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A new quantitative digital twin maturity model for high-end equipment

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ABSTRACT

Digital twins (DTs) have shown great potential in both academia and industry due to their ability to interconnect and integrate physical and virtual worlds. A DT maturity model for high-end equipment is important to accurately evaluate the maturity level of DT and further develop an advanced DT. This paper is one of the early endeavours, to the best of the authors' knowledge, to provide a new DT maturity model for high-end equipment combining qualitative and quantitative analysis. The qualitative analysis of the DT maturity model includes a comparison and assessment of 3 dimensions and 27 rubrics for different DTs of high-end equipment. In addition, 6 maturity levels and their definitions for each rubric are proposed for maturity scoring. The quantitative analysis of the DT maturity model is conducted based on an analytic hierarchy process and a matter-element extension method, which can be used to provide improvement advice according to the rubric importance and its improvement difficulties. The proposed DT maturity model is applied to evaluate the maturity of DTs of three high-end equipment, including underground engineering equipment, a large-scale wind turbine, and an industrial shop-floor. The evaluated maturity results could be used to elevate the maturity of DT by improving rubrics with high significance, low level, and low improvement difficulty.

1. Introduction

High-end equipment is a series of equipment with high value in advanced products, such as industrial manufacturing equipment, energy transmission equipment, and underground engineering equipment, which play a significant role in society and the economy [1,2]. As one of the new and important parts in intelligent manufacturing, digital twin (DT) technology can help high-end equipment capture potential faults and carry out preventive maintenance by interconnecting and integrating the physical and virtual worlds [3]. DT often involves a digital entity representing non-living and living physical objects (e.g., humans, equipment, complex systems, etc.) in the virtual world [4,5].

Recently, DT has shown significant benefits and potential in many areas related to high-end equipment, including reduction of operational costs and risk [6,7], promotion of production efficiency [8], security and reliability of key components [9], and decision-making [10]. DT has attracted increased attention in both academia and industry. For example, the number of publications in the DT field has been exponentially increased in recent years [3]. Particularly, various DT researches have been emerging in recent years with the development of deep learning, the Internet of Things, and 5G technologies [3]. Additionally, DT has been widely applied in multiple industry fields. For instance, Fuller et al. [11] utilized the concept of DT in virtual space to distinguish systems that lack sensing and feedback mechanisms in the real world. Chinesta et al. [12] introduced a DT data transmission method by combining the model order reduction method and data collection technology for a hybrid DT feedback control. However, there is still a lack of a well-recognized and clear definition of DT maturity, and its capability domains are consequently not clearly classified. Hence, it is difficult to distinguish the maturity level of DT development and thus validate its effectiveness. In addition, other technologies such as physical simulations or condition monitoring based on real-time sensing data are also referred to as "DT technologies". It is indeed an urgent task to build a DT maturity model that can be used to qualitatively and quantitively evaluate the maturity of DTs of different high-end equipment.

To evaluate the state or quality of a DT, the notion of a maturity model is proposed, which is defined as a kind of model with several levels that can describe the development of the DT of high-end equipment over its lifecycle [12]. Each level in the maturity model contains

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criteria or characteristics that need to be satisfied [13]. Thus, the maturity model can serve as a reference framework to implement a systematic and well-directed DT of high-end equipment based on a set of criteria to ensure quality, avoid errors, and assess entities' capability on a quantitative and comparable basis [12,14]. For instance, the 5-level capability maturity model integration (CMMI), which is the most widely recognized maturity model, is utilized to evaluate the maturity of software and to provide a way guiding the further development of specific software [15].

A literature survey found that maturity models have often been applied in building information modelling (BIM) design [16,17], software process improvement [18], and artificial intelligence applications [14]. With increasing interest in DT research, measuring maturity levels of DT will be a highly focused topic in the near future, which can be used to evaluate the deficiencies of existing DTs and provide guidelines for further improvement [19]. Although maturity model research has been introduced in more than 20 fields, maturity model research in software development and software engineering disciplines is the dominant focus [14]. In addition, most maturity models are qualitatively analysed by simply treating all capability domains of the maturity model as equivalent and adding the score of each capability domain with the same weight for evaluating the final maturity level, while these capability domains in engineering practice often show different significance. To the best of our knowledge, there have been few attempts in maturity models to evaluate and distinguish the importance of capability domains of DT of high-end equipment.

Multiple-criteria decision-making (MCDM) methods are widely applied in diverse fields and can be used to assign a deterministic weight to each criterion. In the field of high-end equipment, the MCDM methods have been successfully employed in selecting the optimal manufacturing process [20,21], machine tool [22], and best location [23]. The analytic hierarchy process (AHP) is considered one of the most popular methods for evaluating multiple criteria among all MCDM methods. The AHP method combines separate evaluations to obtain an overall priority rank of the entity based on a pairwise comparison from the judgement of multiple experts. Recently, the AHP method has been successfully applied in the selection of manufacturing processes of high-end equipment such as tunnel boring machines (TBMs) [24] and wind turbines [25]. The AHP method has also been introduced to the field of maturity modelling to identify the importance of different capability domains. For instance, Bai et al. [26] used the AHP-based method to define the weight of each capability domain and further created the environmental management maturity model. However, for existing maturity models, it is difficult by using a single indicator (i.e., weight for criteria) to determine the future direction of improvement strategies. Therefore, multiple indicators (significance, improvement difficulty, and maturity level of rubrics) are proposed to guide the mature development of DT of high-end equipment in this paper.

This paper develops a new DT maturity model for high-end equipment combined with qualitative and quantitative analyses, which can reflect the maturity level and provide advice for further improvement towards a high DT maturity level. The contributions of this work are threefold:

(1) A new qualitative analysis framework including 3 dimensions and 27 rubrics is proposed to compare and assess the DT maturity level;
(2) Definitions of 6 levels of each rubric in the DT maturity model are developed, which provide a guide for scoring different levels of rubrics;
(3) A new quantitative analysis process is proposed based on an AHP method and a matter-element extension method, which can be used to provide advice according to the rubric significance and its improvement difficulty.

The remainder of this paper is organized as follows. Section 2 presents the detailed explanation of the qualitative analysis framework and the quantitative analysis process, followed by the case studies of maturity evaluations of three DTs of high-end equipment in Section 3. The results and discussion are provided in Section 4. Finally, conclusions, limitations, and future work are given in Section 5.

