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Research article

A generic framework for qualifications of digital twins in maintenance

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A R T I C L E I N F O

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A B S T R A C T

Digital twins have emerged as a promising technology for maintenance applications, enabling organizations to simulate and monitor physical assets to improve their performance. In Operation and Maintenance (O&M), digital twin facilitates the diagnosis and prognosis of critical assets, forming the basis for smart maintenance planning and reducing downtime. However, there is a lack of standardized approaches for the qualifications of digital twins in maintenance, leading to low trustworthiness and limiting its application. This paper proposes a novel framework for the qualifications of digital twins in maintenance based on five pillars, namely fidelity, smartness, timeliness, integration, and standard compliance. We demonstrate the effectiveness of the framework through two case studies, showing how it can be implemented on digital twins for preventive maintenance and condition-based maintenance. Our proposed framework can help organizations across different industrial domains develop and implement digital twins in maintenance more effectively and efficiently, leading to significant benefits in terms of cost reduction, performance improvement, and sustainability.

1. Introduction

The digital revolution is currently sweeping the globe [1]. Advanced sensor technologies have made digital twins a crucial instrument in the digital revolution [2,3]. A digital twin is a virtual representation of a physical object or system, used to simulate and monitor its performance [4,5]. Many review articles discussed the definitions of digital twins, such as Jones et al. [6], VanDerHorn et al. [7], and Liu et al. [8]. They suggest a wide range of definitions for digital twins and provide generalized characteristics to differentiate digital twins from other models. On the other hand, industries follow the definitions given by international standards, such as ISO 23247-1:2021 for manufacturing [9] and ISO 23704 for cyber–physically controlled smart machine tool systems [10]. In this study, a digital twin consists of three components: physical assets, digital replicas, as well as their connections. In addition, it also takes into account the designed functions and industry requirements of the applications.

It is anticipated that many facilities and systems would use digital twins to enhance their adaptability so they can independently optimize production parameters and maintain standard operations [11]. In maintenance, a digital twin can be used to predict potential failures and plan maintenance activities [12]. It enables real-time monitoring and analysis of equipment performance under different operating scenarios, forecasting equipment failures, and shedding light on maintenance planning and scheduling. The technology has been widely used for maintenance across various industries and systems, as evidenced by the number of journal papers published in each area (shown in Table 1). The table is generated from search results on the Web of Science with keywords “maintenance” and “digital twin” in journals' topics at the end of March 2023. In the manufacturing industry, for example, digital twins have been applied to optimize production processes and maintenance decision-making [13–15]. The digital twin of a manufacturing system monitors the system performance in real-time and identifies potential issues before equipment failure or production delays. In the transportation industry, digital twins strengthen predictive maintenance of vehicles [16] and infrastructure [17,18], reducing downtime and increasing safety. Other applications include control system monitoring and optimization [19], visualized inspections [20], and structural health monitoring [21]. Overall, digital twins offer significant advantages for maintenance operations by improving safety and reliability, reducing downtime and maintenance costs, and increasing production efficiency.

However, the adoption of digital twins in maintenance is still limited due to the lack of a standardized approach to qualifications, as too many different types of digital twins exist, with varying levels of accuracy, complexity, and reliability. Digital twin qualification is the process of verifying and validating a digital twin to ensure it accurately represents the physical object or system it represents [22]. This may include testing the digital twin's data inputs, outputs, and algorithms to ensure they match real-world behavior, and comparing the digital twin's predictions to actual performance. Digital twin qualification can

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Table 1
Statistic of journals about digital twins applications in maintenance.

Applied industry	Application area	No. of journal papers
Manufacturing	Manufacturing	73
	Production	29
	Others	8
Transportation	Infrastructure	62
	Vehicles	23
	Operations	7
Equipment	Equipment	77
Systems	Monitoring system	8
	Process system	7
	Automation system	4
	Others	28
Construction	Buildings	43
	Offshore construction	3
Energy	Power system	32
	Wind turbine	17
	Nuclear	5
	Battery	2
	Others	4
Others	General	27
	Factory/plant	11
	Education	2
	Materials	2
	Medicine	2
	Laboratory	1
	Aquaculture	1

help organizations evaluate the suitability of digital twins for their specific needs, select the appropriate digital twin technology, and ensure the quality and reliability of their digital twin models. Additionally, it can provide a common language for stakeholders to communicate and share information about digital twins, and promote the adoption and standardization of digital twin technology in maintenance.

