Understanding Stakeholder Requirements for Digital Twins In Manufacturing Maintenance

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UNDERSTANDING STAKEHOLDER REQUIREMENTS FOR DIGITAL TWINS IN MANUFACTURING MAINTENANCE

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ABSTRACT

Digital twin has emerged as a key technology in the era of smart manufacturing and holds significant potential for maintenance. However, gaps remain in understanding stakeholders' requirements and how this technology support maintenance-related decisions. This paper aims to identify stakeholders' requirements for digital twin implementation and examine the role of digital twin in supporting maintenance actions and decision-making process. Semi-structured interviews and a workshop involving manufacturing practitioners and researchers were conducted to attain these goals. Furthermore, an in-depth qualitative analysis of the interview data was carried out. The results shed light on the current state of digital twin adoption, implementation challenges, requirements, supported decisions and actions, and future demand characteristics. By integrating the findings from the literature review and interview analysis, this study outlines the requirements for the digital twins as expressed by industry stakeholders that will be used and tested in the drone factory digital twin model.

1 INTRODUCTION

The advent of Industry 4.0 technology has brought a new era of smart manufacturing, with digital twins emerging as a significant development. Digital twins, virtual replicas of physical systems that are synchronized in real time, facilitate the simulation and analysis of performance, behavior, and potential outcomes using real-time data (Segovia and Garcia-Alfaro 2022). As digital twin gains attraction, it becomes crucial to comprehend the objectives, requirements, characteristics and challenges associated with their integration into manufacturing processes, specifically how they can support maintenance actions and decisions.

While digital twin shows promise in the realm of manufacturing, especially in smart maintenance, there remains a gap in understanding the exact needs of stakeholders and how these technologies can assist in maintenance-related decision-making (Aivaliotis et al. 2019). Stakeholders also have challenges how digital twins can support their work. This gap has become a significant barrier to the practical implementation of digital twins in industry (Rasheed et al. 2020).

Our study endeavors to bridge this gap by investigating user needs for digital twin applications in manufacturing. This paper aims to identify the requirements for implementing digital twins in manufacturing, focusing on maintenance decision-making. We also sought to gain insight into the current challenges and opportunities associated with implementing digital twins, as well as the characteristics required for digital twins to match future needs and expectations of manufacturing companies.

Our research methodology encompasses a literature review, semi-structured interviews with industry experts and professionals experienced in digital twin technology or maintenance, and a workshop with researchers from the academic discipline of production systems. We employed a qualitative research approach to delve into the interview responses and workshop's various dimensions (Gioia et al. 2013). Interviewees provided valuable insights into the goals and key requirements for implementing digital twins in manufacturing, and how digital twins can support decision making and analysis. The industry experts, especially in the maintenance field, provided details about the current status of digital twin implementation and elaborated on the importance and potential of digital twins in this field.

In Section 2, literature reviews on digital twins decision support and challenges in maintenance are shown, followed by interviews and qualitative analysis method in Section 3. In Section 4, by synthesizing the findings, we present a comprehensive overview of stakeholder requirements for digital twin implementation. We conclude the paper by applying these insights to our drone factory digital twin model and proposing a road map for future experimentation.

2 STATE-OF-THE-ART

2.1 General Characteristics of a Digital Twin

A digital twin is an executable virtual model of a physical thing or system, aiming to use big data and machine learning for predictions and individualization (Schleich et al. 2017). Although the terms Digital Model, Digital Shadow, and Digital Twin are often used interchangeably, their data integration towards physical, digital, and cyber layers varies. A *Digital Model* lacks a real-time link to a physical object, a *Digital Shadow* involves one-way real-time data communication, while a *Digital Twin* features bi-directional real-time data communication (Aheleroff et al. 2021).

Digital twins exhibit characteristics such as robust connectivity, communication capabilities, simulation, software programmability, modularity, and adaptability, making them suitable for diverse applications across various domains (Minerva et al. 2020). They can accurately simulate and predict physical systems' behavior under specific scenarios (Gao et al. 2019), enabling functional distribution across disparate processing environments (Minerva et al. 2020). Digital twins' strong modularized capabilities allow for the design and customization of products and production modules (Rosen et al. 2015), interaction with virtual reality, and real-time mapping (Yao et al. 2023). Their inherent software programmability facilitates seamless integration with programming codes (Burghardt et al. 2020). These versatile and adaptable attributes position digital twins to contribute to numerous applications within smart manufacturing and beyond.

