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The role of Digital Twins in electronic devices lifecycle: unlocking potential for Circular Economy practices

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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

Recently, both academic and scientific debates have been strongly focused on the issue of electronic waste, given the significant environmental and economic challenges associated with it, encouraging therefore circular economy (CE) practices at their end-of-life management. Smart waste management has emerged thanks to the rapid development of digital technologies. Among these, thanks to their capabilities, Digital Twins (DTs) have recently emerged as promising for advancing CE initiatives; however, their functionalities in the electronics sector in supporting CE practices have not been analysed to a great extent. This article aims to provide a comprehensive view on current functionalities of DTs across electronic devices lifecycle, assessing how and for which purpose they are applied, highlighting challenges to CE. The article presents a systematic literature review which focuses on DT functionalities such as level of application (i.e., component, product, process levels), lifecycle phases supported, and the types of data collected in current DT applications. The main findings reveal that most of current DT implementations overlook CE aspects, mainly due to the limited data reuse across lifecycles. Building on these results, the paper proposes a conceptual scheme of guidelines that systemically incorporates DTs into CE workflows, optimizing their use for enhanced circularity throughout electronic devices lifecycle at different levels of application. The developed analysis aims at presenting how to advance DTs as enablers of circularity and provides practical insights for electronics value chain actors in transitioning toward circular practices, by leveraging the potentials of DTs.

1. Introduction

Electronic waste is one of the fastest-growing types of waste globally due to the increased need and consumption of electronic devices (Misra et al., 2021). To cope with waste generation, proper recycling and recovery strategies are essential to manage these products once they reach their end-of-life (EoL). As Europe moves towards Circular Economy (CE), environmental challenges have led to the creation of several regulations and policies (Mishra et al., 2024). In particular, CE emphasizes strategies such as recycling, reusing, remanufacturing and refurbishing, which help extend material circulation and reduce environmental impacts while also creating economic opportunities through innovative business models (MacArthur Foundation, 2013). Indeed, the transition towards CE is crucial in electronics production, given the rapid obsolescence rate of electronic devices and the continuous significant amount of electronic waste generated. Additionally, since electronic products contain valuable materials (e.g., copper, silver, gold, indium), implementing CE practices could ensure an efficient recovery of these materials (Awasthi et al., 2018). Indeed, strategies like design for disassembly and extended producer responsibility can facilitate the recovery of valuable materials from discarded electronic devices, contributing to a more sustainable lifecycle.

Academic research highlights the importance of these strategies in transforming waste management practices and promoting sustainable development (Najar et al., 2024). However, a great amount of global waste from electronic products is still not correctly managed. Indeed, from an industrial point of view, usually the waste issue is considered mainly only once the product reaches its EoL and not throughout its entire lifecycle. The challenge that a manufacturer faces relates to the identification of the optimal route for EoL products, to understand whether their components need to be reused, recycled, or will end up in a landfill (Iakovou et al., 2009). An integrated approach on the application of CE strategies such as eco-design practices, including design for disassembly, design for recovery and design for recycling at the beginning of products' lifecycle (BoL), can support managing from the early life of the product the optimal EoL route and reduce the environmental

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impact brought by incorrect management of the waste from these products. However, due to the complexity of application of such strategies, usually they are not implemented by manufacturers, neglecting therefore the relevance of integrated decisions across lifecycle stages. Nevertheless, these challenges also open opportunities for digital technologies to support manufacturers in overcoming barriers to CE adoption. Among the digital technologies, the role of Digital Twins (DTs) in recent years began to be considered as prominent. DT is one of the most well-known Industry4.0 (I4.0) technologies, defined as the virtual representation of a system and characterized by the synchronization between the virtual and real system thanks to sensed data and connected smart devices, mathematical models and real time data elaboration (Negri et al., 2017; Kritzinger et al., 2018). Indeed, compared to other I4.0 technologies, DTs are able to integrate various sources and data across a product lifecycle, from design to EoL, to support the continuous monitoring, optimization and traceability of materials and resources. Additionally, as also discussed in the next sections, DTs are capable of simulating different scenarios – such as evaluating product designs, to evaluate the optimal solution – and offer a complete transparency across a product's entire lifecycle (Brossard et al., 2018). In current literature, only a few studies offer overall analyses on how to use DTs for CE. Examples include research focusing on the construction sector (e.g., Banihashemi et al., 2024; Z. Chen and Huang, 2020); studies on DTs usage for enhanced sustainability in manufacturing, focusing on extending product lifecycles and promoting recycling through behavioural insights (Juarez et al., 2024); qualitative analysis based on semi-structured interviews to show how industries are more interested in promoting sustainable and circular production (Timperi et al., 2024); review addressing the roles of DTs for CE extended to various sector highlighting companies' technology readiness level (Mügge et al., 2024). DTs can help mitigate manufacturers' concerns by providing a virtual representation of products and their components across the lifecycle. Through real-time monitoring and predictive simulations, DTs can reduce uncertainty about EoL scenarios, support eco-design decisions at the BoL, and identify optimal reuse or recycling routes at the EoL. However, to the best of the authors knowledge, to date, there has been limited exploration on how to incorporate DTs into the CE workflow within the electronic sector.

The objective of this paper is to investigate how DTs can be used throughout the lifecycle of electronic devices to enhance CE practices, as this is still an underexplored topic. Therefore, a systematic literature review (SLR) has been conducted, as detailed in Section 3. The paper structure has been guided by the following research questions (RQs).

- "How are DTs currently applied across the lifecycle stages of electronic devices?" (RQ1) – this RQ addresses the specific functions and applications that DTs currently assume across different stages of the lifecycle (e.g., supporting eco-design, enabling predictive maintenance, or optimizing EoL management). This framing allows to identify not only where DTs are currently applied but ultimately highlight challenges to CE practices implementation;
- "How can DT application purpose and data flows be structured to enable CE benefits across the lifecycle of electronic devices?" (RQ2) – while RQ1 maps the current state, it does not yet explain how DTs could be reoriented toward CE objectives. Existing DT applications often operate in silos, focusing on short-term efficiency objectives rather than lifecycle integration. However, achieving CE requires continuity of information flows across BoL, middle-of-life (MoL), and EoL, enabling decisions such as reuse, repair, or recycling. RQ2 therefore starts from the gaps identified in RQ1 and aims to explore how DT data and functions can be aligned and structured to support CE practices in an integrated way.

In particular, starting from literature findings this paper proposes a conceptual scheme of guidelines for stakeholders in the supply chain of electronic devices, aimed at promoting enhanced CE through effective DT usage across the lifecycle. Given the primary role of data in DT applications, the presented guideline emphasizes how the type of data gathered by DTs can be repurposed across different stages to yield benefits aligned with CE principles.

Given these objectives, the rest of the paper is structured as follows: Section 2 provides an analysis on the research context, focusing on the key characteristics and capabilities of DTs that are relevant for CE. Section 3 presents the applied research methodology. Section 4 presents the results of the SLR. Section 5 presents the discussion of the results, including the schema of guideline for applying DTs to support CE practices throughout electronic devices lifecycle. Finally, Section 6 provides the conclusions and future research directions.

2. Theoretical background

2.1. Digital Twins

The Industry4.0 paradigm has emerged with the objective of integrating digital technologies into traditional manufacturing systems, leading to more efficient and automated processes, higher quality and customized products. DTs play a pivotal role for the manufacturing industry and their application can support decision-making in autonomous systems, which even addresses both the product and process levels for parts, machines and factories (Posada et al., 2015; X. V. Wang and Wang, 2019). The effectiveness of DTs is linked to the quality and volume of data they use; indeed, high-quality data is essential for accurately reflecting real-world scenarios and enabling predictive analytics.

Nowadays, the concept of DT is well-known in the field of industrial engineering research; however, emphasizing its benefits and capabilities is essential to illustrate its potential applications. The following DTs capabilities are presented given their relevance for this paper.

2.1.1. Digital Twins capabilities

The implementation of DTs is favorable given the advantages they provide, which can be grouped into (Singh et al., 2021): a) the ability to predict problems and errors of their physical counterpart (or physical twin); b) optimization of solutions and improved maintenance, by foreseeing defects and damages; c) accessibility, since the physical device can be controlled and monitored remotely using its DT; d) waste reduction as using the DT to simulate and test product or system prototypes in a virtual environment can significantly reduce wastes; e) documentation and communication: indeed, to develop a DT it is relevant to synchronize data from different sources and the DT itself can be used to store data and document all the behaviours and mechanisms of a physical counterpart; f) speed of prototyping: thanks to the DT, design and analysis cycles are reduced, making the prototyping or redesigning process easier and faster.

Furthermore, a relevant distinction of DTs application, as proposed by M. Liu et al. (2021), depends also on the different lifecycle stages of a product or system where they can be applied, which include: i) design phase through strategies such as iterative optimization where the DT can be applied to realize design optimization between static configuration and dynamic execution (Q. Liu et al., 2019) and improve the accuracy and efficiency for product material selection (Xiang et al., 2019). Additionally, at this phase the DT can be applied to provide data integrity, as well as to allow virtual evaluation and verification to reduce inconsistencies between the actual and expected behavior (M. Liu et al., 2021; Tao et al., 2019); ii) manufacturing and assembly phases for real-time monitoring, production control, workpiece performance prediction, process evaluation and optimization, production planning; iii) service phase for predictive maintenance, fault detection and diagnosis, state monitoring, performance prediction and virtual test; iv) Retire phase; once the product or system is no longer useful in its current state. Such lifecycle phases can be grouped under three macro-ones, mainly: BoL, including the design, manufacturing and assembly phases; MoL, including distribution, service phase of a product (i.e., when the product is used) and monitoring of products state and processes execution and parameters; EoL, representing the retire stage.

