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How will the digital twin shape the future of industry 5.0?

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ABSTRACT

Industry 5.0 is on the horizon, but the role of digital twins (DTs) as one of its major technological enablers is far from being understood. This article begins with a bibliometric analysis and a systematic review, followed by a discussion of insights obtained from the literature through the lens of strong structuration theory. The results include a description of the new paradigm of future-oriented and responsible physical-digital convergence, a research agenda, and the proposal of the structure – agency (SA)–DT framework to guide advances in Industry 5.0 with digital twins. A concept-centric analysis is used to identify use cases, impacts, redesigned forms of physical–digital interaction, challenges, and the changes in both human and non-human agents increasingly intertwined in more advanced DT solutions. Moreover, this study reveals how digital twins can be deployed to address, in an integrated manner, the three main pillars of Industry 5.0: human-centric, sustainable, and resilient industry transformation. Practitioners may find our contribution helpful for their Industry 5.0 roadmaps, which require more ample interaction with society at all levels and evidence of responsible practices for current and future generations.

1. Introduction

The industrial agenda has a new priority. Having its roots in the fourth industrial revolution, which promised to transform manufacturing with advanced technologies and cyber-physical systems (Schwab, 2017), Industry 5.0 aims to responsibly accomplish this mission.

Technological advances offer common ground for research on industry transformations. However, instead of focusing on particular technology adoption for manufacturing efficiency like Industry 4.0 (e.g., artificial intelligence (AI) to improve maintenance practices, deploying sensors and advanced communication technologies to achieve real-time monitoring of production), Industry 5.0 requires their integration into more complex systems that must, by design, (1) include humans in the development of more advanced digital capabilities; (2) measure the impact of decisions in the organization and its environment; and (3) be future-oriented (Cannavacciuolo et al., 2023; Ghosh et al., 2022). The shift to “5.0” is significant because it places individuals at the center of industry development, improving resilience in processes and supply chains, which have become so crucial in an era of global disruptions, and ensuring more circular and sustainable practices to address grand challenges of our society (Maddikunta et al., 2022b). The European Commission is one of the most active proponents of Industry 5.0 (European Commission, 2021, 2023).

It was already recognized that the digital twin (DT) “is a key enabling technology for both Industry 5.0 and Society 5.0, which enables the connectivity between cyberspace and physical space” (Huang et al., 2022), shaping the ongoing physical-digital convergence (García et al., 2022). Defined as a digital replica of physical objects or systems (Glaessgen and Stargel, 2012), a DT can monitor, control, or improve decision-making using data collected from the real environment at different stages of the product or system lifecycle (Semeraro et al., 2021). DT affordances offer an extraordinary opportunity to implement Industry 5.0; however, “few studies combine a DT with analysis methods to make integrated decisions” (Hao Wang et al., 2023a), and though “scientific literature has analyzed the adoption of DT in the optimization of products life cycle, few contributions have yet focused on the exploitation of DT to assess and improve the sustainability performances of whole value chains” (Semeraro et al., 2021).

This research, therefore, uncovers the role of DTs in Industry 5.0, presenting (1) a bibliometric analysis; (2) a concept-centric assessment of the literature addressing the interplay of physical and digital parts of DT and the changing role of human and non-human agents in industry transformation; (3) a framework for developing a new generation of

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human-centric DTs prioritizing resiliency and sustainability; and (4) an agenda for future research on the creation of DTs that contribute to the tenets of Industry 5.0. Our analysis of the literature and framework proposal are made in light of strong structuration theory (Greenhalgh and Stones, 2010; Stones, 2005).

The remainder of this paper is organized as follows. Section 2 provides the background for Industry 5.0 and DTs. Section 3 explains the methodology used, and the results are detailed in Section 4, which includes the bibliometric and concept-centric study. Section 5 discusses the findings, outlines the structure – agency (SA)–DT framework, and summarizes future research opportunities. Section 6 concludes the study and presents the main conclusions, limitations, and implications for theory and practice.

2. Background

2.1. Industry 5.0: a quest for responsible transformation in manufacturing

Industry 5.0 has gained increasing attention in both research and practice in recent years. It describes the next phase of industrialization, characterized by the integration of advanced technologies and human capabilities. As such, Industry 5.0 causes a cross-sectoral and societal-driven transformation of manufacturing (Barata and Kayser, 2023).

Several facets of Industry 5.0 are being researched, most notably sustainability, resilience, mass personalization, and human-machine collaboration (Aheleroff et al., 2022). Sustainability in Industry 5.0 refers to adopting circular processes that prioritize resource reuse, reduction of waste, and environmental impact, contributing to a circular economy for improved resource efficiency (Xu et al., 2021). Resilience entails bolstering industrial production against disruptions, enabling it to serve as critical infrastructure during crises and swiftly adapt to geopolitical changes and natural emergencies (Xu et al., 2021). Moreover, Industry 5.0 responds to the demand for personalized products that reflect unique requirements while remaining affordable (Aheleroff et al., 2022). This movement towards mass personalization represents a key driving force in the use of technology to amplify human contributions to manufacturing (Aheleroff et al., 2020).

Industry 4.0 already included the integration of advanced technologies in manufacturing productivity (Özköse and Güney, 2023). Examples of technological enablers of human-machine collaboration include augmented reality, virtual reality, communication technologies, AI, robotics, or the Internet of Things (IoT), and the vital role of wearable technologies in optimizing industrial processes (Maddikunta et al., 2022b; Perno et al., 2022). However, there is an ongoing debate on the challenges and opportunities of automation, including concerns about job displacement and the need for upskilling and reskilling. Industry 5.0 advances these issues by shifting its focus from human replacement discussions to collaborations between humans and machines (Majerník et al., 2022). This approach highlights the importance of human skills (Kolade and Owoseni, 2022) and expertise in conjunction with intelligent machines.

Human centricity aims to integrate human needs into digital transformation efforts, enabling collaboration with autonomous robots within shared workspaces (B. Wang et al., 2024). For example, Kaasinen et al. (2022) present three possible approaches for human-machine collaboration design. First, complex networks formed by interactions between humans and non-humans should be analyzed, emphasizing the capacity of technology as an influential actor and considering human-machine interactions in digitalized networks to understand roles, interactions, and processes. Second, operations in Industry 5.0 serve as user-oriented documents that describe system characteristics from the end user's perspective, focusing on operational goals, constraints, system elements, interfaces, and high-level user requirements. Finally, an ethically aware design of human-machine collaboration, aimed at respecting workers' autonomy, privacy, dignity, and meaningfulness, is achieved through methods such as value-sensitive design, ethical impact assessment, and creating ethical guidelines to ensure responsible design choices (Kaasinen et al., 2022). Broader perspectives can also be considered for human centricity, not limited to the worker using technology (e.g., a machine, robot, AI system, or other), but also all the system's stakeholders, internal and external to the organization, in the present or the future. Hence, Industry 5.0 has the potential to revolutionize the industrial sector, not restricted to productivity and operational aspects.

