Adopting Artificial-Intelligence Systems in Manufacturing: A Practitioner Survey on Challenges and Added Value

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Abstract: Artificial-Intelligence Systems (AIS) are reshaping manufacturing by optimizing processes, enhancing efficiency, and reducing costs. Despite this potential, their adoption in practice remains challenging due to limited understanding of technological complexities and practical hurdles. In this study, we present findings of a survey involving 26 manufacturing AIS practitioners, highlighting key challenges, strategies for implementing AIS more effectively, and perceived added value. Data preparation, deployment, operation, and change management were identified as the most critical phases, emphasizing the need for robust data management and scalable, modular (i.e., configurable) solutions. Predictive maintenance, driven by supervised learning, dominates current AIS, aligning with industry goals to reduce downtime and improve productivity. Despite the benefits, broader applications, such as real-time optimization and advanced quality control, seem to remain underutilized. Overall, the study aims to provide insights for both practitioners and researchers, emphasizing the importance of overcoming these barriers to facilitate the adoption of AIS in advanced manufacturing.

1 INTRODUCTION

In the context of Smart Manufacturing (SM), machines, their components, and mobile devices (e.g., cyber-physical systems, their sensors, and robots) consistently generate vast amounts of data (Xiang et al., 2024). This data holds significant value for applications that leverage it to create added value through applying machine-learning (ML) tasks and operations, such as classification using neural networks (Schuh and Scholz, 2019). Here, a variety of working areas arise, for example, recommender systems, visual object recognition, or robotics, offering added value, such as optimizing manufacturing efficiency, saving time, or reducing costs (Monostori et al., 2016; Plathottam et al., 2023). When ML is integrated into a comprehensive system, encompassing data collection, processing, and actionable insights, to deliver such added value, the resulting system is typically called Artificial-Intelligence Systems (AIS) (Chryssolouris et al., 2023).

There is already a variety of AIS solutions for manufacturing in research, for example, in the context of condition monitoring or predictive maintenance (Romanssini et al., 2023; May et al., 2023b; Ross et al., 2024). However, the transfer of such solutions from theory into practice is often impaired, i.e., only a few approaches from science are implemented in manufacturing companies (Schuh et al., 2020; Naz et al., 2024). Nevertheless, to benefit from the advantages of AIS and maintain competitiveness, some companies still have integrated AIS into their manufacturing workflows (Kovič et al., 2024). In research (cf. Section 5), there are currently studies that investigate their adoption, motivating further research and developments by following best practices (Plathottam et al., 2023). Nevertheless, there is limited understanding how manufacturing experts, i.e., practitioners who actively deal with AIS, their development, and integration, consider AIS key challenges and their actual added value as essential incentives to adopt such systems in real-world settings. Consequently, there is a gap in research to expert knowledge and experiences related to the conception, implementation issues, and application of AIS in practice. Unfortunately, in-depth know-how and experiences in AIS are still rare, given the slow adoption of AIS and the novelty of them in manufacturing companies (Schuh et al., 2020).

To explicitly address this gap, we report a survey of 26 European AIS experts from the manufacturing domain in this paper. By relying on the sample size selected, the quantity of insights is balanced with the depth of qualitative analysis considering the limited pool of experienced specialists in this niche field. Based on the insights, **our goal is ⚠ to understand the state of challenges AIS practitioners face in manufacturing including handling strategies, and 📈 to what extent AIS are currently valuable from a real-world perspective**. To the best of our knowledge, there is currently no comparable study (i.e., thematic focus, sample) focusing on AIS expert opinions, in particular from a software-oriented perspective, in this context.

Overall, our contributions are:

- Insights into ⚠ current challenges AIS practitioners face in manufacturing and how they can be addressed.
- Insights into 📈 the extent to which the introduction of AIS in manufacturing is currently valuable.
- A repository containing the questionnaire and all participants responses for replication purposes.[1]

Overall, our study aims to provide a deeper understanding of challenges and the perceived added value of AIS in manufacturing. In this way, we hope to support both researchers and practitioners to ensure more optimized development and adoption processes. Note that some challenges and insights might be transferable to other domains or domain-independent, which, however, emphasizes their relevance even more. Moreover, our results have not yet been validated, which, however, is already planned in future follow-up studies.

The paper is structured as follows: After giving a thematic introduction in Section 1, we provide some further essential information on SM and AIS in Section 2. After that, we go into detail regarding our method applied in Section 3, precisely, we present the study's goal and research question and describe the study design and conduct. In the following Section 4, we provide an overview of the survey results. These results are then discussed in Section 5, structured according to the research questions. Additionally, we describe potential threats to the validity in this section. Finally, after giving an overview of related work in Section 6, we conclude our paper in Section 7.

