not the only determinant. It also depends on the AI readiness of a firm, which is characterized by the availability of use-cases for implementation and the availability of resources needed for the successful integration. Therefore human resource skills, the established technology base, such as software and infrastructure and the financial allocation towards AI use-cases are influencing factors (Dora et al., 2022; Kurup & Gupta, 2022; Shahzadi et al., 2024). IT infrastructure is seen as the most vital enabler among the technological factors (Merhi & Harfouche, 2024) and therefor insufficient infrastructure, like outdated systems or a low level of digital maturity can be considered a major challenge in the adoption process (Shahzadi et al., 2024). This includes the compatibility of AI applications with the existing tools and systems of a firm (Merhi & Harfouche, 2024; Seethamraju & Hecimovic, 2023). The importance of compatibility and integration possibilities for successful adoption is shown by Heimberger et al. (2024) who identified 15 papers in a systematic literature review which considered the compatibility an important requirement for AI adoption in production.

An appropriate infrastructure is also important because it ensures an efficient use of data (Heimberger et al., 2024) which is the necessary resource that determines the output of AI systems (Uren & Edwards, 2023). And since data is such a crucial part of the development and successful deployment of AI methods, data issues are a significant factor hindering or slowing down the adoption process. The meta-review of Li et al. (2024) reveals that the most common issues are lying in the phase of preparing and processing data before they can be used. This includes the challenge of data quality, which can stem from incompleteness or imbalance in the datasets; and the different natures, such as structure, type or format. Additional challenges arise from data sources and collection of data with insufficient or excessive data or overly diverse data sources. Data access can be hindered by regulatory factors and data storage often requires cost-efficient solutions that allow scalability and enough performance. Other issues are data integration, interoperability of the actual AI models and preprocessing data (Jöhnk et al., 2021; Li et al., 2024). At last, data security and data privacy is also a critical factor that needs to be considered in the adoption and implementation process of AI (Dora et al., 2022; Li et al., 2024; Singh et al., 2023).

2.2.2. The Organisational Context

Tornatzky & Fleischer (1990) describe the organizational context as the structures and processes that affect a firm's capacity to adopt new technologies. Key factors include organizational structure, informal linkages, top management behavior, and the firm's size and slack. Firms with lateral communication, decentralized leadership, high networking, and diverse occupational roles are more likely to adopt new innovations compared to more rigid, mechanistic structures. Effective linking structures and subsystem differentiation aid in scanning the external environment for emerging technologies to identify important technologies. Interchangeable systems can speed up the reaction to changes in the technology landscape.

The literature on AI technology adoption presents various influencing factors of the internal context of an organisation. These factors can be grouped into three themes: a strategic component, a resource component encompassing the availability and allocation of resources, and an organisational readiness component containing organizational structures and processes and the ability of successful change-management. To foster successful AI adoption, firms must have a clear understanding of the potentials of AI for their business and be able to create a vision on how AI can transform their business. A clear vision and understanding can be transformed into actionable strategies and ensures that AI initiatives are aligned with business goals (Dora et al., 2022; Shahzadi et al., 2024). Defined roadmaps are an enabling factor for the adoption process because they will provide the procedure on how to implement AI into strategies on the one hand, but also include the actual integration into business operations (Neumann et al., 2024). It is crucial for management to understand the business potential of AI and be able to identify areas where AI has a relative advantage over traditional means. This will be important to identify promising use-cases to solve relevant business problems or create new opportunities (Jöhnk et al., 2021). As AI has a wide-reaching impact on organisations, affecting employees at all levels, the ability of effective change management becomes a critical factor in the adoption process.

Whether organizations are more successful or faster in AI adoption is unsurprisingly affected by the availability and allocation of resources. These are mainly financial and human resources and do positively affect AI adoption if ready and available (S. Gupta et al., 2022; Seethamraju & Hecimovic, 2023). AI solutions especially are very cost intensive, because they need to be adapted to the specific organizations context as well as the respective data needed (Jöhnk et al., 2021). The high required investment and resource allocation towards these projects (Heimberger et al., 2024) makes the availability of financial resources critical; and unsurprisingly, the lack of funds do hinder AI projects (Neumann et al., 2024). Since managers often decide their investments cautiously due to financial constraints, the calculation of the return on investment (ROI) for AI projects is important to justify the high initial investment (Heimberger et al., 2024). In auditing, for instance, the ROI also played a significant role in the decision-making, however a delayed return discouraged adoption (Seethamraju & Hecimovic, 2023). The investment in human capital is equally vital to ensure successful AI adoption (Heimberger et al., 2024; Jöhnk et al., 2021; Morandini et al., 2023). Firms need to focus on upskilling and reskilling their workforce, as Morandini et al (2023), especially in transversal skills, that "include critical thinking, problem-solving, communication, and collaboration, which are essential for working effectively with AI systems". Provided training and development opportunities are necessary to build AI related skills, like development and design of AI models, but also for the use of this technology (Heimberger et al., 2024; Seethamraju & Hecimovic, 2023). This helps in building AI awareness among employees and a better understanding of AI capabilities, which in turn helps in use-case discovery throughout organizations. Important roles are on the one hand business analysts, which combine good domain knowledge and the applicability of AI and can act as a translator between business functions and AI specialists. On the other hand AI experts are needed for development of tools (Jöhnk et al., 2021).

2.2.3. The Environmental Context

External factors such as industry competition, supplier relationships, market and regulatory pressure, and technological support play a key role in driving technology adoption. Highly fragmented or competitive industries often adopt innovations more quickly to gain a competitive edge (Tornatzky & Fleischer, 1990). Tornatzky & Fleischer (1990) also highlight the importance of a robust technology support infrastructure, including availability of skilled labour and access to technology service providers.