2.2. Digital Twins for Circular Economy

In line with the increased discussion on the I4.0 paradigm, in recent years CE started to be coupled with I4.0. Recent studies focused on the relations between CE and I4.0, such as the one reported by Rosa et al. (2020), that revealed how I4.0 technologies are known as enablers of CE. Accordingly, by leveraging the DTs capabilities discussed in the previous sub-section, it should be explored how their usage can facilitate the implementation of CE practices.

A broad analysis on DTs uses across various sectors, conducted by the authors of this paper, identified six key ways in which DTs can contribute to CE goals. These categories, illustrated in Fig. 1, are described as follows.

a) *Lifecycle extension*: digital technologies, including DT, can help extend the useful life of products (i.e., prolong their service lifetime) by providing relevant information to stakeholders at the right time throughout the product's lifecycle (Mügge et al., 2024). Information integrity throughout a product lifecycle can enhance product's design for facilitated repair, remanufacturing or reuse, which in turn extend product's or part of product's lifecycle. Additionally, a DT serves as a virtual collection of information regarding a product and its entire lifecycle (Preut et al., 2021), enabling continuous status monitoring and informed decision-making. For instance, a DT can facilitate predictive maintenance and timely repairs, thereby preventing premature failures and extending the product's useable life. Such data-driven interventions directly contribute to longer product lifespans in line with CE principles.
b) *Recovery of materials*: Wang and Wang (2019) presented a DT-based waste from electrical and electronic equipment (WEEE) recycling, recovery and remanufacturing system. Similarly, Rocca et al. (2020) used a DT to study a disassembly process that could simplify the remanufacturing systems for reuse and recycling purposes. Indeed, efficient recovery strategies require facilitated access to components and materials; therefore, improving disassembly practices is relevant since it can improve component recovery and even extend product lifecycle by enabling for example refurbishment or reuse of parts (Vanegas et al., 2018).
c) *Design for circularity*: CE principles should influence the design phase of a product to ensure durability, reparability, reusability, recyclability etc. at the EoL. However, there is often a lack of feedback from the EoL phase back to the BoL phase, leading to design choices that do not fully account for EoL processes. Mangers et al. (2023), in a PET bottles case study, proposed a method to collect, process and apply EoL process data through DTs, feeding this EoL knowledge into a CE-adapted design assessment for new products. Ke et al. (2023) argued that redesign is a key component of effective remanufacturing; they developed an intelligent DT-based method to redesign used products. By using DT data to guide product improvements and redesigns, the remanufacturing process becomes more efficient, and products can be reintroduced into use cycles with enhanced performance or longevity.
d) *Resources usage efficiency*: the application of DTs can optimize the use of resources such as energy and materials during production, use, and EoL operations. For instance, Rocca et al. (2020) demonstrated that integrating a DT with virtual reality allowed real-time monitoring and optimization of the energy performance in a disassembly process. This led to reduced energy consumption and improved process efficiency, aligning with CE goals of minimizing resource use and waste. DTs enable better resource usage efficiency by providing insights into operations (e.g., identifying energy losses or material waste) and enabling adjustments that save energy, water, and other inputs.
e) *Closed-loop supply chain*: information asymmetries are the main challenge restricting the development of closed-loop supply chains (Chen and Huang, 2021). DTs help overcome this challenge by improving information management and transparency across the supply network, ensuring all parties have the data needed to circulate materials optimally. Preut et al. (2021) discussed the potential of DTs in managing circular supply chains, showing that better cross-lifecycle information sharing can facilitate the economic and ecological implementation of material loops. In practice, a DT can track a product's condition and location through its use phase and into the recycling phase, enabling coordinated decisions on collection, reprocessing, or redistribution. This visibility and data-driven coordination help realize effective closed-loop supply chains by connecting end-of-use products back into production cycles.
f) *Data traceability throughout the lifecycle*: in the I4.0 era, the emergence of new digital technologies changed the traditional ways for designing, building and managing asset data. Obstacles related to fragmented information, interoperability, transparency and big data management are the main drivers for change that the manufacturing industry needs to address (Brandín and Abrishami, 2021). DTs offer the capability to record information about products throughout their lifecycle, making processes more transparent and traceable. Numerous studies have explored this DT-enabled traceability. For example, Zhuang et al. (2021) developed a DT-based assembly data management framework to achieve process traceability for complex products. Dyck et al. (2023) presented a DT approach to provide historical data logging, real-time monitoring, and future states predictions to improve traceability in post-harvest handling. Michael et al. (2021) demonstrated a DT application case study in the consumer electronics industry aimed at efficient recycling, emphasizing that recyclability should be considered early in all product lifecycles. Moreover, DTs are often combined with other digital technologies to enhance secure data sharing and provenance; for example, Hasan et al. (2020) integrated blockchain with DTs to guarantee secure and trusted traceability, accessibility, and immutability of transactions, logs, and data provenance.

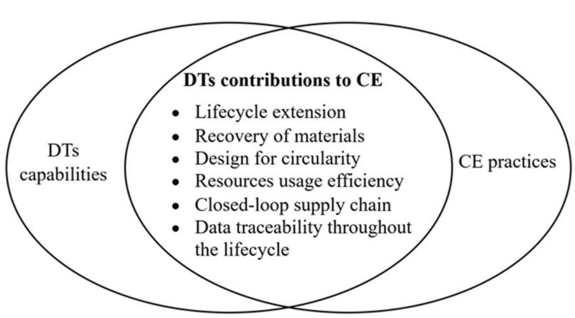

Fig. 1. Contributions of Digital Twins to Circular Economy.

3. Methodology

Given the advantages that DT applications have demonstrated in the manufacturing industry and given current limited research in literature regarding their role in supporting CE practices in electronic devices lifecycle, the next Section proposes a systematic literature review (SLR) that responds to RQ1 (i.e., *"How are DTs currently applied across the lifecycle stages of electronic devices?"*) focusing on DTs usage in the lifecycle of electronic devices to understand their application purpose, the type of data collected and to assess the gaps to CE practices. Conducting this review is a critical first step toward identifying current challenges and proposing effective solutions in achieving CE benefits leveraging DTs.

Following the approach used by Sassanelli et al. (2021), the review process has been carried out in three steps: collection, evaluation, and analysis. The latter is presented in the next section. During the *collection* step, keywords searches have been conducted on Scopus, Web of Science (WoS) and IEEE, that include the most used scientific databases for industrial engineering (Ren et al., 2019), to cover a wide number of papers. As shown in Table 1, the first part of the search string had the aim to detect papers dedicated to DTs usage, while the second part of the search string, linked to the first part by an "AND" logical connector, used keywords as "electronic*", "electronic* waste", "electronic* component*", "printed circuit board*", "substrate*" etc. in order to include only papers focused on electrical and electronic devices, or their main components (e.g., printed circuit boards, substrates).

After the elimination of duplicates, a total of 1097 papers resulted from the search, among which several had to be excluded during the evaluation step. Fig. 2 details the *evaluation* process, highlighting the exclusion criteria (EC) implemented. Since the concept of DT applied to electronic devices lifecycle is still limited, the analysis did not consider any constraints on the publication year, and evaluated journal papers, conference papers and book chapters written in English. In particular, after title and keywords reading, papers where the prior focus was not on DTs or electrical and electronic devices have been eliminated together with non-scientific documents; indeed, papers have been excluded since they explored other sectors not related to electronics (e.g., automotive, agriculture, healthcare, plants physiology, etc.), while others were more focused on an analysis on humans' duality in manufacturing environments and on immersive learning activities for humans. Furthermore, after abstracts reading, only papers focusing on DTs in the domain of electronics have been considered. Finally, after full-text reading, papers not presenting relevant information on the DT applications, and therefore not classifiable under the categorisation presented in Section 4, have been excluded. This process led to the result of 60 papers, which are carefully analysed in the next sections.

4. Result

During the *analysis* step, the 60 resulting papers have been analysed according to the following categorisation. The results from the analysis are presented in the next sub-sections.

- "Type of electronic devices" (Section 4.1): by categorizing the electronic devices, this analysis reveals the main application areas of DTs in the current literature and gaps in underexplored areas of DTs usage in the field of electronics.
- "Type of models" (Section 4.2): DTs can be developed using various modelling approaches; according to the type of model, they can replicate and analyse different behaviours of the physical counterpart.
- "DT level of application" (Section 4.3): this category describes the extent of detail represented by the DT, which, according to the results from the literature, has been categorised in three levels: component, product and process.
- "Application purpose of the DT" (Section 4.4): aimed at classifying for which purpose DTs are applied across electronic devices lifecycle.
- "Type of DT-data in lifecycle phases" (Section 4.5): this category has been considered given that a core feature of DTs is their reliance on data; therefore, it evaluates the type of data collected by DTs throughout the lifecycle phases of implementation and explores how these data are used. The final aim is to assess how their usage can support decision-making at different stages of the lifecycle.
- "CE relevance" (Section 4.6): building on the key ways in which DTs can contribute to CE goals discussed in Section 2.2, this categorisation captures papers that explicitly address CE practices enabled by DTs. It therefore allows a comparative analysis with studies that discuss DTs without a clear CE orientation.