2.2 Digital Twin for Decision Support in Maintenance

The application of digital twins in manufacturing is rapidly growing, offering significant potential to improve efficiency, reduce costs, and increase quality across various applications such as predictive maintenance, quality control, production optimization, and supply chain management (Cimino et al. 2019). Digital twin technology enhances the production process by monitoring and optimizing it through the virtualization of manufacturing machines and system architecture development (Angrish et al. 2017), while monitoring various production aspects (Botkina et al. 2018; Liu et al. 2019; Sujová et al. 2019). Primarily supporting maintenance decision-making by creating virtual replicas of physical assets (Rojek et al. 2020), digital twins help optimize maintenance decisions through the analysis of collected data, providing early warnings of potential equipment failures, and simulating different maintenance scenarios (Errandonea et al. 2020). Applied in preventive maintenance strategies, digital twins predict asset states (Neto et al. 2021), helping eliminate unnecessary maintenance activities and extending time intervals between them. Overall, digital twin technology has the potential to revolutionize the maintenance work by providing a virtual platform for real-time monitoring, analysis, and simulation of physical assets, leading to more informed decision-making and optimization of manufacturing process. These real-time capabilities can be seen as part of the requirements of smart factories (Mohammed M. et al. 2018), which can transform how maintenance is performed in the context of the industry 4.0.

2.3 Challenges in Implementing Digital Twin in Manufacturing Maintenance

Three primary challenges need to be addressed for the successful application of digital twins across industries: organizational, methodological, and technical (Kober et al. 2022). Organizational challenges encompass issues related to company employees at various hierarchical levels and organizational structure. Common organizational challenges include culture (e.g., difficulty transitioning from gut-feeling decisions to data-driven ones), costs (e.g., high initial investments), and fear (e.g., employees' concerns about job loss due to advanced technology) (Kober et al. 2022). Methodological challenges stem from a lack of clarity on implementation benefits, communication issues, unclear business objectives, and inefficient model development. Technical challenges primarily involve limited digitalization expertise and knowledge of communication and information technologies for complex systems. These challenges may include standardization (e.g., harmonizing interfaces, protocols, and data flows), data acquisition from legacy machines, interoperability (e.g., integrating different data formats), and inadequate user interfaces (Kober et al. 2022). It is possible to find technical challenges as the ones that repeat the most in different projects, being system integration and security issues the most repeated through different articles (Perno et al. 2022). For maintenance, all three challenge types persist, with technical challenges such as data quality and availability being particularly critical. The need to improve data availability emerges when integrating information from disparate sources to enable the evolution of basic maintenance strategies into prescriptive maintenance strategies (Errandonea et al. 2020). While these challenges represent barriers for implementation, there are also enablers that make this possible, which help to identify digital twin requirements. For instance, the use of IoT as an enabler can overcome data transmission issues (Perno et al. 2022), making it an essential requirement.

3 METHODOLOGY

To map stakeholders' requirements, we conducted several individual interviews and a workshop with practitioners and researchers, and then analyzed the interview data using a qualitative method.

3.1 Interviewee Pool

A total of six industry stakeholders from different Swedish industry companies were selected for individual interviews based on their expertise and experience in manufacturing or maintenance, while an additional twenty academic researchers participated in a workshop. The interviewees represented diverse backgrounds and experiences, including roles as technician, industrial intern, former researcher, team leader, management personnel, and CEO in the manufacturing field. Some interviewees possessed a conceptual understanding of digital twins, while others had practical experience with the technology. However, their experiences with digital twins varied in terms of complexity and application, ranging from simple simulation models to digital shadows. The researchers in workshop were mainly from industrial engineering field, providing diverse and in-depth perspectives on digital twins. Participants were encouraged to share their insights and experiences, with data collected through semi-structured interviews and workshop discussion.

3.2 Interview Design

The research design centered around a semi-structured interview to gather insights from industry experts about their experiences, perspectives, and expectations regarding the implementation and use of digital twins in manufacturing, particularly in the context of maintenance. First, the interview assessed participants' backgrounds and experiences with digital twins to establish their familiarity with the technology and comprehend their personal experiences in using digital twins for industrial projects. It also examined the specific purposes, challenges, and barriers in implementing digital twins. The interview then delved into the general aspects of digital twins in manufacturing, discussing the types of analysis, actions, or decisions they can support, implementation requirements, and scalability and adaptability to changing processes. Finally, participants' opinions on the most suitable architecture for their projects, how digital twins support maintenance decision-making, and future demand in the maintenance context were explored.

