Uncovering Common AI Challenges Across Industrial Domains in the Transition to Industry 5.0

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***Abstract*—AI adoption in industrial applications has been slower than analysts expected due to the lack of best practices and industrial-grade solutions. In response, the Artificial Intelligence in Manufacturing leading to Sustain- ability and Industry 5.0 (AIMS5.0) project introduces 20 use cases from world-renowned companies, providing an opportunity to thoroughly analyze the challenges of implementing AI in industrial settings. This paper presents the first taxonomy of AI adoption challenges, organized by AI domains across the use cases, highlighting issues such as data collection, algorithmic limitations, and other deficiencies in current solutions. Based on these challenges, we outline the AIMS5.0 AI Toolbox, which offers various solutions to address them, as detailed in the paper. The challenges are validated through two sample, mature use cases, demonstrating how they manifest in different industrial applications.**

***Index Terms*—industry5.0, AI, AI toolbox, AI adoptation, AI application, aims5.0, machine learning**

I. Introduction

AIMS5.0 is a collaborative project aimed at enhancing European digital sovereignty and sustainable production by implementing AI-enabled hardware and software across the entire industrial value chain. This project focuses on creating human-centric, climate-friendly production environments through new technologies like IoT, semantic web ontologies, and AI, driving the transition from Industry 4.0 to Industry 5.0. AIMS5.0 motivation is to lead the European industrial transformation by placing humans' well-being at the center of manufacturing systems, thereby achieving social, economic and technological goals beyond employment and growth to provide prosperity robustly for the sustainable industrial development in numerous domains. This can only be achieved by analyzing in depth the main challenges of different application industrial areas [1]. Several questions arise here, such as:

- what challenges do the various industrial domains face in connection with AI adaption?
- what are the barriers to adaptions?
- how they can be addressed, solved, or mitigated?

The key contribution of this paper is the development of a taxonomy that categorizes AI-related challenges across various industrial AI domains, derived from the 20 use cases contributing in AIMS5.0 project. This taxonomy serves as a tool to identify and compile recent, critical issues in the application of AI methods, offering potential strategies to address these challenges and support the integration of AI into different industrial sectors. Additionally, the paper provides an overview of the use cases by categorizing them into relevant AI domains, covering a significant portion of the AI field.

AIMS5.0 addresses the challenges outlined in this paper through several approaches, with the most important being the development of an AI Toolbox. This toolbox is designed to address the issues that arise across different AI domains and use cases. The paper presents solutions to these challenges within the framework of the AIMS5.0 AI Toolbox. The Toolbox not only identifies common challenges and patterns across various applications but also establishes a unified and standardized approach to guide an effective adaptation of AI tools in any industrial domain.

The paper is organized as follows. Section II presents the related works, the broad overview of the AIMS5.0 project, and also the introduction of the AIMS5.0 AI Toolbox. Section III shows the categorization of the use cases of the AIMS5.0 into different AI domains. Section IV creates the taxonomy of different AI related challenges present in AIMS5.0 industrial use cases and also form how the AI Toolbox addresses those issues practically. Finally, Section V demonstrates that these challenges are indeed present in the contributing use cases, with two in-depth examples used to validate this claim.

II. Related Works

Moving towards Industry 5.0 by processes manufacturing digitization to increase productivity through mass personalization and human-oriented solutions across the whole industrial value chain is evidently crucial and one of AIMS5.0's driving motivations [2]–[5].