Table 1
Selected keywords for the SLR.

Search string focus	Search string keywords
1. DTs usage	("digital twin*" OR "cyber twin*" OR "virtual twin*") AND
2. Electronic devices	("electronic*" OR "WEEE" OR "semiconductor*" OR "electronic* waste" OR "waste from electronic*" OR "electronic* material*" OR "electronic* component*" OR "electric* device*" OR "printed circuit board*" OR "PCB*" OR "substrate*")

4.1. Type of electronic devices

The analysis focused on electrical and electronic equipment (EEE), categorizing the devices into specific groups based on their functionality and applications. Table 2 provides an overview of the type of electronic devices for which DTs are applied in the reviewed studies. Power electronics, including devices such as inverters, converters and controllers are the most represented category, with 23 studies exploring DT applications in this area. Printed circuit boards (PCBs) are highlighted in eight studies. Consumer electronic products, also represented in eight papers, demonstrate a growing interest in applying DTs to devices such as smartphones. Finally, 21 studies focus on generic EEE, where the DTs are analysed across multiple devices types without specificity.

4.2. Type of models

DTs are implemented using different modelling approaches, each tailored to specific applications and requirements. The SLR allowed identifying six main types of modelling approaches, summarized in Table 3 with references to the papers; the authors are aware that the list provided in the table is not mutually exclusive nor exhaustive, indeed other type of modelling approaches may be applied, according to the sector and purpose of application. The approaches resulted from the SLR are categorised as follows.

- Dynamic modelling adopted in 25 % of the reviewed papers. This approach captures system that evolve over time, updating their state based on new input data – e.g., Lei et al. (2023) used a dynamic model for power electronic converters, enabling the system to adjust to variations in input voltage while maintaining optimal control performance. This adaptability is crucial for real-time applications where system parameters frequently change.
- Predictive modelling is used in 20 % of the papers, focusing on using historical and real-time data to forecast future performances and outcomes. Many DTs leverage machine learning or statistical models for prognostics. As example, Kumar Bhoi et al. (2023) trained an artificial neural network using operational data on the performance of semiconductors in a power electronic converter to train an artificial neural network. The DT could then accurately predict the junction temperature of power electronic converters, providing insight into component health. Consequently, this data supported predictive maintenance operations, ensuring optimal functioning of the electronic components.
- Discrete Event Simulation (DES) modelling is used in 10 % of the papers. DES models represent systems in terms of a sequence of discrete events in time, which is useful for capturing operational workflows or processes. Several DT studies simulate manufacturing or maintenance processes using DES to analyse system behaviours at key events. For example, Balderas et al. (2021) replicated the PCB assembly process, modelling events such as drilling operations and tool changes at discrete intervals. Lima et al. (2022) applied a DES-based DT at the component level to monitor electronic converters during their usage stage, analysing input and output voltages and currents in discrete intervals.

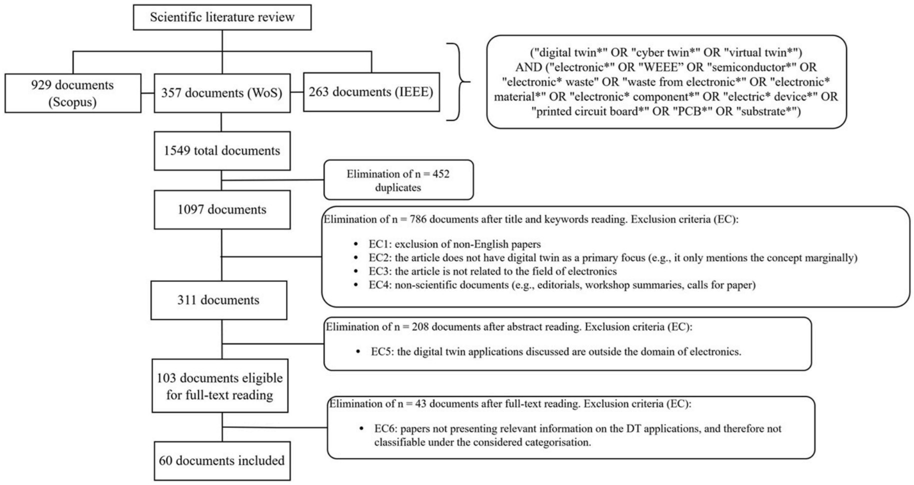

Fig. 2. SLR: Papers evaluation process.

Table 2
Type of electronic devices, divided by papers references.

Type of electronic devices	Number of papers	References
Power electronics	23	(Lei et al., 2023; Kuprat et al., 2024; Elsotohy et al., 2023; Mansour et al., 2023; Sifat et al., 2024; Choksi et al., 2023; Patel et al., 2023; Diz et al., 2023; Sun et al., 2023; C. Zhang et al., 2023; Kumar Bhoi et al., 2023; Sado et al., 2023; Gutierrez-Escalona et al., 2023; Lima et al., 2022; Zhou et al., 2022; Xiong et al., 2022; Ahmadi et al., 2021; Wunderlich and Santi, 2021; S. Chen et al., 2021; Peng et al., 2021; Milton et al., 2020; Di Nezio et al., 2022; Yuce and Hiller, 2022)
Printed circuit boards (PCBs)	8	(Sassanelli et al., 2021; Sheng et al., 2023; X. Li et al., 2023; Dong et al., 2023; Yang et al., 2023; Race et al., 2022; Balderas et al., 2021; Karanjkar et al., 2018)
Consumer electronics	8	(Sai et al., 2024; W. Liu et al., 2024; Sai and Rastogi, 2023; Jeon et al., 2024; Yan et al., 2022; Zhao et al., 2022; Cupek et al., 2019; Dwight, 2019)
Generic EEE	21	(X. V. Wang and Wang, 2019; Rocca et al., 2020; J. Wang et al., 2024; Kabir et al., 2023; X. Zhang et al., 2024; Jamshidi et al., 2024; D. Zhang et al., 2023; Ryabchenko and Lankin, 2023; Topolsky et al., 2023; Ryabchenko et al., 2023; D. Zhang et al., 2022; Vauzelle et al., 2022; J. Li et al., 2022; D. Zhang et al., 2021; Lu et al., 2021; Hegedus et al., 2021; Tozanli et al., 2020; Altun and Tavli, 2019; Changming et al., 2020; Changming et al., 2019; Walter et al., 2024)

Table 3
Types of DT models, papers references.

Type of model	Number of papers	Papers reference
Dynamic model	15	(Lei et al., 2023; Elsotohy et al., 2023; Diz et al., 2023; Sun et al., 2023; C. Zhang et al., 2023; Sado et al., 2023; Gutierrez-Escalona et al., 2023; Zhou et al., 2022; Xiong et al., 2022; Ahmadi et al., 2021; Race et al., 2022; Sai et al., 2024; W. Liu et al., 2024; Yan et al., 2022; Zhao et al., 2022)
Predictive model	12	(Kuprat et al., 2024; Mansour et al., 2023; Sifat et al., 2024; Choksi et al., 2023; Kumar Bhoi et al., 2023; Milton et al., 2020; Yuce and Hiller, 2022; Jeon et al., 2024; Kabir et al., 2023; X. Zhang et al., 2024; Jamshidi et al., 2024; D. Zhang et al., 2023)
DES model	6	(Rocca et al., 2020; Lima et al., 2022; Dong et al., 2023; Balderas et al., 2021; Karanjkar et al., 2018; Tozanli et al., 2020)
3D model	3	(Sheng et al., 2023; X. Li et al., 2023; Hegedus et al., 2021)
Kinematic model	2	(Yang et al., 2023; Vauzelle et al., 2022)
Acquired data	18	(X. V. Wang and Wang, 2019; Patel et al., 2023; Wunderlich and Santi, 2021; S. Chen et al., 2021; Peng et al., 2021; Di Nezio et al., 2022; Sai and Rastogi, 2023; Cupek et al., 2019; Dwight, 2019; Ryabchenko and Lankin, 2023; Topolsky et al., 2023; Ryabchenko et al., 2023; D. Zhang et al., 2022; Lu et al., 2021; Altun and Tavli, 2019; Changming et al., 2020; Changming et al., 2019; Walter et al., 2024)

- 3D modelling adopted in 5 % of the papers. 3D models provide a spatially accurate, geometric representation of the considered system, often based on CAD data. For instance, X. Li et al. (2023) utilized CAD-based DT to simulate the PCB assembly process. The DT incorporated data from 3D camera sensors to monitor the position and orientation of PCBs and components during assembly. By rendering the assembly in three dimensions, the DT allowed to observe clearance, fit, and spatial alignment of parts, helping to prevent assembly errors.
- Kinematic modelling considered in 3 % of the papers. Kinematic models focus on geometry, movement, and positioning of parts in motion. In DT applications involving robotics or moving mechanisms, kinematic modelling is used to mirror the physical motion in the virtual space with high precision. For example, Yang et al. (2023) used a kinematic model for robotic arms in a flexible electronics assembly cell. The model tracked robotic joint movements and positions of components during assembly.
- Data-driven, considered in 30 % of papers, where the DT does not use an explicit physics-based modelling approach (such as the types described above) but instead use direct data acquisition and analysis from the physical counterpart. In these cases, the DT is a data-driven twin which aggregates sensor data, and other measured parameters to mirror the state of the physical device, and uses these information for decision support. For example, Walter et al. (2024) constructed a DT for robot-assisted disassembly system using a pragmatic bottom-up approach. Rather than formulating a detailed analytical model, the authors integrated existing data representations of the robot and process, focusing on real-time sensor data collection to inform the DT. In their implementation, an Asset Administration Shell (AAS) was used to organise and provide access to both static information (e.g., component specifications) and dynamic data

related to the robotic system did not rely on a specific type of modelling approach but rather emphasized the use of acquired data to inform the DT, which has been constructed using a pragmatic bottom-up approach that integrates existing data representations while focusing on real-time data acquisition through sensors to support the disassembly process.
- The rest of the papers provided only qualitative analyses regarding DT implementation without considering specific modelling methodologies.