3.3 Workshop Design

The workshop was specifically targeted towards researchers in industrial engineering with varying levels of experience in digital twin applications and a deep understanding of the concept. The workshop was structured around four main topics: What are the challenges and limitations that constrains the digital twin implementation in scale? What are the goals and key requirements for implementing digital twins in manufacturing? How do digital twins support operational actions (e.g. maintenance, production services) and decision making? What characteristics and functionalities does a digital twin need to match the future manufacturing demands? Researchers are encouraged to share their unique viewpoints and have thorough discussions about each research topic. Given the divergence in research orientations within their respective disciplines, the outcomes derived are inherently varied.

3.4 Data Analysis

In this study, we utilized thematic analysis to examine the collected interview responses. Thematic analysis is a qualitative research method that concentrates on identifying, analyzing, and interpreting patterns of meaning, or themes, within the data (Braun and Clarke 2006). Qualitative research is a methodological approach aimed at gathering descriptive data to investigate and understand complex phenomena or experiences from the perspective of the individuals involved (Green 2014). Our approach adhered to Braun and Clarke's six-phase thematic analysis process (Braun and Clarke 2006). First, we meticulously read the interview transcriptions, followed by data reduction to generate an initial code, which was subsequently consolidated into an overarching theme that encapsulated the information. Next, we pinpointed data that supported the theme and established an overall theoretical perspective. Ultimately, we refined the theme definition and conducted a comprehensive analysis, culminating in a detailed presentation of our findings.

To analyze the workshop responses, we first transcribed and summarized the answers, subsequently categorizing them based on emergent themes. We employed Gioia's method to systematically derive first and second-order structural codes from the workshop data (Gioia et al. 2013). This approach enabled us to recognize commonalities among the responses, identify key themes, and establish aggregate dimensions to comprehend the relationships between distinct themes or categories. Consequently, we obtained a data structure for each workshop question consisting of three layers: basic codes, categories, and aggregate dimensions. The qualitative data analysis method is shown in Figure 1.

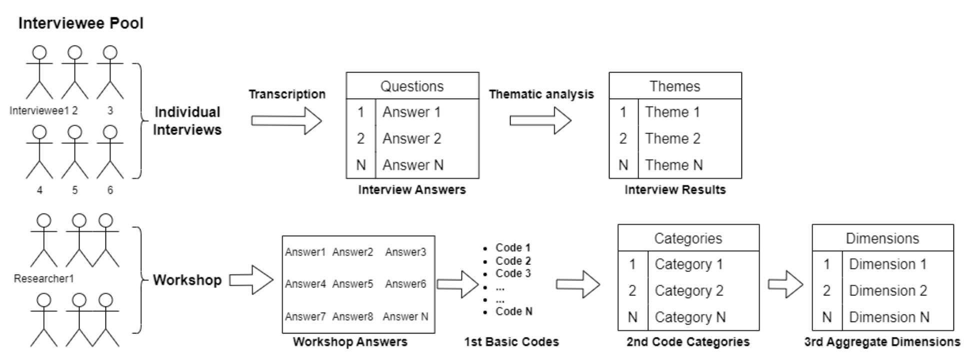

Figure 1: Methodology for qualitative data analysis.

3.5 Demonstrator of Drone Factory

The Stena Industry Innovation Lab (SII-Lab), a national test bed for industrial digitization, is situated at Lindholmen, Chalmers. It houses a drone assembly production line with five branch-assembly stations and a main final assembly station (Chávez et al. 2022). Each station features a designated maintenance workspace, and in-house logistics facilitate subcontractor transportation. A digital twin model, created in Tecnomatix Plant Simulation (Siemens 2023), simulates the production line based on a conceptual model (see Figure 2) derived from a thorough analysis of production factors. This digital twin accurately replicates the real system's behavior and assesses its performance under various scenarios. To maintain precision and reliability, relevant data and parameters, such as processing time, are incorporated. Several experiments have been conducted, including bottleneck and inefficiency identification, with further experimentation done upon user requirement identification in the future.

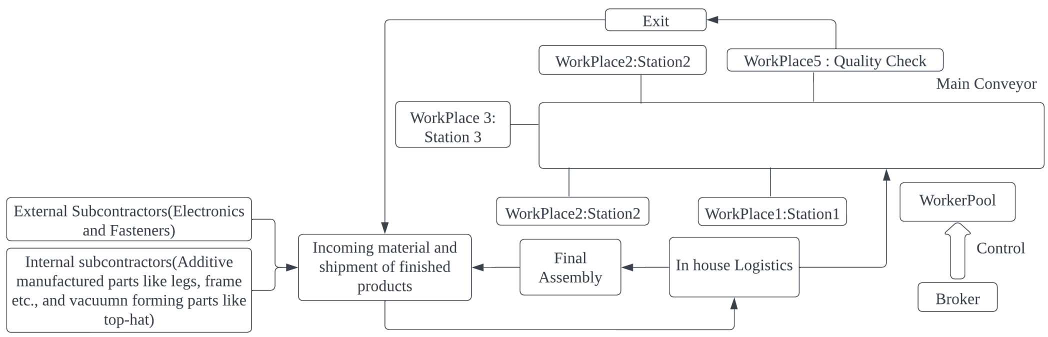

Figure 2: Conceptual model of drone factory production line.

