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Towards A Methodological Framework For Early Qualitative Assessment Of The Ecological And Economic Costs Of Digital Twins In Industrial Maintenance

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Over the last decade, the use of digital twins (DTs) has expanded significantly across a variety of sectors. They often take various forms, with an emphasis on the underlying technologies (IoT, Cloud Computing, AI, virtual reality, etc.). However, one question remains: once deployed, will these digital twins be utilized in a manner that is both cost-effective and sustainable? Digital twins originated in maintenance applications, which is where these technologies are currently the most mature. Previous work shows that in the literature, most articles concern predictive maintenance applications, which implies the frequent use of artificial intelligence and therefore the management of large volumes of data. However, in recent years, we have seen the emergence of virtual reality technologies for training and augmented reality for intervention assistance, which require both significant hardware and software resources.

The aim of this article is to propose a qualitative methodology for classifying industrial maintenance digital twins. This methodology will enable the assessment of the economic and environmental costs of DTs, making it possible for decision makers to ask the right questions even at the earliest stages of the DT's conception. This is especially helpful since, at those early stages, designers often lack quantitative information. This approach offers a more accessible starting point for eco-design, unlike more quantitative methods, such as Life Cycle Assessment (LCA), which require higher precision in data collection and a significant amount of time. This qualitative methodology will be applied to recent literature, providing a preliminary analysis of the digital twins currently in operation.

Keywords: Digital Twin, Industrial Maintenance, Economic and ecological impacts.

1. Introduction

The integration of Digital Twins (DTs) into industrial maintenance marks a transformative shift in managing equipment and processes, driven by the ongoing evolution of Industry 4.0. Despite numerous efforts to define DTs, a standardized and universally accepted definition remains elusive (Abdullahi, Longo, and Samie 2024). DTs can be described as dynamic virtual replicas of physical systems that facilitate real-time monitoring, simulation, and optimization (Soori, Arezoo, and Dastres 2023). These technologies are integral to predictive maintenance (Viaron, Julien, and Hamzaoui 2024), enabling industries to anticipate failures, minimize downtime, and optimize resource utilization. However, the increasing adoption of DTs also raises pressing concerns about their ecological and economic implications.

From an ecological standpoint, the adoption of Digital Twins (DTs) demands significant data processing and equipment acquisition, which drives up energy consumption. Additionally, the production and disposal of the sensors and IoT devices that power DT systems raise concerns about electronic waste and the sustainability of materials. On the economic front, while DTs are recognized for minimizing downtime and enabling proactive maintenance, their implementation comes with high initial costs for hardware, software, and workforce training. These trade-offs underscore the importance of carefully assessing the balance between the benefits of DT technology and its sustainability and cost-efficiency objectives.

Based on our recent research, there has been no comprehensive study on the direct ecological and economic impacts of Digital Twins. For this reason, we propose an initial qualitative review that is broad enough to be applied across various Digital Twin applications. Unlike more quantitative methods, such as Life Cycle Assessment (LCA), which demand higher precision and granularity, this approach offers a more accessible starting point.

This paper introduces in part 2 the context and previous works, then proposes in part 3 an initial framework for qualitatively assessing the ecological and economic impacts of Digital Twins (DTs) through three key criteria: DT maturity, physical equipment acquisition, and the user experience. This approach is applied in part 4 to representative maintenance DT examples from literature, and its limitations and perspectives are discussed in part 5 before the conclusion.

2. Context

Multiple studies have been conducted not only to define but also to classify Digital Twins, with the aim of proposing a standardized methodology for their conception. Among these, we can find the typology of DTs proposed by Julien and Martin (2020), the 5D model introduced by Tao, Zhang, and Nee (2019), the extended version proposed by Hamzaoui and Julien (2022), and the Digital Twin Capabilities Periodic Table ("Digital Twin Capabilities Periodic Table," n.d.). These frameworks offer valuable perspectives on the structure, functionality, and applications of Digital Twins, providing a solid understanding of the key elements that characterize this technology and consequently, contribute to the ecological and economic impacts of the DT.

From an ecological and economic perspective, a study by ADEME (the French Agency for Ecological Transition) and Arcep (the French Regulatory Authority for Electronic Communications, Postal Services, and Press Distribution) on the environmental impact of digital technology in France ("Etude ADEME – Arcep sur l'empreinte environmental du numérique en 2020, 2030 et 2050" 2023) reveals that nearly 80% of the environmental impact of digital products and technologies comes from physical equipment such as IoT devices and computer screens. The remaining 20% is distributed between data processing and storage, networks and communication. This categorization is also known as the "three-tier architecture."