4.3. DT level of application

DT implementations have been classified by their level of application, therefore the scale of the system that the DT represents. In this review, three levels of application have been identified – component, product, and process. Below, each category is clarified, as summarized in Table 4 where the levels of application are classified together with the application purpose of the DT presented.

- Component-level DT: this level focuses on individual electronic parts or subsystems rather than the overall product - such as power electronic modules, semiconductors, electric grids, electronic units, and PCBs. A component-level DT provides a detailed examination of specific components, providing insights into their design specifications and performance metrics. For example, by monitoring a component health and performance closely, the DT can inform maintenance and repair actions to prolong that component's life. Although "electric grids" can be treated as a separate grid-level category – as done by Shen et al. (2023) – in the context of this review they are classified under the component level since they represent functional electronic subsystems rather than standalone products or manufacturing processes. Specifically, grid-related DTs typically model electrical and thermal behaviours of power electronics or subsystems (e.g., converters, inverters, distribution units) within a larger electronic system, providing detailed insights into component performance, energy flow, and degradation.
- Product-level DT: this level considers a product as a whole (e.g., consumer electronic such as a smartphone). A product-level DT analyses the performance and condition of the complete product, rather than focusing on individual components. This broader perspective facilitates a comprehensive analysis of product specifications, user interactions, and overall functionality. In this holistic approach, by integrating data from various components, DT users can assess how changes in one part affect the entire product.
- Process-level DT: this level models an operational process involving multiple steps or multiple entities. In electronics manufacturing and EoL management, process-level DTs are common for modelling complex workflows such as assembly lines, disassembly sequences, or recycling operations. The goal is to capture the dynamics of the process – i.e., how inputs (materials, components, products) flow through a sequence of operations and transform into outputs. Examples include PCBs or smartphones disassembly processes or electronic wastes recycling. This level of analysis can support organizations in improving processes efficiency for example by identifying bottlenecks.

The proposed classification ensures consistency within the context of electronics manufacturing and lifecycle, where component denotes an electronic part, product denotes the finished device, and process denotes a sequence of operations on those devices. These levels are not mutually exclusive since in some cases a single study might implement DTs at multiple levels. Out of the 60 papers reviewed, 30 papers focus on component-level analysis, 11 papers examine product-level applications, and 21 papers investigate a process-level usage. In particular, X. V. Wang and Wang (2019) examined DT applications across both product and process levels, including an analysis on the DT usage in the entire

Table 4
Papers references divided by DT application purposes and level of application.

Lifecycle phase	DT application purposes	DT level of application		
		Component	Product	Process
BoL	**Design optimization**	(Gutierrez-Escalona et al., 2023; Zhou et al., 2022; Ahmadi et al., 2021; Race et al., 2022; Kabir et al., 2023; Jamshidi et al., 2024; Ryabchenko and Lankin, 2023; Hegedus et al., 2021)	(X. V. Wang and Wang, 2019; Dwight, 2019; Topolsky et al., 2023; Vauzelle et al., 2022; Lu et al., 2021)	(Sheng et al., 2023; Yan et al., 2022; Zhao et al., 2022)
	Manufacturing and production	Gutierrez-Escalona et al. (2023)	(Sai et al., 2024; W. Liu et al., 2024; Sai and Rastogi, 2023; Cupek et al., 2019)	(Balderas et al., 2021; X. Zhang et al., 2024)
	Assembly			(X. Li et al., 2023; Dong et al., 2023; Yang et al., 2023; Karanjkar et al., 2018; D. Zhang et al., 2023; D. Zhang et al., 2022; D. Zhang et al., 2021; Changming et al., 2020; Changming et al., 2019)
MoL	**Real-time monitoring during usage**	(Lei et al., 2023; Kuprat et al., 2024; Elsotohy et al., 2023; Mansour et al., 2023; Sifat et al., 2024; Choksi et al., 2023; Patel et al., 2023; Diz et al., 2023; Sun et al., 2023; C. Zhang et al., 2023; Kumar Bhoi et al., 2023; Sado et al., 2023; Gutierrez-Escalona et al., 2023; Lima et al., 2022; Zhou et al., 2022; Xiong et al., 2022; Ahmadi et al., 2021; Wunderlich and Santi, 2021; S. Chen et al., 2021; Peng et al., 2021; Milton et al., 2020; Di Nezio et al., 2022; Yuce and Hiller, 2022; Ryabchenko et al., 2023; Hegedus et al., 2021)	(X. V. Wang and Wang, 2019; Sai and Rastogi, 2023; Jeon et al., 2024; Topolsky et al., 2023; Lu et al., 2021)	Karanjkar et al. (2018)

(continued on next page)

Table 4 (*continued*)

Lifecycle phase	DT application purposes	DT level of application		
		Component	Product	Process
	Maintenance, repair	(Elsotohy et al., 2023; Sifat et al., 2024; Kumar Bhoi et al., 2023; Sado et al., 2023; Ahmadi et al., 2021; Changming et al., 2019)	(X. V. Wang and Wang, 2019; Altun and Tavli, 2019)	
	Fault analysis or prediction	(Sun et al., 2023; Lima et al., 2022; Xiong et al., 2022; Ahmadi et al., 2021; Wunderlich and Santi, 2021; S. Chen et al., 2021; Changming et al., 2019)	(Jeon et al., 2024; Lu et al., 2021)	
EoL	**EoL management**			(X. V. Wang and Wang, 2019; Rocca et al., 2020; Sassanelli et al., 2021; J. Wang et al., 2024; J. Li et al., 2022; Tozanli et al., 2020; Walter et al., 2024)

lifecycle of electronic product, from its design until the EoL, considering also disassembly, recycling and recovery data. Changming et al. (2019) used the DT at both component and process levels by considering both the structural design of an electronic equipment and its assembly process.

4.4. Application purpose of the DT

Having identified what the DTs model, which modelling approaches are used and at what level they are applied, this sub-section wants to focus on why these DTs are implemented – i.e., the purpose of DT applications across the electronics device lifecycle. This analysis maps each DT application to its primary role and the lifecycle phase(s) it supports. In particular, the main emerging purposes include: i) design optimization, manufacturing and production, assembly at BoL; ii) real-time monitoring during usage, maintenance and repair, fault analysis and prediction at MoL; and iii) EoL management. Many studies indicate that DTs often fulfill multiple purposes.

In Table 4, papers references have been categorised according to both DT application purposes and the level of application of the DT, presented in the previous sub-section.

- At the BoL phase, 16 of the analysed papers used DTs for *design optimization.* Here the DT can be used at: i) component or product level when the design addresses component- or product-levels of detail; for example, Kabir et al. (2023) utilized the DT for early design and development of electronic control units, enabling designers to make optimal design choices; or ii) at process level when the focus is on process design, such as Yan et al. (2022) who used the DT for the design of an electronic assembly line. Additionally, seven papers apply DTs in *manufacturing and production* contexts, and similarly to the design purpose, the application is conditioned by the different levels of detail depending on whether the focus is on the component or product manufactured or if the focus is on the manufacturing process itself. For example, Sai and Rastogi (2023) implemented DTs for remote manufacturing of consumer electronics, creating virtual showrooms and facilitating collaborative design efforts; while X. Zhang et al. (2024) considered a DT that aims to optimize process parameters, address quality issues, and improve overall performance in the production line of insulated-gate bipolar transistors. Furthermore, nine studies explore DT applications in *assembly processes*; D. Zhang et al. (2023) proposed using DT for smartphone assembly, adopting a predictive control approach to optimize energy use on electronic assembly lines. It is relevant to recognize that in this context, since the focus is on products (i.e., electronic devices), manufacturing, production and assembly are part of the BoL phase.
- At the MoL phase, nine papers used DTs for *fault analysis and prediction*, specifically at component or product level. For instance, Lu et al. (2021) applied the DT to replicate an electromechanical product to facilitate iterative design optimization alongside fault diagnosis and prediction during the operational stage. Eight studies focused on *maintenance and repair applications* at component or product levels – e.g., Kumar Bhoi et al. (2023) used the DT at component level to assess the reliability of power electronic converters through real-time monitoring and predictive maintenance aimed at evaluating health and performance metrics. Furthermore, 31 papers leveraged DTs for *real-time monitoring during the usage phase.* For example, Lei et al. (2023) applied the DT during the active use of power electronic converter systems to monitor their behaviour including thermal condition, while Karanjkar et al. (2018) considered the DT usage for real-time monitoring of a PCB assembly line for its energy optimization.
- Finally, at the EoL phase, seven papers addressed *EoL management* through DTs at process level, such as J. Li et al. (2022) who analysed recycling processes for WEEE, or such as Rocca et al. (2020) who considered DT usage for WEEE disassembly.