2. Methodologies

The DT maturity model for high-end equipment is developed following the top-down approach [27] and consists of qualitative and quantitative analysis, as shown in Fig. 1. In the qualitative analysis, the dimensions and rubrics are developed through a comprehensive literature survey [13,26,28–30]. In addition, 6 maturity levels and their definitions are proposed for each rubric. In the quantitative analysis, each rubric of the DT maturity model is scored by experts. The weights for the dimensions and the rubrics are obtained by the AHP method. Based on the calculated closeness (i.e., improvement difficulty) of each rubric, rubrics that are better to be improved are identified by the matter-element extension method. Finally, the maturity level and score of each dimension and the DT are calculated.

2.1. Qualitative analysis

2.1.1. Dimensions and rubrics

To reasonably evaluate the maturity of DT of high-end equipment, a qualitative analysis framework of the DT maturity model is first developed based on a comprehensive study of multiple aspects or dimensions that a maturity model needs to consider. The Gemini principles proposed an index system to evaluate the DT in the aspects of purpose, trust, and function, which create a strong foundation to guide the evaluation of DT maturity [31]. Chen et al. [30] referred to the Gemini principles to create an maturity evaluation model for digital asset management of DT. Since DT maturity is a general concept that is currently being developed, it is difficult to summarize all possible capabilities in limited classes. To classify a matured DT in a proper way, this paper utilizes the concept of the Gemini principle and integrates the common requirements of high-end equipment to propose a framework for the DT maturity model including 3 dimensions, i.e., the value, the function, and the reliability of DT. Various capabilities of DT of high-end equipment in this paper are defined as rubrics and classified into these 3 dimensions.

The value of DT is used to evaluate the benefits of outcomes by utilizing DT in the life cycle of high-end equipment [31], including direct economic benefits and potential benefits in many other aspects [32]. On the one hand, DT needs to improve the value of the operation process [33], such as improving production efficiency and reducing maintenance cost [34,35]. On the other hand, DT is supposed to create potential value in relevant experiences for the future development of high-end equipment [32]. For instance, Havard et al. proposed a co-simulation environment for the design and assessment of industrial workstations, which indicates that twin data for next-generation equipment are essential [36]. DT data can be used to explore the failure mechanism of key components of high-end equipment and improve the design of next-generation equipment [37,38]. Furthermore, the DT of high-end equipment should provide the value of public goods, including social outcomes based on the requirements of end users. The well-organized high-end equipment operation process, engineer training programs, and communication technologies between different users are also considered in the maturity evaluation for the DT of high-end equipment [3,37,39]. Table 1 summarizes the surveyed references, which are used for defining the rubrics of the value of DT.

The DT function is used to evaluate whether the development of DT meets the purpose of high-end equipment effectively and satisfies the customized needs of users [31]. Table 2 summarizes the rubrics of the function of DT of high-end equipment. First, to integrate different functions in high-end equipment, a proper updating process of the model is significantly important for different DT applications [41].

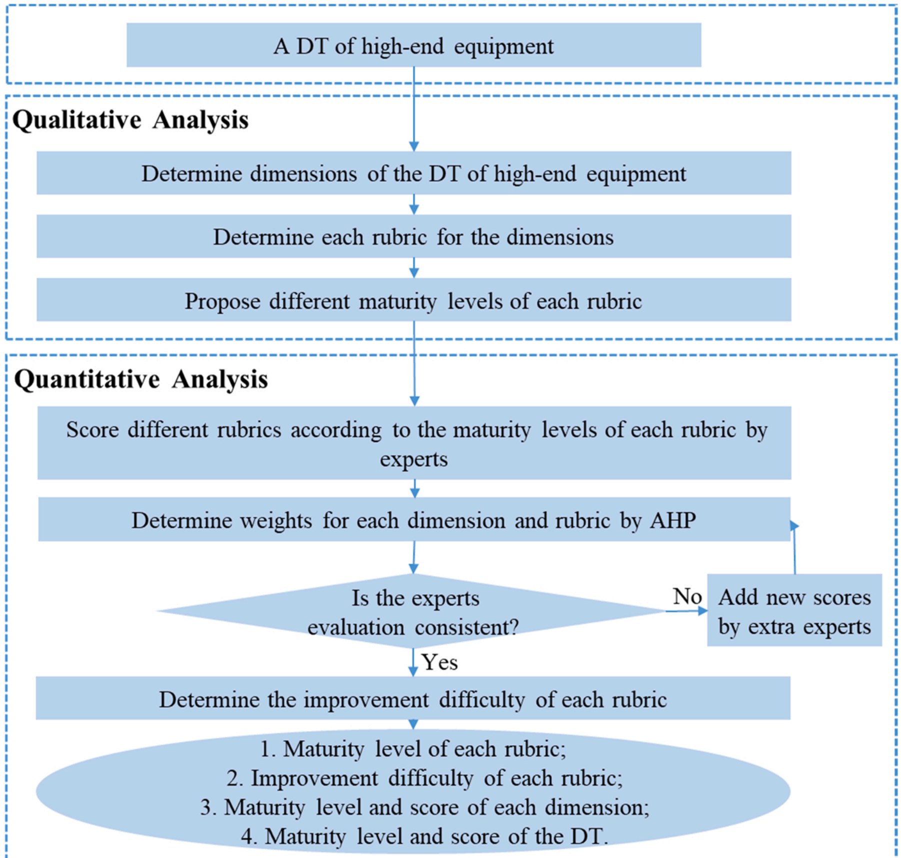


Fig. 1. Framework of the proposed DT Maturity Model.

Table 1
Rubrics of the value of DT.

Rubrics Symbol	Reference	Rubrics Definition
V_1	[37,38]	Real-time connection between equipment and services
V_2	[36]	Offline DT data or model available for the design of next-generation equipment
V_3	[33]	Efficient planning of equipment technological design and optimization
V_4	[34,35]	Performance improvement by DT during equipment operation
V_5	[7,40]	Quality control of equipment by DT during operation
V_6	[32]	Creation of DT-relevant capabilities
V_7	[39]	Organization of efficient operation procedure of high-end equipment
V_8	[37]	Training program organization for engineers
V_9	[3,37]	Communication among engineers within the organization

Table 2
Rubrics of the function of DT.