The "three-tier architecture" outlines the environmental impact of digital technologies across three core components:

- *Equipment*, this first tier encompasses all end-user devices, such as smartphones, computers and IoT devices, with significant impacts stemming from their production, usage, and disposal.
- The second tier, *data centers*, refers to facilities responsible for processing and storing digital data, which are energy-intensive due to high electricity consumption and cooling requirements.
- The last tier, *networks*, includes the infrastructure enabling data transmission, such as mobile networks, fiber-optic cables, and internet systems, which demand substantial energy.

By combining these findings, we assume that most Digital Twins, with the highest ecological and economic impact, are those requiring substantial equipment and advanced levels of interoperability, typically representing the most mature versions of this technology. Therefore, we conclude that the maturity of a Digital Twin is a critical factor driving its economic and ecological impacts.

As nearly 80% of the ecological impacts of Digital Twins are linked to the equipment or physical components they require, their ecological impact can vary greatly; for instance, a DT that operates on existing computers and utilizes data from preinstalled sensors has a lower ecological footprint than one that necessitates acquiring new equipment. In conclusion, the extent of new equipment acquisition is a key factor driving the environmental impact of DTs.

Additionally, the user experience, as defined in the Digital Twin Capabilities Periodic Table ("Digital Twin Capabilities Periodic Table," n.d.), may also vary from a simple dashboard and basic visualizations to a complete immersive environment and gamification. Thus, it plays a significant role in determining the ecological footprint of a DT, especially because advanced user experience will often require more hardware and software resources.

In conclusion, the three key factors identified as most impactful from both an ecological and economic standpoint are the maturity of the DT, the extent of new equipment acquisition, and the user experience.

3. Assessment methodology

3.1. *DT Maturity*

DT maturity has been defined in numerous ways across different studies. In our proposed methodology, we draw inspiration from the definition of DT maturity put forward by Hamzaoui and Julien (2024), which outlines five levels of maturity. (Fig. 1)

- *Digital Mirror:* In this first level, the physical object and its behavior are represented, there is also no direct interaction between the physical and digital components.
- *Digital Shadow*: This level tracks the physical object's data and activities, offering a one-way representation of its changes.
- *Control DT:* At this stage, the physical object and its digital counterpart are integrated, enabling two-way communication and feedback loops for partial or full control.
- *Cognitive DT:* The DT evolves to predict future behaviors and outcomes based on real-time data.
- *Collaborative DT:* The highest level, where the DT autonomously makes decisions and controls the physical object without needing human intervention.

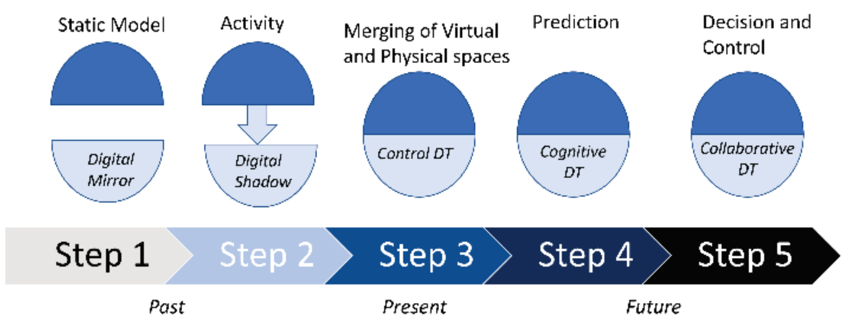


Fig. 1. The five levels of DT maturity according to Hamzaoui and Julien (2024)

3.2. *Equipment acquisition*

We hypothesize that a Digital Twin requiring more extensive new equipment acquisition for its implementation will have greater ecological and economic impacts. Accordingly, we propose five levels of equipment acquisition from L1 to L5, with each level representing progressively higher impacts.

- *L1:* No new equipment is acquired. The DT relies entirely on preexisting equipment and uses data collected by it.
- *L2:* New sensors and other IoT technologies are acquired, but no new user terminals are introduced. A user terminal refers to devices such as computers, tablets, smartphones, or similar devices.