4.5. Type of DT-data in lifecycle phases

A DT is caracterised not only by its virtual model, but also by the data exchange loop that keeps it in synchronization with the physcal world. Emerging information technologies facilitate real-time data collection through different means. Sensors, Internet of Things (IoT) devices, mobile devices which support the collection of data on multiple parameters (e.g., temperature, pressure, current, etc.), while cloud computing and industrial data platforms (e.g., Manufacturing Execution System (MES) and Enterprise Resource Planning (ERP) system) provide the infrastructure to aggregate and process these data streams (M. Zhang et al., 2021).

DTs data collection methods vary and may involve *physical sources* – which include data gathered from sensors installed on equipment, materials or personnel and can measure different parameters, such as temperature, pressure and operational performance; or *virtual sources* – where data can be generated from simulation models that mimic real-world scenarios, or from algorithms embedded in services, as well as data resulting from human knowledge (M. Zhang et al., 2021). It is relevant to recognize also that certain data sources can have a "borderline" classification. For example, MES or Programmable Logic Controllers (PLC) originate from interactions with the physical counterpart, however they generate digital representations by aggregating sensors inputs. For this reason, they can be classified as virtual sources. A challenge in DT implementation is deciding which data are truly needed to fullfil the DT's purpose. Different DT users can play different roles, and therefore each can require specific data tailored to their roles – e.g., field operators require on-site operational data, technicians need process data, managers work with market data, etc. (M. Zhang et al., 2021). Specifically, the use of data depends on what is the aim to achieve with the DT. Research proposed by Kober et al. (2023) has emphasized the importance of calculating the DT fidelty with the aim to increase objectivity within the DT fidelty elaboration. This concept is also linked to finding the optimal amount and type of data. Kober et al. (2023) argue that an optimal DT fidelity exists for each use case, where the net benefit is maximised. Therefore, it should be identified what decisions the DT needs to support and ensure it gathers the necessary data for those outcomes. From the literature analysis, when derivable from the papers, the authors of the current paper were able to classify the type of collected data by the DT and mapped them to the lifecycle phase in which the DT was applied.

- *BoL phase – design and production data.* During the design and manufacturing phase, DTs mostly utilise data that define the product's architecture, configuration, manufacturing and assembly processes - (Changming et al., 2020; Balderas et al., 2021; Yan et al., 2022; Zhao et al., 2022; Sheng et al., 2023; Kabir et al., 2023; D. Zhang et al., 2023) - and data on shape, materials, and components which allow DT to perform tasks such as virtual assembly of components - (Cupek et al., 2019; Dwight, 2019; X. Li et al., 2023; Dong et al., 2023; Yang et al., 2023; Sai et al., 2024; W. Liu et al., 2024). As example, Yang et al. (2023) noted that for assembling electronics with robots, the DT needed also to capture robot motion data (i.e., kinematic data) to ensure the virtual assembly is accurate. Additionally, another subset of BoL data relates to predictive models and simulations used before production. For example, Ryabchenko and Lankin (2023) employed mathematical models to predict the behaviour of an electronic unit prior to its actual production.
- *MoL phase – usage and operation data.* Once the product is deployed and in use, the DT shifts to collecting operational data that reflect the product and process performance during its service life. As first category, from the SLR it resulted that these data include electrical and performance parameters of the devices. Many studies fed their DTs with real-time electrical measurements, such as current flow, voltage, power outputs - e.g., (Wunderlich and Santi, 2021; Lima et al., 2022; Yuce and Hiller, 2022; Lei et al., 2023; Choksi et al., 2023; Patel et al., 2023; Sun et al., 2023; Sado et al., 2023). Another key set of MoL data is thermal conditions and energy usage. Indeed, electronics often fail due to overheating, therefore DTs could incorporate temperature readings as well as energy consumption metrics (e.g., battery level, power consumption over time) - e.g., (Wunderlich and Santi, 2021; Lima et al., 2022; C. Zhang et al., 2023; Sado et al., 2023; Kuprat et al., 2024). Finally, a third data category is degradation condition and health state. Some DTs include sensors or algorithms to assess wear, corrosion, or other degradation phenomena - e.g., (S. Chen et al., 2021; Di Nezio et al., 2022; Yuce and Hiller, 2022; Elsotohy et al., 2023; Jeon et al., 2024).
- *Combined BoL and MoL data usage.* Some studies spanned DT applications across both BoL and MoL phases. In such cases, the DT combines data from both design and development and usage stages - i.e., (X. V. Wang and Wang, 2019; Gutierrez-Escalona et al., 2023; Zhou et al., 2022; Ahmadi et al., 2021; Sai and Rastogi, 2023; Topolsky et al., 2023; Lu et al., 2021; Hegedus et al., 2021). As examples: X. V. Wang and Wang (2019) described a DT instantiated with design data at the BoL, and then updated with field data during MoL. In their study, the DT at BoL held information on the product's initial specifications, and during MoL it considered user-provided updates on the product's status (e.g., maintenance events, upgrades performed). Zhou et al. (2022) and Gutierrez-Escalona et al. (2023) similarly built DTs that start with a base of design and manufacturing data and then integrate sensor data from the product's operational phase.
- *EoL phase – disassembly and recycling data.* In the EoL phase, DT implementations are fewer, but those that exist concentrate on data relevant to product retirement processes such as disassembly, recycling, and material recovery. Some authors have proposed using DTs together with other digital technologies (such as blockchain) for information tracking. J. Wang et al. (2024) considered a system where a DT, combined with blockchain and generative artificial intelligence, managed data about e-waste collection and processing. In their case, the DT handled logistics data (i.e., collectorID, location, destination, collection time), disassembly information and reprocessing data (i.e., recovered materials, input/output components, recycled parts). Rocca et al. (2020) emphasized the need for disassembly performance metrics at the EoL, including also the energy consumption data of the disassembly line. Sassanelli et al. (2021) proposed an analysis on simulation models, including DTs, focused on the disassembly of PCBs and highlighted the need for data like disassembly sequences, the type of PCBs components and positions, etc. to effectively model the process. J. Li et al. (2022) provided a more conceptual discussion focusing on DT application for WEEE recycling, and the need of data that captures information on how the product is disposed of or recycled, including outcomes of the recycling processes and results of material recovery efforts. Walter et al. (2024) presented a case of using a DT to program and guide a robot through disassembly tasks. In that context, they leveraged the Asset Administration Shell (AAS) concept to structure the DT's data - both static data like the robot's CAD model and dynamic data like sensor feedback during disassembly. The AAS made it easier to integrate and retrieve the necessary data for autonomous planning.
- *Cross-lifecycle data integration.* A few cases illustrate how DT data from one phase can be reused in later phases, which is central to CE. X. V. Wang and Wang (2019) examined DT usage at the EoL, relying also on data from previous lifecycle phases (i.e., BoL, MoL). In particular, the DT was applied in the BoL phase to support product design and simulation, enabling the documentation of functional and environmental features. In the MoL phase the status of the product can be updated by the end-user, allowing for interactions such as repairs, maintenance, and upgrades. In particular, at the MoL phase data from interaction with DT models provided insights into product performance during use. And finally during the EoL phase, where the DT played a crucial role by linking WEEE specification knowledge to support recycling and remanufacturing operations, detailing aspects like materials and disassembly strategies necessary for recovering valuable materials; therefore requiring data related to materials and components that need to be recovered and data on recycling specifications. Similarly, Tozanli et al. (2020) used DT and blockchain for e-waste recovery systems requiring continuous monitoring data about recovery operations. The DT relied on data from OEMs, end-users, reprocessors and recyclers, therefore also from BoL and MoL phases.

4.6. CE relevance

Building on what has been discussed in Section 2.2, this section provides a comprehensive overview on how DTs of the reviewed papers contribute to CE. In particular, as previously mentioned, DTs can contribute to CE in the following key ways.

a) "*Lifecycle extension*": the usage of DTs allows the evaluation of products status, enabling optimized decision-making throughout the lifecycle;
b) "*Recovery of materials*": this includes EoL management strategies such as disassembly, reuse, and recycling;
c) "*Design for circularity*": DTs can facilitate design methodologies that ensure products are durable, repairable, reusable, and recyclable at the EoL stage;
d) "*Resources usage efficiency*": DTs can optimize energy performance and materials usage, contributing to overall efficiency;
e) "*Closed-loop supply chain*": effective communication among stakeholders is essential for CE; DTs can support this process by providing real-time data and insights;
f) "*Data traceability throughout the lifecycle*": DTs enable comprehensive tracking of product information throughout its lifecycle, which is crucial for implementing effective CE strategies.

Considering these benefits, papers have been analysed according to a CE perspective and, as presented in Table 5, it resulted that within the 60 papers reviewed, only eight papers (i.e. (X. V. Wang and Wang, 2019; Rocca et al., 2020; Sassanelli et al., 2021; J. Wang et al., 2024; Topolsky et al., 2023; J. Li et al., 2022; Tozanli et al., 2020; Walter et al., 2024),) considered CE aspects, seven of which focused on the EoL phase, thereby highlighting the critical role of EoL analyses for CE. From the table, it is possible to see that Topolsky et al. (2023) included CE benefits even if their focus was not on the EoL phase; their paper focuses on the creation of electronic passports (e-passport) for materials as a foundation for DTs, discussing their role in enhancing decision support systems and the integration of different type of data for comprehensive information representation, including design, manufacturing and operational data. It is also relevant to note that among the studies reported in the table, few of them leveraged CE benefits by integrating the DT with other digital tools, such as virtual reality (VR) to virtually tests a WEEE disassembly plant configuration (Rocca et al., 2020) and blockchain that supported data traceability (J. Wang et al., 2024; Tozanli et al., 2020).