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2 BACKGROUND

In this section, essential background information are given. Precisely, the theoretical foundation integrates SM as the primary application domain and AIS as the enabling technological framework, exploring their interaction in transforming manufacturing processes.

2.1 Smart Manufacturing

SM is defined as the integration of advanced technologies and data-driven processes to enhance production systems. Examples of such technologies include Internet-of-Things-enabled sensors for real-time monitoring, AI-driven analytics for predictive maintenance, and robotics for automated assembly lines (Kusiak, 2018).

The advanced technologies are intended to enable greater flexibility, efficiency, and quality in production through the networking and integration of machines, plants and systems. It is predicated on the principles of production management, which focus on the design, planning, monitoring, and control of production systems to achieve strategic goals of timeliness, cost efficiency, and quality (i.e., the strategic triangle) (Schuh and Schmidt, 2014). These goals are typically interconnected, whereby optimizing cost efficiency, for example, might lead to streamlined processes that also improve production quality but could potentially increase delivery times if not carefully managed (Bolstorff and Rosenbaum, 2007). To address these challenges, SM incorporates lean-manufacturing principles, aiming to optimize processes and increasing organizational profitability through continuous improvement (Jeziorek, 1994; Scholz, 2022).

Central to SM is the utilization of data, which forms the basis for deriving information, knowledge, and actionable wisdom. Data quality is critical for the successful implementation of ML and other advanced technologies in production systems. It encompasses attributes such as consistency, relevance, and accuracy (Vogelsang and Borg, 2019). The quality of data must meet specific criteria, including interpretability, consistency, relevance, completeness, accessibility, timeliness, editability and freedom of errors. This transformation of traditional manufacturing into a dynamic, technology-driven ecosystem is a response to the modern demands of the manufacturing industry (Schuh et al., 2020).

2.2 Artificial Intelligence Systems

AIS are designed to perform tasks traditionally associated with human intelligence (Scotti, 2019). It is achieved by leveraging advanced computational methods to process large volumes of data and recognize patterns (Mehak et al., 2023). The concept of AI was first introduced by John McCarthy in 1956 and has since evolved into a pivotal technology in the data-intensive landscape of Industry 4.0 (Mijwil and Abttan, 2021). The increasing variability and complexity of process and product data renders traditional manual approaches increasingly impractical, particularly for human operators (Ridzuan and Zainon, 2019). AIS efficiently address these challenges by automating decision-making processes and optimizing operational procedures.

At the core of AIS are ML algorithms, which construct computational models based on training data as opposed to explicit programming (Rebala et al., 2019). Through an iterative process of refinement and adapting their internal architecture during training, these systems are capable of continuously improving their ability to meet specific task objectives (El Naqa and Murphy, 2015). The quality of the training data is of high importance for the attainment of reliable and effective outcomes. The employment of advanced techniques, such as deep learning, for example, by utilizing neural networks inspired by the human brain, enables AIS to analyze complex, high-dimensional data with precision (Mijwil and Abttan, 2021; Schuh et al., 2020). AIS employ a wide range of learning strategies, including supervised learning, unsupervised learning, reinforcement learning, and hybrid strategies (e.g., semi-supervised learning) to adapt to a variety of tasks, for example, classification or regression (Monostori, 2003; Kotsiantis et al., 2007; Ge et al., 2017; May et al., 2023b). The practical impact of AIS is exemplified by their working areas and applications in industrial production, such as the prediction of machine breakdowns or the optimization of process controls (Rowley, 2007).

3 METHOD

Next, we go into detail regarding our method used. More specifically, our goal and research questions are first described, followed by an overview of the study design and the study conduct (cf. Figure 1).

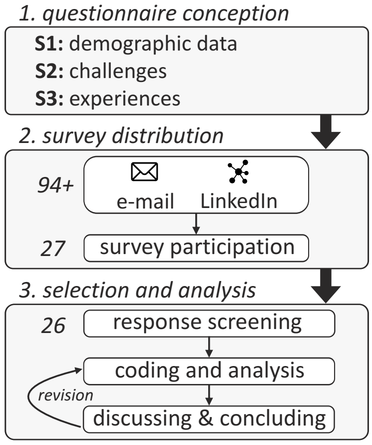

Figure 1: Methodological overview of the survey study; numbers indicate amount of practitioners.

3.1 Goal and Research Questions

The goal of our study was to understand the state of challenges AIS practitioners face in manufacturing, their strategies in handling these and to what extent AIS are currently valuable from a real-world perspective. We defined two Research Questions (RQ) that drive our research:

RQ$_1$ ⚠ **Which challenges do practitioners face in AIS development, and how are they addressed?**
First, our goal was to identify current trends of AIS development challenges. Furthermore, our focus is on insights in handling such challenges effectively as well as open issues to be considered in the future.