- *L3:* A maximum of one simple user terminal is acquired (e.g. PC screens, computers, or tablets).
- *L4:* A maximum of one "augmented" user terminal is acquired. An "augmented" user terminal combines a simple user terminal (e.g. a computer, tablet, or PC screen) with XR equipment, such as a VR headset or AR devices.
- *L5:* Multiple user terminals, either simple or "augmented", are acquired.

3.3. *The User Experience (UX)*

As noted earlier, the user experience is a key factor influencing the ecological footprint of a DT. Based on the Digital Twin Capabilities Periodic Table ("Digital Twin Capabilities Periodic Table," n.d.), we have identified five distinct levels of user experience. Like the previous two factors, each level reflects progressively higher impacts.

- *L1:* The DT offers basic visualizations, such as static dashboards or simple graphs that display the results of simulations or data monitoring. These visualizations provide a basic overview without interactivity.
- *L2:* Advanced visualizations providing more detailed information, such as layered data displays, charts, and interactive elements that allow the user to explore the data in greater depth.
- *L3:* Integration of 3D models enhancing the visualizations and enabling the user to interact with as well as manipulate the virtual representation of the physical object or system.
- *L4:* Extended Reality (XR) is introduced, incorporating Virtual Reality (VR) or Augmented Reality (AR) technologies. XR provides a more immersive user experience, allowing users to engage with the DT in a virtual environment or through augmented views of the real-world system.
- *L5:* The user experience includes gamification elements, turning the interaction with the DT into a more interactive and engaging experience. This could involve game-like scenarios enhancing user participation and understanding.

Table 1. The evaluation grid used to evaluate the impacts of a DT.

	Maturity	Equipment	UX
L1	Mirror	No new equipment	Basic visualizations
L2	Shadow	IoT	Advanced visualizations
L3	Control	One simple user terminal	3D modelisation
L4	Cognitive	One augmented user terminal	Extended Reality (XR)
L5	Collaborative	Multiple user terminals	Gamification

3.4. *Evaluation proposal*

To interpret the ecological and economic impacts of a DT, we propose to assign scores based on the three criteria: DT maturity, equipment acquisition, and user experience, with each factor having levels from 1 to 5. The total score (TS), as the sum of the three factors, ranges from 3 to 15, where higher scores indicate greater ecological and economic impacts.

Scores can be categorized as follows:

- Low Impact DT: TS ≤ 6
- Medium Impact DT: $7 \leq$ TS ≤ 10
- High Impact DT: TS ≥ 11

Low-impact DTs are less resource-intensive and cost-efficient, representing early-stage versions of a DT or sustainability-focused implementations. Moderate-impact DTs achieve a balance between performance and sustainability, while high-impact DTs demand significant resources and investment for advanced functionalities such as augmented reality or gamification. These scores offer a valuable initial framework for decision-making, aligning industry needs with sustainability objectives and desired performance outcomes.

However, since the three previous factors contribute differently to the ecological and economic impacts of a DT, we propose applying weights similar to those suggested by the "three-tier architecture" by attributing 80% to the equipment acquisition criteria. For the remaining 20%, we assigned equal weights to the other two factors as an initial approach, given that determining specific weights for these factors is less straightforward.

Table 2. Initial proposed weights

	Maturity	Equipment	UX
Weight	10%	80%	10%

By incorporating the weights, the new evaluation method calculates the weighted total score (WTS) using the following formula "Eq.(1)":

$$WTS = (DT\ Maturity\ score\ \times 0.1) + (Equipement\ Acquisition\ score\ \times 0.8) + (User\ Experience\ score\ \times 0.1) \quad (1)$$

The weighted total score reflects the relative contributions of the three factors to the overall ecological and economic impacts of the DT. The total score ranges from 1 to 5, with higher scores indicating greater impacts.

Interpretation of the scores:

- Low Impact DT: WTS $\leq$ 2.3
- Medium Impact DT: 2.4 $\leq$ WTS $\leq$3.7
- High Impact DT: WTS $\geq$3.8

4. Application examples

4.1. *Cognitive DT in predictive maintenance*

In the following section, we apply the proposed grid to a DT example presented by Li et al. (2024), which describes a Digital Twin-Driven Intelligent Operation and Maintenance platform for large-scale hydro-steel structures. This platform integrates real-time monitoring, 2D/3D visualization, predictive maintenance, and intelligent decision-making to optimize the management of hydraulic engineering systems. It is applied to structures such as radial gates, spillways, and flood discharge orifices. By leveraging IoT data, advanced models, and virtual-real interaction, the platform enhances safety, reduces equipment failure rates, and improves maintenance efficiency.