5. Discussion

The paper had the objective to examine the role of DTs in supporting CE across the lifecycle of electronic devices, addressing two research questions: RQ1 – *"How are DTs currently applied across the different lifecycle stages of electronic devices?"* and RQ2 – *"How can DT application purpose and data flows be structured to enable CE benefits across the lifecycle of electronic devices?"*. The discussion builds on the SLR findings, highlighting both potential and the limitations of DTs for CE and proposing a guideline for their reorientation toward circular objectives.

5.1. Insights from the systematic literature review

By contributing to RQ1, the SLR findings showed that DT implementations occur at multiple levels (component, product, and process) and fulfill various purposes. Each application purpose involves the collection of specific types of data that are fundamental for specific decision-making. However, a major gap emerged: most current DT applications are not lifecycle-oriented and do not explicitly target CE objectives. In practice, DT data are often used within a single phase of the lifecycle, with little consideration for EoL or cross-phase reuse of data.

Understanding the distinct objectives associated with each lifecycle phase is essential for identifying how DTs can facilitate various CE practices. While the EoL phase is critical for specifically managing e-waste, it is equally important to recognize the roles of DTs at the BoL and MoL phases and the data gathered from these stages, and this is the reason why the SLR has been extended to papers applying DT in electronic devices even if not mentioning CE explicitly, since the aim was also to assess DTs roles at BoL and MoL, and evaluate how data collected during these phases could contribute to CE.

Indeed, data gathered in current DT applications are relevant, however a guideline on how to reuse them to bridge the gaps to CE is lacking.

- Currently, the analysis revealed that, during the BoL phase DTs are primarily utilized for designing and assembling products or components (e.g., smartphones, PCBs). They enable engineers to simulate, test, and optimize designs virtually, helping to catch design flaws or assembly issues early. For example, studies have shown that DT-driven design can improve design choices and avoid costly redesigns by detecting errors more precisely than traditional trial-and-error methods (e.g., Kabir et al. (2023)). Data collected in this phase typically centers on specific objectives such as component specifications, assembly tolerances (e.g., D. Zhang et al. (2023), (Jamshidi et al. (2024)), and cost estimation for manufacturing. These short-term optimisations – such as reducing errors and improving assembly – provide benefits in production quality and cost. However,

Table 5
CE benefits resulted from the SLR.

Ref.	Lifecycle phase(s)	CE relevance	Description
X. V. Wang and Wang (2019)	BoL, MoL, EoL	Recovery of materials, data traceability throughout the lifecycle, closed-loop supply chains	○ DT-based system for the WEEE recovery to support the manufacturing/ remanufacturing operations throughout the electronic product's life cycle, from design to recovery. ○Usage of an internationally compliant data model which enabled tracking of product specifications, materials, components, assembly, disassembly, recycling and recovery information across the lifecycle. ○By relying on ISO standard data structures, the system supported the analysis of a multi-stakeholders perspective throughout the lifecycle, from producers at the BoL phase, to users and service providers at the MoL phase, and recyclers at the EoL phase.
Rocca et al. (2020)	EoL	Recovery of materials (disassembly), resources usage efficieny	○Laboratory application case showing how the integration of DT and VR can support CE practices by virtually testing a WEEE disassembly plant configuration. ○Energy performance monitoring of the WEEE disassembly system.
Sassanelli et al. (2021)	EoL	Recovery of materials (disassembly)	○Review on the role of simulation for PCBs disassembly, including also the role of DTs in improving the disassembly process.
J. Wang et al. (2024)	EoL	Recovery of materials (recycling), data traceability	○Comprehensive data management solution for WEEE recycling based on blockchain technology.
Topolsky et al. (2023)	BoL, MoL	Resources usage efficieny, closed-loop supply chains, data traceability throughout the lifecycle	○Storing of data on composition, structure and properties, that enable optimization of resource use while minimizing waste in material production and usage. ○Concept of "e-passport" designed to enhance material tracking throughout a product's lifecycle, including materials design and usage data. This approach involves multiple stakeholders that contribute in providing the necessary data.
J. Li et al. (2022)	EoL	Recovery of materials (recycling)	○Integrated modelling approach for WEEE recycling workshop to address challenges such as limited product knowledge and loss of valuable

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Table 5 (*continued*)

Ref.	Lifecycle phase(s)	CE relevance	Description
			materials during mechanical processing.
Tozanli et al. (2020)	EoL	Recovery of materials, closed-loop supply chains, data traceability throughout the lifecycle	○Study about the effects of DTs on trade-in policy-making by simulating a product recovery system through blockchain technology, employing a discrete event simulation model to replicate the behavior of product recovery activities based on predictive indicators. ○Blockchain and IoT-powered DT platforms facilitate transparency and interconnectivity across value chains, removing the need for intermediaries. For OEMs, the DT enables real-time performance analysis and provide access to precise product conditions at EoL. This supports OEMs in offering tailored services for disassembly and remanufacturing operations and improving customer service. The paper discussed how the data integrity allowed by the blockchain enables the collection of data from OEMs, end-users, reprocessors and recyclers.
Walter et al. (2024)	EoL	Recovery of materials (disassembly)	○Enhance the flexibility and efficiency of robot-based disassembly applications by enabling autonomous planning, real-time data integration, and intelligent action generation for the disassembly of WEEE.

DT BoL applications tend to have a narrow focus, lacking a holistic view of the product's entire lifecycle. In practice, most BoL DT implementations do not gather comprehensive data about a product's circular attributes (e.g., material composition for recyclability or ease of disassembly). They focus on immediate objectives (e.g., design feasibility, manufacturability, cost reduction) and overlook data that would be useful for EoL recovery.

This fragmented approach limits the potential of DTs to contribute to CE objectives. Indeed, to better harness DT capabilities for CE, data from the BoL phase should be integrated and reused throughout the entire lifecycle. This means expanding the scope of BoL DTs beyond design and manufacturing efficiency. For instance, establishing a comprehensive database to record information on components, materials, and assembly processes during BoL would create a valuable resource for later lifecycle stages. If a DT captures detailed BoL data (e.g., bill of materials, material properties, component geometry, assembly sequence), that same information can be leveraged during EoL. To avoid unnecessary complexity, only critical design data which directly influence recyclability, ease of disassembly, material recovery, or remanufacturing feasibility should "flow" forward to EoL – for example, material composition, hazardous substances, components connection types, or assembly sequences. Such data can enable accurate identification of components, prediction of disassembly effort, and assessment of recoverable materials.

- In the MoL phase, DTs are primarily used to monitor the performance of electronic devices. This includes tracking parameters such as current flow, thermal conditions, energy consumption, and overall health or degradation status of components or products (e.g., (Lei et al., 2023; Kuprat et al., 2024; Elsotohy et al., 2023; Choksi et al., 2023; Patel et al., 2023; C. Zhang et al., 2023; Jeon et al., 2024), etc.). Similar to the BoL phase, there is a need of prioritising also MoL data that have a clear functional link to specific CE practices. For instance, by incorporating CE-specific metrics into DT monitoring systems (e.g., repair frequency, patterns of component degradation, or indicators of inefficient operation), valuable insights that support circular practices can be gained. Additionally, DTs can support in tracking repair frequencies to highlight opportunities for design improvements that extend product lifespans. Monitoring energy efficiency and resource consumption patterns can also inform decisions about product optimization, by assessing whether a device is operating optimally. Moreover, data collected during the MoL phase can be utilized to create detailed usage profiles and predict future performance trends (Mügge et al., 2024). This information can also be fed back into the BoL phase to enable design iterations that account for real-world usage patterns. Establishing a continuous feedback loop also between the BoL and MoL phases allows DTs to align product design with CE principles, ensuring that products are optimized for longevity and circularity throughout their lifecycle. Furthermore, MoL data can play a crucial role in informing EoL decision-making. By monitoring product conditions during the MoL phase, it can be possible to predict when products will reach their EoL stage. Understanding components and products condition and composition enables DTs to recommend appropriate EoL strategies - whether reuse, remanufacturing, or recycling - and share this information with relevant stakeholders (e.g., recyclers) to facilitate efficient processing.
- Finally, at the EoL phase, as mentioned in Section 4.5 under "Cross-lifecycle data integration", few studies adopt a lifecycle perspective where DTs support recovery or circular supply chains (i.e., X. V. Wang and Wang (2019); Tozanli et al. (2020)); while the other studies consider the single stage, focusing mainly on recyling or disassembly. At the EoL, for a cross-lifecycle integrated approach, a key requirement is information about the product's composition and condition as it reaches the final stage of the lifecycle. In particular, for a DT to effectively guide disassembly and recycling, besides focusing on the EoL process itself, it needs also to know "what it is dealing with": what components and materials are present in the product, and what state they are in. This information should be inherited from the BoL phase by considering detailed design and material data, and updated with MoL data thanks to usage history, modifications, and current condition. Indeed, it is important to recognize that "as-designed" data do not always correspond to the "as-built" or "as-used" in practice since manufacturing deviations, components replacement, or possible undocumented repairs and modifications can lead to discrepancies that limit the applicability of BoL information for EoL decision-making. By the time a product enters the EoL stage, a well-implemented DT should therefore contain integrated and updated representation on: i) as-designed data, ii) as-built data, therefore including deviations introduced during production or assembly, iii) as-used data, including repair history, performance degradation, and remaining condition. With such integrated data, the DT can reliably support decisions such as which components can be reused, which should be remanufactured, and how to optimize the recycling for the remaining materials.