4 RESULTS

4.1 Interview Result

The results of our study indicate that the adoption of digital twins is still at an early stage, with the majority of respondents reporting the use of digital twins only at the digital shadow stage. Moreover, a senior maintenance practitioner has not yet utilized digital twin models, despite his awareness of the concept from his own or his colleagues' projects. These findings suggest that, despite of the digital twin concept developing for a long time, its implementation rate remains relatively low, particularly for more advanced digital twin models such as digital control and digital proxy. Further efforts are needed to enhance the awareness and understanding of the benefits and applications of digital twins, as well as to develop more sophisticated models to meet the evolving needs of various industries.

As for the types of analysis, actions, or decisions digital twins can assist with, several key themes emerged. Interviewees highlighted the use of digital twins in pre-planning phases, optimizing factory systems, simulating various stages of the production process, predictive maintenance, condition monitoring, and decision-making processes. They also mentioned the potential for digital twins to improve planning through 3D visualization, enhance early equipment management, and enable more effective route planning at facility and asset levels. Overall, the interviewees emphasized the versatility of digital twins in addressing various aspects of manufacturing, from production planning and maintenance to decision-making and educational applications, ultimately contributing to more efficient and effective production processes.

Several key requirements for implementation of digital twins in the manufacturing industry are shown here. Accurate and reliable data emerged as a common theme in all responses, highlighting its critical role as the foundation for effective decision-making. This includes ensuring data quality, accuracy, and availability,

Table 1: Stakeholders individual requirement for digital twins.

Interviewee	Requirement
1 Technician	Widespread adoption, accurate data, in-depth production knowledge
2 Management Personnel	Clear business case, strategic vision
3 Industrial Intern	Reliable data collection, data handling, visible platforms
4 Team Leader	Cybersecurity, real-time connectivity, low latency, transparency
5 Former Researcher	Data quality, accuracy, availability, accessibility for stakeholders
6 CEO	Cost-effective, accurate model and organizational processes for updates

as well as appropriate processing, filtering, and pre-processing. Another crucial aspect emphasized by the interviewees is the importance of human expertise in maintaining, understanding, and verifying the results of the digital twin, underscoring the value of expert involvement in the process. In addition, the interviewees emphasized the need for a clear business case, long-term strategic vision, and investment in resources and technology to address industry-wide challenges such as low digital maturity, limited connectivity between machines, and information system integration. Organizational challenges require the establishment of processes to ensure regular updates, particularly when changes are made to the physical systems they represent. A summary of each interviewee's individual requirements can be found in the Table 1. In future research, we will differentiate their requirements per person and conduct a more in-depth analysis based on each individual and in relation to their role and experience. In summary, successful implementation of digital twins in the manufacturing industry requires a combination of accurate data, human expertise, organizational processes, strategic vision, and investment in technology.

A shared idea among the interviewees is the importance of simulation and predictive maintenance in supporting decision-making in today's industry. They emphasized that digital twins enable companies to test various maintenance strategies and scenarios without facing real-life consequences, allowing for better planning and optimization of maintenance approaches. Additionally, digital twins can predict machine failures based on historical data and relevant parameters, enabling companies to prioritize maintenance tasks and focus on crucial machines.

The unique ideas presented by the interviewees showcase the versatility of digital twins in maintenance decision-making. One interviewee mentioned the value of digital twins as a digital library, providing maintenance technicians with easy access to information on tools, equipment, and designs. Another interviewee discussed the potential of digital twins to help companies transition from reactive to proactive, predictive, and ultimately autonomous maintenance strategies. Additionally, the short-term and long-term benefits of digital twins were emphasized, with short-term benefits primarily focused on planning and preparation, and long-term benefits centered around strategic decision-making and optimization of maintenance strategies. This analysis demonstrates the diverse applications of digital twins in supporting various aspects of maintenance decision-making, making them an invaluable asset in modern industry.

4.2 Workshop Result

In this section, four data structures from the analysis of the workshop responses and the most representative instances of the data are shown.