A. AIMS5.0 Operation and Use Cases

This project is structured into nine work packages, each designed to support the integration of AI into the digitalized industry as part of the transition towards Industry 5.0 illustrated in Figure 1. WP1-WP3 focus on developing sustainable AI-enabled technologies, including components, systems, algorithms, and architectures. WP4 provides an open-access platform for industrial solutions, while WP5 and WP6 validate

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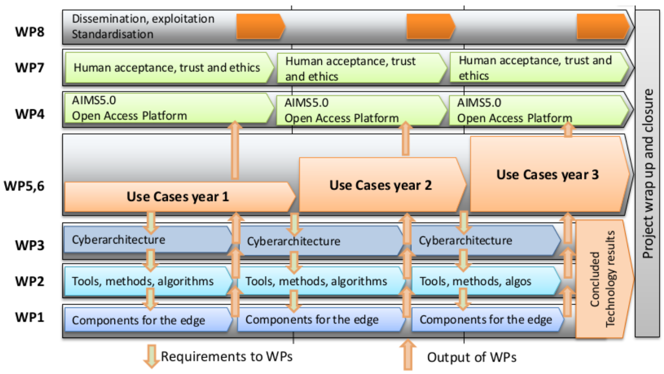

Fig. 1: The structural operation of the AIMS5.0 project.

these solutions for OEMs, tier-1, and tier-2 suppliers, ensuring practical collaboration without AI differentiation between supplier levels [6], [7]. WP7 addresses AI acceptance, trust, and ethics, and WP8 is tasked with maximizing the project's impact across Europe. WP9 is dedicated to project management, ensuring that all activities are coordinated effectively and that the project progresses smoothly towards its objectives. This structure ensures efficient, transparent collaboration within the consortium.

Key AI goals for the participating 20 use cases (presented in Table I) include the development of AI-based lifecycle management systems to optimize energy consumption and reduce CO2 emissions, the creation of intelligent robotic systems for automated production and logistics, and the implementation of AI-enhanced decision-making tools for more efficient production cycles. Many use cases also highlight the use of AI for predictive maintenance, process optimization, and enhancing human-machine collaboration, particularly in complex manufacturing environments like semiconductor production.

Overall, these use cases aim to demonstrate the potential of AI in transforming industrial practices, enabling more sustainable and resilient production systems, and fostering innovation in areas such as autonomous robotics, digital twins, and AI-driven supply chain management. The document underscores the interdisciplinary nature of these AI applications, which are designed to be scalable and adaptable across various industries, ultimately driving forward the digitalization and automation of manufacturing processes.

B. AIMS5.0 AI Toolbox's Formulation

The AIMS5.0 project has introduced the AI Toolbox to address AI-related challenges and revolutionize industrial operations [8]. It targets to transform how industries function, drive innovation, optimize processes, and enhance productivity. The AI Toolbox is designed to facilitate human-centered digitalization, promoting industrial synergy, reducing time-to-market, improving production quality, and boosting energy efficiency, all while advancing European sovereignty and sustainability. Hence this standardized platform – so called the AI Toolbox [9] – encapsules all AI tools consumers who

TABLE I: List of AIMS 5.0 use cases

Use case #	Use case name
1	Development of Green AI-Lifecycle Management Approaches
2	AI Enhanced Value Chain
3	Servitization and service delivery enabled by Zero administration
4	AI based improved connection between production and logistics
5	AI techniques at different layers in Machine Tool Domain
6	Reconfigurable AI-based automated conveyer feeding by a robotic system
7	Digital Automated Luminaire Manufacturing platform
8	AI supporting and strengthening human and manufacturing cycles
9	Energy-aware Scheduling of Batch Processing Machines in Wafer Fabs
10	MES concept based on AI Improving Production Cycle
11	AI-supported Industrial IoT for Indoor Food Production
12	Human-Centred AI for the Optimization of Robust and Competitive Semiconductor Manufacturing Networks
13	Intelligent Sensors improving Robustness of Automated Wafer Transportation and Storage Systems
14	Speeding-up the Benefit of Automation by Virtual Commissioning through Digital Twins
15	Productionized Machine Learning models at scale
16	AI enhanced production and performance of RF transceivers for civilian SATCOM and radar applications
17	Intelligent Contamination Management & Prescriptive Control Plans and Process Flows
18	Using semantic Data Model as base for AI optimized economic & ecologic/societal supply chain improvements
19	Extension of Digital Reference Ontology for Smart Sustainable Business Planning and incident handling
20	Harmonization of Automated Digitized Equipment Control

will ultimately share, utilize, and spread the agreed-on and rigorously tested best practices which in turn can ease the transformation and expedite time to market.