Although there is no widely recognized qualification methods for digital twins, various classification methodologies exist as listed below. Kritzinger et al. proposed a classification approach for digital twins based on integration levels, dividing them into digital models, digital shadows, and digital twins [23]. Altamiranda et al. classified digital twins into six capacity levels: standalone, descriptive, diagnostic, predictive, prescriptive, and autonomy [24]. Julien et al. developed a generic definition of digital twins and classified them based on three dimensions: data and models, usages, and applications [25]. Agnusdei et al. developed a classification framework for digital twins in safety applications based on data processing, data acquisition, and safety issues related to human- or machine-based risks [26]. Newrzella et al. analyzed and classified digital twins based on a five-dimensional cross-industry model that includes the scope of the physical entity, the feature (s) of the physical entity, the form of communication, the scope of the virtual entity, and the user-specific outcome/value created [27]. Yu et al. classified digital twins based on their behavior (static, multiple, and transient states), connection (indirect, one-way direct, and two-way direct), likeness (1-D, 2-D, or 3-D representation) and scale (physical and time scale) [28]. Finally, Uhlenkamp et al. developed a maturity model for classifying digital twins into seven categories based on their potential functionalities and properties, including context, data, computing capabilities, model, integration, control, and human–machine interface [29]. Overall, these different classification frameworks and methods provide a useful starting point for understanding and categorizing digital twins on various attributes and dimensions. They can help organizations identify the appropriate type of digital twin for their specific needs, classify their digital twin applications, and make informed decisions about their implementation. Additionally, having a common language and understanding of digital twins can facilitate communication and collaboration among stakeholders in different industries and domains, and promote the adoption and standardization of digital twin technology. Nevertheless, the lack of research on digital twin qualification renders users uncertain about the quality of the digital twins they utilize.

We have proposed four evaluation indices for digital twin qualification in The International Federation of Automatic Control World Congress (IFAC WC) 2023 [30] : Fidelity, Real-time, Interactions, and Standard Compliance [30]. Fidelity reflects the accuracy and uncertainty level of digital twins. Real-time means the digital twin operates in response to external events at the same speed without any noticeable delay. Interaction refers to the bidirectional data flow and mutual influence between the physical and digital objectives. Finally, Standard Compliance refers to the extent to which a digital twin adheres to established standards, regulations, or guidelines.

There are still some limitations in the current digital twin qualification indices for maintenance. First, the application of digital twins for maintenance is not a one-size-fits-all process. Instead, it requires taking into account various user scenarios and end-user requirements. Digital twin applications for a single piece of equipment, for instance, will differ from those for a complex system. To verify that the technology is addressing the unique demands of end users, these variances must be taken into account throughout the qualifying process for digital twins. Second, while the existing classification methods made valuable contributions to the literature of digital twins, none of them can cover all features to ensure the quality of digital twins intended for maintenance application. As such, it is essential to develop a more comprehensive framework for evaluating the accuracy, reliability, and suitability of digital twins in maintenance domains. Thirdly, qualification indices may have certain limitations even though they can be useful instruments for determining digital twin qualification. For instance, certain indices may have limited precision and scope, and the grading levels may be excessively vague and lacking in specifics. For example, the present Standard Compliance grade does not distinguish between different levels of competence, resulting in an incomplete profile of digital twin quality. To address these limitations, we present the complete framework and novel metrics for digital twin qualification in the next section.

The objective of the paper is to further improve the qualification framework for digital twins in maintenance, assist the readers in understanding the proposed model as well as provide guidelines for tailored digital twins selection. The rest of the paper is structured as follows: Section 2 presents the generic framework and its main elements, showing how they contribute to the overall effectiveness of digital twins in maintenance. Application of the suggested framework is demonstrated in Section 3, which also provides insights on selecting a suitable digital twin for maintenance to avoid the risk of implementing digital twins that are under or over-qualified. Finally, the article concludes with Section 4.