4.2.1 Challenges and Limitations

Figure 3 presents the data structure summarizing the academic workshop on challenges and limitations of implementing digital twins. Technical challenges, such as data-related issues, computational power demands, software development and maintenance costs, and synchronization difficulties, pose significant barriers to large-scale digital twin implementation in manufacturing. At a system of systems level, they can lead to conflicts between comprised data, services, and models (Michael et al. 2022), and they can be particularly prohibitive for smaller enterprises. Organizational and human factors are critical for successful digital twin adoption. Decision-making challenges, such as identifying use cases and securing management commitment, can impact digital twin effectiveness in operations. Human factor challenges, including fostering trust in technology, addressing skill gaps, and managing human unpredictability, can influence the integration and effectiveness of digital twin technology. Overcoming these challenges is crucial to ensure that digital twins enhance operational efficiency and productivity.

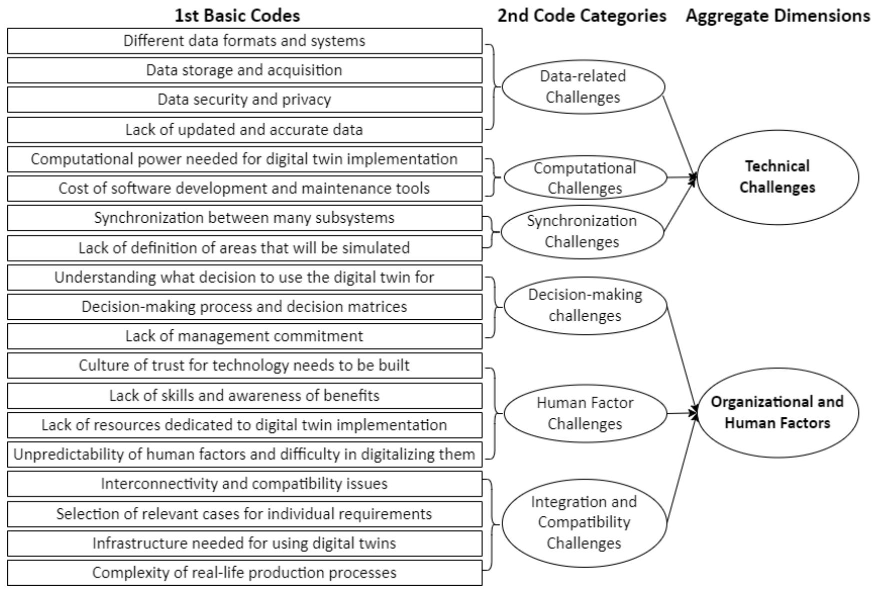

Figure 3: Data structure for workshop question1, challenges and limitations.

4.2.2 Goals and Requirements

Figure 4 presents the goals and key requirements for digital twin implementation in manufacturing, as identified by respondents. The first column lists the goals, while the second column enumerates the requirements corresponding to the attainment of these objectives. Digital transformation and process improvement encompass digital control, enhanced visibility, and real-time monitoring, necessitating IoT devices, 3D modeling, and instantaneous data processing. Agility and adaptability mandate digital maturity, an entrepreneurial mindset, data interoperability, and synchronization protocols. Collaboration and communication dimension involves interdepartmental cooperation, comprehension of real-time system dynamics, and stakeholder trust, achievable through customizable interfaces, robust business models, dependable data, and skilled personnel. To achieve enhanced decision support and better visibility of production processes, seamless data interoperability and digital maturity are crucial for decision support and planning enhancement. User experience and adoption targets include a positive work atmosphere, maximized understanding of system dynamics, and accessible interfaces, requiring simplified designs, intuitive support functions, and reliable synchronization protocols. Reasonable implementation timelines and a defined data implementation vision promote successful digital twin integration in manufacturing contexts.

4.2.3 Decision Support

Figure 5 illustrates participants' perceptions on how digital twins can support manufacturing operations and decision-making, organized into four aggregate dimensions: maintenance planning and forecasting, decision-making support, collaboration and training, and root cause analysis. They believe digital twin plays a pivotal role in maintenance support by facilitating predictive planning, visual preventive measures, early problem detection, maintenance opportunity window identification, and anticipation of needs, ultimately