This AI Toolbox leverages advanced AI algorithms to optimize manufacturing through data-driven decision-making [10] and supports reconfigurable [11] AI solutions that can swiftly adapt to new industrial applications. It aggregates a diverse range of AI tools that work seamlessly together, offering standardized interfaces and reusable components. Rather than replacing existing solutions, the AI Toolbox extends them, providing a unified platform for knowledge exchange and best practices in industrial AI applications.

The primary objectives of the AIMS5.0 AI Toolbox include reducing time-to-market through rapid prototyping, enhancing system reliability and security, enabling quick evaluation of industrial proof-of-concepts, and optimizing energy-efficient production processes. Additionally, it aims to fine-tune the existing AI solutions and develop new ones (when needed) to bridge between the existing technological gaps, thereby strengthening European digital sovereignty and supporting sustainable industrial digitization.

III. Categorization of use cases into AI domains

Categorizing AI domains is challenging due to the diverse and multifaceted nature of AI, which lacks a universally accepted definition or coherent taxonomy across research communities, literature, and industry reports. Despite this complexity, certain common themes and topics emerge in the various definitions and taxonomies we analyzed. Drawing from these insights, we have classified the AIMS5.0 use cases into distinct AI domains (presented in Table II), each further broken down into relevant subdomains based on [12] and [13]. This approach provides a structured framework for understanding and organizing the wide-ranging applications of AI.

Computer Vision focuses on enabling machines to interpret and analyze visual data through tasks such as image classification, segmentation, object detection, and 3D reconstruction, even extending to emotion recognition from images. **Speech and Sound Processing** deals with the analysis and interpretation of audio data, including converting speech to text, analyzing sound similarity, separating audio sources, and conducting sentiment analysis based on audio. **Computer Linguistics** encompasses language-related AI, such as translation, text classification, sentiment analysis, and the development of conversational systems, all aimed at understanding and processing human language. This domain is also closely related to the current hype surrounding LLMs [14], which represent a significant breakthrough in AI by enabling advanced natural language understanding and generation.

Robotics integrates AI to enhance robot capabilities in motion planning, mapping, human-robot interaction, and mobile and drone robotics, with a focus on adaptive control and collaboration. **Forecasting** involves using AI to predict future events, relying on time series analysis and dependency-based methods. Discovery utilizes AI for data analysis, including segmentation, clustering, anomaly detection, and causal inference, to uncover patterns and relationships within data. **Planning and Scheduling** deals with optimizing multi-agent systems, logistics, and strategic decision-making through policy development and scheduling techniques. Lastly, **Creation** leverages AI for creative tasks, including generating and manipulating images, audio, and text, as well as style transfer and AI-augmented engineering, driving innovation in art, design, and content creation.

IV. Challenges in application of industrial AI

The project has been underway for over a year, and the list of challenges is still evolving. In the following section, we will outline the key common challenges associated with various AI tasks identified across 20 use cases so far. While this list is not exhaustive, these challenges have been observed repeatedly across multiple industrial domains.

To address these issues and challenges, the AIMS5.0 AI Toolbox proposes different means to overcome them. The challenges and the proposed solutions offered by the AI Toolbox are outlined in Table III.

A. Data related problems

In AI-related industrial use cases, several common data challenges frequently arise. One significant issue is the presence of **unlabelled data**. In many applications, acquiring labelled data is expensive and time-consuming, leading to a reliance on unlabelled data that can be difficult to interpret and utilize effectively for training AI models. This lack of labels can hinder the development of accurate and reliable models, as supervised learning algorithms depend heavily on well-annotated datasets.