2.2. Digital twin: a living model of critical assets for intelligent production

A DT is a digital replica of a physical object or system, also called a living model, because of its capacity to evolve using data (GE, 2016). With its initial applications in NASA's efforts to assist in the aerospace program (Glaessgen and Stargel, 2012), the DT integrates simulation capabilities with real-time data of the physical twin and historical data. Nevertheless, it is essential to differentiate DTs that include bidirectional, real-time communication between physical elements and the digital replica from other concepts, such as digital models (no real-time communication) or digital shadows that only support real-time communication from the physical to the digital replica (Aheleroff et al., 2021).

DTs are rapidly changing to more advanced architectures that include sensors to obtain (increasing volumes of) real-time data from a product or its environment throughout the entire lifecycle, with the aim of dealing with complexity and unpredicted events (Grieves and Vickers, 2016). The DT predictive presented by Aheleroff et al. (2021) is a paradigmatic example revealing the role of machine learning in the capacity to incorporate knowledge in the DT, exploring big data.

Research on DTs has grown exponentially since 2017. The use cases in manufacturing are particularly relevant, including (1) product design, identifying problems in the working environment and accelerating the process; (2) replicating manufacturing equipment, with an emphasis on predictive maintenance capabilities; (3) modeling the workshop to optimize production or minimize waste; (4) providing after-sale services, collecting data from the product in use, and (5) integrating data from all the product lifecycle stages previously presented, accumulating relevant historical data and allowing a comprehensive informational model of the product (Fang et al., 2022).

Production optimization, improving product performance, and assisting in industry decisions are well aligned with the traditional goals of industry digitalization. For example, Semeraro et al. (2021) found that the main functions of DTs include more operational usage goals like "[a]ccelerating the product development speed; [i]dentifying customers' needs; [p]erformance optimization and validation [e.g., preventing failures and downtime, reduce quality costs, optimize resource allocation]; [r]emote commissioning and diagnostics", which is crucial for competitiveness but, when compared to the new priorities of Industry 5.0, also reveals a gap that needs to be addressed. Recent applications have shifted from specific objects (e.g., manufacturing machines) to systems of systems, integrating multiple DTs at different levels of abstraction (Boyes and Watson, 2022; Hao Wang et al., 2023a). It is now possible to discuss supply chain DTs that go beyond factory boundaries, which is particularly relevant to ensure visibility and resiliency (Dolgui et al., 2020; Barata, 2021). However, these and other examples, such as indoor safety or human DTs, are still emerging in the literature (Liu et al., 2023). Moreover, the factory of the future will not be isolated from the surrounding society, which may indicate that industry DTs will be part of wider smart cities/regions DTs (Hao Wang et al., 2023a).

Important open challenges for DT research also fall within the scope of Industry 5.0. For example, there is a need to research DT interoperability and interaction with humans, as well as the shortcomings of studies addressing the use of DTs for circular economy and sustainability (He and Bai, 2021). Additionally, most DTs focus on a single lifecycle stage (e.g., design, production, or service) and are limited in support of the multisectoral and societal view of Industry 5.0.

Table 1
Strong structuration applied to DTs in Industry 5.0

Quadripartite component	Ontology-in-situ
External structures	Institutional, political, and technological forces affect DT adoption, which must simultaneously ensure human-centricity, sustainability, and resilient industry practices.
Internal structures	Several technologies are available to create DTs, but their integration with other DTs and also with humans is not yet the norm in industry practices. The increase in technology agents is challenging human work practices, not yet exploring the predictive capacities of technology for decision-making and providing evidence of compliance with the three pillars of Industry 5.0.
Active Agency/Agent's practices	More advanced DT use cases are necessary to make Industry 5.0 a reality.
Outcomes	Multiple questions emerge: how current structures can be changed with DTs, how they adhere to Industry 5.0 priorities, and their impact on both human agents and digital transformation strategies.

3. Methodology

This study follows the guidelines proposed by Durach et al. (2017), Okoli and Schabram (2010), and Webster and Watson (2002) for a systematic literature review. According to Durach et al. (2017), the usual steps include "(1) defining the research question, (2) determining the required characteristics of primary studies, (3) retrieving a sample of potentially relevant literature, (4) selecting the pertinent literature, (5) synthesizing the literature, and (6) reporting the results" (Durach et al., 2017). Okoli and Schabram (2010) also suggest that the researchers train literature search before starting the analysis, particularly when the work is done in parallel by multiple researchers, while Webster and Watson (2002) provide essential suggestions for structuring the study and conducting a concept-centric analysis.

The first stage (planning) defined our goal of understanding the role of DTs in the emerging needs of Industry 5.0, the literature survey, and the synthesis protocol by two reviewers. Bibliometric network analysis preceded the second stage (selection) to identify relevant keywords and clusters in the main pillars of Industry 5.0. The team evaluated publications indexed in Scopus using VOSViewer (van Eck and Waltman, 2010) using the main keywords "Industry 5.0" AND ("digital twin" OR "digital twins") and variants for human-related studies, sustainability, and resilience. Subsequently, the authors screened titles, keywords, and abstracts to identify studies that were clearer in framing the study with the two topics using the Scopus and Web of Science samples. Each researcher performed an initial analysis on a small sample of ten papers to ensure that the inclusion criteria were consistent. The team obtained 93 publications for full-text reading, excluding duplicates from both the databases. Content analysis revealed 57 publications that the team could access, coded in Mendeley reference management software, and classified in a table with more specific information about each paper to assist in grouping concepts for discussion.

In the selected context, human and technology dimensions are deeply intertwined. Among the several possible theoretical lenses for understanding the phenomena, strong structuration theory (Stones, 2005) stands out. According to this theory, systems that include the behaviors of the actors at the micro (e.g., individual), meso (e.g., organization), and macro (e.g., country or region) levels, and structure (resources and rules that are used and created by humans) are inseparable (Giddens, 1984). Structures support society's actions and are shaped by the results of these actions. More recently, strong structuration theory has appeared to clarify the duality of structure, providing a theoretically helpful lens for understanding technology developments, which have already been adopted in critical settings such as healthcare and management (Greenhalgh and Stones, 2010; Jack and Kholeif, 2007).

Stones (2005) posits that structure and patterns of action should be studied through hermeneutics, suggesting the identification of position-practice networks (ontology-in-situ) involving humans and non-human agents (e.g., technology). Four main components must be addressed in studies adopting the theory, called the quadripartite nature of structuration: (1) external structures (forces that affect agents' behaviors independently of their will); (2) internal structures of agents (knowledge or agent roles); (3) active agency, referring to the types of actions performed; and (4) outcomes of actions, where structures can remain the same or change (Greenhalgh and Stones, 2010; Stones, 2005). Table 1 explains how strong structuration theory was adopted in our work to study DTs in Industry 5.0.

After completing the paper selection, each was evaluated in full to extract relevant concepts and integrate them according to the lens of strong structuration theory.