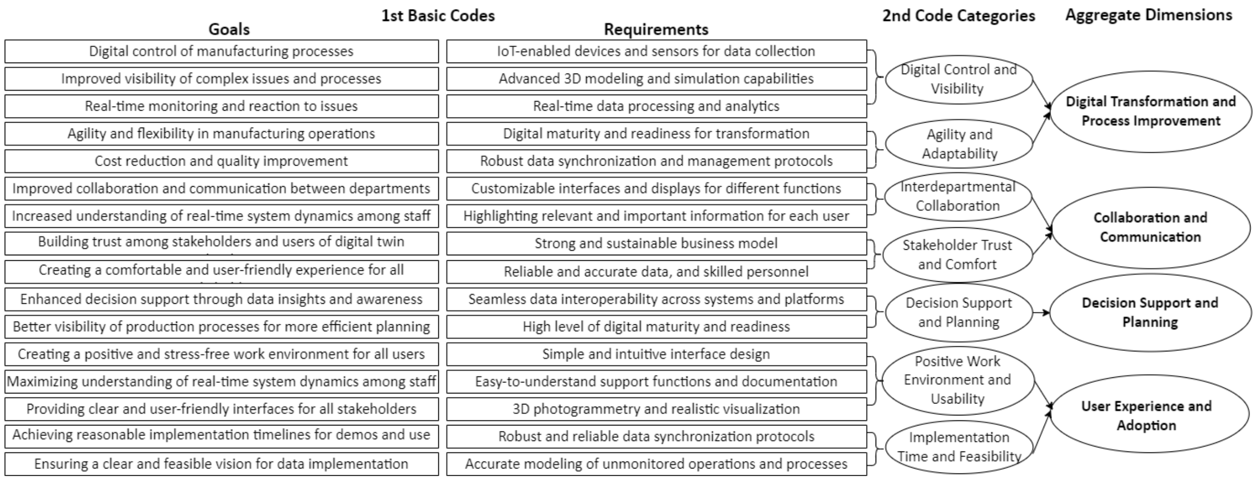

Figure 4: Data structure for workshop question2, goals & requirements.

leading to efficient strategies, minimized downtime, and reduced costs. It could contribute to real-time operations support, decision-making, collaboration, training, scheduling, and automation. It enables real-time monitoring and control such that, through machine virtualization, improves the production process (Angrish et al. 2017). It also provides action recommendations, and deliver live alerts for accelerated response times. Moreover, it can support data-driven decision-making, precise predictions, and optimization algorithms, while promoting collaboration and communication between departments and remote collaborators. Furthermore, digital twin could serve as valuable training tools for maintenance staff and assist in production planning, maintenance work scheduling, and policy selection. Digital twin also bolsters problem-solving and analysis through accurate fault detection, root cause analysis, risk prioritization, and bottleneck identification. It enhances automation and optimization by enabling automated decision-making, testing of alternative scenarios through simulation (Errandonea et al. 2020), and improving system resilience.

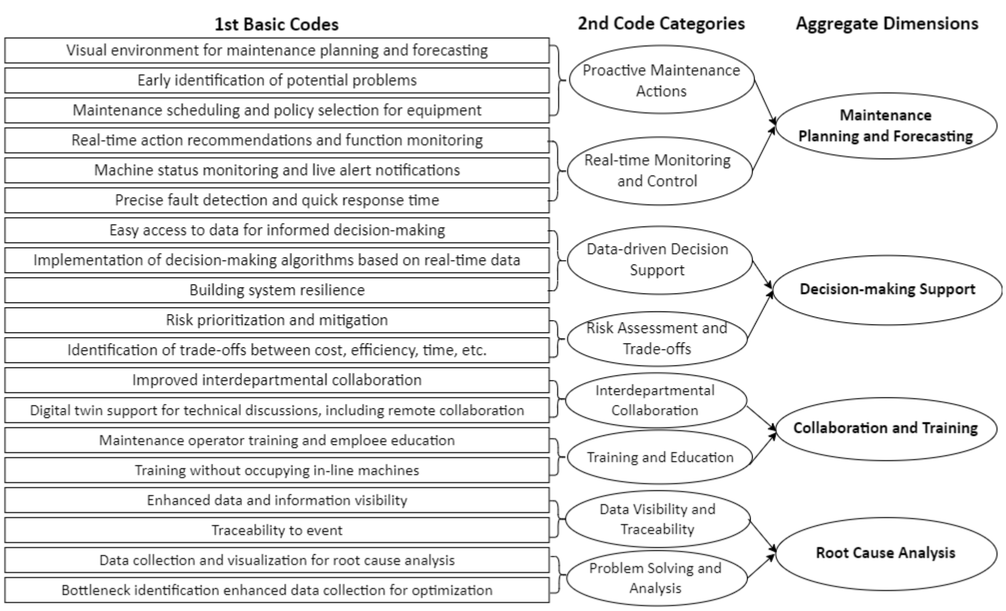

Figure 5: Data structure for workshop question3, decision support.