Another challenge is an **inadequate data scheme**, where the structure and organization of data do not align well with the requirements of the AI tasks at hand. Poorly designed data schemas can lead to inefficiencies and inaccuracies, as the data may not be easily accessible or interpretable for model training and evaluation. Additionally, **merging with external or public data** sources presents its own set of difficulties. Integrating disparate data sources often involves reconciling different formats, standards, and quality levels, which can complicate the process and introduce inconsistencies.

Data representation problems also pose significant hurdles. Effective AI models require data to be represented in ways that capture relevant features and patterns. Inadequate data representation can lead to suboptimal model performance and missed insights. Moreover, the issue of **under-understood data**—where the true value or implications of the data are not fully grasped or are overestimated—can lead to misguided decisions and ineffective models. Finally, the **lack of sufficient data**, particularly in controlled environments where data simulation is used, can limit the ability to build robust models. Simulated data may not always accurately reflect real-world conditions, leading to discrepancies and reduced model performance when applied outside the controlled setting.

B. Algorithmic problems

In the realm of AI-related industrial use cases, several algorithmic problems frequently emerge. A critical challenge is the **lack of knowledge** about best practices, especially in scenarios where teams may not include experienced data scientists. Without a deep understanding of advanced algorithms, model selection, and tuning techniques, organizations may struggle to develop effective AI solutions. This knowledge gap can lead to suboptimal model performance and missed opportunities for leveraging AI effectively.

Trustworthiness is another significant concern, encompassing several dimensions such as explainability, security, safety, reliability, transparency, and privacy. AI systems must be able to provide clear explanations for their decisions to gain user trust and meet regulatory requirements. Additionally, ensuring that AI systems are secure from vulnerabilities, safe in their operation, and reliable in their outputs is crucial.

TABLE II: Use case categorization to certain AI domains in the AIMS5.0 project

	Use cases																			
AI domains	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
Computer Vision				x	x	x	x													
Speech and sound processing						x														
Computer Linguistics (NLP/LLMs)		x				x	x				x							x	x	
Robotics	x				x	x	x		x											
Forecasting												x					x			
Discovery				x	x	x				x			x		x			x		
Planning and Scheduling	x			x			x		x	x				x						x
Creation			x											x		x				

Transparency in AI processes and the protection of privacy further contribute to the overall trustworthiness of the system, making it imperative to address these aspects comprehensively.

The phenomenon of **AI overuse**, driven by a fear of missing out (FOMO), also presents challenges. Organizations may rush to adopt AI technologies without fully understanding their implications or without appropriate strategic planning, leading to potential inefficiencies or misaligned solutions. This rush can be driven by the desire to stay competitive but often results in deploying AI solutions that may not be well-suited to the specific needs or contexts. Finally, achieving a **fast-time-to-market** is a common pressure point. The demand to rapidly deploy AI solutions can lead to compromises in model development, testing, and validation processes. While speed is important for competitive advantage, it is crucial to balance it with thoroughness to ensure that the AI systems are robust, reliable, and ready for real-world applications.

C. Deployment problems

Deployment problems in AI projects often revolve around issues related to computing power and MLOps practices. One major challenge is the **lack of computing power**, particularly in edge AI scenarios where resources are constrained. Edge AI involves deploying AI models on devices with limited processing capabilities, such as IoT devices or mobile phones. These constraints can significantly impact the performance of AI systems, requiring careful optimization and resource management to ensure that models run efficiently and effectively in real-time environments.

Another critical issue is the **shortage of expertise in MLOps**—the practices [15] and tools used to manage the lifecycle of machine learning models. MLOps encompasses a range of activities including model deployment, monitoring, scaling, and updating. Organizations that lack a deep understanding of MLOps may struggle with integrating AI models into production environments, leading to operational inefficiencies and difficulties in maintaining and improving model performance over time. Proper, and industry-tailored MLOps practices [16] are essential for ensuring that AI systems are robust, scalable, and continuously aligned with business needs.