The literature confirms that vendor support is especially crucial for adopting highly complex technologies like AI, as they can offer technical support and training (Ahmadi et al., 2015; Merhi & Harfouche, 2024). The impact of government regulations and standards is twofold in the literature. Horani et al. (2023) discovered in their study, that regulations impact adoption behaviour negatively, because they can create a unpredictable environment and reduces the organizations flexibility to implement new technologies. Seethamraju & Hecimovic (2023) stated that the standards in the auditing industry were already outdated and in the insurance industry regulatory concerns were the most significant obstacle (S. Gupta et al., 2022). However, with well suited policies and supportive regulations governments can create an environment to guide AI adoption (S. Gupta et al., 2022; Horani et al., 2023; Shahzadi et al., 2024). Optimally they are developed in consultation with practitioners (Seethamraju & Hecimovic, 2023). Regulations become a barrier to adoption if they block the access to necessary datasets and are further complicating data usage (Li et al., 2024). The competitive pressure in an industry can accelerate the adoption process especially when firms believe their competitors gain greater productivity, reduce costs or improve accuracy through AI adoption, and they themselves fear falling behind (Horani et al., 2023). Shahzadi et al. (2024) and Dora et al. (2022) explain that also the market dynamics, the uncertainties and volatilities in the demand are putting pressure on firms to adopt new innovative technologies as AI, because it allows them to operate with a higher level of agility and react faster and better to fluctuations.

3. Methodology

This chapter outlines the research methodology used in this study and the steps taken for data collection and analysis. First, the research question and the research objectives are presented, then the research methodology and the method of data collection is explained. In the subsequent section the interview procedure is disclosed, and the final section provides the description of the data analysis process.

3.1. Research Questions and Objectives

The research question addressed in this study is "How is artificial intelligence being adopted within the automotive industry?". The overall aim of this research is to generate insights into automotive companies to explore how they handle the adoption of AI and what influencing factors they face during this process. To answer the research question, the following research objectives were defined:

(1) Explore the process of how companies in the automotive industry are identifying and implementing AI applications.

(2) Identify key driving forces of AI adoption within the organisational, technical and environmental context of companies in the automotive industry.

(3) Identify key challenges of AI adoption within the organisational, technical and environmental context of companies in the automotive industry.

By understanding both drivers and barriers, as well as the process of AI adoption this research provides valuable insights and aims to enable managers in automotive companies who aim to increase AI integration to strategically focus on further strengthening the drivers of AI adoption while systematically reducing the barriers. These insights can also contribute to existing research by identifying new drivers and barriers or empirically reinforcing the current literature base.

3.2. Research methodology

The methodology of this study consists of comprehensive literature combined with qualitative research to gain deep understanding of the research topic. The literature review in Chapter 2 includes a thorough review of the underlying framework of this research which is then followed by an extensive review of both peer-reviewed and non-peer-reviewed literature to identify drivers and barriers in the existing research on AI adoption. These identified factors were subsequently mapped to the different contexts of the framework. This review establishes the research context and assures that the study is grounded in the findings of the current research. This allows to build upon and contribute to the existing research. To gain insights into automotive companies and explore how they are adopting AI, a qualitative research approach is chosen, and primary data is collected through semi-structured expert interviews. Venkatesh et al (2024) also calls for a qualitative and exploratory study to identify the influencing factors of the adoption process. The semi-structured interviews provide the exploratory character which makes it a suitable approach for this research.

3.3. Data Collection Method

To get the necessary insights into automotive companies, semi structured interviews were chosen, because they offer both consistency across interviews and enough variation to explore context-specific insights thorugh follow-up questions. The semi structured interview guide was developed in several phases (Kallio et al., 2016). First prerequisites and required knowledge were drawn from the literature review. With this knowledge, a preliminary structure was created and open-ended questions were formulated to take advantage of follow-up questions and give participants the ability to elaborate more. The interview guide was tested, restructured and shortened, while the first and second interview were also used to receive feedback on the structure. The resulting interview guide consisted of three sections. The first section was used to get information about the professional background and the second section aimed to get insights into the decision-making process of AI use-case adoption. The third section was further divided into three parts to allow for specific questions about drivers and challenges in the organisational, technical and environmental context. The interview guide is disclosed in the appendix.

The selection of interviewees was based on their capacity and expertise to provide the necessary information to address the research question. The researcher intended to select and contact experts with experience and knowledge in AI applications, as well as involvement in AI-related projects. However, the selection was based on the best judgement and knowledge of the researcher. This purposive sampling strategy was used to overcome the researcher's resource limitations (Campbell et al., 2020). Selected experts were contacted and invited to participate in interviews, which were conducted via Microsoft Teams video calls, recorded and then transcribed. Prior to recording, participants were informed of the use of the recording and consent was obtained from each interviewee. All audio files and transcripts were numbered to remove personal and company information to ensure anonymity.

3.4. Data Analysis Methodology

The next step after the interviews were conducted and recorded, a transcript of each was created. Transcription was initially done by Microsoft Word's 'transcribe' add-in, but later by Whisper, an open AI machine learning model because it achieved higher accuracies. Still, transcripts had to be proof-read and corrected manually before the coding process was started. The data analysis in this research was carried out using an inductive grounded theory approach (Mohajan & Mohajan, 2022). Initially, an open coding phase was conducted that started with the development of a preliminary code book which is based on the TOE framework including organisational, technical and environmental context which were subdivided into "driver" and "barrier" and can be seen in Table 1. Additionally, there was one category for topics about the ideation and decision process of AI projects. With this preliminary codebook, each transcript was meticulously reviewed, and every instance of a driver or barrier to AI adoption was coded and assigned to its respective category. Afterwards, an axial coding phase was undertaken. The codes of each barrier and driver sub-category were revisited and analysed separately, and ultimately recurring topics were clustered into emerging themes. This sequential coding process yielded themes and patterns and facilitated the development of well-defined, empirically grounded thematic categories (M. Williams & Moser, 2019).