Fig. 2. DT of a platform for large-scale hydro-steel structures presented by Li et al. (2024)

Classification based on the proposed grid:

- *DT Maturity*: The platform's integration of predictive maintenance positions it at Level 4 (Cognitive), reflecting its advanced functionality and intelligent decision-making capabilities.
- *Equipment Acquisition*: The platform relies on IoT technologies, including sensors for vibration, stress, and environmental monitoring, aligning with Level 2 (IoT).
- *User Experience:* The DT features 2D/3D visualizations and VR-enabled inspections but does not incorporate gamification, which corresponds to Level 4 (Extended Reality (XR)).

Table 4. Evaluation of the cognitive DT

	Maturity	Equipment	UX
Level	Cognitive	IoT	Extended Reality (XR)
Score	4	2	4
Weight	10%	80%	10%
Score * weight	0.4	1.6	0.4

Based on our initial proposed grid, this Digital Twin would receive a total score of 10, placing it in the medium impact category. If we now apply the proposed evaluation method using the suggested weights, the new total score is 2.4, also placing this DT in the medium-impact category. This conclusion does not differ from our previous evaluation using the simple method without weights, highlighting the importance of determining the appropriate weights to obtain the most realistic results.

4.2. *Collaborative DT for remote maintenance*

In this case study presented by Oppermann, Buchholz, and Uzun (2023), the digital twin is integrated into an industrial metaverse application. This system enables remote collaboration between experts and on-site technicians. Experts interact with the digital twin in a virtual reality (VR) environment, using it to visualize, annotate, and guide problem-solving. On-site technicians, equipped with augmented or mixed reality (AR/MR) headsets, see both the real machine and the digital twin overlaid in their view. This setup facilitates real-time collaboration, reduces the need for physical travel and minimizes downtime.

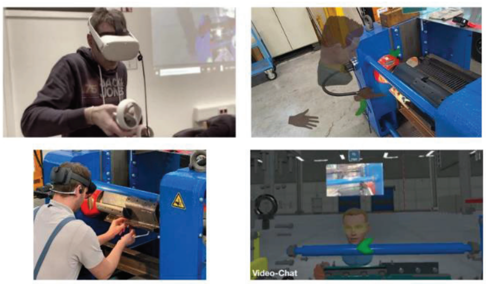


Fig. 3. Collaborative DT For Remote Maintenance (Oppermann and al, 2023)

Table 5. Evaluation of the collaborative DT

	Maturity	Equipment	UX
Level	Collaborative	Multiple user terminals	Gamification
Score	5	5	5
Weight	10%	80%	10%
Score * weight	0.5	4	0.5

This example represents a high-impact digital twin with an overall weighted score of 5. This DT necessitated the acquisition of various XR equipment, enabling advanced functionalities and enhancing collaborative capabilities.

5. Discussion and limitations

To highlight the limits of our proposed evaluation methodology of the economic and ecologic impacts of DTs, we present in this section an application example of the proposed grid to a Dynamic Reliability Digital Twin (DRDT) for the predictive maintenance of standalone steel industrial components (D'Urso et al. 2024). These components are prone to fatigue damage caused by cyclic mechanical loads, and the DRDT is specifically designed to predict their remaining useful life (RUL).

The DRDT does not rely on physical equipment, such as sensors or IoT devices, for real-time data collection. Instead, it operates entirely on synthetic data generated through computational techniques and physics-based models. By combining these models with artificial intelligence, the system analyses cumulative fatigue damage and provides accurate RUL predictions. As there is no direct connection between the Digital Twin and the physical entity, the maturity level is classified as a digital mirror. Additionally, there is no direct information regarding the user experience offered by the DT, but we assume it involves basic visualization features such as dashboards, as the DT version discussed in the article appears recent. The DRDT enables optimized maintenance scheduling, reducing unnecessary interventions and associated costs while enhancing the reliability and efficiency of industrial operations.