RQ$_2$ 📈 **To what extent do AIS implementations currently add value in manufacturing practice according to practitioners' perceptions?**
Second, the aim was to determine whether the introduction of AIS is considered valuable from a practical point of view. In addition, the current incentives for implementing AIS in manufacturing and trends in actual implementation are analyzed.

3.2 Study Design

In the following paragraphs, the design of the survey study is described, focusing on the questionnaire design and structure and the participant selection.

Questionnaire. Our survey was oriented toward established guidelines and quality criteria for conducting surveys with (online) questionnaires in software-engineering research (Molléri et al., 2016).

Generally, the third and fourth author created the draft of the questionnaire (English), followed by several major adaptions by the first author based on discussions with the second, third and forth authors. This step led to an introduction text including a basic consent form for all participants and 11 questions classified into three sections; taking around 10–15 minutes to answers. The other authors contributed as reviewers during a single round of questionnaire evaluation.

The survey was created based on the Microsoft Forms platform. All data was anonymized (i.e., no conclusions about participants or organizations could be drawn) and securely stored on a German server (i.e., considering privacy standards of the European Union).

Section 1 (demographics): The first section refers to the participants' demographic data. Here we asked for the years of experience (Q_1, single choice), the companies' main industries (Q_2, multiple choice), and the practitioners' employment area in their company (Q_3, multiple choice). For Q_2 and Q_3, the practitioners had the opportunity to select an *other* (free text) option. Additionally, for each of the questions, we offered the option to select *prefer not to say*, ensuring a higher degree of privacy if needed.

Section 2 (challenges): In the second section, we focused on the challenges AIS practitioners face in manufacturing. Precisely, first we asked whether AIS are already deployed/implemented in their company as part of their day-to-day business practice (Q_4, 5-level Likert scale on agreement). The following questions referred to the development phases where the greatest challenges occur (Q_5, multiple choice), the key challenges (Q_6, free text), and strategies to overcome the challenges (Q_7, free text).

Section 3 (experiences): In the last section, we asked for own experiences the practitioners made while developing AIS. For reasons of clarity, they had to focus on one AIS that has been implemented most frequently in their company and they have been most involved with. Here, we first asked for the use case of the considered AIS for context purposes (Q_8, single choice). The following question referred to the implemented learning strategies (Q_9, single choice). For Q_8 and Q_9, we additionally offered the option to select *other* (free text). Finally, we focused on the added value of the implemented AIS, involving two questions on the actual reasons for implementing the AIS (Q_{10}, free text) and whether the implementation was worthwhile from an economic point of view challenges (Q_{11}, 5-level Likert scale on agreement).

Participants. We only recruited practitioners who actively work in the field of AIS, for example, including programmers or data scientists who have in-depth experience with AIS in real-world contexts. Precisely, to be able to answer our research questions satisfactorily, we focused solely on AIS practitioners in the manufacturing industry, strictly limiting the sample size to a specific niche field. We did not define any further restrictions.

To reach potential participants, we relied on four channels for distribution, including: 1) the professional network of the authors, 2) a manually created mailing list that included AIS practitioners, 3) the LinkedIn network of the first author, and 4) distributing the survey invitation through participants (i.e., snowballing). Note that all invited people work mainly in one European country, limiting the external validity of our study.

3.3 Conduct

The survey was distributed by the first author on May 22, 2024 based on the defined channels, leading to a total of 89 practitioners reached via mail, five participants recruited via LinkedIn (i.e., a post in the first author's personal network), and an unknown number of practitioners we reached via the other two channels (i.e., professional network, unrestricted number of snowballing iterations). All data was systematically collected in a shared Microsoft forms project (i.e., a total of 27 responses), providing the option to download an Excel spreadsheet with all results. As an initial step, the first author screened all data to check whether all responses have a sufficient data quality (i.e., quality validation and verification), resulting in the exclusion of one participant due to empty response fields. After that, the first author considered a total of 26 participants for the data analysis after a short discussion with the third and forth authors.

Overall, the data analysis was performed by the third and forth authors. Besides the questions which already offered certain categories, we built on open coding and card sorting for all free-text responses (e.g., Q_6, Q_7). More specifically, the third and fourth authors identified recurring patterns and assigned suitable categories, which were reviewed, discussed, and partly revised with/by the first and second authors in two rounds until consensus was reached. An overview of all relevant methodological steps is given in Figure 1.