Rubrics Symbol	Reference	Rubrics Definition
F_1	[41,42]	Information collection based on data and model update
F_2	[43]	Data storage, exchange, and sharing
F_3	[44,45]	Data visualization
F_4	[7,48]	Data generation, update, and collection
F_5	[46]	Information sharing
F_6	[47]	Service integration, registration, and updating
F_7	[49]	Learning of user preferences
F_8	[50]	Prediction of multiscale features and multi-physical properties
F_9	[51]	Design and decision-making under different circumstances

Wang et al. proposed a DT-based information collecting method to diagnose the possible faults for rotating machinery by the collected running data [42]. In addition, to mirror the function of the physical entities, data storage, exchange, sharing [43], and visualization [44,45] are essential. The design of next-generation high-end equipment requires the existing DT of high-end equipment to collect necessary data, which can also be used to update the existing DT model. Furthermore, the DT of high-end equipment should provide a sharable database so that all lifecycle data can be collected and fully used [46]. Hence, the integrated model can use the database to estimate the performance of high-end equipment for fault detection [47]. Finally, the constructed DT of high-end equipment can learn user preferences and predict multiscale features and multi-physical properties, consequently making decisions based on probability.

The reliability of DT is the ability to ensure the stable and correct operation of the DT system under external disturbances. To achieve this goal, a mature DT of high-end equipment needs to satisfy the requirements of high security [6] and high openness. A highly mature standard needs to be developed. For instance, the integrity and accuracy of the digital thread model as well as the data resources need to be well ensured to achieve the security of DT [42,52]. In addition, necessary standards and protocols will lead to a stable and continuous message exchange, which further enables the reliability of data [53]. Furthermore, a reliable DT of high-end equipment needs to have a mature part or component replacement system, which could be used to keep records of the broken parts [54]. Some visualization technologies, such as virtual reality or mixed reality, will also be applied to ensure the operation of equipment [36], which may guide engineers to repair the broken parts [34]. Thus, the DT of high-end equipment could use these tools to provide formal service and data sustainable operation regulations [55]. Table 3 summarizes the proposed definitions of rubrics of the reliability of DT.

The proposed dimensions and rubrics of the DT maturity model for high-end equipment are shown in Fig. 2, which consists of 3 dimensions and 27 rubrics as listed in Tables 1, 2, and 3, respectively. As the maturity evaluation of DT is still in its early stage, it is possible that new capabilities/rubrics may be added in the DT maturity model in the future.

2.1.2. Maturity levels of dimensions and rubrics

The maturity levels here qualitatively evaluate the development degree of DT's dimensions and rubrics. To qualitatively determine the maturity levels of rubrics, experts are invited to score the maturity of each rubric (total score 100) based on prescribed definitions of maturity levels of rubrics. Here, six levels and their definitions for each rubric are proposed and provided in Appendix Tables A.1-A.3 based on comprehensive survey of existing maturity model references [13,14,27,29,30,57]. The maturity levels of rubrics are then determined based on the mean scores located in a certain score range. The maturity levels of dimensions are determined by the maturity scores of dimensions which are quantitatively calculated based on the maturity scores of rubrics (see details in Section 2.2). The maturity levels 1 – 6 for both dimensions and rubrics corresponds to the score ranges of [0, 50), [50, 60), [60, 70), [70, 80), [80, 90), and [90, 100], respectively.

2.1.3. Maturity levels of DT

Similarly, the overall maturity levels of DT are determined by the mean maturity scores of DTs which are quantitatively calculated based on the calculated maturity scores of dimensions (see details in Section 2.2). The DT maturity levels 1 – 6 corresponds to the score ranges of [0, 50), [50, 60), [60, 70), [70, 80), [80, 90), and [90, 100], respectively. In this paper, the CMMI [58], Kerzner project management maturity model (K-PMMM) [59], organization project management maturity model (OPM3) [60], and portfolio, program, and project management maturity model (P3M3) [29] are referred to propose the 6 maturity levels of DT, including the Basic Level (Level 1), the Connection Level (Level 2), the Integration Level (Level 3), the Perception Level (Level 4), the Interaction Level (Level 5), and the Autonomy Level (Level 6). The maturity levels of DT are improved gradually, i.e., the higher level satisfies all the requirements of the lower level. The characteristics and hierarchy of maturity levels of DT are schematically shown in Fig. 3. Detailed definitions of each maturity level of DT are summarized below.

Basic Level (Level 1): At this level, the DT of high-end equipment should include some basic functions of DT. For example, control and data collection capabilities on key components of high-end equipment are required in the basic level to support the following maturity levels of DT (e.g., communication and integration).

Connection Level (Level 2): At this level, the DT of high-end equipment is supposed to implement communication technology (5G and IoT) on the key components to equip them with the ability of connection between the virtual and real worlds.

Integration Level (Level 3): At this level, the DT of high-end equipment should evolve from separate data acquisition and communication to an integrated implementation. For instance, during the manufacturing procedure, the DT with an integration level should complete digital and networking improvements to enable standardized data collection and sharing in the whole factory.

Perception Level (Level 4): At this level, the DT of high-end equipment has an operation monitoring system, management system, and other support systems, which are fully utilized to realize the perception of the real working condition of high-end equipment based on a knowledge database, expert database, historical database, and collected data.

Interaction Level (Level 5): At this level, the DT of high-end equipment should be able to take interaction between the environment and high-end equipment based on machine learning, deep learning, and other methods. Thus, DT can provide sharable knowledge and value, which may be used to design the working schedule of high-end equipment appropriately.

Autonomy Level (Level 6): At this level, the DT of high-end equipment should carry out automatic prediction and operation under different unknown working conditions. The DT of high-end equipment can autonomously make decisions to robustly maintain the safety of high-end equipment.

Table 3
Rubrics of the reliability of DT.

Rubrics Symbol	Reference	Rubrics Definition
R_1	[52]	Ensure the integrity and accuracy
R_2	[6,56]	Information security
R_3	[53]	Specify standards and protocols
R_4	[54]	Component information record
R_5	[46]	Support for virtual/mixed reality and interaction with users
R_6	[42]	Integrity, accuracy, and openness of data resources
R_7	[42]	Implementation guide for specific high-end equipment
R_8	[34]	Continuous assurance of operation quality
R_9	[55]	Formal service and data sustainable operation regulations

2.2. Quantitative analysis

The quantitative analysis of the DT maturity model incorporates the analytic hierarchy process (AHP) method and the matter-element extension method, which can not only estimate the significance of each rubric but also provide the improvement priority of different rubrics for improving DT maturity.

2.2.1. Maturity score calculation

The AHP method is utilized to determine the weight of each rubric (or dimension) by comparing the importance of rubrics (or dimensions) in pairs [61]. Following Saaty et al. [62], the comparison score of one rubric (or one dimension) compared to another one is selected based on the pairwise comparison as shown in Table 4. Since multiple experts participate in the pairwise comparison, the comparison score of a rubric (or a dimension) equals to the mean of comparison scores by all experts.