5.2. Technical and organisational challenges

The findings highlight several cross-cutting and phase specific challenges that explain why DTs are not yet effective enablers of CE.

- Data silos and interoperability issues: Implementing CE through DTs involves many heterogeneous stakeholders (e.g., manufacturers, suppliers, recyclers, etc.), but data exchange among these parties is limited (Mügge et al., 2024). Additionally, DT systems typically involve software and hardware from multiple vendors using different data formats, which makes it difficult to integrate and utilise their outputs (X. V. Wang and Wang, 2019). Although initiatives such as the ISO 23247 propose frameworks for data transmission between different parts (Shao, 2024; Erdal ÖZBEK, 2024), they have yet to demonstrate effective support for EoL data integration, reflected in the scarcity of studies where a DT is maintained through all lifecycle stages.
- Lifecycle disconnection: As discussed in Section 5.1, the reuse of data collected in BoL and MoL phases is limited, hindering their value for CE. For example, design and assembly data are seldom structured for recyclers or repair centers, while monitoring data from use are not fed back into design processes. This lack of lifecycle continuity prevents CE-oriented decision-making.
- Stakeholders collaboration and trust: DT implementation requires sharing sensitive data across organisational boundaries, but many stakeholders can be reluctant due to privacy, priop(sic) prietary rights, or misaligned incentives. As highlighted by Kober et al. (2025), success criteria for value-oriented DT development include building trust among stakeholders and demonstrating clear business value, both critical for fostering data sharing and collaboration. Studies emphasize that incentives, trust, and governance are needed to overcome this barrier (Mügge et al., 2024). In practice, clear data governance and security controls (e.g. role-based access, classification of sensitive data, decentralised data spaces) can balance openness with privacy (Walden et al., 2021). By articulating concrete benefits (e.g., cost savings, regulatory compliance, access to shared insights) and ensuring robust data sovereignty, stakeholders are more likely to participate in a DT ecosystem (Tripathi et al., 2024).

5.3. Emerging solutions and integration approach

As discussed earlier, some solutions integrate DTs with other digital tools to enhance data interoperability and traceability – i.e., blockchain, e-passport. This combination offers significant potential for improving lifecycle DT-data integration in electronic devices. In particular, blockchain is already adopted in many fields to draw common data lifecycle; its ability to provide frameworks for building a distributed ledger can provide consensus, provenance, immutability and finality of transaction data (Vo et al., 2018). Similarly, the e-passport reflects the role of the emerging digital product passport (DPP) concept, which recently is gaining significant attention being a key element of the European Commission Circular Economy Action Plan (European Commission, 2022). Indeed, defined as a container of product's lifecycle data (Walden et al., 2021), the DPP is gaining prominence as a tool to digitise and modernise product data, supporting industries transition towards CE (Galatola, 2022), additionally it is considered as a promising data sharing tool since its main function is to make product data accessible to different stakeholders within a product system (World Business Council for Sustainable Development, 2023). DTs have also received attention in the context of DPPs; indeed, some authors (e.g. Walden et al., 2021; Saenz et al., 2024; Rebelo Moreira, 2024) have already recognized the potential of integrating DTs with DPPs to provide a powerful tool to improve data accuracy and timeliness (Monteiro et al., 2024). DTs are perceived as a potential technology to drive the DPP due to their potential to function as unique identifiers of their corresponding physical counterparts, by containing specific product, component and material-related data and gathering real-time data over the entire lifecycle of a product. However, both blockchain and DPPs have in common the need for building a robust DT architecture for supporting information required to enhance CE practices; therefore, the focus of this paper is devoted on how DTs can serve as the central tool that enables CE-oriented implementation.

Achieving CE in the electronics sector requires a systemic shift in DT functionality, rather than isolated uses. In practice this means aligning each DT application purpose with circular goals. As presented in Fig. 3, existing DT application purposes – design optimization, production and assembly planning, operational monitoring, predictive maintenance, and EoL management – can be reoriented: for example, DT-driven design can emphasize circular design principles (e.g., modularity, ease of disassembly), and DT-powered monitoring and maintenance can extend product life and improve resource efficiency, for example by monitoring parameters such as thermal condition, which cause product's degradation. Process-level DTs can also optimize resources efficiency, such as energy and material use during assembly and maximise material recovery at EoL. These CE benefits are fully achievable when DT applications are not siloed, but rather integrated across the entire product lifecycle. Indeed, a holistic and connected DT ecosystem as an enabler of circularity requires "data traceability throughout the lifecycle" and "closed-loop supply chains", as also highlighted in the figure.

5.4. Toward a CE-oriented DT

Building on the findings and challenges discussed in the previous sections, to address RQ2 (i.e., "How can DT application purpose and data flows be structured to enable CE benefits across the lifecycle of electronic devices?") a guideline for DT users, presented in Fig. 4, has been proposed. This guideline shows how DT data and purpose can be aligned and structured to support CE practices throughout the lifecycle of electronic devices - i.e., BoL including design, manufacturing and assembly; MoL including usage, maintenance and repair; EoL including collection and EoL management processes such as disassembly, remanufacturing and recycling.

The figure represents an actionable guideline scheme for stakeholders across electronic devices supply chain. It enables users to identify which data are required (left side of the figure), where these data originate (as shown by the directional arrows connecting data to stakeholders), and how they can be used to achieve specific CE-oriented DT objectives.

In particular, stakeholders – acting as the DT users - represent the main decision-makers throughout the lifecycle. Each phase of the lifecycle involves distinct stakeholders who can both provide and utilise data - distinguished in the figure through directional arrows and detailed in the figure legend - critical for DTs implementation:

BoL stakeholders:

- Original equipment manufacturers (OEMs) and electronics designers responsible for product design, engineering, material selection and manufacturing. They provide foundational data on the product's structure and composition (Fofou et al., 2021; Seegrün et al., 2023);
- Material and component suppliers provide data related to materials, components, and manufacturing services delivered to OEMs (Fofou et al., 2021; Schützer et al., 2019);
- Electronics producers and assemblers who generate data during manufacturing and assembly processes (Schützer et al., 2019), crucial for monitoring and optimizing production processes and ensuring product quality;

MoL stakeholders:

- Repair centers offer valuable insights into product performance and failure modes by providing data on repairs and maintenance activities during the use phase (Seegrün et al., 2023);
- Consumers can act as passive data sources during the usage phase, generating data on performance, health status, and product degradation through embedded sensors and or connected systems;

EoL stakeholders:

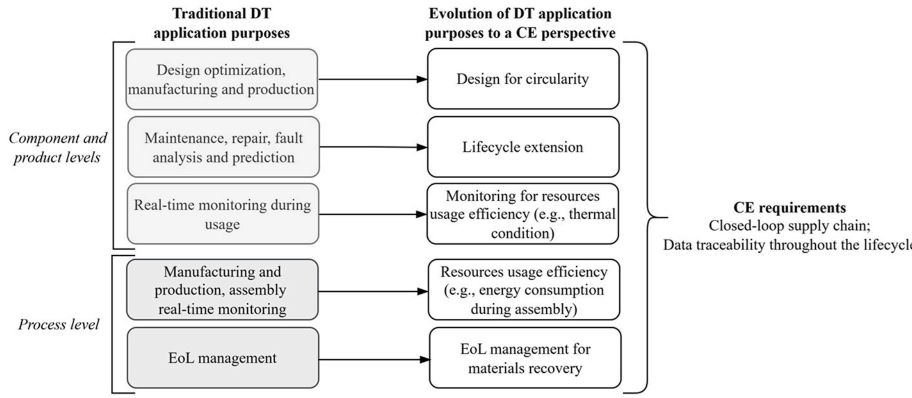

Fig. 3. DT purposes considering a CE viewpoint.