Table 1: Preliminary Codebook for Coding Process

Context	Subdivision
Organisational Context	Drivers
	Barriers
Technical Context	Drivers
	Barriers
Environmental Context	Drivers
	Barriers
Ideation and Decision Process	

4. Results and Analysis

The objective of this study is to understand how organisations in the automotive industry are adopting AI and to explore the influencing factors they face during the adoption and implementation. The study aims to identify and analyse the various drivers and barriers that emerge during this process. To achieve these objectives and gain insights into automotive companies, the researcher carefully analysed the interview transcripts and structured the emerged findings and results. The findings are presented in the subsequent chapters.

4.1. Description of the sample

The sample collected for this research is a purposive sample, consisting of eleven experts who have been involved in at least one AI-related project or an department that drives AI initiatives, or are in a managerial or directorial position. The selection of these experts was based on their active role in AI adoption initiatives and their experiences with AI within the automotive industry. The professionals in this sample hold a variety of roles. These roles include two data scientists, four associates or managers from departments that can be categorised as Centers of Excellence (CoE) in AI & Analytics that drive central AI initiatives, two functional domain experts, a managing director, a project manager for generative AI, and an AI consultant. The participants originate from key business areas, including production, order processing, in-house consulting, human resources and IT. This sample contributes to an understanding of both the strategic and operational dimensions of AI adoption and is presented in Table 2. The experts are all employed in the automotive sector. Nine of these experts work for leading European automotive manufacturers. Among them, eight are employed by major German original equipment manufacturers (OEM), two of them based in southern Germany. One of these nine expert is employed by a multinational manufacturer based in Europe. Another expert is employed at an automotive supplier, and one is working for a consultancy firm with a strong automotive focus. The firms OEM1, OEM3 and OEM4 can be considered equally mature in their AI adoption phase and all three have established specialised teams that are actively exploring and implementing AI solutions. The supplier is starting to adopt first AI solutions and is exploring how to expand solutions across the production site, and AI maturity is relatively low to moderate. The production site of OEM2 is greatly automated but no AI solutions have been deployed, and AI maturity can be considered emerging as they explore possibilities for AI adoption. The consulting firm with well-developed data and AI practices shows high AI maturity and routinely implements AI solutions for automotive clients.

Table 2: Demographic Characteristics of the Sample Population

n	Job Type	Company Type	Business Area	experience with AI/Data Analytics
1	enablement manager, CoE AI	OEM 1	production, CoE AI	~3 years
2	funct. domain expert	OEM 1	order processing	~1-2 years
3	funct. domain expert	OEM 1	production	~2 years
4	manager, CoE AI	OEM 1	center of excellence AI	~4 years
5	data scientist	supplier	production	~2 years
6	senior manager	OEM 2	production	N/A
7	manager Data Analytics & AI	OEM 3	procurement	~2 years
8	project manager	OEM 3	human resources	~1,5 years
9	senior manager	consulting firm	Consultancy AI / Data	~8+ years
10	leading manager, CoE AI	OEM 4	center of excellence AI	~8+ years
11	project manager, CoE AI	OEM 3	human resources	~5-6 years

4.2. Findings

This section first examines how automotive firms are adopting by ideating, prioritising and implementing AI use-cases. The analysis then details the key drivers and barriers to AI adoption that automotive companies face during the adoption process which are mapped to each of the specific context of the TOE framework. Specifically, technological factors such as robust IT infrastructure and effective data management, organisational factors including strategic AI enablement, governance, and resource constraints, and environmental factors like regulatory and policy constraints collectively shape the pace of AI adoption. Moreover, the study highlights the interconnection between these contexts, demonstrating that organisational decisions, technical capabilities, and external pressures interact dynamically to drive or hinder the adoption process.

4.2.1. How Automotive Firms are Adopting AI

In the surveyed companies, the process of adopting AI typically initiates with an ideation or initiation phase, which involves finding and identifying potential use-cases where AI can be used to solve relevant business problems. This phase is characterised by departments or individuals approaching central AI and Data Analytics Teams with suggestions for potential applications. In certain instances, these teams also proactively engage with departments. Afterwards the gathered ideas are funnelled into an assessment process to evaluate their feasibility and strategic alignment. One key criterion is the technical viability, which revolves around the question of data availability: "Do we already have the data available?" [INT1], "Is there even a foundation for this in the form of data?" [INT11]" or "is a separate IT project necessary" [INT1]. This is also connected the key criteria of cost-benefit ratio. Many participants stated that they mostly prioritize use-cases according to the implied costs calculated against the resulted benefits of a use-case. One interviewee highlighted this approach by explaining "we have a classic impact and effort assessment, i.e. how much efficiency do we achieve? […] And on the other hand, yes, effort, what are change costs, what are run costs?" [INT7]. Other criteria include whether the use-cases address data privacy and IT security, whether they fit into the organisation's AI strategy, and whether the impact is wide-ranging and does not just benefit individual teams. At one company, this selection process is supported by a separate portfolio and value management for AI use-cases is established. Use-cases that pass these initial criteria are then developed in workshops and pitched to senior management. One participant explained that after this pre-selection, they can develop an initial proof of concept of the AI application with the departments to see if it meets expectations. If so, they will move on to the actual development process of use-cases to create an enterprise-ready application that brings real value and efficiency to the departments.