The 9-level comparison score is utilized to evaluate the significance of all 9 rubrics in each dimension (and the significance of the 3 dimensions when conducting the pairwise comparison of dimensions) using a comparison matrix. For n rubrics (or dimensions), the comparison matrix $A_{n\times n}$ is expressed as follows:

$$A_{n\times n} = \begin{bmatrix} 1 & c_{12} & \cdots & c_{1n} \\ 1/c_{12} & 1 & \cdots & c_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/c_{1n} & 1/c_{2n} & \cdots & 1 \end{bmatrix} \tag{1}$$

where c_{ij} is the comparison score of rubric i compared to rubric j, and $c_{ji} = 1/c_{ij}$. The significance indicated by weights w_i for different rubrics (or dimensions) are determined by:

$$A_{n\times n} \begin{bmatrix} w_1 \\ \vdots \\ w_n \end{bmatrix} = \lambda_{\max} \begin{bmatrix} w_1 \\ \vdots \\ w_n \end{bmatrix} \tag{2}$$

where $\lambda_{\max}$ is the maximum eigenvalue of the comparison matrix and $[w_1, w_2, \ldots, w_n]^{\mathrm{T}}$ is the corresponding eigenvector. Considering the potential inconsistency of comparison scores provided by different experts, the consistency analysis of the pairwise comparison conducted by different experts is utilized [61,62]. The consistency ratio (CR) is defined as:

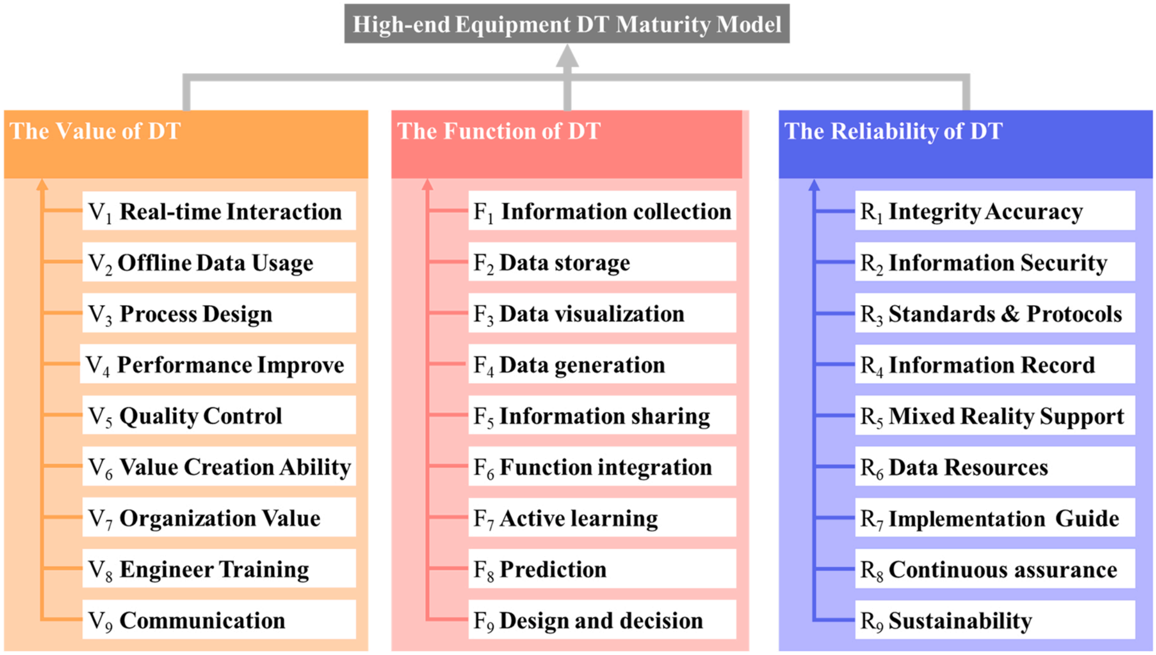


Fig. 2. The dimensions and rubrics of the proposed DT maturity model.

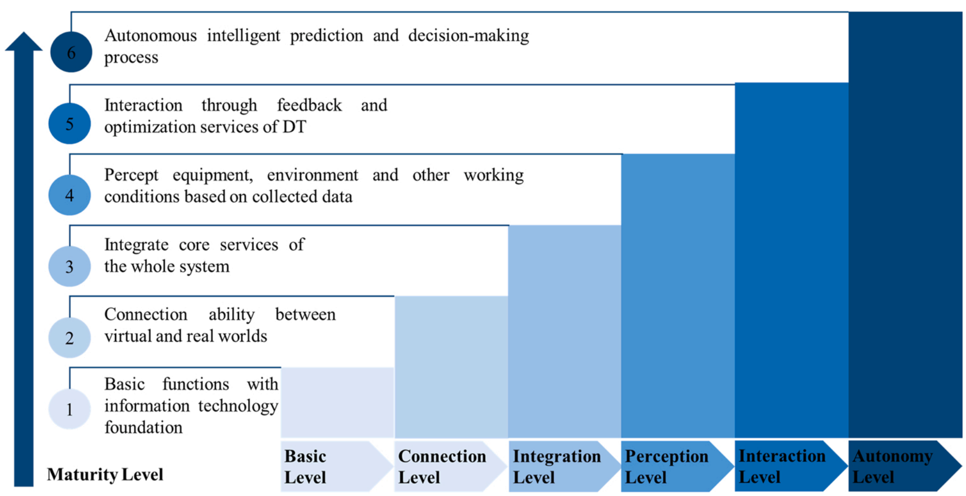


Fig. 3. The proposed maturity levels of DT of high-end equipment.

$$CR = \frac{CI}{RI} \tag{3}$$

where CI is the consistency index determined by:

$$CI = \frac{\lambda_{\max} - n}{n - 1} \tag{4}$$

where n is the number of rubrics (or dimensions). RI is the random index calculated by:

$$RI = \frac{\lambda_{avg} - n}{n - 1} \tag{5}$$

where λ_{avg} is the average value of all eigenvalues of the comparison matrix. Following Satty et al. [61], the 10 % threshold of the consistency ratio is utilized in this paper. If the calculated consistency ratio is smaller than the threshold, the pairwise comparison by the experts complies with the consistency analysis. Otherwise, the pairwise comparison process needs to be repeated (e.g., re-compare and re-calculate the CR) until the CR is smaller than the threshold.