4.2.4 Characteristics and Functionalities for Future Demand

Figure 6 emphasizes the essential characteristics and functionalities that digital twins need to embody in order to address future manufacturing demand. Modularity is a vital feature that enables customization and scalability, which is already stated in the literature (Rosen et al. 2015), along with seamless integration with external systems, adaptable communication protocols, and compliance with diverse industry standards and regulations. Robust data management and processing capabilities, encompassing efficient storage, real-time analytics, predictive modeling, machine learning, AI-driven algorithms, and data quality assurance, are imperative. Data visualization and reporting capabilities furnish users with actionable insights. User-centered design is very important, incorporating intuitive interfaces, adaptable display options, user-oriented data presentation, and collaboration features for multiple stakeholders, as well as mechanisms to facilitate user feedback and engagement. Integrated resilience entails various aspects, such as automation, security, flexibility, and sustainability. Ensuring cost-effectiveness, energy efficiency, and minimized environmental impact is crucial for sustainable manufacturing. Comprehensive training resources, dependable data, and realistic simulation capabilities contribute to the reliability and accuracy of digital twin technology, solidifying its value as an indispensable tool for addressing future manufacturing challenges.

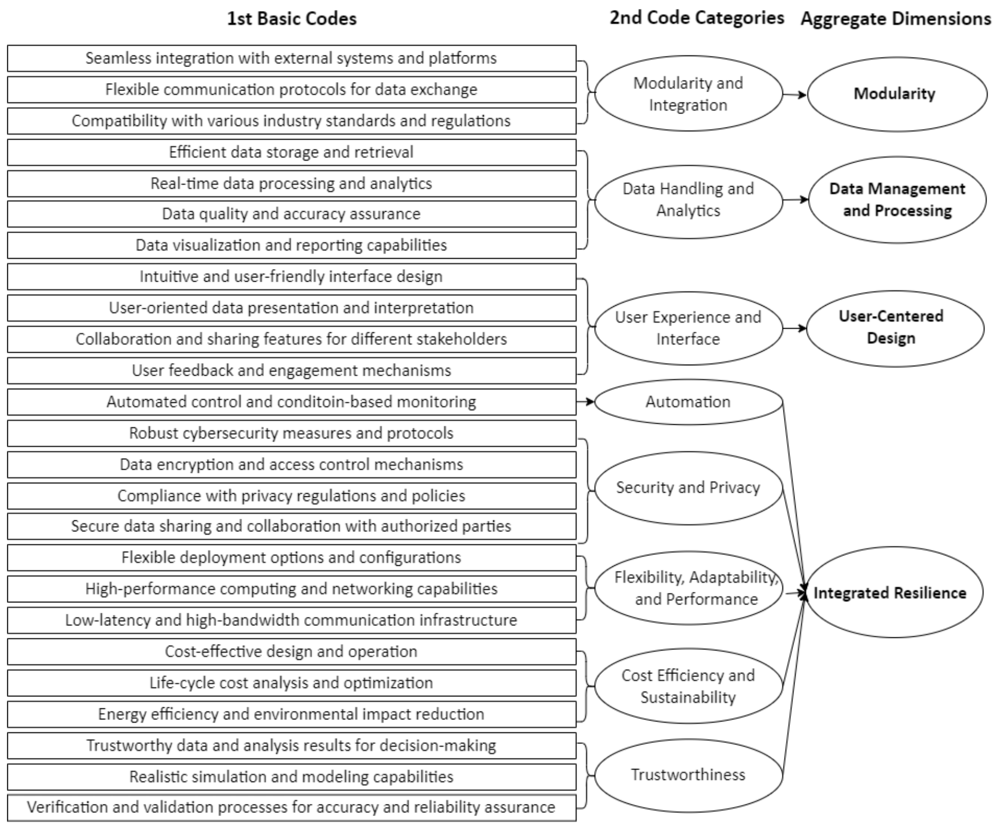

Figure 6: Data structure for workshop question4, characteristics for future demand.

5 DISCUSSION AND DEMO DEVELOPMENT

We aimed to clarify the requirements of stakeholders in the manufacturing field for digital twin implementation and explore how digital twins can support maintenance actions and decisions. Our comprehensive analysis, which combined insights from a literature review, interviews with manufacturing stakeholders from the Swedish industry, and a workshop with academic researchers, sheds light on the evolving landscape of digital twin applications in recent years. The stakeholders' perspectives, coupled with our literature review findings, provide a holistic understanding of the current state and future prospects of digital twins in smart maintenance.