4.2.2. Barriers of AI Adoption

This section examines the main barriers to AI adoption in automotive companies, identified in the eleven expert interviews. The analysis revealed organizational, technical, and environmental challenges, that were grouped into primary categories and subtopics. Organizational barriers were mentioned most often, offering deeper insights. Each context and its specific barriers are detailed below, and a summary is provided in Table 3a and Table 3b.

Organisational Barriers

The organisational context received the most mentioned barriers resulting in a total of six primary categories. These are financial resource constraints, compliance and regulatory barriers, culture and strategy, human resource constraints, organisational readiness and organisational structure barriers.

Financial resource constraints were the most mentioned barrier to AI adoption with almost every participant citing financial resources as a major barrier. Almost half of them said that limited budgets and insufficient funding for AI projects had limited their ability to execute projects, and that more could be possible with the right funding. One issue is that Centre for Excellence departments often have to fund themselves, which shifts the financing responsibility of AI projects to functional departments. This is “a big barrier, which often leads to no realization of projects” [INT10]. Another participant from a different company however mentioned, “I can say I work with departments, that have the money” [INT4]. High upfront investment required for AI projects was noted as a significant barrier, particularly when cost-effectiveness and rentability are key considerations. One participant noted that while investment in tools and data infrastructure is necessary, the immediate benefits of AI remain unclear, creating uncertainty about these initial costs. High expenses in data collection and preparation often contribute to these challenges.

Organisational compliance and regulatory barriers emerged as a key challenge. Participants described lengthy approval processes for data usage or project initiation, noting that they had to navigate multiple committees and board meetings, which prolonged project timelines. In particular, the workers council was mentioned in five different interviews as a “challenge, because they have very strict regulations” [INT10]. This barrier is mainly stemming from the question of “who owns the data and am I allowed to access the data” [INT1] and data rights and protection was mentioned nine times across almost all interviews. Especially when it comes to “personnel data, […] confidential data; that’s when the process was prolonged, sometimes even two to three months” [INT11]. Although many participants mentioned the compliance and regulatory issues as a major barrier, all argued that they are important to ensure security standards, as well as ethical and moral considerations.

Many elements were categorized as organisational cultural and strategic barriers. A significant challenge was the original heritage of traditional automotive companies. They have a strong background in mechanical engineering and are “long existing company[ies], […] with many legacy-systems. In the 1980s nobody was thinking about the need for Big Data and in a certain quality” [INT11]. The processes and infrastructure were not created for the demands of the digital era and now need to be revised and updated. Another participant reflected that they will “not be a leading technology-pioneer […]. This was of course born out of the fact that we are ultimately a mechanical engineering company” [INT3]. They see it as a challenge “to deal with issues that are not [the] original area of business” [INT8] but still recognise the need for it. It was also mentioned that these companies traditionally require a lot of detailed planning and documentation before project initiations, which hinders iterative experimenting and important learning processes. The interviews also revealed AI projects often receive a lower priority compared to larger, more established initiatives, leading to resource constraints and delays. Moreover, the intense hype surrounding AI contributes to inflated expectations regarding its immediate impact. Participants mentioned that there is the “expectation of AI to solve all our problems, but the willingness for upfront investment is missing in many places” [INT10]. Similarly, another interviewee points out that they are faced with strange expectations, which may arise from the perceived ease of use of tools such as ChatGPT or fast development of proof-of-concepts, sometimes leading stakeholders to underestimate the complexity and time required to develop fully approved, live applications. This hype, in some cases, drives departments to pursue AI use-cases merely for the sake of adopting the technology, sometimes even “searching a problem for [the] technology […] or even creating one, many use-cases will fail” [INT7].

The human resource constraints emerged along two main dimensions. Participants highlighted barriers in both the functional departments and in IT and AI related departments. Within functional departments, a significant barrier is the limited availability of domain experts to participate in these projects. Often AI experts are relying on domain experts to explain the underlying data, and this is “only possible with people that know the data inside out” [INT4]. Limited capacity can arise from underprioritizing AI projects, as one participant mentioned it. Moreover, a notable skills gap and lack of basic understanding of AI technologies exists in functional departments. Often there is less to almost no knowledge on basic functions of AI, even though they are driving upskilling and qualification initiatives to “offer many things […] like live events, online talks, meetings, courses […] and awareness campaigns. […] This shows us that it is a very important component” [INT10]. This deficit presents a challenge to the effective identification of AI use-cases, as a fundamental understanding is essential to determine where AI can be appropriately applied. In IT and AI departments, while the technical expertise is generally sufficient, personnel bottlenecks remain a challenge due to overall capacity constraints. Participants observed that teams are frequently operating at near-full capacity “and are doing many things with a small percentage of their capacity” [INT11]. The problem is amplified by the fact that all companies try to fill vacancies internally, and "the internal labour market for such positions is highly contested" [INT11]. And even on the external labour market, "these job profiles are rare" [INT9].

Organizational structure was identified as a barrier by several participants, particularly due to the functional division of these companies. It is challenging to keep track of all AI projects in large functionally divided companies which leads to “many positions dealing with the same topics” [INT10]. In particular with resource constraints and the need for efficient resource allocation, this becomes a significant hurdle. Additionally, cross-functional projects can face challenges in data accessibility because it can be hard to identify “which data do I need, where are they, and then getting them somehow” [INT9] when they are stored across different departments.