After passing the consistency analysis for rubrics and dimensions, the maturity scores of the whole DT can be calculated as follows:

$$S_{DT} = \sum_{i=1}^{3} w_i^d S_i^d \tag{6}$$

where S_{DT} is the DT maturity score, and $w_i^d, i = 1,2,3$, are the weights of the dimensions of value, function, and reliability, respectively, calculated by the AHP method.$S_i^d, i = 1, 2, 3$, are the maturity scores of the dimensions of value, function, and reliability, respectively, and are calculated by:

$$S_i^d = \sum_{j=1}^{9} w_{ij}^r S_{ij}^r \tag{7}$$

where $w_{ij}^r, i = 1, 2, 3; j = 1, 2, \ldots, 9$ are the weights of jth rubric in ith dimension calculated by the AHP method. $S_{ij}^r, i = 1, 2, 3; j = 1, 2, \ldots, 9$ are the mean maturity score of jth rubric in ith dimension provided by

Table 4
Comparison score of rubrics and dimensions.

Comparison score	Importance	Definition
1	Same importance	Two rubrics or two dimensions make equally contribution to the overall DT maturity
3	Moderate importance	Experience and judgement slightly favour one rubric or dimension above the other in terms of their contribution to the overall DT maturity
5	Essential importance	Experience and judgement strongly favour one rubric or dimension above the other in terms of their contribution to the overall DT maturity
7	Very strong importance	One rubric or dimension is dominate than the other in terms of the contribution to their overall DT maturity
9	Absolute importance	One rubric or dimension is the absolutely important than the other in term of their contribution to the overall DT maturity
2, 4, 6, 8	Intermediate importance	Importance between the neighbouring two importance

the evaluation experts.

During the evaluation process of DT maturity, there is an uncertainty due to the different scores provided by different experts and different evaluation processes. Here the standard deviation (SD) of the maturity scores is calculated to indicate this uncertainty. The maturity evaluation process with a smaller SD of the evaluated score is considered to be more robust than that with a larger SD. For a maturity improvement process, the improvement difficulty of different rubrics should also be considered, which will be introduced in the next section.

2.2.2. Determination of rubrics to be improved

The matter-element extension method is a multielement analysis method that is often used to assess improvement difficulty of each evaluation element in a matter and provide the element(s) with priority to be improved in the future [63]. In this study, due to the comprehensiveness of the proposed DT maturity model, there are often incompatibilities in selection of rubrics to be improved for future DT maturity development. The purpose of combining the AHP method and the matter-element extension method is to utilize the closeness function in the matter-element extension method to determine the rubrics to be improved. To construct the closeness function, the distance D_k between the maturity score S_{ij}^r of a rubric and the scoring range of kth maturity level is defined as:

$$D_k\left(S_{ij}^r\right) = \left|S_{ij}^r - \frac{1}{2}(a_k + b_k)\right| - \frac{1}{2}(b_k - a_k) \tag{8}$$

where a_k and b_k are the lower bound and the upper bound, respectively, of the scoring range of kth maturity level. To evaluate the improvement difficulty of a rubric, the degree of closeness C_k^r of the maturity score S_{ij}^r towards kth maturity level is adopted from [63] and defined as follows:

$$C_k^r\left(S_{ij}^r\right) = \begin{cases} -\dfrac{D_k\left(S_{ij}^r\right)}{|b_k - a_k|}, S_{ij}^r \in [a_k, b_k] \\ \dfrac{D_k\left(S_{ij}^r\right)}{D_{\max}\left(S_{ij}^r\right) - D_k\left(S_{ij}^r\right)}, S_{ij}^r \notin [a_k, b_k] \end{cases} \tag{9}$$

where $D_{\max}$ is defined as

$$D_{max}\left(S_{ij}^r\right) = \left|S_{ij}^r - \frac{1}{2}(a_m + b_m)\right| - \frac{1}{2}(b_m - a_m) \tag{10}$$

where a_m and b_m is the lower bound and the upper bound, respectively, of the whole scoring range (i.e., $a_m = 0$, $b_m = 100$). Based on Eqs. (9)-(10), if the maturity score of a rubric is outside the range of kth maturity level, then $C_k^r\left(S_{ij}^r\right) < 0$. If the maturity score of a rubric is in the range of kth maturity level, then $C_k^r\left(S_{ij}^r\right) \geq 0$. Meanwhile, a smaller non-negative value of $C_k^r\left(S_{ij}^r\right)$ indicates a lower improvement difficulty. All the 27 rubrics can be monotonically increasingly ranked according to each non-negative $C_k^r\left(S_{ij}^r\right)$. The rubrics corresponding to small non-negative $C_k^r\left(S_{ij}^r\right)$ are suggested to be improved in order to advance the DT maturity.

3. Case study

In this section, three practical DTs of high-end equipment are selected to evaluate the proposed DT maturity model as follows: (1) DT of underground engineering equipment, (2) DT of a wind turbine, and (3) DT of a shop-floor. Fig. 4 shows a schematic diagram of these three DTs.

Fig. 4(a) shows the DT of underground engineering equipment, which aims for the high-fidelity DT simulation of underground engineering equipment to avoid potential risks under complex and changing working conditions. The DT of underground engineering equipment includes: (1) virtual modelling, including import of virtual entity and working environment, assembly information expression, and kinematics and dynamics database building, (2) the collection, fusion, and transmission of multisource heterogeneous sensing data in virtual and real space, (3) the whole life-cycle perception and state mirror mapping between virtual entity and physical entity of underground engineering equipment, (4) consistency analysis between simulation models and the physical reality of underground engineering equipment DT, and (5) development of DT of underground engineering equipment systems based on mixed reality.

Fig. 4(b) illustrates the DT of a wind turbine, which integrates performance attributes such as load, stress, strain, and fatigue into the simulation and constructs a data communication platform for condition monitoring of the wind turbine. The DT of the wind turbine includes: (1) the integration of different functions, such as the aerodynamic load calculation and the finite element simulation, (2) the fatigue damage prediction based on the calculated stress, (3) virtual visualization in 3D software with high-quality wind turbine rendering and analysis results, and (4) real-time mirror-mapping of the wind turbine based on sensoring data and analysis results.