4. Unfolding the literature

4.1. Bibliometric analysis

Our initial assessment of the studies used VOSViewer (van Eck and Waltman, 2010). This section presents the results of the Scopus sample because it provides a broader list of studies. The results reveal that Industry 5.0 gradually diverges from the traditional stream of the 4.0 literature. The human aspects of digital transformation, such as accident prevention, operator 4.0, and the influential paradigm of Society 5.0, are more evident in the former. Nevertheless, key technological trends such as big data, IoT, and AI are shared by both the productivity-centered Industry 4.0, and its new 5.0 counterpart, and can also be found in the structural elements of a DT.

Figs. 1–3 provide an overview of the bibliometric network created for the three main Industry 5.0 pillars. Fewer relevant terms or synonyms were removed. We also omitted the node "Industry 4.0" to identify only the most relevant links with Industry 5.0. Each cluster of papers is identified by a color representing notes with a closer relationship. The size of each node/line increases proportionally to its relevance in terms of the number of papers.

Fig. 1 provides an overview of the clusters restricted to "Industry 5.0" AND ("digital twin" OR "digital twins") AND human" which resulted in 1027 papers. The topics of ergonomics, accident prevention, and human-robot collaboration appear in the red (digital twin) cluster in parallel with human resource management and training. Several technologies appear in the green cluster (e.g., AI, IoT, and Blockchain). Two smaller clusters present research on metaverse (purple) and cyber-physical systems (yellow). The focus of Industry 5.0 in sustainability and supply chains can be found in the blue cluster. Fig. 2 presents the results for the sustainability pillar.

A total of 1047 results were obtained with the keyword combination "Industry 5.0" AND ("digital twin" OR "digital twins") AND (sustainability OR sustainable). Consistent with the vision that Industry 5.0 is not restricted to company borders, the supply chain node, life cycle analysis, and circular economy also emerge in this sample. The technological cluster in blue is also visible, but we expect a clearer link with circular economy concepts. The network also reveals a red cluster of papers addressing social sustainability, with touchpoints on the human-centric sample previously presented. The keyword resilience (although the node is not significant) also appears in this network, which is the third pillar, as shown in Fig. 3.

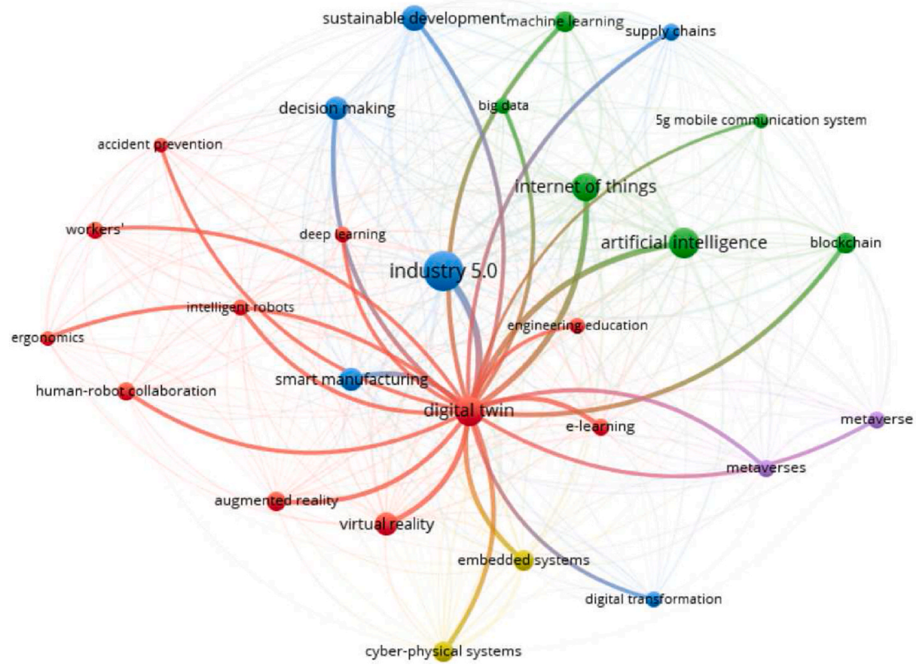

Fig. 1. Co-occurrence of keywords in Scopus for human-centric research (SCOPUS sample obtained in March 2024, all fields).

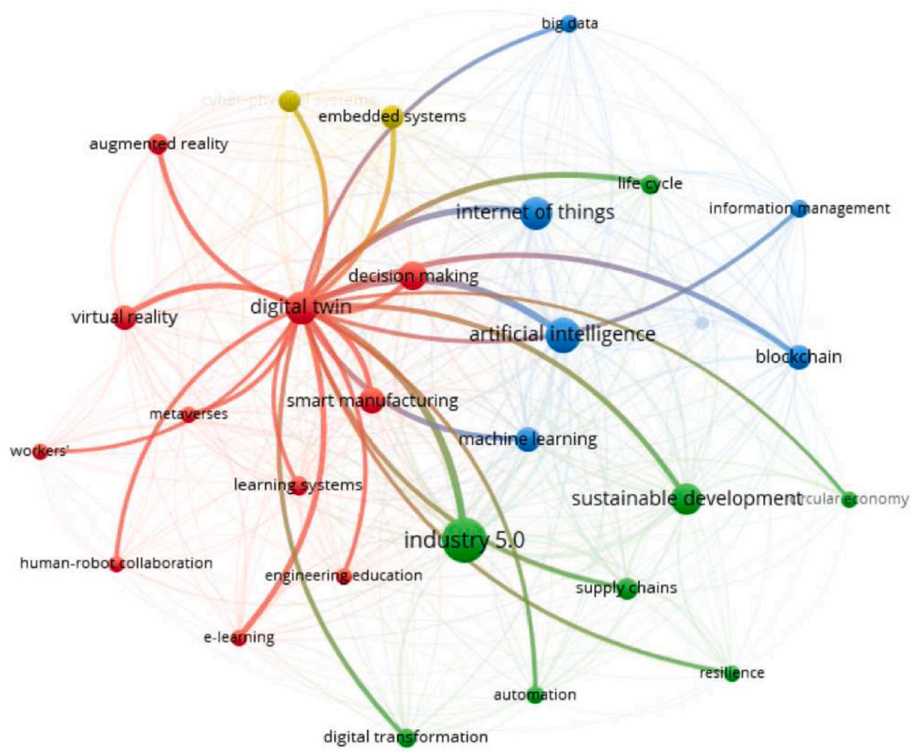

Fig. 2. Co-occurrence of keywords in Scopus for sustainability (SCOPUS sample obtained in March 2024, all fields).

Restricting our search with the keyword "Industry 5.0" AND ("digital twin" OR "digital twins") AND resilien*" returned 614 results, which may indicate less emphasis on DTs to assist this critical facet of industrial transformations. Several combinations include the supply chain, but also reveal the role of cybersecurity. Articles proposing DTs to predict/prevent and respond to disruptions in production flows can be found in this sample.