Organisational readiness refelcts whether the underlying IT infrastructure is prepared for AI adoption. Almost half indicated that their organisation's underlying infrastructure or technology base was not fully ready yet. Particularly when it comes to AI use-cases at the shop floor level, where one participant describes that "new components of an IT-OT architecture [are needed] that don't exist here yet." [INT1]. This calls for enterprise-wide strategic initiatives to update the technology base if companies want to foster greater AI adoption.

Technical Barriers

Among all barriers, technical factors received the second highest number of references with all participants relating to this section. The emerged technical barriers could be clustered into the following primary categories: Infrastructure and Legacy Systems, Data Quality and Preparation, Data Availability and AI Models and Development

Infrastructure and legacy systems is mentioned by all eleven respondents, highlighting the importance of this technological barrier. Many mentioned legacy systems or outdated IT systems, which pose several challenges. These included the time it takes to integrate data from legacy systems and the potential for errors especially in the production environment, production equipment running on old software, and the increased effort for integrating data from legacy systems One participant illustrates this by saying that with the latest "flagship projects, we need to help ourselves with workaround solutions" [INT1]. This comes with further integration or interface issues. Either integrating the data from older source-systems into cloud and on-premise development systems or integrating proof-of-concepts poses challenges. Another one said "it is not the software development itself that is the challenge, but the ecosystem in which you want to integrate, which makes it more complex" [INT8]. Some also mentioned the lack of a centralised data storage system, such as a unified name space (UNS) or a data lake as barrier.

The majority identified data quality and data preparation as a significant barrier to the implementation of AI projects. The references in this primary category relate to quality issues in the underlying data required for use-cases. Across all companies, this issue was described as a barrier because the required data was either in a questionable or unusable state. Problems arose from differences in data formatting, problems in databases with missing row and column descriptions, or imbalances in data sets. One participant also described the problem of relying on data from other departments, because not every department places the same level of emphasis on data quality. This highlights the need for centralised data quality initiatives. This issue is so important because without high quality data, the “technology is not helpful, on the contrary, it is even dangerous because it then provides false recommendations” [INT9]. To overcome this problem, a lot of focus needs to be put on data preparation. Another participant describes that they "actually always have a major data cleansing process in advance of every project" [INT10]. Four of the eight participants describe that the preparation and preprocessing is very time consuming and therefore slowing down AI adoption. And sometimes even "80 per cent of the work is actually in the pre-processing" [INT7].

In addition to quality issues, six participants described problems with data availability. Problems arise from the often-fragmented data sources across organisations, which then need to be integrated and made available for training AI models. To ensure that the latest data is available for training purposes, an interface needs to be installed between local data, often from on-premises systems, and the cloud applications where most AI development takes place. One participant identified the need for an interface as one of the main barriers to AI projects, because this typically requires a dedicated IT project. However, to make initial use-cases enterprise-ready, "you need integration and that is costly, time consuming and has to be justified by a positive return on investment" [INT9].

Environmental Barriers

Environmental barriers were mentioned in seven different interviews. The emerging barriers could be attributed to regulatory and policy constraints, the rapidly evolving AI landscape, and the external labour market. Six of these participants mentioned external policies as a barrier, mainly the EU AI Act and the German data protection regulation DSGVO, which make it more difficult to access and use data for AI development and increase the various aspects that need to be considered. "So a very big part is: What do we want to do? Who do we need to talk to and what are we allowed to do when and how, or under what circumstances, before a single finger is lifted" [INT8], and another says that due to these "legal and regulatory requirements [...] many good ideas fail" [INT5]. The very rapidly evolving AI landscape was mentioned by three participants as a barrier, on the one hand because it is very time-consuming to keep up with the latest changes in AI framework and model ecosystems, as well as the growing number of vendors of e.g. large language and AI models. Two participants mentioned noticeable constraints coming from the external labour market, where "[they] actually had problems with the senior roles. So [...] 3 to 5 years plus, that's difficult" [INT4]. On the other hand, another one said that at the low scale he is looking for professionals, he doesn't notice constraints.

Table 3a: Key Barriers to AI Adoption in the Automotive Industry

context	primary category	topics	n
organisational barriers			**11**
	financial resource constraints		**10**
		– financial constraints	5
		– high upfront investment	4
		– high cost of data collection	3
		– finance. model of AI excellence departments	2
		– lack of funding resources	2
	compliance and regulatory barriers		**8**
		– approval processes	7
		– data rights and protection	6
		– bureaucracy and legal constraints	3
		– IT related decision making	2

Table 3b: Key Barriers to AI Adoption in the Automotive Industry

context	primary category	topics	n
organisational barriers			**11**
	culture and strategy		**8**
		– organisational heritage	5
		– strategic priority and resource allocation	4
		– expectation management	3
	human resource constraints		**6**
		– functional department	5
		– IT or AI department	4
	organisational readiness		**5**
		– foundational infrastructure	5
	organisational structure barriers		**4**
technical barriers			**11**
	infrastructure and legacy systems		**11**
		– architectural readiness and legacy systems	6
		– systems integration and interfaces	6
		– centralised data storage	4
	data quality and preparation		**8**
		– quality issues	8
		– data preparation	4
	data availability		**6**
	AI models and development		**5**
		– model development	4
		– reliability and trust	3
environmental barriers			**7**
	regulatory and policy constraints		**6**
	rapidly evolving AI landscape		**3**
	employee market constraints		**2**

4.2.3. Drivers of AI Adoption

This chapter presents the main drivers of AI adoption in automotive companies, identified from eleven expert interviews. These drivers emerged from the organizational, technical, and environmental contexts and were grouped into primary categories with subtopics where relevant. Organizational drivers were mentioned more frequently and covered a broader range of topics, while technical and environmental drivers showed lower information density. Each context is explored in detail, and Table 4 provides a summary of all identified drivers.