4 RESULTS

In this section, we describe the results of our survey, structured according to the questionnaire sections.

Table 1: Response overview for demographics (n=26).

question	answers	responses	
Q_1: years of experience	0 to 2	2	8 %
	3 to 5	7	27 %
	6 to 10	7	27 %
	11+	10	38 %
Q_2: main industry	manufacturing	20	42 %
	IT	14	29 %
	research	10	21 %
	logistics	3	6 %
	prefer not to say	1	2 %
Q_3: employment area	research & development	23	89 %
	operations	11	42 %
	quality	3	12 %
	management	2	8 %
	other	2	8 %

Table 2: Response overview for experiences (n=26).

question	answers	responses	
Q_8: use case	*Prediction*		
	failures	13	50 %
	quality parameters	4	15 %
	Assistance		
	parameter control	2	8 %
	scheduling/planning	2	8 %
	other	5	19 %
Q_9: learning strategy	supervised	20	77 %
	not known	3	12 %
	semi-supervised	1	4 %
	unsupervised	1	4 %
	other	1	4 %
Q_{10}: added value	effort/downtime	12	46 %
	system efficiency	11	42 %
	quality	8	31 %
	costs	6	23 %
	decision making	5	19 %
Q_{11}: worthiness	Agree	15	58 %
	Neither agree/disagree	7	27 %
	Strongly agree	4	15 %

4.1 Demographics

Most participants (65%) have at least six years of experience in developing AIS in the manufacturing domain (Q_1), including 38% with more than 11 years and 27% with six to 10 years. The remaining practitioners have between three and five years (27%) or a maximum of two years of experience (8%).

The companies' main industries (Q_2) are quite diverse, ranging from manufacturing (42%) over information technology (29%) and research (21%) to logistics (6%). One participant selected the prefer not to say option. The practitioners' employment areas (Q_3) mainly relate to research & development (89%) and operations (42%). Others include quality (12%), management (8%), and risk analysis (4%). All responses concerning the demographics are given in Table 1. Note that participants could select more than one option for Q_3.

4.2 Challenges

Overall, not surprisingly, 69% of the practitioners agreed or strongly agreed that AIS are currently implemented in their company and part of the day-to-day business practice (Q_4). 27% neither agreed nor disagreed and 4% disagreed. As illustrated in Figure 2 regarding the most challenging phases (Q_5), 73% referred to data preparation. Interestingly, 65% each selected deployment, operation, and change management. Less practitioners selected testing (37%). The least challenging phases seemed to be design (27%) and implementation (23%). Typical challenges (Q_6, cf. Figure 3) mainly relate to data quality and the AIS customization and configuration process (46% each). System adaptability and meeting stakeholder expectations were described by 23% each. Others relate to data handling (19%), system efficiency (15%), change management, and system scalability (12% each).

Strategies for handling such challenges (Q_7) are quite manifold, such as ensuring high data quality (46%), more traditional testing or validation of data quality or functions (42%), using AIS templates as basis for designing new systems (27%), or making more effort in ensuring high data (processing) quality (23%). Two solutions referred more to the requirements-engineering process (12%) and clear stakeholder communication to avoid change management efforts (19%). Others are related to iterative feature integration (12%). Interestingly, some practitioners (12%) stated that it is currently hardly possible to handle common challenges and that experience is key.

4.3 Experiences

As shown in Table 2, the most use cases (Q_8) focused on the prediction of machine or component failures (50%). Less relate to the prediction of quality parameters (15%), assistance of scheduling or planning tasks, or manufacturing parameter control (8% each). Five use cases were only selected once, such as fraud and solvency risk management. Interestingly,

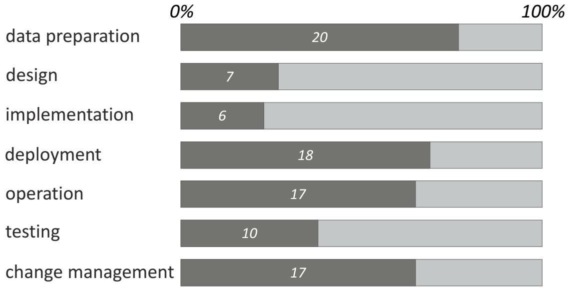

Figure 2: Development phases ranked by their perceived challenge (Q_5); numbers indicate participants who selected each phase (multiple selections possible).

regarding the learning strategies (Q_9), AIS are mainly based on supervised learning (77%). Others are significantly less mentioned, such as unsupervised learning and semi-supervised learning (4% each). 12% of the practitioners stated that they did not exactly know the implemented learning strategies.