Our bibliometric networks suggest that the DT can be integrated with the three pillars of Industry 5.0, emphasizing the human-centric and sustainability lines of research. It also suggests that human centricity tends to be studied internally within companies and employees (e.g., relationships with robots, accident prevention, and improved interaction via extended reality), probably overlooking other relevant stakeholders for a socially responsible industry. The focus of the sustainability pillar is on the environment, which is understandable but insufficient to assist the development of circular manufacturing and a comprehensive

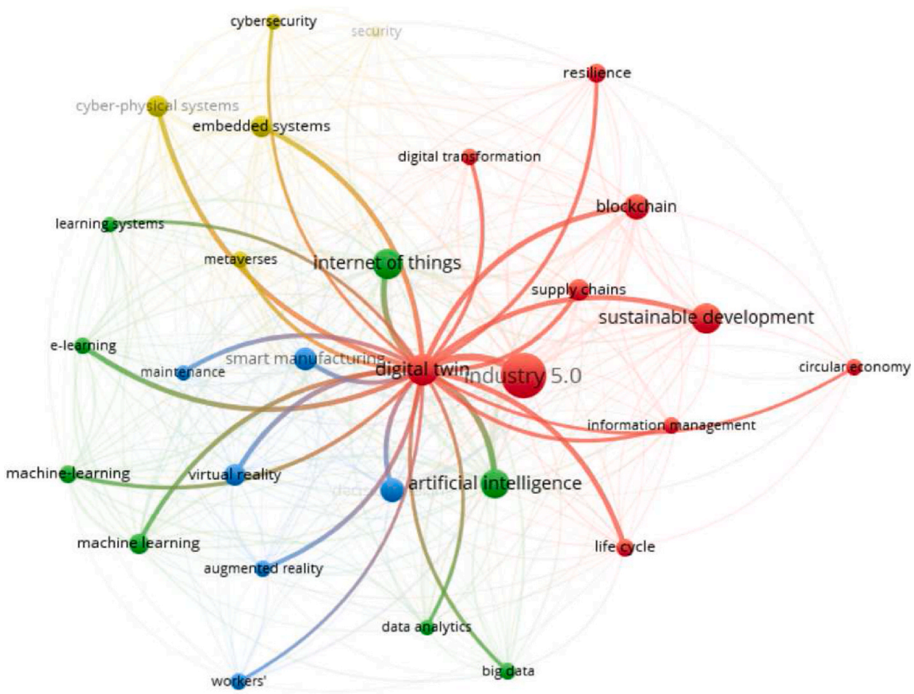

Fig. 3. Co-occurrence of keywords in Scopus for resilience (SCOPUS sample obtained in March 2024, all fields).

reduction of all forms of waste. Finally, resilience is evolving alongside the supply chain literature, which is interesting and desirable to prevent disruption in physical flows using DTs. The popularity of blockchain in the three samples was surprising, requiring a deeper analysis of its role at the intersection of Industry 5.0 and DTs.

4.2. Concept-centric analysis

The majority of the 57 papers selected were published in 2023 (51%), followed by 2022 (33%), 2024 (already 11%), and 2021 (5%). The human-centric stream of research reaches 71% of the papers, while sustainability (13%) and resilience (16%) are more balanced in our sample.

A concept-centric analysis of the literature (Webster and Watson, 2002) is subsequently presented according to the lenses of strong structuration theory (Greenhalgh and Stones, 2010), which, addresses (in 4.2.1) the networks of position-practice relationships of humans and technology, and (4.2.2) human and technology agents in focus.

Table 2
Use cases of DTs in Industry 5.0

I5.0 Pillar	Context	References
Human-centric	Human health and safety Work assistance and error reduction Training Fair decision making	Wang et al. (2022), Pang et al. (2023), Choi et al. (2022), Ruppert et al. (2022), Ignatius and Bahsoon (2023), Haoqi Wang et al. (2023b)
Sustainability	Environmental protection Energy optimization Waste reduction	Rios et al. (2023), Guruswamy et al. (2022), Choi et al. (2022)
Resilience	Health monitoring and disaster prevention Supply chain continuity Manufacturing flexibility Secure data storage	Rios et al. (2023), Choi et al. (2022), Minca et al. (2022), Zhang et al. (2021), Dewangan and Chandrakar (2023)

4.2.1. The interplay of physical and digital agents

Most studies on DTs can be integrated into position practice networks, which can be explained by their purpose of representing and optimizing complex sociotechnical contexts.

4.2.1.1. Use cases of digital twins in industry 5.0. Examples of relevant DT use cases are listed in Table 2.

There are relevant sector-specific use cases of DTs in different areas of society, including healthcare, agriculture (Taj and Jhanjhi, 2022), and important industries. For example in construction, Wang et al. (2022) create a DT framework that assists in all stages of the construction lifecycle and propose a virtual reality interaction module, while Rios et al. (2023) discuss the potential adoption of DTs for bridge design, management, and operation. According to the authors, a multimetric bridge health-monitoring system can explore historical and real-time data on the structural, environmental, and operational conditions of the bridge. The critical food supply chain is another appealing context for DT adoption, aiming to assist decisions in reducing food waste (Guruswamy et al., 2022) or ensuring equity and equality in decisions (Ignatius and Bahsoon, 2023).

Supporting manual assembly in manufacturing is another important use case for the human-centered adoption of DTs, as illustrated in the research of Pang et al. (2023), considering the (1) scene, which defines the assembly sequence, (2) assembly model, and (3) parts model. The system may verify positional errors, part selection errors, or positional errors, for example, by comparing physical and digital results (Pang et al., 2023).

Flexible manufacturing can contribute to a more resilient industry. For example, Minca et al. (2022) consider DTs in the context of multi-functional flexible manufacturing technology and explore the key motivations for their use, such as remote monitoring. Another example is presented by Zhang et al. (2021), who introduce a "lightweight" DT approach for parallel manufacturing that focuses on core dimension information, employs digital simulation, and enhances production efficiency through reverse control, thereby facilitating flexible and iterative improvements of the production line.

Several affordances can be identified for DTs in Industry 5.0. For example, testing dangerous situations before they are implemented in practice, monitoring human health or training (Ruppert et al., 2022), enhancing student motivation and learning through practical simulations, allowing the exploration of real-world scenarios and complex systems (human-centric), addressing environmentally relevant purposes, such as e-waste management (sustainability), ensuring data security and data privacy (Dewangan and Chandrakar, 2023), and managing the risks of disruptions (resilience) in supply chains (Choi et al., 2022). These examples are not exhaustive but illustrate the potential of DTs in the three main pillars of Industry 5.0.

4.2.1.2. Resiliency-aware digital twin. A good example can be found in Ivanov (2023) and the digital supply chain twin, including (1) the virtual representation of physical objects, (2) the technological portfolio for DT creation, (3) system description/visualization, and (4) system prediction/prescriptive analytics. Expanding the scope of the "worker", the social aspects of supply chain DTs also include population needs. DTs may help in sustainability analysis, such as fair trade and regulatory compliance (Ivanov, 2023), clearly spanning the borders of each organization participating in the supply chain. Additionally, DTs embedded with forecasting capabilities inside a warehouse can be useful. However, there is a lack of research on the specific steps of the process, such as packaging (Drissi Elbouzidi et al., 2023) and order picking, in which DTs can be used for occupational health and safety purposes to check if working conditions are appropriate, including noise exposure or body posture (Grosse, 2023).