2. The proposed qualification framework

In this section, we present the proposed framework for digital twin qualifications, which is illustrated in Fig. 1. The framework not only takes into account the gaps and limitations observed in current classification and qualification methods, but also considers the distinctive characteristics of maintenance models. The objective is to provide a more effective and comprehensive approach to qualifying digital twins. In the following subsections, we delve into the details of the framework, including its underlying principles, evaluation criteria, and practical implementation aspects. We believe that this framework will make a significant contribution to the advancement and practicality of digital twins in maintenance. It will facilitate improved decision-making, enhance performance, and foster the sustainable development of diverse industries.

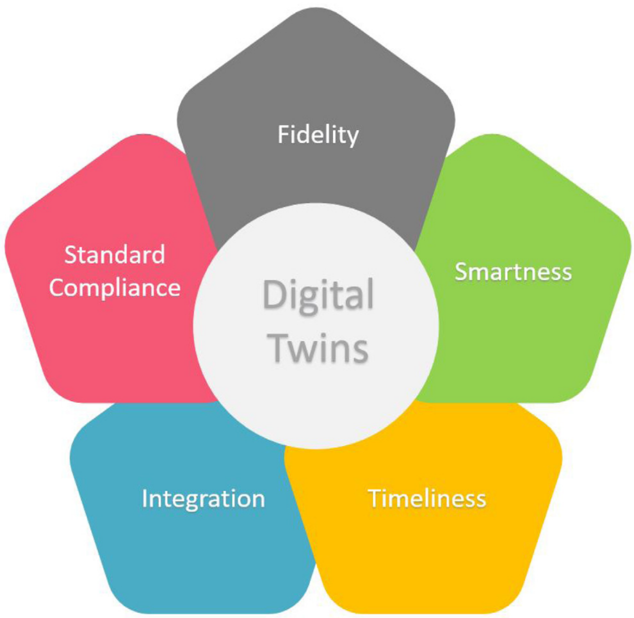

Fig. 1. The proposed framework for qualifications of digital twins in maintenance.

Fidelity assessment matrix		No. of input parameters		
		Few	Most	All
Output accuracy	Not precise	Very low	Low	Low
	Precise only for specific working conditions	Low	Low	Moderate
	Precise for normal working conditions	Low	Moderate	Moderate
	Precise for all working conditions	Moderate	Moderate	High

L0: Very low | L1: Low | L2: Moderate | L3: High

Fig. 2. Fidelity assessment matrix for digital twins.

2.1. The generic qualification framework

The new framework includes five evaluation indices, namely fidelity, smartness, timeliness, integration, and standard compliance. They refine and extend the initial four indices by providing more detailed grading levels and wider coverage of requirements, as discussed below.

Fidelity of a digital twin indicates *how closely it replicates the behavior of the physical system* [31]. The level of fidelity of digital twins is determined by the number of shared parameters between the physical and virtual entities, their precision and level of abstraction [6]. High-fidelity digital twins are essential for maintenance models because they accurately replicate the behavior, properties, and performance of the physical system. In contrast, a low-fidelity digital twin may be a simplified or abstracted version of the real-world system. The fidelity of a digital twin significantly impacts its usefulness and effectiveness in maintenance, simulation, and optimization. Grading the fidelity levels of digital twins is crucial for satisfying the specific requirements of end-users and ensuring effective application in maintenance scenarios. In light of this, we suggest a four-level grading system based on the quantity of input parameters and the precision of the outcomes (see Fig. 2). (Only the pertinent and measurable parameters should be considered.) According to the grading scheme in the figure, the level of fidelity increases with more input parameters and more working conditions remaining precise output. The capability of the digital twin is greater when there are more input parameters than when there are fewer, even if the output accuracy remains at the same level. Accordingly, the digital twin is more advanced than those who use fewer parameters because it can handle more data and information from the target system. When the numbers of input parameters are the same, the digital twins have a higher fidelity level if they can maintain accurate outputs for more working conditions. It is a challenge to handle an abundance of dynamic data collected from physical objects and external environments. To have more working conditions with precise output, it is helpful to implement system identification and data-driven modeling techniques in digital twins [32,33]. High-fidelity digital twins can help with more complicated systems and are preferable to low-fidelity ones. Although high-fidelity digital twins provide numerous advantages, their implementation may be restricted by factors such as sensor availability, computational capacity, and system expertise. As a result, designers and users must select an appropriate fidelity level based on their budget constraints and genuine needs.