We defined five categories related to the incentives for implementing AIS (Q_{10}). The major incentives are the reduction of effort and system downtime (46%), improvements in system efficiency (42%), and the optimization of process quality (31%). Furthermore, some participants referred to saving costs (23%) and enhanced decision making (19%). Not surprisingly, the majority of the participants selected regarding the worthiness of AIS implementations in manufacturing business practice (Q_{11}) that they (strongly) agree (73%). 27% neither agreed nor disagreed; none of the practitioners expressed disagreement.

Looking solely on responses related to the prediction of machine or component failures, such solutions are typically based on supervised learning (85%) and implemented to reduce efforts and downtime (54%) as well as to save costs (39%) and increase system efficiency (31%). Surprisingly, besides 61% who (strongly) agreed that the implementation was worthwhile, 39% neither agreed nor disagreed.

5 DISCUSSION

In the following section, the results are discussed according to the RQ related to ⚠ challenges (RQ_1) and 📈 added value (RQ_2), also providing statements made by the participants in the survey. Precisely, we present 10 relevant insights based on the survey results. Note that these insights might be transferable to other domains or even domain-independent, emphasizing their value.

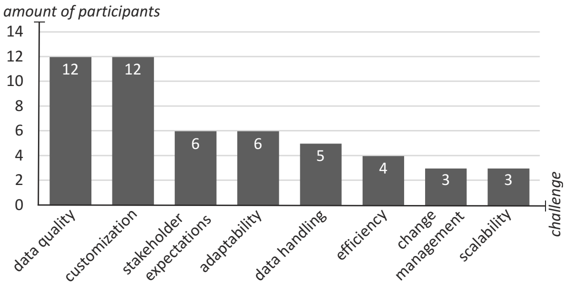

Figure 3: AIS key challenges (Q_6); numbers indicate amount of participants.

5.1 RQ_1: ⚠ Challenges

Our data highlights several insights, including implications and trends, surrounding the challenges practitioners face in AIS development within the manufacturing domain.

Insight$_1$: Data Readiness. Not surprisingly, the prominence of data preparation as a challenging phase (73%) suggests a systemic issue related to data readiness. Overall, this findings is already know and likely stems from fragmented legacy systems and a lack of standardization in data formats within manufacturing environments (Meyer et al., 2018). The implication here is that companies may need to prioritize foundational investments in data management infrastructure before pursuing advanced AIS initiatives that possibly lead to cost-intensive issues, i.e., being aware of the "garbage-in garbage-out" principle (Kilkenny and Robinson, 2018). We argue, that automated, strictly verified tools for data preprocessing, cleaning, and enrichment could become increasingly important to address this bottleneck (Kovalenko et al., 2023), as also stated by one participant:

> *"[...] consider infrastructure requirements early in the system design process [...] apply techniques for data augmentation / synthesis to enrich datasets" (P14)*

Insight$_2$: Post-development issues and change management. Interestingly, equally challenging phases, such as deployment, operation, and change management (65%), indicate persistent difficulties in post-development phases (cf. Figure 2), for example, regarding new manufacturing workflows, varying target environments, or data (source) variability over time (Sorensen et al., 2018). These challenges are likely to be intensified by the known problem of staff resistance to change and the complexity of integrating AIS into existing manufacturing workflows (Arias-Pérez and Vélez-Jaramillo, 2022). This highlights the need for robust change-management strategies and the design of user-centric systems that facilitate smoother transitions. Clear stakeholder communication and iterative system rollouts may provide competitive advantages by addressing such barriers directly (Sorensen et al., 2018). Additionally, IT compliance and meaningful governance structures should be integrated into these strategies, as they play a crucial role in ensuring sustainable deployment and operation, particularly in multi-site settings.

Insight$_3$: Experience Dependency and Stakeholder Integration. Interestingly, some practitioners emphasized that handling post-development and change-management challenges effectively is typically experience-based, pointing to a gap in standardized frameworks or best practices for AIS development and usage:

> *"[...] experience is important and [you need] a bit of luck" (P10)*

We argue that the dependency on individual expertise highlights the need for greater formalization of knowledge sharing (Lepore et al., 2022). This also includes actively involving manufacturing employees as key stakeholders, leveraging their process expertise, and fostering collaboration with AI developers. By qualifying and incentivizing employees, organizations can address concerns about automation, reduce the need for costly recruitment, and may ensure long-term knowledge retention. Empowered employees are better positioned to identify potentials, co-design solutions, and support AIS deployment and data preparation, ensuring alignment with production realities (Jaiswal et al., 2023). We argue that these challenges arise mainly in deployment, operation, and change management (cf. Figure 2) but influence all development stages. Early stakeholder communication and timely user feedback are crucial for adapting AIS to real-world needs and ensuring sustainable organizational development (Sorensen et al., 2018).