Organisational Drivers

In the context of organisational analysis, nearly all participants identified strategic and leadership perspectives as critical to the adoption of AI. A key driver is the strategic enablement of AI within organizations, which is often facilitated by central Data Analytics teams or AI Centers of Excellence. These specialized teams play a vital role by supporting functional departments in deploying AI applications. Enablement also includes initiatives that drive organisation-wide programs to provide necessary IT infrastructure or "provide capabilities compliant for the company in order to simply increase acceptance and ultimately, of course, to increase security when we use these tools" [INT11]. Another important factor is the establishment of an organisational structure that effectively connects AI experts with domain experts. This facilitates the monitoring and coordination of use-case identification across different departments, ensuring that similar initiatives are identified and streamlined. By optimising the allocation of both financial and human resources, this structure helps to overcome resource constraints, such as the capacity of AI experts, thereby accelerating the adoption of AI. The strategic governance and sponsorship for AI initiatives is another driving force. This is characterised by a top-down, organisation-wide endorsement of AI adoption. Participants have indicated the establishment of separate AI boards, the presence of distinct AI strategies and roadmaps, and the implementation of organisation-wide initiatives to facilitate data exchange and enhancing data quality. This emphasis is further underscored by the explicit statement of nearly half of the participants who identified top management support as a pivotal driving force. This is pivotal in facilitating the provision of essential resources and financial funding whilst simultaneously ensuring that adequate priority is set for corresponding projects.

The business value of AI projects has emerged as a significant driver. This implies that if AI projects deliver a clear benefit, such as cost savings, increased efficiency or improved quality and customer satisfaction, organisations are more likely to invest in AI applications, despite potential barriers, as highlighted by one participant who said that AI projects are often "complex and technically challenging. But if the return on investment behind it is high enough, then it can be solved” [INT9].

A significant proportion of the participants identified the skills and qualifications of employees as a pivotal factor. The necessity in upskilling and development of employees understanding of AI technologies is identified as a key priority, given the crucial role they play in identifying use-cases across various departments. This is further supported by the following statement from one company: "One pillar in the AI strategy is also qualification and upskilling of the employees" [INT11]. The presence of employees within functional departments who already possess AI know-how has been shown to significantly accelerate project progress by bridging the technical knowledge of AI teams with the domain knowledge of a department. “If you have someone who has a basic understanding of AI, they can help you in a completely different way and give you insights into their work and the data and also the results” [INT4].

As previously discussed, a key barrier to the adoption of AI is the increased effort required for regulatory and legal work as result of lengthy and traditional processes. Consequently, it is evident that the enhancement of such processes is a crucial factor in facilitating AI adoption. Participants from various companies independently noted that these processes previously required up to twelve months, but were reduced to two to three months, thereby accelerating the implementation time.

Furthermore, participants noted that a centralised funding model for AI use-cases can be beneficial because it allows individual business units to access essential AI resources, such as APIs to AI models or computing power, without incurring significant upfront investment costs. This facilitates the initiation of new use-cases with minimal financial constraints for individual departments, which are often constrained by financial resources.

Technical Drivers

From a technical standpoint, influencing factors were mainly the available infrastructure and how data management was handled by firms. Effective data management can lower the barrier for new AI projects by ensuring that data is already available and accessible and thereby reducing overall effort. This is a key factor that firms typically need to consider for new AI use-cases, as one participant illustrates: "And when it comes to the technical aspects, we have to look at whether the basis for this is actually there, in the form of data" [INT10]. Several participants explained how effective data management looks like at their company. It is also important to set up a central data storage system where data from different systems is stored, creating a single point of asset for data. It is also crucial to ensure that the data is made available to the various departments that require specific data for their AI use-cases. The accessibility of data is facilitated through mechanisms such as a "data-shopping process and a data shopping catalogue" [INT10] or a "data exchange platform […]] where you can publish and consume data products relatively easily via an API hub" [INT7]. From the perspective of AI model development and frameworks for development, driving factors include the creation of blueprints after use-cases, so similar new uses cases can build on already created blueprints and therefore save resources in the adoption process, or the design of agnostic, modular systems so AI models from external service providers can be replaced interchangeably. This is especially important in a rapidly changing landscape of external service providers to ensure relatively independent operations.

Environmental Drivers

The prevailing factors from the external environment are mainly attributed to the perceived competitive pressure in the automotive industry. Participants have indicated that there is a general expectation that all companies will enhance their efficiency and improve customer satisfaction through the implementation of AI. This puts pressure on companies to adopt AI, and not doing so "is of course also a risk, because AI will certainly change the competition" [INT1]. This is further elaborated by another participant, who says: "that you are simply forced to increase efficiencies through AI because many companies are doing this and those who are not doing it now. I think they are at a disadvantage" [INT11].