D. Other problems

In deploying AI solutions, several problems related to use-case targets, legal considerations, human factors, human-machine cooperation, and ontological consistency often arise.

Use-case target problems involve challenges related to defining and refining the specific objectives and requirements of an AI application. Misalignment between the AI solution and the actual needs of the use case can lead to ineffective or inefficient outcomes. Clearly understanding and articulating the target problem is crucial to ensure that the AI system addresses the right issues and delivers value.

Legal problems are another significant concern. AI deployments must navigate a complex landscape of regulations and compliance issues, including data protection laws, intellectual property rights, and industry-specific regulations. Ensuring that AI systems adhere to legal requirements is essential to avoid potential legal liabilities and to maintain ethical standards. AI-based industrial systems face several challenges related to data privacy, intellectual property, and regulatory compliance. *Data privacy* concerns arise as these systems often collect vast amounts of sensitive information, requiring stringent measures to protect user and company data. *Intellectual property* issues involve ownership of AI-generated innovations and potential violations when AI systems use copyrighted materials. Also, *regulatory compliance* becomes complex due to evolving AI-specific laws, particularly regarding transparency, accountability, and safety standards, which vary by region. Balancing innovation with ethical and legal obligations remains a critical challenge in deploying AI at scale. It is important to note, that the legal issues are not in the central scope of the AIMS AI Toolbox.

Human-centric problems highlight the importance of designing AI systems that consider human needs and values. This includes addressing issues such as user experience, accessibility, and the impact of AI on individuals' jobs and privacy. AI solutions should be designed with a focus on enhancing human well-being and ensuring that they do not inadvertently cause harm or exacerbate existing inequalities. **Human-machine cooperation** problems involve challenges related to integrating AI systems into human workflows and ensuring effective collaboration between humans and machines. This includes designing interfaces and interactions that support seamless cooperation, managing expectations, and addressing any potential disruptions to established work processes.

Finally, **ontology** issues refer to the challenge of ensuring that the concepts and terminology used by AI systems align with those understood by humans. Ontological consistency is critical for effective communication and interpretation of data.

Challenges	Solution
Data collection problems	
Unlabelled data	Best practices in different industrial domains on how to collect data
Unbalanced data	Best practices regarding specific algorithms on how to avoid learning issues in unbalanced datasets
Inadequate data scheme	Best practices and examples on adequate dat schemes
Merging external data sources	Predefined tools to access and collect external data
Data representation problem	Best practices on data collection and data representation
Under-understood data	Examples and tools on data explore and analysis
Data simulation problem	Predefined tools for simulation in different industrial domains
Legal problems	N.A.
Algorithmic problems	
Lack of best practices	Providing industrial-strength best practices by industrial partners.
Trustworthiness	Provide tools to explainability. Best practices to safety, reliablility transparency and privacy.
AI overuse	Guides to different applications emphasising AI usage practices.
Fast time to market	Developing granular, interoperable tools.
Deployment problems	
Lack of computing power	Efficient algorithms, best practices on optimization.
MLOps shortage	Guides on ML Ops methods and practices.
Use-case target problems	Presenting examples for use cases included in AIMS 5.0.
Legal problems	N.A.
Human-centric problems	
Human-machine cooperation	Best practices and tools for efficient and safe human-machine cooperation.
Ontology issues	Providing reference to industrial-strength ontologies and application practices.

TABLE III: How AI Toolbox addresses the challenges. N.A. means that the challenge is not in the scope of the AI Toolbox.

Discrepancies between human and machine understanding can lead to misinterpretations and reduce the effectiveness of the AI system. Addressing these issues requires careful design and alignment of the conceptual frameworks used by both humans and AI.