Insight$_4$: Integration Across Technological Variability. An essential insight of our study is that several challenges also lie in configuration processes, particularly in adapting models and systems dynamically to varying environments and parameters. Reliable as well as secure configurations and adaptions during deployment and operation are essential but complex, with misconfigurations being a significant bottleneck (López Martínez et al., 2010; Zhang et al., 2022). Recurring issues here may primarily refer to AIS misbehavior (May et al., 2024b), for example, due to the integration of older and newer technologies, which must work together within systems characterized by varying production volumes and fluctuating product mixes. This variability, combined with diverse technological requirements, often leads to unique error patterns that are difficult to detect and learn from due to limited data in low-volume scenarios (Windmann et al., 2024). We emphasize that AIS incidents can also threaten IT security and functional safety (May et al., 2024b). In particular, adversarial attacks (Li et al., 2022) exploiting vulnerabilities that emerged due to misconfigurations may lead to compromised and/or false model outcomes. In this case, AI technology is deliberately misused by malicious actors who want to harm a company. In the worst case, such issues can result in cyber-physical systems' failure and large economic damage (Hasan et al., 2024; Alharthi and Brandão, 2024). Moreover, misbehavior of AIS, for example, related to robotics, may lead to risks to human life (May et al., 2024b).

We argue that the key to managing this complexity is the use of scalable and adaptable AIS, i.e., AIS that securely integrate dynamic configuration mechanisms (Lee et al., 2019; Yavich et al., 2023). For example, techniques such as product-line engineering including feature modeling can help to maintain variants (i.e., configurations) of an AIS family while relying on cost-effective reusability of features Pohl et al. (2005); May et al. (2023a, 2024a). Additionally, we argue that (highly-)configurable systems can be trained on high-volume products with well-documented error patterns and then applied to other products with different characteristics. This transferability allows for more effective handling of technological and production variability, particularly during the critical phases of design, deployment, and operation.

Insight$_5$: Balancing configurability, Feature Prioritization, and Stakeholder Alignment. Surprisingly, we identified that that some practitioners relied on the use of templates as a foundation for AIS systems (27%) and iterative feature integration (12%). These trends reflect a growing trend toward configurable and agile development practices (Schuh et al., 2020; May et al., 2023b). Such approaches enhance flexibility and adaptability, allowing teams to respond to evolving requirements efficiently. Future AIS development may focus on plug-and-play components, no-code/low-code solutions, and iterative refinements to support integration and configuration efforts, while ensuring scalability, alignment with stakeholder needs, and future-proof design (May and Adler, 2024). Early involvement of stakeholder representatives is essential to define scenarios, use cases, and user stories, ensuring a shared understanding of the ”big picture”, even in agile settings (Sorensen et al., 2018). Developers and customers must align their priorities, balancing critical features with long-term benefits, such as lifecycle cost reductions and efficiency improvements. Establishing a Minimum Viable Product (MVP) with a stable scope and scalable design allows for lower-priority features to be considered later without jeopardizing project timelines or budgets (Soldatos, 2024). However, such approaches may also limit general feature richness, as noted by one participant in the context of using restricted templates:

> *“[. . .] however, you restrict the number of possible features which are potentially interesting for customers [leading to a] problem of customer satisfaction” (P7)*

Interestingly, while restricting the number of features is partly perceived as a limitation, other practitioners explicitly utilize such limitations to reduce development effort and focus on the stakeholders’ actual needs, for example, in the context of basic features versus attractive features (Brandt and Scharioth, 1998; Chitturi et al., 2008):

> *“limiting [. . .] function[s] as much as possible to fit the need of the stakeholders” (P15)*

Insight$_6$: Integrative Development Strategies. We found several relationships between challenges and strategies. For example, the frequent mention of data quality issues obviously aligns with the widespread effort to improve data quality, its validation, and processing. Similarly, the acknowledgment of change-management difficulties corresponds to a focus on clear stakeholder communication. At best, several strategies are applied in a connected way (i.e., workflow) as suggested by one participant:

> *“[1.] continuous communication and feedback loops between development team and operator/user who works with the results. [2.] trying to fix wrong MLS decisions through fast data rework. [3.] visual inspection of results.” (P19)*

We note that although our findings may be relevant and useful in certain contexts, not all challenges and strategies are equally important in every context. So, some challenges and strategies might be more relevant to specific subdomains depending the the unique settings in every company, for example, technological variability in the context of software or hardware in drilling or sawing AIS (e.g., condition monitoring, predictive maintenance). Here, practitioners have to prioritize according to the specific requirements of use cases and sometimes have to deal with contradictory recommendations.