Resilience can also be achieved through decentralization of manufacturing structures, as suggested by Leng et al. (2023). These authors present a blockchain-based DT prototype to manage more complex production networks that require synchronization and constant adjustments in the flow of products and materials. The use of DTs to improve human-machine collaboration in large-scale manufacturing that requires personalization is an appealing avenue for future research (Nguyen et al., 2022a).

4.2.1.3. Physical - digital interaction. Several technologies can be used to create interactive DTs for energy optimization or gathering data to improve product design (Bhattacharya et al., 2023). For example, using augmented, extended, or virtual reality (although not required to be considered a DT, as explained by Turner and Garn (2022)) to improve workplace conditions. A method for integrating extended reality and DTs to improve user interaction with equipment was proposed by Tu et al. (2023). The four main building blocks of the architecture include a visualization module (e.g., 3D model of the equipment, dashboards, warnings), a control module that allows the operation of different devices such as cranes exemplified in the paper, a module that establishes data flows between the real and virtual environments, and an identification component using a QR code. Another example involving cranes (Yang et al., 2022) also focuses on virtual representation and improved interaction between humans and machines. Virtual reality is an important enabler of user-friendly DT adoption in Industry 5.0 (Lv, 2023).

Aiming at a more inclusive society, a digital-twin human-machine interface can use gestures to control electronic peripherals and improve the expression ability of non-verbal individuals (Mo et al., 2023). In addition, at the interface of the human and artificial, Xian et al. (2023) emphasized that a DT is central to personalized collaboration between humans and machines. Nevertheless, as presented in recent studies by Li et al. (2023) S. Wang et al. (2024) and Zhong et al. (2024), DTs can also be adopted to ensure safe and reliable human-robot collaboration.

A DT can mirror the structural aspects of a plant (e.g., machines and production lines), allowing their optimization at the levels of supervision, interaction, and prediction, thereby reducing waste (Turner and Garn, 2022). However, it is challenging to create parsimonious DTs solutions that are capable of representing and acting in the most critical parts of the physical system. Additionally, DTs still lack standardization to increase their interoperability.

4.2.1.4. Challenges for the digital twin evolution. DT potential is vast for Industry 5.0 with analytics, synchrony between the physical and digital realms, prediction of faults and technological bottlenecks, and automation of repetitive tasks that would not be interesting for humans. Yet, the barriers are not less significant, namely, the existence of an information technology infrastructure integrating sensors and data processing, quality and consistency of source data, privacy, security, and trust in a system that will become central to manufacturing operations, standardization, and support for DT modeling (Sasikumar et al., 2023).

Cybersecurity in DT design is a common concern (Alcaraz and Lopez, 2023; Choi et al., 2022). Suhail et al. (2023) presented one of the most recent examples of an explainable DT solution to ensure the security of cyber-physical systems. Their solution addresses the three main pillars of Industry 5.0, for training people (human-centric), detecting anomalous behavior (sustainability), and predicting attacks (resilience). However, significant research gaps exist in the practical development and implementation of DTs, such as the lack of interoperability among different software used along the DT model generation track, performance improvement of anomaly detection algorithms, and the direction for the creation of macro-DTs that integrate the DTs of individual infrastructure assets (Rios et al., 2023).

Responsible DT use requires the explainability of AI components to remove unsafe DT outputs (Bhattacharya et al., 2022). Other challenges include the development of practical DT models and addressing human behavior uncertainties. The privacy and security of DTs involve solutions such as federated learning, blockchain technology, and role-based access control (Xian et al., 2023). Other challenges lie in integrating DTs with metaverse-enabled systems, addressing security and privacy issues, and establishing standardized governance and regulations for this transformative socio-technological shift (Jagatheesaperumal and Rahouti, 2022). We agree with Balogh et al. (2023) that "the ad-hoc solutions that are currently in use are not sustainable in the long term and are difficult to integrate into other systems and DT environments".

4.2.2. Agents-in-focus

Human DTs are becoming popular in the literature (Asad et al., 2023; He et al., 2024; B. Wang et al., 2024). Motion tracking systems, biological (e.g., electrocardiograms), and environmental sensors can provide a comprehensive overview of operations. The latter is more common and includes, for example, temperature, humidity, and noise. The combination of wearable technology and environmental sensors offers a very interesting solution to occupational health and safety, also assisting in auditing/certification purposes. Therefore, application domains for human DTs include ergonomics, avoiding collisions between humans and robots, testing and training robots and humans (Eriksson et al., 2022; Kaarlela et al., 2022), security simulation, and the most immediate application in health management, including rehabilitation and well-being in the industry (Asad et al., 2023; Davila-Gonzalez and Martin, 2024).

Operators' 5.0 can be trained using DTs (Verdugo-Cedeño et al., 2023). The case study presented by Eriksson et al. (2022) for higher education is an example illustrating the application of a DT of a laboratory-scale production line, while Kaarlela et al. (2022) found positive results for DTs supporting robotic teleoperation and providing training when resources are unavailable on-site. In addition, in this study, the authors stress the importance of cybersecurity in ensuring sustainable online platform use.

Hybrid collaboration scenarios via cobots can use DTs in scenario impacts, and a deeper exploration of performance (Yao et al., 2022). Turner and Oyekan (2023) underline the need for an integrated approach that combines human expertise and automation, guided by sustainability principles. For example, automatically identifying unsafe states, such as "running" or "entering the dangerous zone" (Haoqi Wang et al., 2023b). Activity recognition is part of this line of study, which can enhance smart factory environments (Nagy et al., 2022). Nevertheless, virtual reality-DT interfaces can cause higher anxiety and mental/physical demands for the operator. Eye-tracking analysis indicates that user attention is more focused on the interface device than on the robot twin, potentially compromising safety (Kuts et al., 2022).

The human profile can also be embedded into the DT model (Cutrona et al., 2023), allowing interaction with a DT to be adapted to the worker's skills or needs. This idea is presented by Modoni and Sacco (2023) and tested with assembly operators. Human DT requires a model of the behaviors and attributes of workers, supported by real-time sensor data (Asad et al., 2023). The review conducted by Paul et al. (2021) clearly shows that a DT is a core element of the future of data-driven ergonomics. Nevertheless, there are challenges in using personal data in industry settings (He et al., 2024), a critical issue for industry managers, which can compromise the practical adoption of human DTs in the short term or force them to restrict their architecture to digital models or digital shadows.

The intrinsic characteristics of DT technology include connectivity through sensors, homogenization of sensor data, digital trace representation, reprogrammability, and modularity (Jagatheesaperumal and Rahouti, 2022). The list of DT "traditional" technology components continues, for example, with IoT, Big Data, and AI (Raja Santhi and Muthuswamy, 2023). The human-centric DT perspective increases the complexity to another level with computer vision, simulation tools, game engines, 3D visualization, and virtual and augmented reality (Asad et al., 2023; Zhironkina and Zhironkin, 2023). Therefore, integration is key to DTs for Industry 5.0. (Montini et al., 2022).