Table 4: Key Barriers to AI Adoption in the Automotive Industry

context	primary category	topics	n
organisational drivers			**10**
	strategy and leadership		**9**
		– strategic AI enablement	6
		– strategic governance and sponsorship	5
		– top management support	4
	business value of AI projects		**7**
	skills and qualification		**6**
		– upskilling	4
		– existing knowledge	4
	improved governance and regulation processes		**4**
	centralized funding		**3**
technical drivers			**10**
	infrastructure and data management		**8**
		– centralized data structure and accessibility	7
		– data quality and availability	5
	AI models and frameworks		**4**
environmental barriers			**7**
	competitive market pressure		**5**

5. Discussion and Conclusion

5.1. Discussion

The objective of this study was to explore the adoption of AI in the automotive industry, with the aim of identifying the main barriers and drivers to this adoption process. The analysis of eleven expert interviews revealed many influencing factors of this process, while far more challenging factors were mentioned than facilitating factors. Several use-cases came up in the interviews, such as improved accuracy in delivery times, maintenance support, enhance production quality control and better knowledge management, that align with literature on impact areas of AI in operations management (Choi et al., 2022; Lenin, 2023; Loureiro et al., 2021). The findings of this study revealed that organisational factors emerged as the most frequently mentioned influence on AI adoption. Within this domain, financial and human resource constraints, internal compliance and regulatory challenges as well as the strategic orientation and culture of firms were the most significant barriers. The findings, that a lack of funding is a critical factor especially with the needed high upfront investment for costly AI solutions (Heimberger et al., 2024) and the allocation of resources as a determinant for successful adoption aligns with previous research (S. Gupta et al., 2022; Heimberger et al., 2024; Jöhnk et al., 2021; Seethamraju & Hecimovic, 2023). Consequently, participants stated that increased strategic priority and top management support for AI projects can significantly drive AI adoption in organisations. This commitment is demonstrated by organisation-wide initiatives that build the necessary technical and organisational foundation for AI projects. Research also identified the importance of clear strategy and vision, as well as a roadmap on how to integrate AI and generate business value from it (Dora et al., 2022; Neumann et al., 2024). The literature notes the importance of management level to understand the potential of AI and in turn drive the implementation through increased use-case identification (Jöhnk et al., 2021) which did not appeared in the interview, because a bottom-up approach was usually mentioned for identification of application areas. Jöhnk et al. (2021), as well as the findings of this study, notice the value of business analysts who can bridge between the business functions and AI experts. The findings further revealed lengthy approval processes, mainly stemming from data rights, protection rules or imposed challenges by the workers council, are slowing down the development of AI solutions and cause project delays, higher risk and higher resource demands. One participant also attributed these delays to outdated documentation requirements, which Koenigstorfer et al. (2024) identify as hindering broader AI adoption. Consequently, improved organisational governance and regulatory processes were noted as key drivers. Together, the results and the literature show that a clear strategic direction, dedicated funding and improved governance and compliance procedures in combination with understanding the business value of AI projects, can serve as an important enabler as well as an important role in overcoming organisations barriers in AI adoption.

Additionally, the results showed that companies face substantial technical challenges due to complex systems infrastructures, fragmented data sources and issues in data quality and availability. Barriers largely arise from legacy IT systems that complicate system integration or data collection. Further challenges are due to low data quality and the involved preparation effort to increase this quality. These barriers align closely with prior research also identifying insufficient infrastructure, legacy systems and a low level of digital maturity as most vital hurdle (Merhi & Harfouche, 2024; Shahzadi et al., 2024). Likewise, the literature states high quality data as crucial for AI (Uren & Edwards, 2023) and most data related issues were found to be in preparing and preprocessing data

(Li et al., 2024) as well as in the data sources and its collection (Jöhnk et al., 2021; Li et al., 2024). The interviews reinforce these claims, noting that a lack of a centralized data storage solution, data quality issues and data availability due to technical or compliance reasons are significant barriers. Overcoming these hurdles through improved infrastructure and data management simultaneously appeared to be the most significant technical driver in the analysis. A centralized data structure, resulting in improved accessibility, data quality and availability and a modern IT infrastructure leading to easer AI model integration (Heimberger et al., 2024; Merhi & Harfouche, 2024; Seethamraju & Hecimovic, 2023) were most mentioned drivers during the interviews. Organisations can achieve this through organisation-wide initiatives that improve data governance and modernise their IT infrastructure, additionally creating synergies across departments and reducing the technical challenges of individual AI projects. This improves the AI readiness of companies by preparing the software and hardware as well as the technical base and increase the availability of potential use-cases (Dora et al., 2022; S. Gupta et al., 2022; Seethamraju & Hecimovic, 2023).

The analysis indicated that the influencing factors from the external environment are mainly due to challenges from regulatory and policy constraints and the rapidly evolving AI landscape, and competitive pressure as a key motivator for increased AI adoption. Additionally, the shortage of skilled senior AI or data analytics experts in the external labour market emerged as a notable barrier in the findings as well as the literature. Research highlights the importance of external technology providers and vendor support, especially for complex technology (Ahmadi et al., 2015; Merhi & Harfouche, 2024). Although all participating companies relied on external vendors, none specifically identified this as a driver or a barrier. This suggests that while access to external technology can be considered a necessary baseline for AI adoption, internal factors are more significant for successful AI adoption at the current state.

Governmental regulations and policies as well as outdated standards (Horani et al., 2023; Seethamraju & Hecimovic, 2023) are considered the most significant external obstacle (S. Gupta et al., 2022) underscoring the results of this study. Especially restrictions to data access as a barrier (Li et al., 2024) was mentioned across all interviews. The competitive landscape of the automotive industry can be seen as a major driver of the adoption of AI because all participating companies are feeling the need to implement AI to not fall behind peer competitors. Market dynamics and the fear of AI's disruptive capabilities are also identified drivers in the current literature (Dora et al., 2022; Horani et al., 2023; Shahzadi et al., 2024).