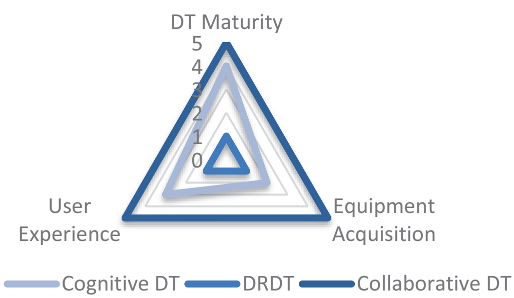
Table 6. Evaluation of the DRDT

	Maturity	Equipment	UX
Level	Mirror	No new equipment	Basic visualizations
Score	1	1	1
Weight	10%	80%	10%
Score * weight	0.1	0.8	0.1

The weighted total score for this DT is 1, classifying it as a low-impact DT. This classification is partially accurate, given that there is no direct link between the DT and the physical entity, and the system does not rely on physical equipment. However, this last point is not entirely correct, as the system utilizes a substantial amount of synthetic data as well as artificial intelligence. These elements not only enhance the system's ability to analyze and predict the remaining useful life (RUL) of components accurately, but also significantly increase the ecological and economic impacts of the DT.

Another important aspect to highlight is that the proposed methodology provides an initial image of the current impacts of DTs. Thus, an updated version of our assessment methodology should include the assessment of the impacts of the DT across its entire life cycle. This limit explains the significant differences observed between the three case studies, as shown in Fig. 4. where we compare three DTs in different maintenance applications: the DRDT for predictive maintenance, the cognitive DT for intelligent decision-making and the collaborative DT for remote maintenance.

Fig. 4. Representation of the evaluation of the three DT examples



Therefore, the proposed grid represents an initial framework that requires further development. To refine its applicability, it should be tested not only on examples from the literature but also in real industrial applications. This process will help identify key factors, weights and nuances that are essential for enhancing the grid's relevance. By doing so, it can be made more versatile, applicable to a broader range of Digital Twin use cases across diverse industries, and more effective in providing valuable insights.

In addition, in our proposed methodology, we assume that an increase in economic costs aligns with higher ecological impacts, which is not always the case. Therefore, our proposed grid must evolve, not only to include additional relevant criteria and accurate weights, but we also foresee the need to differentiate ecological and economic impacts by potentially employing two separate grids.

Lastly, qualitative approaches, such as the one proposed in this article, come with the risk of questioning whether the results of this assessment are reliable enough to support decision-making. This is particularly true when considering that the benefits provided by the digital twin are not weighed against its environmental and economic impacts. This limitation highlights that not all aspects of this innovative technology are currently addressed in the proposed assessment methodology.

Conclusion

To summarize, our proposed methodology aims to qualitatively evaluate the economic and ecological costs of Digital Twins (DTs) based on three key criteria that we assume significantly influence these costs. The first factor is *DT maturity*, as a more mature DT typically offers better and more advanced functionalities, such as prediction and enhanced decision-making, which require substantial amounts of data. The second factor is the amount of *new equipment acquisition*, representing nearly 80% of the ecological costs, since we assume that a DT operating on existing hardware has a lower ecological footprint compared to one that requires acquisition of new equipment. Lastly, the *user experience* provided by the DT plays a critical role in determining both the ecological and economic footprint. For example, a DT that offers basic visualizations, such as dashboards for simulation results, has a lower impact than one integrating virtual or augmented reality technologies.

To assess the ecological and economic impacts of a DT, we propose assigning scores based on the previous three criteria: DT maturity, equipment acquisition, and user experience. Each factor is ranked across five levels, ordered by increasing ecological and economic impacts. The total score is the sum of each criterion's score, ranging from 3 to 15, with higher scores indicating greater ecological and economic impacts. This approach supports decision-makers by helping them ask the right questions, and subsequently, provide them with a more accessible and quicker starting point for eco-design. In contrast to more quantitative methods like

Life Cycle Assessment (LCA), which require significant resources, this methodology offers a more streamlined alternative.

Although our proposed evaluation method is easily applicable to a wide range of DT use cases, it has certain limitations, such as not directly addressing data management aspects or taking into consideration the full lifecycle of this technology and not distinctly separating economic costs from ecological impacts, which do not always evolve in the same manner.

In conclusion, our proposed methodology provides an initial understanding of the ecological and economic impacts of DTs, but it needs further development and refinement to become more reliable.

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