A DT can be adopted at different levels of abstraction, such as in wind farms, factories, or smart cities (Maddikunta et al., 2022b). The DT holds the potential for customized product development, improved business functions, defect reduction, and innovative business models at a larger scale. But more intelligent DTs are necessary for Industry 5.0 to ensure human awareness of problems and assist in decisions (Alimam et al., 2023). The focus on intelligent DTs is also selected by Chen et al. (2021) for the case of a wind turbine, supporting the training of AI models for decision-making. According to these authors, "the role of the human is elevated to a supervisory level. Human intelligence (HI) provides essential inputs to the system to make greater high-level decisions based on perception-driven strategies", suggesting a new form of human-DT collaboration. More recently, Lauria and Azzalin (2023) facilitate decision-making and predictive maintenance strategies, reducing environmental impacts, which aligns with the important role of cognitive DTs for the achievement of UN sustainable development goal 9: industry, innovation, and sustainability (Sharma and Gupta, 2024).

The future-oriented paper presented by Maddikunta et al. (2022a) highlights the importance of connectivity using DTs to improve collective intelligence. The role of blockchain is also expected to increase, owing to the advantages of regulatory models. The concept of a fleet (a network of multiple DTs) is well aligned with these authors' vision of 6G. Nevertheless, studies addressing DT fleets are still rare in the literature, despite evidence that this characteristic is one of the most promising ways to increase DT learning speed and accuracy (GE, 2016).

The analysis of the 57 publications provided essential insights into the emerging networks of position-practice relations of DTs in Industry 5.0, and how human and non-human actors are increasingly connected.

5. Discussion

5.1. Physical-digital convergence for human-centric, resilient, and sustainable industry transformations

According to Uhlenkamp et al. (2022), DT "development and use is a process of continuous improvement". Following, for example, the popular Plan-Do-Check-Act (PDCA) (Deming, 1993; Shewhart, 1939) cycle, DTs can be used in the early stages of designing (P) a new system (a machine or more ample physical scenarios such as production lines, or supply chains) to improve the usability of the new system, simulate disruptions that can affect it (e.g., safety risks, disruptions in materials or information flows, energy consumption), monitor and supervise the system in use (D), allowing self-adjustments (e.g., adjusting operation to optimum consumption levels of resources), warnings (e.g., security menaces), and enhanced interaction between humans and physical assets, continuously assessing via a single DT or the fleet (C) predicting critical events; and (A) assisting in the decisions that may be relevant to the three pillars of Industry 5.0.

However, there are also shortcomings in the existing generations of productivity-centered DTs. First, fleets have rarely been discussed in literature. Industry 5.0, which is cross-sectoral, will need to use technology at larger scales in systems, supply chains, and business ecosystems, requiring innovative DT architectures (Boyes and Watson, 2022). For example, at a City 5.0 level (Rosemann et al., 2021), integrating data of all factory DTs in the region (the fleet) can provide an aggregated measurement of environmental impacts (sustainability), accident prevention (human-centric), or alternative (local) supply in case of disruptions (resiliency). Major differences compared to the traditional DT of a single factory or organization (van der Aalst et al., 2021) are (1) the interest of the community in the key performance indicators of each physical asset, which requires proving data accuracy and ensuring at the same time that private data (e.g., commercial secrets and financial agreements) are also protected; (2) the need to share data in the manufacturing ecosystems (e.g., digital product passports for end customers, product traceability from suppliers, parallel manufacturing data for partners); (3) the pressure for more open data to support quick response in case of resiliency problems (as happened, for example, during the previous pandemic). DTs can be used as a single point of truth for Industry 5.0 compliance, including (1) evidence monitored in real-time and (2) the data used to support decision-making; however, data governance (e.g., data quality, privacy, retention, etc.) is more complex in distributed DT architectures.

One of the first qualitative studies on the value of DTs in business ecosystems is presented by Rantala et al. (2023), who conclude that human centricity is mostly increasing in DTs within factory boundaries (e.g., providing training, documentation, instructions, process safety, and historical data). The authors also concluded that companies "are not yet ready to shift their value creation logic from internal to ecosystem-level utilization" (Rantala et al., 2023). Interestingly, some of the known barriers to deploying DTs that include integration and interoperability, security, performance, data quality, suppliers preparation and other external factors, and problems "in identifying clear value propositions associated with DT solutions" (Perno et al., 2022) are amplified if companies want to trust in this solution for resiliency.

Human factors in DT research are advancing rapidly but reveal a focus (albeit an important one) on the worker. First, in contrast to the traditional social aspects of computing that emphasize humans as users and developers of technology, DTs can include humans in their own internal structure, representing them entirely (human DT), preparing human interactions with the environment (training), helping humans (assistance), and mediating how humans deal with the environment (B. Wang et al., 2024). Simon (1996) anticipated that humans would be deeply related to the artificial, and the new generations of DTs in Industry 5.0 prove that vision. Nevertheless, similar to other disruptive technologies, DTs may affect human activities in two ways: supportive or substitutive (Grosse, 2023). Additionally, DTs in Industry 5.0 do not necessarily have to integrate personal data (which can be challenging in organizations), and there are other, perhaps more short-term opportunities to develop the concept of organizational DTs (van der Aalst et al., 2021) for resilience. Future research is necessary to understand "what emerges from the usage and adaptation of the IT and the formal and informal processes by all of its users" (Paul, 2007). Therefore, a broad understanding of the human-centric priority to future DT developments in Industry 5.0 can be appealing to industry managers, which can include the organizational and societal interests of the DT outcomes, not restricted to the individuals interacting with physical assets inside the company borders.

But are the physical and social realms prepared to be mirrored and changed in real-time, intermediated by a digital replica? Ethics, regulations, privacy, security, and industrial relations need to adapt (Asad et al., 2023; Jagatheesaperumal and Rahouti, 2022). While the "4.0 paradigm" worked perfectly inside company borders and control, the "5.0 paradigm" will require more data exchange and collaboration between different entities. For example, the transparency and evidence-based decisions that are part of the "digitalization with a purpose" in Industry 5.0, will allow for the creation of more advanced benchmarking platforms to assist companies and consumers in their informed decisions about responsible practices.

A DT relies upon other technologies to be put into practice (Boyes and Watson, 2022; Perno et al., 2022). A DT cannot be reduced to a mathematical model, a network of sensors connected by 5G to extract data from real objects, a distributed and immutable database supported by blockchain to ensure trust in data (for example, for sustainability audits), or a 3D representation of a specific system. Interestingly, it is all of this assembled in a composite solution that requires in Industry 5.0 (1) better design principles, (2) innovative architectures, (3) interoperability standards, and (4) a new role in academic curricula of computer science and information systems courses. Moreover, DT interfaces must be redesigned for new users (humans, such as suppliers, partners, insurance companies, auditors, or regulators or non-humans such as machines and other DTs in the fleet) and more user-friendly interactive technologies, for example, with natural language processing. The multidisciplinary nature of DT development offers more collaboration with different experts in the technological domain (e.g., information systems, communication and telematics, software engineering, and AI researchers), and between them and other crucial fields in industrial engineering and social sciences.