Smartness denotes the capability of a digital twin to have higher-order functions and to perform more advanced operations when the intelligence level of the models increased. This implies considering the functions, objectives, and goals of digital twins. The degree of smartness in digital twins is classified into four distinct levels: descriptive, diagnostic, predictive, and decision-making. Moreover, higher grades incorporate the abilities of lower smartness levels. The grading system is intended to fulfill the maintenance model requirements of diverse levels and may be correlated with the capability levels defined by Altamiranda and Colina [24].

- L0 — descriptive: mirror and describe the physical system, visualize the system, and help people understand the behavior of systems. A digital twin with a descriptive level of smartness provides a basic understanding of the current state of a physical system. It collects data from sensors and other sources and generates reports and visualizations that provide insights into the behavior of the system. For example, a descriptive digital twin of heavy-duty trucks can monitor the truck status and provide maintenance support which relies on experienced maintenance technicians and various complex instruments and maintenance tools [34].
- L1 — diagnostic: identify a particular failure or abnormal state using data and system symptoms. A digital twin with a diagnostic level of smartness goes beyond a descriptive level, it is to identify the root causes of problems or anomalies in a physical system. It uses a Bayesian network, machine learning, or other algorithms to analyze data and identify patterns that indicate potential issues. For example, a diagnostic digital twin of a robotic assembly line could assure the system performance through more rapid diagnosis than traditional methods [35].
- L2 — predictive: predict the remaining useful life or potential failures of systems by analyzing the available data and resources. A digital twin with a predictive level of smartness uses machine learning algorithms and historical data to predict the future behavior of a physical system. It can forecast changes in system performance, detect potential problems before they occur, and identify opportunities for optimization. For example, a predictive level digital twin can detect faults and predict the future state of Air Handling units components through the continually updated data combined with digital twin techniques. The early detected operating faults could save several thousand dollars annually by the optimized maintenance schedules [36].
- L3 — decision-making: help users make informed decisions through reliable predictions and simulations. Further, the system could have autonomous maintenance without humans involved. A digital twin with a decision-making level of smartness is capable of making autonomous decisions based on the data it

Table 2
Timeliness assessment matrix for digital twins.

Levels	Range	Time unit (t)	Convert to seconds	$log_{10}(t)$
L0	$log_{10}(t) \geq 6$	Year, Month	$3.15 * 10^7$ $2.59 * 10^6$	7.50 6.41
L1	$4 \leq log_{10}(t) < 6$	Week, Day,	$6.05 * 10^5$ $8.64 * 10^4$	5.78 4.93
L2	$0 \leq log_{10}(t) < 4$	Hour, Minute, Second,	$3.6 * 10^3$ 60 1	3.56 1.78 0
L3	$log_{10}(t) < 0$	Millisecond, Microsecond, Nanosecond,	10^{-3} 10^{-6} 10^{-9}	−3 −6 −9

collects and analyzes. It uses advanced analytics techniques such as optimization algorithms and reinforcement learning to make decisions that optimize the performance of the physical system it represents. Although autonomous maintenance has the potential to optimize maintenance decisions and actions, it is currently not a viable option as these tasks are primarily the responsibility of maintenance engineers and operators. In general, organizational structure and management information are not involved in digital twins, and the workflow of job management is also challenging to be covered by digital twins. However, autonomous models can be implemented if they can perform better than humans, or if there are too many decisions to be made that exceed human capacity. In such cases, the models must meet high accuracy standards to be considered plausible alternatives to human decision-making.