5.2. Conclusion

European carmakers face growing competition from lower-cost Chinese manufacturers, and AI becomes essential to maintain productivity, efficiency, and a competitive advantage. This study therefore explored how traditional European automotive firms adopt AI and identified the key organisational, technical, and external drivers and barriers shaping that adoption process. Drawing on eleven expert interviews within German automotive companies the research identified organisational factors as the most frequent determinants to AI adoption. The lack of financial resources due to lack of funding and high costs of AI projects in addition to bureaucratic hurdles and long approval and regulatory processes are slowing down the adoption. Conversely, companies can overcome these constraints with strong executive sponsorship and a reduction of bureaucratic effort. This means organisation-wide funding models and large initiatives to update internal regulation processes are necessary. Additionally, the successful identification of high impact use-cases is crucial for AI adoption which in turn is driven by AI Excellence Teams that are well connected to domain experts in functional departments. From a technical perspective, companies face legacy IT infrastructure, siloed data sources and poor data quality as major barriers. Individually, also challenges regarding the development of AI models, lacking reliability and lack of trust were coming up. Despite these challenges, the findings also reveal clear driving forces in the technical context, in particular a centralized data structure for better data access and improved data quality and a modern IT infrastructure that enables easier AI systems integration. Especially for smaller manufacturing sites high industrial standards and automation are a key prerequisites because this ensures that the data, which is necessary for AI solutions, is already available. Externally, restrictive data protection policies and government regulations are the most challenging barriers and can significantly slow down AI development and implementation timelines. However, our findings also reveal that almost every participant identified these regulations as highly important. Thus, the effort to speed up the internal process that are necessary to meet regulations and compliance is crucial. The external competitive pressure is the main external driver for adoption efforts because companies fear the risk of falling behind competitors, thereby losing out on the benefits of AI and loose the competitive edge. The study also revealed that AI solutions are mainly developed locally and are different each time. The study revealed that AI solutions are typically developed locally, often with unique characteristics. However, they share common technical, organizational, and environmental challenges, and departments tackling these independently would mean missing opportunities to use organisational synergies. Consequently, organisation-wide, high-level initiatives for overcoming these barriers are crucial.

This study contributes to research by deepening the understanding of the AI adoption process in the automotive industry and elaborating the influence of organisational, technical and environmental factors to this process. Therefore, meaningful insights are generated for managers in the automotive industry that want to drive AI adoption. Additionally, the study lays the groundwork for further investigations that seek cross-regional comparison or statistic validation of the influencing factors.

Several notable limitations appeared. First, the time constraints limited the data to a relatively small sample, consisting of eleven expert interviews. This raises the possibility that thematic saturation was not reached, and consequently additional influencing factors of AI adoption remain undiscovered. Second, the almost exclusive focus on German automotive companies limits generalizability and the findings may not be transferred to other industries or other automotive companies outside of Germany. Third, the qualitative approach of this research relies on the contributions of participants which cannot be verified, and the results are interpretative rather than objective.

Future research should address these limitations by expanding and diversifying the sample size until data saturation is achieved. Incorporating a mixed-method approach in future research could statistically validate the identified key drivers and barriers. A particularly valuable extension would be a cross-regional comparison with Chinese automotive manufacturers. This direction could contrast the organisational, technical and environmental dynamics of AI adoption in established, long existing European car makers versus rapidly evolving and relatively young Chinese companies. This would yield deeper insights into firm-specific approaches and competitive strategies.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of my written thesis, "Exploring AI Adoption in the European Automotive Industry: Drivers and Barriers", ChatGPT was used for the following tasks: Literature review assistance (e.g., searching for scientific papers or quickly retrieving information from papers by summarizing documents), Writing and editing (e.g., suggestions for improved language, feedback on the clarity and strucuture of the text). In addition, the AI model Whisper from OpenAI and the Microsoft Word build-in tool "Transcribe" was used to transcribe interviews from audio files to text. DeepL Write was used to improve writing and find synonyms. After using these tools/services, I reviewed and edited the content as necessary, and I take full responsibility for the content of the work presented.

I also declare that I am aware of and respect the Artificial Intelligence Rules of Conduct of Católica Porto Business School.

<u>Example of prompts used for large language models:</u>

- Please find papers that study the adoption process of AI?
- Can you summarize this document and list the main points in bullet points please?
- Can you please give me feedback on this paragraph in terms structure and clarity?
- Please give me Feedback on my Interview Guidelines.
- Please check my references and tell me if my reference section followed the APA6/7 rules? What changes do I have to make?

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Appendix

Appendix 1: Interview Guide used for Expert Interviews

Introduction:

- Explain the objective of the research and structure and purpose of the interview
- Give confidentiality assurance and ask for audio recording (deleted after transcript)

Section 1: Background Information:

- Ask for Interviewee's role and time in the company.
- Ask for Interviewee's experience with AI.

Section 2: Technology Context

1. What are the main reasons for AI adoption and implementations of AI applications?
2. Please explain the decision-making process for AI adoption. What are key factors?
3. How well do your company's existing technologies (IT and IS) support the adoption of AI applications?
4. Which improvements or changes are/were necessary for effective adoption?
5. What technical challenges have you encountered in previous projects?

Section 3: Organization Context

1. How would you describe your companies stand towards AI?
   (AI as necessity, value creator, is it in the strategy integrated?)
2. What is the role of top management in the adoption process of AI?
3. How would you describe the readiness of your organization to adopt AI? (skills, financial resources, human resources, commitment, structures and culture)
4. What kinds of internal or external support have been important for AI adoption in your organization? (service providers, AI consultants, AI teams)
5. What barriers to AI adoption do you see in your organization? Or:
   What improvements or changes would you suggest, so your company can adopt AI more effectively?

Section 4: Environment Context

1. How do your supply chain partners influence the decision to adopt AI technologies?
2. How is competitive pressure influencing the adoption decision?
3. Can you describe the role of the government and regulations in the adoption decision?
4. What external factors, such as market dynamics or regulations, have impacted your decision to adopt AI technologies?