DT intelligence can become the foundation for collective intelligence projects that explore the fleet. Our review found several studies that adopted machine learning techniques to create decision models for specific objects (Nguyen et al., 2022b). However, we could not find a single empirical study in our sample exploring the collective intelligence of multiple DTs that can be of a similar nature (fleet), for example, multiple twins of a specific machine assisting its manufacturer, or different nature – DTs built at different levels of abstraction (e.g., how DTs of specific machines collaborate to reduce consumption at the factory DT level). For example, the DT of a smart city/region can be composed of more specific twins for vehicles, environmental conditions (e.g., carbon emissions), buildings, or emergency service capacity response to optimize the entire city/region, producing a synergistic effect. Collective intelligence (Malone et al., 2010) may contribute to creating new solutions for the ambitious agenda of sustainability and resilience in Industry 5.0.

Our work also confirms the relevance of strong structuration theory for digital transformation studies. Following previous studies in healthcare and management (Bamel et al., 2023; Greenhalgh and Stones, 2010; Jack and Kholeif, 2007), our work is the first to integrate DTs and Industry 5.0 based on this theoretical lens. Several advantages can be pointed out in its use, namely, (1) the focus on the instantiated interactions between humans and technology, (2) the possibility of separately evaluating the human/technology in focus that reveals different research avenues, and (3) the advantage of reminding researchers to assess the micro, meso, and macro levels of abstraction that pose different challenges in the adoption of new technology. In contrast to Industry 4.0 advancements evaluated by the perception of managers and employees, Industry 5.0 must produce evidence beyond the factory walls. For example, a DT for resilient supply chains in critical products requires the collaboration of multiple entities to be monitored and optimized using digital technologies.

5.2. A framework for digital twins in industry 5.0

There are already several influential frameworks for Industry 4.0, such as RAMI 4.0. Industry 5.0 and DTs, however, have particularities that do not align perfectly with early architectures. Examples include the social aspects and the need to go far beyond the connected world – the last level of the hierarchy in RAMI 4.0 and extended life cycles that include product change (e.g., that need to be more transparent with the digital product passport under development in the European Union, and addressing the entire product lifecycle), and recycling. Therefore, the research team sought inspiration from influential architectures for DTs (Aheleroff et al., 2021), the new requirements of Industry 5.0, and the duality of structure and agency of humans and technologies emerging from strong structuration theory to propose the SA-DT framework (Fig. 4).

The SA-DT framework has two main theoretical foundations, namely, the duality of physical and digital realms (Aheleroff et al., 2021) and the duality of structure and agents in networks of position practices guided by strong structuration theory (Stones, 2005).

Prominent DT architectures differentiate between physical objects and digital objects (the term object is changed to a system in our framework due to the increasing complexity of DT settings) and automatic flows. SA-DT extends these contributions with an additional agent (the social system, which includes humans and culture, which is part of the social structure), creating a double cycle. The DT can receive data from humans (e.g., using wearable technology) or artificial systems (e.g., machines and vehicles) and produce information in real time (Aheleroff et al., 2021). The flow between social systems and the DT is represented by the dashed line because it can include data or knowledge, which is a free choice of humans (agency). A parallel flow can be found on the right with the physical and social environment. Contrasting to traditional object-centric DTs aiming at monitoring and improving the operation of physical objects, human-centric DTs will require sources of data relevant to assist humans and measure impacts in the environment of the decisions made.

Strong structuration theory identifies external forces affecting the social setting – represented in our framework by the pillars of Industry 5.0 described in the outer elements of the framework (resilience on the left, sustainability – social, environmental, and economic, at the top, and human-centric at the bottom). These three pillars are populated in our framework with the priorities and use cases found in the literature review. Moreover, agents can be human or non-human, as represented by the dual cycle of interactions between DTs and both the physical and human systems and their environments that affect and are affected by decisions made. In practical terms, human characteristics and needs must be a requirement for the new DT generation. The analysis made by the research team about the adoption of strong structuration theory can be found in Appendix A.

Integration is represented by the links existing in the four central elements (physical/social systems and their environments) and also the increasing importance of DT fleets. The right part of SA-DT suggests that researchers should address, by design, the endpoints of their DT creations and how they can add to the existing fleets. For example, a supply chain DT required to predict energy consumption in the near future will require inputs from the DTs of its segments (e.g., raw materials, product manufacturing, or logistics). The scale of DTs in Industry 5.0 will probably increase to ensure resilience and effective measurements of sustainability indicators.

Although non-exhaustive, the authors point to essential lines that can be found in the literature review for each one. First, human-centric DTs can be created for human parties that are more related to the manufacturing process (e.g., human DTs, workers, health, and safety compliance in a specific sector of the factory), people not directly involved with the company but affected by their operations (e.g., customers and neighborhoods), and ultimately, as a memorization system for future generations. Second, DTs for resiliency can address several important dimensions, as stated in a recent report issued by Spain's National Office of Foresight and Strategy (Spain's National Office of Foresight and Strategy, 2023) for the European Union, including