Overall, the four levels of smartness in digital twins illustrate a hierarchical progression, starting with fundamental data reporting and ending with sophisticated decision-making abilities, with each level building upon the previous one. As the levels of smartness increase, digital twins' learning capabilities improve, allowing them to continually learn from real-world data and enhance the precise of their models. With the help of this capability, digital twins can continuously improve their accuracy and dependability while adapting to changing systems. Artificial intelligence (AI) algorithms have been used for digital twins [37]. With the assistant of AI technologies, digital twins could develop their learning capabilities and become smarter than they were designed initially. This aspect is particularly important in applications such as predictive maintenance, where the objective is to improve the ability to detect potential failures and schedule maintenance activities. The increasing smartness of digital twins empowers them to provide enhanced insights and optimize physical systems in more sophisticated ways. However, it is worth noting that higher levels of smartness entail greater complexity and resource demands. Therefore, the determination of the smartness level should be based on the practical needs and considerations of end-users.

Timeliness refers to the ability of the digital twin to accurately and quickly reflect changes or updates of the physical system or object that it is modeling, and can be assessed via the time lag between the physical system and the virtual system. The equation below is proposed to access digital twins' timeliness level through the range of the base 10 logarithm ($log_{10}(t)$).

$$L(t) = \begin{cases} L0 & \text{if } log_{10}(t) \geq 6; \\ L1 & \text{if } 4 \leq log_{10}(t) < 6; \\ L2 & \text{if } 0 \leq log_{10}(t) < 4; \\ L3 & \text{if } log_{10}(t) < 0. \end{cases} \tag{1}$$

where t is the time lag in seconds. Table 2 provides some example time units for different levels of timeliness.

The timeliness level of a digital twin is dependent on the model's communication capabilities and the management's decisions regarding the frequency of updates. Factors such as sensor quality, communication channel speed, and data processing ability determine communication capabilities. Furthermore, an effective digital twin identification technique reduces the time required for modeling and minimizes the delay between data collection and the creation of the digital twin [38]. The upper limit of the frequency of updates is mainly determined by technological capabilities of the digital twin. Meanwhile, the management team may decide the update frequency based on the system's specific requirements and application. For example, a monthly update frequency may be deemed adequate in road maintenance applications. A high timeliness level may be necessary for real-time monitoring and decision-making, whereas a lower timeliness level may suffice for long-term analysis and planning purposes.

Integration refers to the level of a digital twin connected both internally, between the digital and physical objects, and externally, to other systems, data sources, and processes within an organization. The integration level can be evaluated by reviewing the automatic data flow (data collection, transmission, and integration) between objects of digital twins and other related systems or resources. Through the automatic data flow, the digital twin could work seamlessly with other systems and processes within the organization's existing infrastructure and operations, minimizing potential disruptions and enhancing interoperability.

The grading of the integration level is similar to the classification given by Kritzinger et al. [23]. It considered the auto data flow internally and externally of the digital twins and divided the digital twin into four levels below:

- L0: digital model. There is no automatic data flow internally or externally. The model is working independently from the physical model and the operation environment.
- L1: digital shadow. There is automatic data flow from the physical object to the digital object of the digital twin, while there is no automatic data flow inversely or with the operating environment.
- L2: digital twin: There is automatic data flow inside the digital twin, while there is no automatic data flow externally. The model is considered integrated internally and separated from the operating environment.
- L3: integrated digital twin: The automatic data flow is both internally and externally. The digital twins are integrated with the operating environment.

The integration level must be set by the organization to gain the maximum benefits of digital twins. However, automatic data flow can lead to issues of data security and privacy. Organizations will be more likely to integrate a digital twin into their infrastructure if they can be assured of the security and confidentiality of the data it generates. In addition, a highly integrated digital twin is more complex than an independent one and may make the system more vulnerable due to poor connections between objects.

Standard Compliance refers to the ability of digital twins to follow the established standards [9,10,39], guidelines and best practices [22, 40]. Standard compliance is critical for ensuring the reliability, security, interoperability, and scalability of digital twins. Compliance with standards not only ensures the quality of digital twins but also helps operators and organizations identify gaps between daily operations and official requirements. The digital twins could be classified into four levels of standard compliance based on the status of following required standards and indicators of compliance (Fig. 3).

- L0: Very low: The digital twin is not following any standard.
- L1: Low: The digital twin follows parts of the required standards, but it cannot provide compliance indicators for all the standards it followed during operations.
- L2: Moderate: There are two conditions for this level. One is the digital twin follows all required standards but it cannot provide indicators for all the standards it followed during operations.

Table 3
Pros and Cons of promoting the proposed framework.