Our key findings emphasize that the adoption of digital twins is still in its early stages, with many practitioners primarily utilizing digital shadow models. Stakeholders recognized the importance of implementing digital twins, but various challenges (Kober et al. 2022) hindered their adoption. Successful decision support (Cimino et al. 2019) and applications in maintenance and real-time operations have become consensus, demonstrating the potential of digital twins. For example, digital twins help in predicting machine failures based on historical data and relevant parameters to prioritize maintenance tasks and focus on crucial machines. It could also serve as valuable training tools for maintenance staff and assist in production planning, maintenance work scheduling, and policy selection. Respondents have a high demand to test what-if scenarios in digital twin models, which is also a noteworthy application scenario to focus on developing.

In comparing the literature review (Perno et al. 2022; Mohammed M. et al. 2018) and stakeholder insights, we observed a convergence of opinions on the key functionalities, decision support, and challenges associated with digital twins in smart manufacturing and maintenance. This alignment between academic research and industry experiences reinforces the validity of our findings and underscores the relevance of digital twins in addressing the complex needs of modern manufacturing. However, it is crucial to acknowledge the differing requirements of academia and industry: academia delves into more integrated dimensions and presents a wider range of challenges and perspectives for digital twin technology, while industry focuses predominantly on practical applications and deployment of digital twin models. This practical emphasis aims to capitalize on the potential of current digital shadows and may even achieve digital control. By recognizing these distinctions, our study contributes to a more comprehensive understanding of digital twins in the context of smart manufacturing and maintenance.

Informed by literature reviews and interviews, decision-making support for maintenance in the SII-Lab model incorporates the following: prioritizing tasks, optimizing schedules, evaluating what-if scenarios, ensuring traceability and visualization, and identifying key performance indicators (KPIs). Further experiments on the SII-Lab model will compare reactive and preventive maintenance, utilizing a prioritization algorithm to establish optimal task priority. Objective functions are tailored to specific concerned KPIs. Future research will also implement real-time bi-directional data transmission and AI-assisted decision-making within the digital twin model. The road map is depicted in Figure 7.

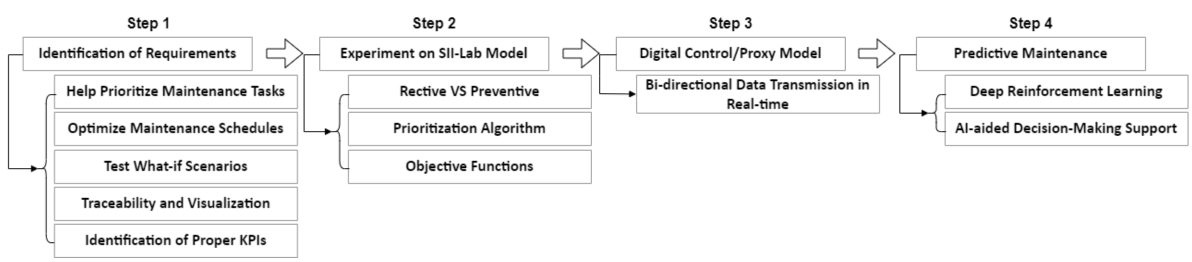

Figure 7: Road map for drone factory demo and future research.

In this paper, while we have made several theoretical contributions that demonstrate requirements for implementing digital twins in both industry and academia, our research has certain limitations that warrant further investigation. Our interviews were driven by the needs and perceptions of the industry participants. However, we did not encompass the full range of industry players, and individual perceptions may significantly influence the impact of our findings. In future research, we will expand our interviews to cover all levels and positions of manufacturing stakeholders to get a comprehensive view of their needs for a digital twin.

6 CONCLUSION

In this study, we sought to incorporate a stakeholder perspective and conduct a pre-study to identify their needs. By interviewing industrial practitioners and academic researchers in the field, we carried out inductive and qualitative research to understand the current requirements of stakeholders for digital twins in manufacturing, with a particular focus on maintenance. We explored the challenges of applying digital twins, their potential for decision-making support, characteristics and the outlook for future demand. Additionally, we identified specific directions for future applications in digital twins. Through these interviews and our research, we have gained valuable insights into the real-world requirements and expectations of stakeholders in relation to digital twin technology in manufacturing, which will be used in our SII-Lab digital twin model and further explored. Our findings contribute to the growing body of knowledge on this subject, while also highlighting areas for further investigation and development. By addressing the challenges and needs identified in this study, researchers and practitioners can collaborate to enhance the adoption and effectiveness of digital twins in the manufacturing industry, especially in maintenance, ultimately leading to more efficient and sustainable operations.

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