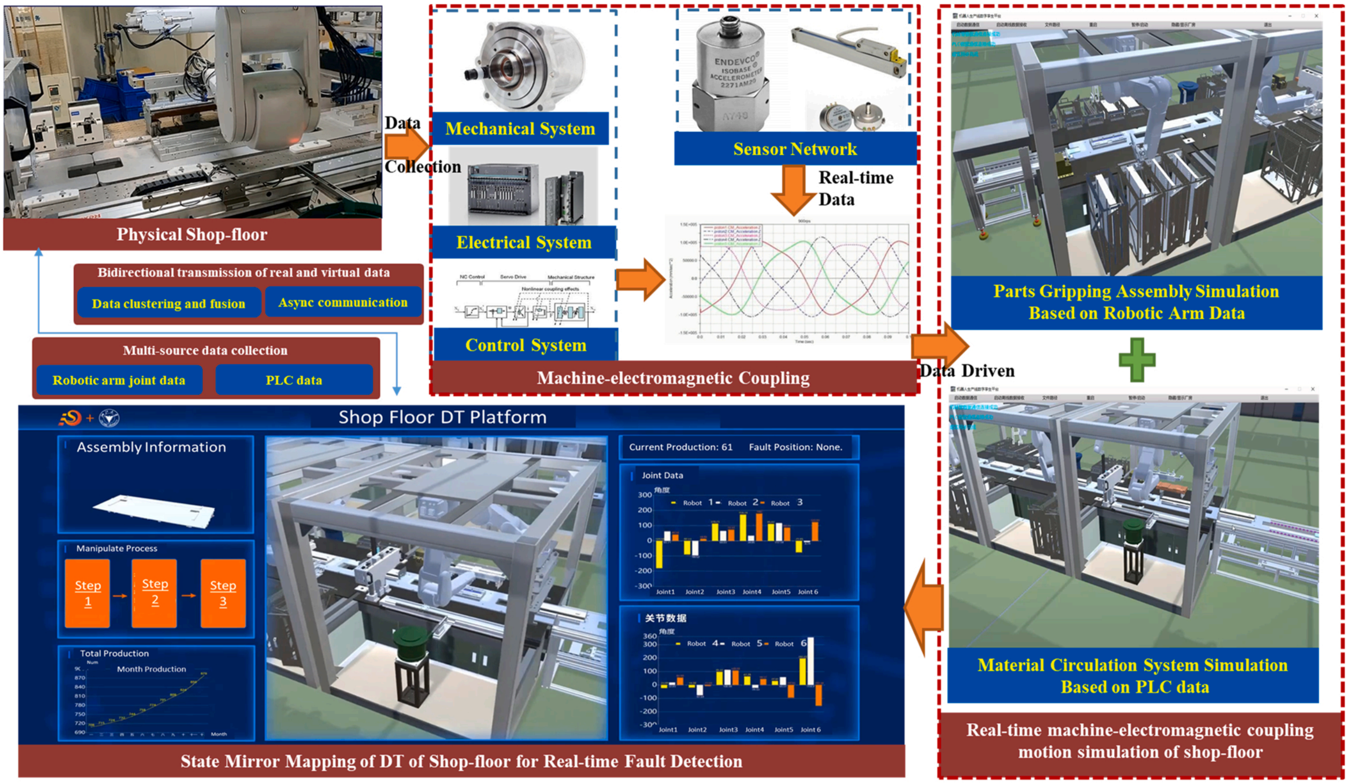
Fig. 4(c) shows the DT of a shop-floor with intelligent production and lean management, which further realizes the function of personalized customization and service extension. The DT of the shop-floor includes: (1) physical entities of product assembly lines with data acquisition systems, (2) data transmission of simulation data and feedback control data for real-time fault analysis and diagnosis decision based on machine-electromagnetic coupling analysis, and (3) mirror-mapping of the virtual and physical shop-floor for real-time fault detection based on real-time motion simulation and transmitted data.

4. Results and discussion

In this study, 16 external experts were invited, including 8 experts providing the evaluated score for each rubric (i.e., one expert from an engineering consulting enterprise and seven from scientific institutions) and another 8 experts conducting the pairwise comparison (one expert from another engineering consulting enterprise and seven from scientific institutions). The maturity scores for each rubric of the three DT maturity models were evaluated based on the relevant data of the input, process, and result of the DTs. The mean maturity scores of rubrics are schematically presented in a rose diagram as shown in Fig. 5.

It is obvious that the maturity level of DT of high-end equipment cannot be directly observed from Fig. 5. Hence, the weights of rubrics

Fig. 4. Schematic diagram of three DTs of high-end equipment.



(c) DT of a shop-floor

Fig. 4. (*continued*).

and dimensions were determined by the AHP method. The evaluation results all pass the consistency analysis explained in Section 2.2.1. The calculated weights of the value of DT, the function of DT, and the reliability of DT are 0.43, 0.42, and 0.15, respectively, while the weights of rubrics are $\boldsymbol{w}_i = [w_{V1},\ldots, w_{V9}, w_{F1},\ldots, w_{F9}, w_{R1},\ldots w_{R9}] = (0.031, 0.014, 0.0095, 0.083, 0.173\ 0.040, 0.055, 0.0077, 0.016, 0.021, 0.010, 0.0048, 0.052, 0.052, 0.010, 0.20, 0.054, 0.021, 0.018, 0.0062, 0.053, 0.024, 0.024, 0.0079, 0.012, 0.0042, 0.0014)$. These weights indicate the importance of different rubrics and dimensions.

The matter-element was built to evaluate the maturity level of three DTs of high-end equipment for the direction of improvement. The degree of closeness was calculated according to Eqs. (8) - (10) considering the distances and evaluated maturity scores of rubrics. Details of maturity level of each rubric and the degree of closeness of rubrics are provided in Appendix Table A.4. The overall maturity levels and the evaluated maturity scores of each dimension, as well as the three DTs, are shown in Table 5.

By utilizing the proposed quantitative DT maturity model, the comparation of maturity between different high-end equipment could be carried out. Table 5 shows that the maturity levels of DTs of the underground engineering equipment, the wind turbine, and the shop-floor are level 5, level 4, and level 4, respectively. The evaluated total maturity score (81.49) of DT of the underground engineering equipment is the highest among those of the three DTs. In addition, the SD of evaluated score of DT of the underground engineering equipment is the lowest among those of the three DT, which indicate DT maturity evaluation for the underground engineering equipment is more robust than those for the other two high-end equipment. Table 5 also shows that although the overall evaluated maturity score of DT of the wind turbine (70.12) is similar with that of the shop-floor (70.43), the evaluation process for DT of the wind turbine is more robust than that for DT of the shop-floor by comparing the SD values.