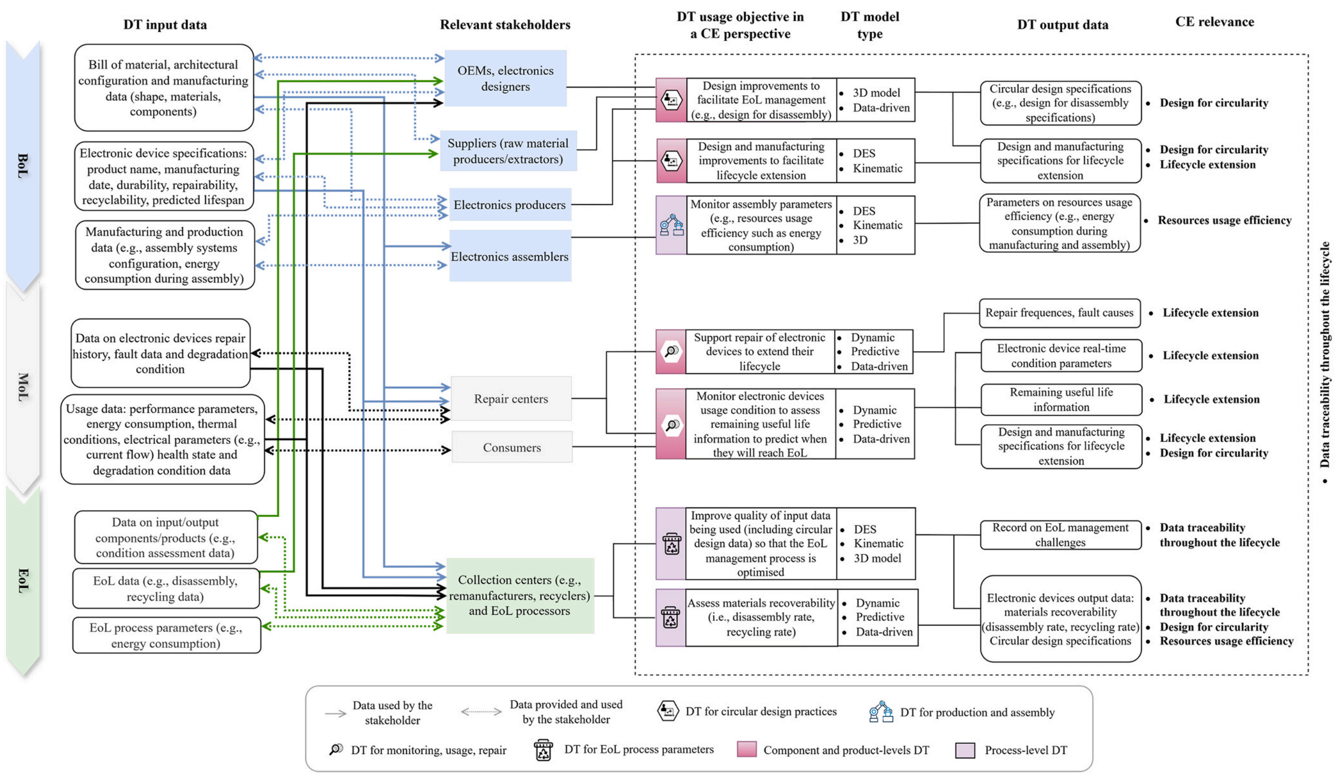

Fig. 4. Guideline for CE-oriented DT application throughout electronic devices lifecycle.

- Collection centers who handle used electronic devices, sorting them for various EoL management routes such as reuse, remanufacturing, or recycling;
- EoL processors, such as recyclers, are responsible for optimizing EoL processes and recovering valuable materials from products at the end of their lifecycle (Fofou et al., 2021; Diaz et al., 2021).

Fig. 4 illustrates the connection between stakeholders – who act as both decision-makers and DT users – and the types of data required to initiate and operate DTs effectively (shown on the left). The arrows linking them have been colour-coded to indicate their lifecycle origin: blue for from the BoL phase, black for data from the MoL phase, and green for data from the EoL phase. As resulted from the literature - presented in Section 4.5 ("Type of DT-data in lifecycle phases") - and further adapted to a CE perspective following the World Business Council for Sustainable Development (2023), the DT input data include.

- design and configuration data (e.g., materials, architecture, bill of materials);
- electronic device specifications (e.g., product name, manufacturing date, durability);
- manufacturing and production process data, repair history data, usage condition data (e.g., performance, degradation, failures);
- EoL-specific data (e.g., disassembly steps, recoverability rates);
- process parameters (e.g., energy consumption).

According to the data used, decision-makers/stakeholders can employ DTs for different CE purposes, as illustrated on the right side of Fig. 4 under "DT usage objective in a CE perspective". Drawing from the literature in Section 4.4 and adapting the findings to a CE viewpoint, DT usage objectives aligned with CE objectives for each lifecycle stage have been defined.

- At the BoL, DTs can enable design improvements to facilitate EoL management (e.g., design for disassembly), design and

manufacturing improvements to facilitate lifecycle extension, monitor assembly parameters;
- During the MoL, DTs can support electronic repair and assembly, monitor electronic devices usage condition, and assess degradation to enable predictive maintenance and lifespan extension;
- Finally, at the EoL, DTs can improve input data for EoL management, enhance recoverability assessment, support disassembly planning, and enhance material recovery efficiency.

In the figure, these DT usage objectives are visualised using red-shaded blocks to indicate component or product-level DT applications and purple-shaded blocks to indicate process-level DT applications. This visual distinction emphasizes that CE benefits can be fully realized when DT data and functions are implemented across multiple lifecycle stages and levels of analysis (i.e., component, product, process).

Under "DT model types", the guideline distinguishes DT models based on their functional roles. According to the findings from the SLR (Section 4.2), dynamic models can be used for real-time adaptation, predictive models for forecasting usage and failure, DES models for event-driven assembly and disassembly, kinematic models for robotic motion and positioning; 3D models for spatial configuration and visual planning; data-driven approaches for real-time analytics. Each model type is selected according to its fit-for-DT purpose in alignment with lifecycle phase and data availability.

Under "DT output data", the types of data generated through CE-oriented DTs are highlighted, including: data on required circular design specifications, parameters on resources usage efficiency, analytical outputs such as usage statistics and failure data, remaining useful life (RUL) estimates, condition-based performance indicators, records on EoL challenges, and EoL management output data such as materials recoverability rates.

Finally, CE-oriented DT applications have been linked to the specific CE outcomes identified in the literature, including: design for circularity strategies (design for reuse, remanufacturing, and disassembly); lifecycle extension (through condition monitoring, repair, and predictive maintenance); resource efficiency (via improved usage, assembly, and recovery processes). It is worth mentioning that data traceability across the lifecycle and closed-loop value chain result as a requirement to enable a full CE, since the achievement of CE benefits is allowed through the integration of data across lifecycle, therefore through information continuity.

The proposed guideline represents a first step toward operationalising CE principles using DTs across the electronic device lifecycle. By explicitly mapping the relationships among stakeholders, data flows, and CE-oriented objectives, it addresses the core challenges identified earlier – namely data silos, lifecycle disconnection, and limited stakeholder collaboration.

Fig. 4 clarifies which actors should provide and use specific data types, and how these data can be systemically reused across BoL, MoL, and EoL phases to inform circular strategies such as design for disassembly, predictive maintenance, and material recovery. From a scientific perspective, the presented guideline contributes by providing a structured, lifecycle-wide data logic that integrates DT inputs, models, and outputs within a CE workflow. It advances current knowledge by shifting the DT focus from isolated, phase-specific applications to integrated, multi-level systems capable of supporting closed-loop decision-making.

6. Conclusions and future work

This study examined the intersection of DT technology and CE practices in the context of electronic device lifecycles. To do so, a SLR has been conducted; the findings show that current DT applications remain fragmented and often fail to address CE objectives. Data collected at different lifecycle stages – BoL, MoL, or EoL – are rarely integrated. The lack of interoperability and standards across vendors and stakeholders, together with organisational barriers such as data privacy concerns and misaligned incentives, restricts collaboration and prevents a unified view across the lifecycle. Furthermore, the limited data reuse across lifecycle limits CE benefits. This paper wanted to address these limitations by providing a guideline for stakeholders (i.e., DT users) on how DTs can be reoriented toward CE objectives; it integrated insights from the literature and positioned them in a lifecycle perspective and emphasized how DTs can support CE across three main phases: enabling circular design at the beginning of life (e.g., design for disassembly), extending product lifespans during the middle of life (e.g., predictive maintenance, repair), and informing efficient recovery strategies at EoL (e.g., disassembly process, material recovery). From an academic point of view, the results highlight the need to integrate standards and governance mechanisms that facilitate data continuity across stakeholders. For industry and policymakers, the proposed guideline highlights how DTs can support emerging regulations and business models that emphasize repair, reuse, and recycling.

Despite the relevance of this study, some limitations emerge concerning the selection of data for DTs development. While the proposed guideline outlines which types of data can support CE-oriented DT applications, the findings do not define operational criteria for prioritising data collection. Additionally, challenges persist in achieving integration throughout the lifecycle. One major issue is the lack of standardisation in data formats and communication protocols (X. V. Wang and Wang, 2019); this fragmentation complicates users' ability to leverage DT data effectively across lifecycles. DT users often operate in isolated systems that do not communicate effectively with other actors in the value chain, resulting in data silos that restrict valuable insight sharing (Tripathi et al., 2024). This issue is linked to the willingness of stakeholders to share information regarding their products and processes. Indeed, often stakeholders focus on optimizing their individual tasks rather than considering a holistic approach to CE practices. As reported by Tripathi et al. (2024), in DT ecosystems, data governance and management encompass aspects such as proprietary rights, managing stakeholders access and trust, addressing confidentiality, adopting decentralization, overcoming infrastructure challenges and utilizing data for insights and enhancement.

Given these challenges, future research should focus on establishing criteria that help stakeholders select which specific data must be collected for specific CE-oriented DT use cases. Furthermore, mechanisms that facilitate transparent data sharing among stakeholders ensuring that the benefits of DT implementations can be fully realized in support of CE objectives, need to be studied. Indeed, the study also provides insights into possible integration of other digital tools with the DT (e.g., DPP, blockchain) to support data integration across the lifecycle; a further analysis on this matter will be addressed by the authors in future works through an application case that will be aimed at identifying the best practices for integrating DT-data across lifecycle to support CE practices in the electronics sector. This approach will not only validate the proposed guideline to a specific case – therefore considering also specific data – but also contribute to developing robust strategies for improving processes such as disassembly and recycling and enhancing sustainability within the electronics industry.

CRediT authorship contribution statement

Laila El Warraqi: Writing – review & editing, Writing – original draft, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Elisa Negri:** Writing – review & editing, Resources, Methodology, Data curation, Conceptualization. **Paolo Rosa:** Supervision, Resources, Methodology, Conceptualization. **Sergio Terzi:** Visualization, Validation, Supervision, Resources, Methodology, Conceptualization.

Disclosure statement

The authors report there are no competing interests to declare.

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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.

Data availability

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

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