V. Validation

This section presents two of the 20 use cases addressed by the project: a Reconfigurable Robotic System for Automated Conveyor Feeding, and a use case focused on enhancing the Production-Logistics connection through the use of 3D scans to generate an accurate and up-to-date digital representation of the production sites. It provides a brief overview of the key features of these use cases, emphasizing their AI-related challenges and validating some of the issues discussed in Section 3.

A. Reconfigurable Robotic System for Automated Conveyor Feeding

The use case number 6 focuses on developing a modular and reconfigurable AI-based robotic system to automate the conveyor feeding process for various types of randomly distributed bottles in industries such as manufacturing, food handling, and waste recycling. This system aims to replace manual labor and expensive, inflexible machinery, enhancing efficiency, adaptability, and reducing environmental impact and operational costs. Through deep learning-based perception, adaptive planning, and context-aware task execution, the system will handle diverse bottle shapes, sizes, and distribution patterns, ensuring rapid adaptation to new scenarios and enabling the reuse of robotic components across different operational environments [17] .

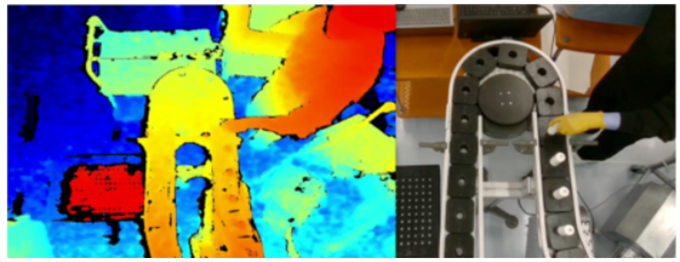

Fig. 2: The depth and the RGB footage of the conveyor belt.

The use case can be divided into two distinctive problem sets: pose estimation of the bottles and motion planning for the robotic arm. The system first estimates the pose of each bottle (e.g., cosmetic bottles in this use case) based on input data, which may include sensory information from cameras. An example RGBD image of the conveyor belt is presented in Figure 2. This estimated pose is then utilized as an input for controlling the robotic arm's motion, ensuring precise handling of the bottles (Figure 3). The robotic arm subsequently manages the placement of bottles onto the conveyor belt and their removal from it, ensuring an efficient and continuous feeding process. By integrating these capabilities, the system can efficiently automate conveyor feeding tasks, eliminating the need for large, complex machinery and enabling flexible, smaller-scale robotic lines that can adapt to various bottle types and production environments.

B. Improving Production-Logistics Connection via 3D Scanning

The use case number 4 aims to enhance the integration between production and logistics at a leading international automotive company by developing an autonomous scanning system that continuously updates digital representations of the company's facilities. This system will utilize 3D scans to create a comprehensive and up-to-date digital image of the production sites, enabling more efficient planning and process optimization. The autonomous scanning device will allow for low-effort re-scanning of the company's production sites, ensuring that the digital data remains accurate and current. The scan data will be leveraged to improve inventory management, streamline assembly lines, and generate updated 2D maps for controlling mobile robotics and transport systems. The digital twin created from these scans will also serve as a training environment for artificial intelligence, allowing the company

(a) The detected bottles using geometric and AI-based algorithms.

(b) The fitted point cloud to the detected bottles.

Fig. 3: Multiple fitting in paralell for the pose estimation.

to accelerate and stabilize automation processes based on real-world data.

The re-scanning process will provide precise information for logistics robots, enabling them to autonomously execute tasks such as exchanging full and empty containers at supply locations. By combining digitalization and automation, the company aims to reduce traffic jams, optimize routing, and minimize unnecessary movements within the production facilities. This integration will ultimately reduce the time needed to plan processes while increasing overall quality. The use case represents a significant step forward in aligning automation with digitalization, creating a symbiotic relationship where digital data improves automated processes, and automation helps generate the data necessary for continuous digital updates.

C. *Challenges Within the Use Cases*

To validate the collected challanges in Section IV regarding Use Case 4 and 6, Table IV shows the severity of the challenges in the specific usecases.