RQ$_1$: ⚠ Challenges

Key challenges include poor data quality, persistent post-development and change-management hurdles, and the complexity of configuring AIS for dynamic and variable environments in a reliable and secure manner. Associated solution strategies should focus on enhancing data readiness, adopting modular development practices for greater flexibility, and implementing robust change-management approaches. Nonetheless, the reliance on individual expertise underscores the need for standardized frameworks/best practices to ensure consistent and scalable solutions.

5.2 RQ$_2$: 📈 Added Value

Insight$_7$: AIS Value and Optimization. Not surprisingly, the perceived value of AIS implementations is widely positive. This finding reflects the significant impact of AIS on improving operational efficiency, reducing system downtime, and optimizing processes. The dominant use case for AIS is the prediction of machine or component failures (50%), highlighting the importance of predictive maintenance in minimizing unplanned downtime and ensuring manufacturing continuity (May et al., 2023b). Beyond predictive maintenance, other use cases such as quality parameter prediction, scheduling assistance, and manufacturing parameter control are less prevalent. However, these applications have a profound impact on manufacturing as they influence decision-making processes critical to production and product quality measurement, as well as production planning. For example, such AIS can optimize machine utilization, sequencing, and material disposition, transforming how production is managed (Soldatos, 2024). Nevertheless, we argue that expanding AIS into strategic and operational domains, such as advanced quality control and real-time process optimization, offers significant potential to enhance their value across a wide range of manufacturing functions.

Insight$_8$: Learning Strategy Dependence. The dependency on supervised learning (77%) indicates a preference for structured and well-defined approaches in manufacturing settings (Schuh et al., 2020; May et al., 2023b). However, the limited mention of unsupervised and semi-supervised learning implies a missed opportunity to explore these methods, which may be particularly useful in identifying hidden patterns or optimizing processes with less labeled data (Qi and Luo, 2022). Encouraging experimentation with diverse learning strategies could broaden the scope of AIS and enhance their adaptability to more complex manufacturing scenarios.

Insight$_9$: Adoption Incentives. The leading incentives for AIS adoption, including reducing effort and downtime (46%), improving system efficiency (42%), and optimizing quality (31%), align with core manufacturing goals of enhancing productivity and minimizing costs which are closely related to the strategic triangle (Schuh and Schmidt, 2014). Not surprisingly, the motivations are often mutually dependent, highlighted by one participant's statement:

> *"Improved accuracy in predicting quality parameters and machine failures, resulting in reduced downtime and maintenance costs, optimized manufacturing processes and improved decision-making capabilities" (P9)*

Insight$_{10}$: Value Perception and Acceptance. Surprisingly, The fact that 23% of the respondents neither agreed nor disagreed with the statement that the introduction of AIS is worthwhile makes it clear that it may be difficult to demonstrate a concrete benefit from the investment. This could be, for example, due to fluctuations in implementation success or the lack of clear benchmarks to measure the contribution of AIS in different contexts. Starting with an MVP that already demonstrates clear value helps practitioners build confidence and support for further investments (Soldatos, 2024). Overall, the results indicate a positive but quite inconsistent acceptance of AIS in manufacturing. While the value of the technology for predictive maintenance and operational efficiency is widely recognized (Romanssini et al., 2023), its wider adoption continues to be hampered by technical and organizational barriers. We believe that future efforts should focus on removing these barriers, in particular by diversifying use cases and improving the reusability, configurability, and scalability of AIS solutions. Here, again, we recommend to consider techniques such as on product-line engineering (Pohl et al., 2005; Uysal and Mergen, 2021). In addition, clearer cost-benefit analysis and success metrics could help confirm the return on AIS investment for practitioners who are still unsure. Furthermore, a careful assessment of trade-offs in applying certain recommendations over others could enhance the decision-making process for practitioners.

RQ$_2$: Added Value

AIS are widely perceived as valuable, with benefits like reducing downtime, improving efficiency, and optimizing quality. The primary application seems to be predictive maintenance, though broader use cases remain underutilized. Despite positive perceptions, inconsistent outcomes, challenges in demonstrating ROI, reusability, and scalability may limit wider adoption.

5.3 Threats to Validity

There are several limitations, i.e., threats to validity, in our work, which are described in the following. In detail, we focus on internal (i.e., extent to which causal conclusions can be drawn), external validity (i.e., generalizability of findings), and construct validity (i.e., how variables are measured).