	Pros	Cons
Fidelity	1. More working conditions fitted 2. Better decision-supporting/making	1. More sensors needed 2. Complex model 3. More knowledge about systems required 4. Heavy load of computers
Smartness	1. More powerful model 2. Easier for operators 3. Better decision-supporting/making	1. More knowledge about systems required 2. Higher fidelity model required
Timeliness	1. Status updated timely	1. High communication capability is required
Integration	1. Uniformed interface 2. Faster communication between physical and digital objects 3. Better connection with related systems	1. Complex model 2. Security issues
Standard Compliance	1. Standardized digital twins 2. Compliance assistant	1. More rules to be considered while building

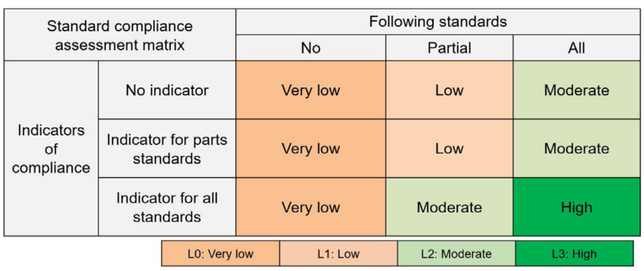

Fig. 3. Standard compliance assessment matrix for digital twins.

The other is the digital twin only follows parts of the standards required but it gives indicators for all standards it followed during operations.
- L3: High: The digital twin follows all required standards and gives compliance indicators for all of them during operations.

2.2. Summary of the proposed framework

The proposed digital twin qualification framework aims to enhance digital twin performance in aspects like operating conditions coverage, functions, interface, and decision-making assistance. However, with the excessive promotion of all the indicators, potential issues may arise. For instance, more sensors are required to comprehensively collect data, and the model becomes more complex as data volume, systems compatibility, and computing power increase. Additionally, the model requires higher knowledge of the system, working environment, higher communication capacity, and standard compliance. The system may become more vulnerable to attacks because of the higher level of integration and automation, which increases the number of interfaces that can be attacked. Table 3 summarizes the pros and cons of the proposed framework which help users to pick up suitable digital twins for their application.

On the other hand, the indicators in the proposed qualification framework are both standalone and interrelated. Each indicator covers a certain aspect of the performance of the digital twin. For example, fidelity considers whether the model can fully emulate the real performance and behavior of the physical system, smartness considers the level of intelligence and functionality of the model, timeliness evaluates the real-time performance and update frequency of the model, integration considers the level of integration of the model internally and with related systems and platforms, and standard compliance is used to standardize the models and assess the degree of compliance of the system. However, these indicators are interrelated and enhancing one might affect others, especially when it has reached a high level. For example, a higher level of fidelity requires a higher level of timeliness, while a higher level of smartness requires both high fidelity and integration levels. Timeliness and integration are inseparable when achieving high levels. And standard compliance helps to standardize the interface and make external integration easier for digital twins.

Overall, this evaluation framework fills a research gap and can help users design, use and standardize daily operations according to their actual needs, thereby reducing costs, increasing productivity, and promoting the sustainable development of the industry. By evaluating the performance of digital twins, users can better understand and trust the model, which in turn optimizes existing workflows and related decisions. By improving the fidelity, smartness, timeliness, and integration level of digital twins, maintenance engineers can optimize related decisions, and reduce downtime and unnecessary maintenance costs. In summary, applying this evaluation framework can greatly enhance the intelligence level of the maintenance industry and generate tangible benefits.

3. Case study: Required qualification level for maintenance strategies

This section will discuss frequently used maintenance strategies and assess the level of digital twin required by the suggested qualification framework based on their unique characteristics. Readers will gain a better grasp of how to use the suggested qualification framework and how to choose the digital twins for various maintenance strategies through this assessment procedure.

3.1. Maintenance strategies

A maintenance strategy is a general rule to choose the way of maintenance. It can be generally classified into reactive maintenance which carries out repair or maintenance to fix failures, and proactive maintenance which implements maintenance before failure occurs. All maintenance plans are thought to benefit significantly by the use of digital twins, but due to their unique qualities, each strategy has its own set of requirements. The topics of preventive maintenance and condition-based maintenance are covered separately in this section.