In Use Case 4, there are a couple of severe challenges. The scanning process has no industrial standard best practices to be applied when designing and implementing autonomous scanning methods. Also, for the 3D clouds, there are a couple of formats to use for representation, however, for industrial applications, it is not straightforward to select the proper one. Thrustworthiness is also a severe challenge, since autonomous scanning vechicles and drones needs to be operated safely and securely near production lines. This human-machine interaction needs to be tested and supervised thouroughly. The representation of human concepts in the 3D scans results in various ontology problems, in order to utilize point clouds in industrial applications. Also, the usage of autonomous robots accompanied by artificial intelligence requires close to real simulations to train, which is a current research problem: to simulate sensors with close to real noise is an unresolved problem.

	UC4	UC6
Data collection problems		
Unlabelled data	Medium	Medium
Unbalanced data	Neglectable	Medium
Inadequate data scheme	Neglectable	Neglectable
Merging with external data sources	Neglectable	Neglectable
Data representation problem	Medium	Medium
Under-understood data	Neglectable	Medium
Data simulation problem	Severe	Severe
Legal problems	Neglectable	Neglectable
Algorithmic problems		
Lack of best practices	Severe	Severe
Trustworthiness	Severe	Severe
AI overuse	Neglectable	Medium
Fast time to market	Neglectable	Medium
Deployment problems		
Lack of computing power	Neglectable	Medium
MLOps shortage	Neglectable	Neglectable
Use-case target problems	Neglectable	Neglectable
Legal problems	Neglectable	Neglectable
Human-centric problems		
Human-machine cooperation problems	Severe	Severe
Ontology issues	Severe	Medium

TABLE IV: Severity of challenges in selected use cases. Three levels are defined: Neglectable, Medium, Severe. The validation of the severity is presented in the text.

In Use Case 6, severe challenges are the simulation issues of depth cameras, since most implementations provide noiseless depth images in robotic simualtions. Also, lack of best practices in intelligent, AI-based robotic solutions is a severe challenge, as well, as the human-machine cooperation with robots, which also poses thrustworthiness problems (i.e. safety issues). Thrustworthiness can be pinpointed in the explainability of the LLM models used to understand problems described in natural languages. Among medium problems, we can find unlabelled data (i.e. the 3D point clouds are clearly unlabelled), data representation and understanding issues as the detectable objects are represented only semantically (i.e. a bottle), AI overuse problems for pose estimation where simple geometric based solution can be applied. All algorithms in Use Case 6 typically requires high computing resources, and fast time-to-market is also self explanatory. For understanding scenes in an industrial setting, ontology issues arise since it is required to synchronize machine perception of the environment to humans.

VI. Conclusion

The AIMS5.0 project presents 20 use cases that span a wide range of AI domains, offering a comprehensive perspective on the various applications of AI technologies. These use cases have been systematically categorized, helping to structure and clarify the different ways AI can be deployed across numerous fields. By analyzing these use cases, we were able to extract a detailed taxonomy of challenges that commonly arise in AI adaptation projects. This taxonomy helps provide a clearer understanding of the obstacles organizations face when implementing AI solutions, and it forms a foundation for future improvements.

To ensure the validity of the extracted challenges, the taxonomy was further evaluated using two sample use cases. This validation has demonstrated that the identified challenges are indeed relevant and applicable to real-world scenarios, confirming the robustness of the categorization process.

Looking ahead, there is still much work to be done. Future efforts will focus on refining the list of challenges and their categorization through a deeper, more thorough analysis of the full set of use cases. By gaining a more in-depth understanding of these challenges, we can identify more precise solutions tailored to specific AI domains and applications. Once these solutions are identified, the next step will be to implement them into the AI Toolbox, providing practical tools and strategies to address the common issues faced in AI development. This ongoing work will help improve the effectiveness and efficiency of AI systems, enabling more seamless integration and greater success in a variety of real-world contexts.

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