Fig. 6 illustrates the cross-comparison of maturity among the three DTs of high-end equipment. The maturity of each dimension of the three DTs of high-end equipment can be inferred in Fig. 6(a). From the perspective of the DT of underground engineering equipment, its value and function are much higher than those of the DT of the wind turbine and the DT of the shop-floor. However, the reliability of underground engineering equipment DT is still in level 3, which may be the focus of future improvement. In addition, even if different DT systems are at the same maturity level and their total evaluated maturity scores are similar, the internal maturity of DT system components can also be compared by the distribution of number of rubrics in each level, as shown in Fig. 6(b). Using the DTs of wind turbines and shop-floor as an example, although the two DTs have a similar overall evaluated maturity score, the DT of wind turbines has more rubrics at relatively high maturity levels (i.e., level 5) than the DT of shop-floor. In addition, the rubrics of DT of the shop-floor are more dispersed in different levels than those in DT of the wind turbine.

Fig. 7 indicates the improvement priority of each rubric considering the rubric significance and difficulty of improvement, which are represented by the weights of rubrics and the degree of closeness, respectively. After evaluating the maturity level of each rubric, the rubrics with high significance, low level, and low improvement difficulty should be improved in priority. For the DT of underground engineering equipment, the identified rubrics to be improved are at a low level and small improvement difficult by referring to Table A.4 and Fig. 7(a), such as R_4, R_9, R_2, and R_3. For the DT of the wind turbine, rubrics with higher significance (shown in Fig. 7(b)) and higher maturity level (shown in Table A.4) are V_2, V_4, V_5, and F_7, which means that the DT of the wind turbine is superior in the field of data storage, operation efficiency improvement, operation quality control, and learning of user preferences. Rubrics of the DT of the wind turbine such as R_3, R_4, F_8, and F_9 with low maturity levels (shown in Table A.4) should be prioritized. Finally, rubrics of DT of shop-floor with low levels, high weights, and low-improvement difficulty (e.g., V_4, F_7, F_8, and R_4) need to be selected

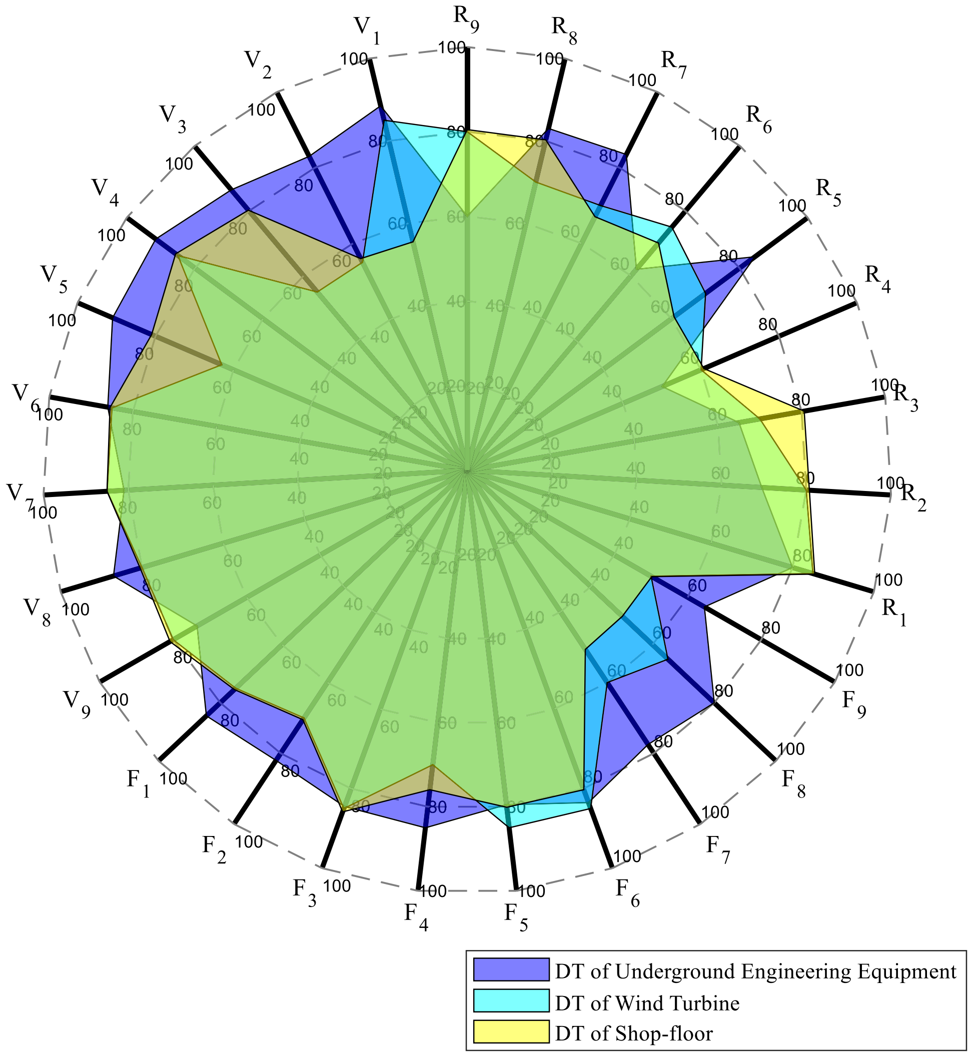


Fig. 5. The rose diagram of maturity scores of rubrics of three DTs of high-end equipment.

Table 5
The maturity level and the evaluated maturity scores of three DTs of high-end equipment.

Dimension	DT of underground engineering equipment			DT of wind turbine			DT of shop-floor		
	Maturity level	Mean of evaluated scores	SD of evaluated score	Maturity level	Mean of evaluated score	SD of evaluated score	Maturity level	Mean of evaluated score	SD of evaluated score
Value of DT	Level 5	88.08	2.43	Level 4	79.44	3.95	Level 4	74.21	4.31
Function of DT	Level 4	79.09	5.73	Level 2	59.63	4.81	Level 3	66.34	4.93
Reliability of DT	Level 3	69.50	4.66	Level 4	72.75	3.59	Level 4	71.01	4.59
Total Maturity	Level 5	**81.49**	4.15	Level 4	**70.12**	4.26	Level 4	**70.43**	4.62

and improved to advance the maturity level of DT.

5. Conclusions

This paper proposes a new quantitative DT maturity model for evaluating the maturity of DT of high-end equipment, which can be used to evaluate whether the existing DTs meet the expected requirement and to improve the DT maturity. Key conclusions are summarized as follows.

(1) The proposed new qualitative DT maturity model for high-end equipment includes 3 dimensions and 27 rubrics. Six different maturity levels and the definitions of different levels of rubrics are proposed, which can be used in expert scoring.
(2) The AHP method is developed for finding the weight of each rubric of the DT maturity model, and the matter-element extension method is utilized to evaluate the degree of closeness between the current maturity level of a rubric and the next level. Thus, improvement advice considering rubric significance and improvement priority can be created to improve the maturity level of DT. In general, the maturity of DT of high-end equipment could be advanced by improving rubrics with high significance, low level, and low improvement difficulty.