3.1.1. Preventive maintenance

Preventive maintenance is maintenance that is regularly and routinely performed on physical assets to reduce the likelihood of equipment failure and unscheduled machine downtime that can be very costly for maintenance and production teams and facility managers [41]. It can be divided into time-based maintenance and risk-based maintenance. The maintenance schedule for preventive maintenance may be created using historical data analysis. Then, based on the calendar or production plan, the operators can have routine inspections. Effective preventative maintenance, on the other hand, is planned and scheduled using real-time data insights, frequently with the aid of software like a CMMS (computerized maintenance management system). To avoid unplanned breakdowns, a preventative maintenance procedure is carried out while the equipment is still functional. Preventative maintenance is an approach that sits between reactive maintenance (sometimes known as "run-to-failure") and predictive maintenance [42].

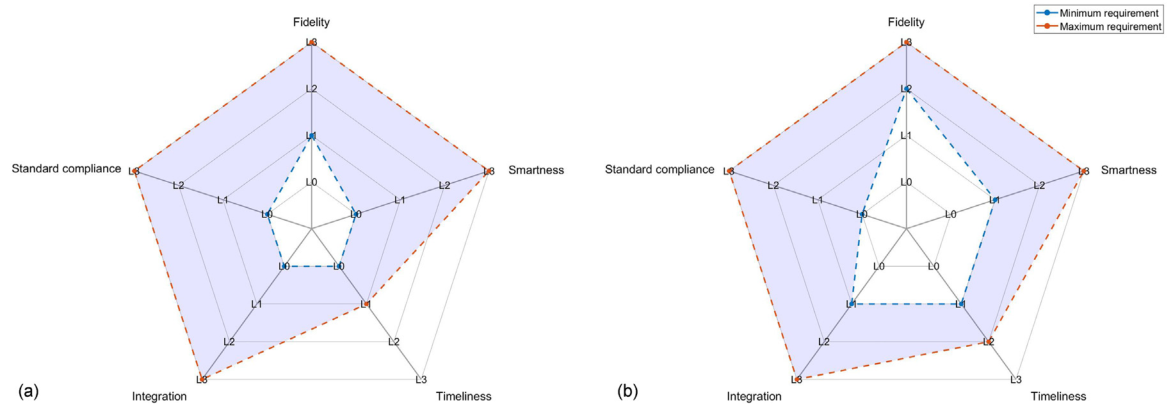

Fig. 4. Minimum and maximum requirements for digital twins in maintenance strategies. (a) Preventive maintenance, (b) Condition-based maintenance.

Table 4
Requirements for Preventive maintenance.

Indicator	Minimum requirements	Maximum requirements
Fidelity	L1: Low	L3: High
Smartness	L0: Descriptive	L3: Decision making
Timeliness	L0: $log_{10}(t) \geq 6$	L1: $4 \leq log_{10}(t) < 6$
Integration	L0: digital model	L3: integrated digital twin
Standard compliance	L0: Low	L3: High

Table 5
Requirements for Condition-based maintenance.

Indicator	Minimum requirements	Maximum requirements
Fidelity	L2: Moderate	L3: High
Smartness	L1: Diagnostic	L3: Decision making
Timeliness	L1: $4 \leq log_{10}(t) < 6$	L2: $0 \leq log_{10}(t) < 4$
Integration	L1: digital shadow	L3: integrated digital twin
Standard compliance	L0: Low	L3: High

3.1.2. Condition-based maintenance (CBM)

CBM is a maintenance strategy that monitors the actual condition of an asset to decide what maintenance needs to be done. The system monitor can use continuous monitoring sensors or a periodic monitor like onsite inspections. There are three working phases for CBM which are failure detection, diagnosis/prognosis, and maintenance activities [43]. Digital twins have the potential to enhance CBM by a more accurate and comprehensive view of the equipment status, real-time monitoring, and scheduling optimization.