Internal Validity. Overall, we might misinterpret certain free-text responses from participants. However, we intentionally included multiple researchers to ensure a balanced analysis. Another threat to the internal validity of our study is the selection bias of participants, as they were mainly recruited through LinkedIn and the authors' professional networks, which could bias our sample of AIS practitioners. To reduce this bias, we asked AIS practitioners to share the survey with other practitioners. Another issue is response bias, as respondents may give socially desirable answers, especially on sensitive AIS topics such as actual added value. To address this, we have provided anonymity and a prefer not to say options.

External Validity. Our study's findings may not be completely generalizable across all AIS professionals, potentially reflecting regional influences. To address this issue, we employed multiple distribution channels and encouraged participants to share the survey. Considering that a larger sample (>26 participants) and a higher return rate (>30%) could enhance generalization, we argue that our findings are still valuable. Further, 65% of the participants bring at least six years of practical experience in AIS development, enhancing our confidence in the results. We note that our results and findings (i.e., insights) have not yet been evaluated (i.e., validated), for examples based on comparing related studies. However, a validation of our study is already planned in the context of future research, in particular related to configuration issues in manufacturing AIS.

Construct Validity. Our questionnaire, which includes concepts like AIS use cases and learning strategies, might have been misunderstood. To mitigate this, we based questions on established terms and definitions of the AIS community, ensuring that these are familiar to experts. While Likert scales and closed-ended questions might miss some nuances, we additionally included open-ended questions for more detailed insights. We also screened responses for outliers in data and response times, resulting in the exclusion of one participant.

6 RELATED WORK

AIS in manufacturing, their challenges, and associated strategies have been addressed in various overview contexts, for example, concerning predictive maintenance, quality control, or operational efficiency. Studies like those by Nelson et al. (2023) systematically reviewed AI applications in manufacturing, discussing societal implications, such as workforce impact and security concerns. Additionally, Kovalenko et al. (2023) discussed the integration of AI into manufacturing systems, emphasizing the necessity for seamless human-AI collaboration and robust data infrastructure. Furthermore, Espina-Romero et al. (2024) did a bibliometric analysis regarding the challenges and opportunities in AI implementation within manufacturing.

Empirical studies focusing on the perspectives of manufacturing practitioners, i.e., work that is closely related to our study, remain rather limited although they offer valuable insights into the real-world implementation and issues of AIS. Culot et al. (2020) reported a delphi study with 76 participants from practice and research to assess most common expectations and issues of Industry 4.0 in manufacturing with AI identified as one essential pillar with associated potentials. Demlehner et al. (2021) conducted a delphi study with 39 practitioners to identify valuable use cases of AIS in car manufacturing with high added value. Kutz et al. (2022) focused on the success factors and barriers of AIS implementation based on ten semi-structured interviews, pointing toward challenges regarding data, operational processes, and stakeholder engagement.

The related work, while clearly underscoring the importance of understanding practitioner experiences, provides somewhat overlapping insights, however, with an other thematic focus or target group. So, unlike prior work that predominantly focused on technical advancements, use cases, or more general challenges, our work explores not only the challenges manufacturing experts face but also their strategies for overcoming them. Additionally, we asked for the practical added value of AIS from a business perspective, providing unique insights into whether AIS implementations are perceived as worthwhile in current manufacturing practices. This practitioner-centered approach offers a novel, additional perspective, complementing existing literature and addressing the gap in understanding the practical realities of AIS adoption in the manufacturing industry.

7 CONCLUSION

In this paper, we explored the practical challenges and perceived value of implementing AIS in the SM industry through a survey of experienced practitioners. Our findings highlight that while current AIS offer significant potential in areas such as predictive maintenance and efficiency optimization, several barriers hinder their wider adoption. Key challenges include data quality issues, complex integration processes, configurability and scalability complexities, and organizational resistance to change. Despite these hurdles, the survey indicates a positive perception of AIS, with most participants agreeing on their economic and operational benefits. However, the need for standardized development frameworks, clearer benchmarks for success, and diversified (i.e., highly-configurable) AIS beyond predictive maintenance remains critical for further advancement. Note that our findings are currently not validated, emphasizing the need for further follow-up case studies and comparative studies based on secondary data sources. Nevertheless, we emphasize that our results are a highly valuable first steps towards a better understanding of AIS, their transferability from theory into practice, actual business needs, and success in real-world manufacturing environments.

Moreover, future research and development should focus on addressing our identified barriers. Here, we strongly recommend to focus on prioritizing modular, configurable, and scalable AIS solutions, enhancing data-management practices, and fostering industry-wide collaboration to share best practices. We believe, by tackling these challenges, the manufacturing industry can further realize the transformative potential of AIS, driving innovation, efficiency, and competitiveness in modern manufacturing.

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