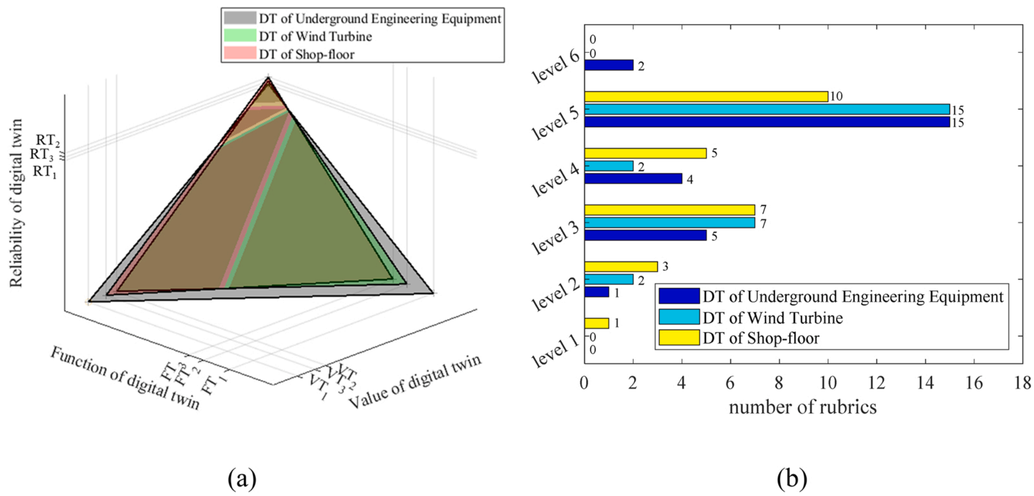


Fig. 6. The cross-comparison of three DTs using the proposed DT maturity model. (a) Development of each dimension. (b) The distribution of rubric maturity levels.

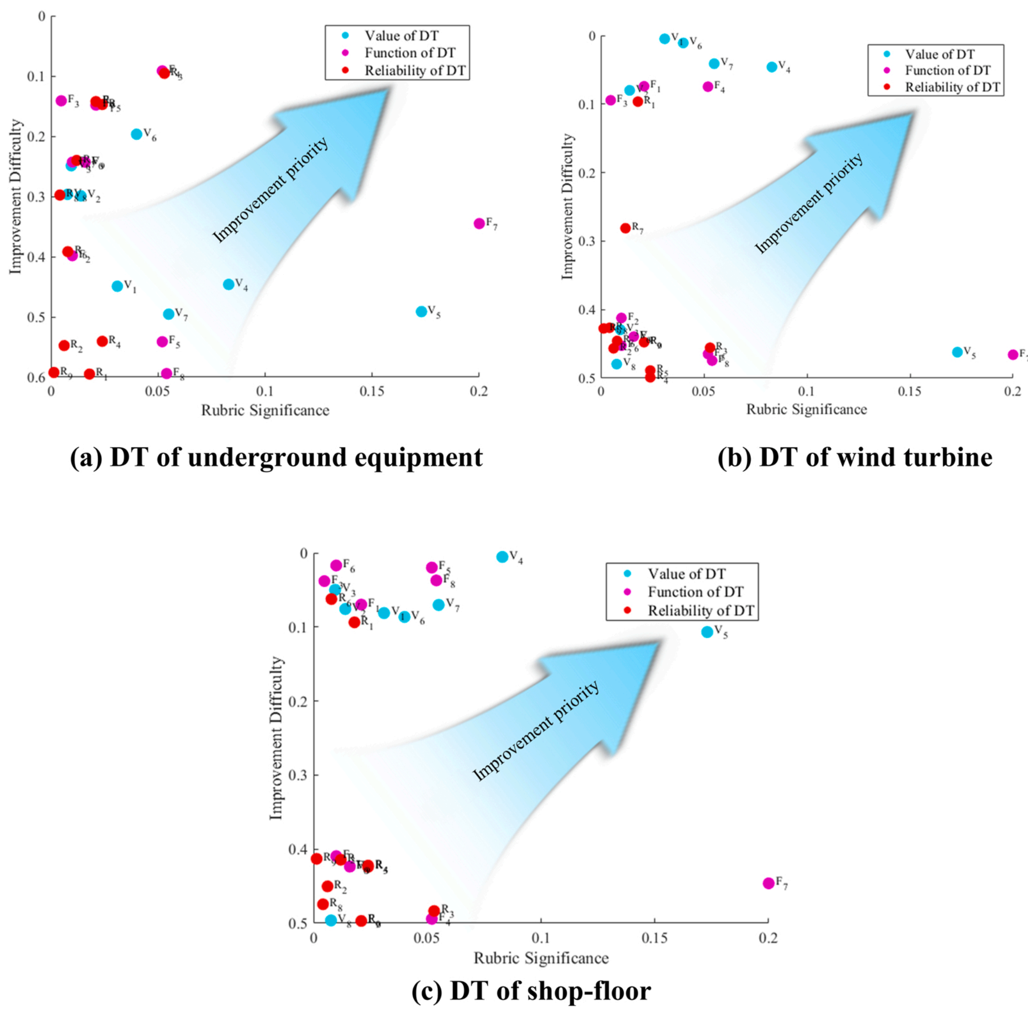


Fig. 7. Improvement priority of each rubric of three DTs of high-end equipment.

(3) The proposed DT maturity model has been applied to evaluate the maturity levels of three DTs of high-end equipment (i.e., underground engineering equipment, wind turbine, and shop-floor). The obtained total evaluated maturity scores are 81.49, 70.12, and 70.43, which correspond to maturity levels of 5, 4, and 4, respectively, for the three DTs.

Some limitations and future work are provided as follows.

(1) The proposed dimensions and rubrics may not cover all aspects of the maturity of a DT of high-end equipment. New dimensions and rubrics may be added into the proposed DT maturity model for a

wide application of DT maturity evaluation of high-end equipment.

(2) The provided maturity scores are probably different from different experts even for the same rubric, and the number of experts will influence the final maturity score. Hence, it is an interesting task to quantify the uncertainty of the maturity score due to different numbers of experts, especially by a small number of experts, which is worth investigating in the future.

(3) Future research may include the applications of the proposed DT maturity model on the DT of high-end equipment during its whole lifecycle.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.jmsy.2022.12.012.

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