3.2. Results and discussion

3.2.1. Preventive maintenance

The qualification results are displayed in Fig. 4a and Table 4. Preventive maintenance schedules are generally based on historical data. Users can accept a digital twin utilizing partial parameters for accurate results under normal working conditions. L1 — Low is the minimum requirement for the level of fidelity. Naturally, a higher fidelity digital twin will deliver more accurate results which assists users in developing more efficient and cost-effective plans. The minimum smartness level necessary is L0-descriptive. This will enable practitioners to identify potential failures from historical data and create a maintenance plan prior to failure. If the digital twin is capable of making auto decisions, it can help the organization update maintenance plans more efficiently. For the indicator timeliness, the requirement for digital twins is not high. This is due to the fact that preventative maintenance plans are often created long-term, and thus do not require frequent updates. For the integration level of digital twins, L0 — digital model may be sufficient since it only uses historical data to make plans. However, an integrated digital twin could benefit the strategy since it could connect with the information within the platform of the organization and make a better maintenance schedule that also considers the production, supply chain, and other resources. High standard compliance levels are preferred for digital twins, although lower levels may be accepted initially as independent digital twins.

3.2.2. Condition-based maintenance

The qualification results are shown in Fig. 4b and Table 5. CBM creates maintenance plans based on the current condition of equipment and systems. Digital twins must be precise in all working conditions, which requires a fidelity level of L2 moderate or higher. The level of smartness must be at least L1-diagnostic to display the system status and provide failure thresholds. The effectiveness of maintenance decisions can be increased with higher levels of smartness. Depending on the needs of the system, digital twins need to be more timely than preventive maintenance. As long as the updating frequency complies with the requirements for maintenance preparation, the timeliness level is acceptable. Thus, there are different timeliness levels, from L1 to L2. The digital twin integration level can begin at L1 — digital shadow model, which requires automatic data flow from physical to digital objects. Like preventive maintenance, integrated digital twins can improve CBM decision-making. For standard compliance, it is beneficial to have a high level of digital twins. Nevertheless, it is deemed acceptable to deploy an independent digital twin at a lower level during the initial stages.

3.2.3. Discussion

The proposed qualification framework can be easily implemented through the qualification process of two maintenance strategies. Since there is no definitive digital twin model, evaluation results can only be expressed as a range. Users should evaluate and rank specific maintenance digital twins based on the advantages and disadvantages suggested in Table 3. For instance, they should balance the advantages of promoting indicators against the extra expense and hazards associated with higher levels of indicators. When choosing a digital twin that meets their business needs, they should also take broader factors like safety, production efficiency, management costs, and market conditions into account.

Users could employ a similar approach to qualify a particular digital twin. By reviewing all proposed indicators, they should rate the digital twin's present levels. Users could then consider the associated benefits, costs, and risks of prospective enhancements.

Overall, the proposed qualification framework is a valuable tool for evaluating digital twins for maintenance strategies and their applications. Users should carefully examine digital twins, taking into consideration suggested benefits and drawbacks, and utilizing the framework to assess and grade digital twins. Additionally, by considering broader factors such as safety and production efficiency, the qualification process can help users to build trust and enhance the effectiveness and reliability of digital twins. It can also assist users in choosing suitable digital twins and avoiding the waste of over-qualified digital twins.

4. Conclusion

In conclusion, our proposed generic framework for digital twin qualifications in maintenance offers a standardized approach for organizations to evaluate the effectiveness and reliability of digital twins. The framework addresses key factors such as fidelity, smartness, timeliness, integration, and standard compliance, offering a thorough method for picking the best digital twin technology and assuring the accuracy and dependability of digital twin models. We have shown how the framework may be used to multiple maintenance strategies and have given recommendations for choosing digital twins with preventive maintenance and condition-based maintenance.

Our proposed framework has significant implications for industries, including performance improvement and sustainability, model and operation standardization. The framework encourages adoption and standardization of digital twins across the board in maintenance operations by fostering confidence in their precision and dependability.

In summary, our proposed framework makes a substantial addition to the subject of maintenance qualifications for digital twins. We hope that our framework will be useful to researchers, practitioners, and policymakers working in this area, and we look forward to seeing it applied and further developed in future work.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Jie Liu reports financial support was provided by Research Council of Norway.

Data availability

No data was used for the research described in the article.

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

During the preparation of this work the author(s) used Open AI — ChatGPT 3.5 in order to improve language and readability. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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