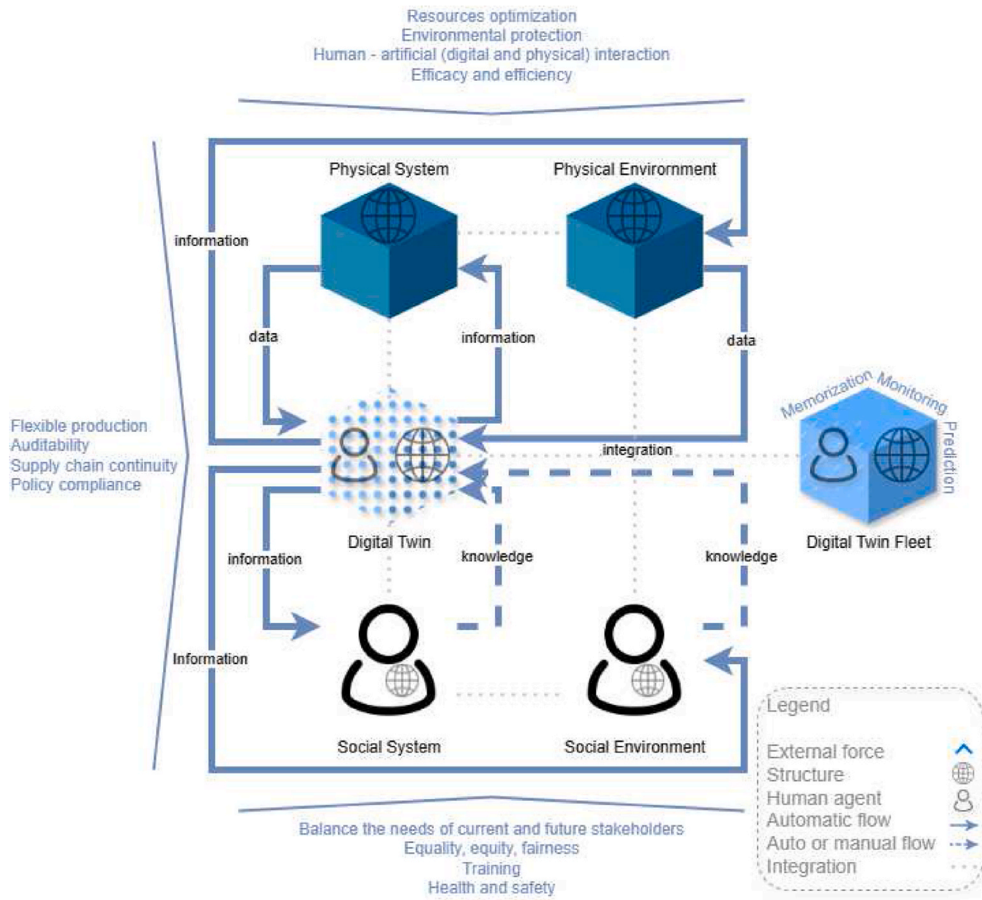

Fig. 4. SA-DT framework for Industry 5.0.

strategic aspects of autonomy in industry, the capacity to deal with changes and disruptions that can be increasingly relevant and more frequent, and the need to anticipate future events. The most critical dimensions represented on the top left are responsibility, resources (energy reduction, material reductions), and (1) monitoring and (2) predicting future states of micro (objects), meso (factories), and macro (cities, regions) that comply with sustainability regulations.

The SA-DT framework can assist future DT contributions to Industry 5.0 (or related initiatives such as healthcare 5.0, or agriculture 5.0) to discuss (1) the forces considered in their work, (2) the particularities of the dual cycle of flows between DT and human/non-human agents, (3) interactions with the (social and physical) environment, and (4) DT interoperability.

5.3. Agenda for future research

Table 3 summarizes important research opportunities in the field.

The priorities included in Table 3 were extracted from the literature as a result of the analysis provided by SA-DT framework for the dual DT cycle of the social and physical reality, spanning company borders. In this reflection, we included several aspects related to structure and agency, which are essential for future DT research.

6. Conclusion

This study sheds light on the sociotechnical and boundary-spanning roles that DTs will play in the new European priority of Industry 5.0. Our systematic literature review started with a bibliometric analysis of publications at the crossroads of Industry 5.0 and DTs, identifying relevant clusters of papers for human-centric, sustainability, and resilient industry transformations. The next stage involved an in-depth concept-centric assessment of 57 papers extracted from Scopus and Web of Science (Durach et al., 2017; Okoli and Schabram, 2010; Webster and Watson, 2002). The changing role of human and non-human agents, as well as their interactions enacted by DTs are discussed. Strong structuration theory (Greenhalgh and Stones, 2010; Stones, 2005) was selected to understand the human, technical, and networks of position practices enabled by the DTs in Industry 5.0.

The main contributions of our study can be summarized as follows: First, we identify use cases, impact, challenges, and opportunities for DTs aiming at more responsible (internal and external) industry practices that can be mirrored in the digital realm, allowing real-time monitoring, supervision and operation, optimization, and more reliable disclosure of industry practices. Second, the SA-DT framework is designed to frame current and future research. The interest in designing DTs internal to the factory floor aimed at specific production assets will undoubtedly continue in the future, but they need to be integrated with a fleet and suitable for use by third-party organizations (e.g., suppliers, partners, supply chain participants, or assessors) to contribute to the 5.0 movement. Third, a research agenda is proposed. This study argues that DTs are the most promising technological enablers to make Industry 5.0 a reality. It will be much more challenging to achieve the ambition of a competitive and sustainable industry that is not replicated in the digital world rigorously, accurately, integrated, trustworthy, and auditable.

Some delimitations and limitations of this study must be stated. The former includes the three pillars of Industry 5.0 selected by the European Commission (European Commission, 2021, 2023). They are currently influenced by technology, geostrategic priorities, and global challenges, including the recent pandemic needs, climate change, the uncertainty of conflicts, and the balance of world power that become extremely visible

Table 3
Priorities for digital twins in Industry 5.0

I5.0 Pillar	Priorities	References
Human-centric	• simulate various workplace designs and conditions, thereby facilitating the identification and mitigation of potential hazards and the enhancement of ergonomics • optimize production schedules and workflows, thereby reducing workloads and alleviating stress on workers • create virtual training environments that enable workers to acquire new skills and practice procedures in controlled environments • training customized to the specific needs of each employee • shared information spaces can be created using DTs, enabling workers to collaborate and exchange ideas • offer workers insights into the performance of their systems and processes, equipping them with the knowledge necessary to make informed decisions on how to optimize them • ethical use of DTs • human DTs for specific roles in industry • DT adoption and usability studies, including how collective intelligence can be formed in cooperation between humans and DTs • balancing the needs of free will with the automatic response of DTs in a more regulated industry	Eriksson et al. (2022) Majerník et al. (2022) Cutrona et al. (2023) Li et al. (2023) Maddikunta et al. (2022a)
Sustainability	• reduction of resource consumption by assisting in production plans optimization • planning and execution of renewable energy systems and eco-friendly production processes • use of renewable energies and sustainable manufacturing materials • monitor and manage the entire lifecycle of a product, from its inception to its end-of-life disposal • cost-benefit analysis and incentives for developments addressing SA-DT priorities – economic sustainability is a gap in existing Industry 5.0 literature • new frameworks to measure the rigor of the DT in representing reality • longitudinal studies to understand medium to long-term implications of DT use in the industry • interfaces between industry DTs and external stakeholders • DT fleets	Bhattacharya et al. (2023) Verdugo-Cedeño et al. (2023) Sharma and Gupta (2024)
Resilience	• monitor performance-specific systems and detect potential disruptions before they occur • simulation of different response scenarios • research on secure DT operation • evaluate scalability in DT implementation at a larger scale (e.g., fleets or supply chains) • resilient and trustworthy DT infrastructure • DTs as a memorization system of industry practices (heritage digital twin), which is particularly interesting in traditional manufacturing or products with cultural relevance	Xian et al. (2023) Maddikunta et al. (2022a)

in the tenets of strong structuration theory. Other pillars may emerge in different parts of the globe or need to be incorporated in the future, owing to the drastic transformations that technology brings to the world. For example, airspace exploration (in which DTs have already proven their utility) will probably justify changes in industry priorities. As for the limitations, we point to the databases used (restriction to Web of Science and Scopus), albeit relevant to scientific research, and to the dynamic characteristics of Industry 5.0 and digital transformation. This is a vibrant field of research, and researchers may also publish papers on related topics without using the terms we selected.

Several implications have been identified for academia and industry. First, it contributes to the accumulation and integration of knowledge dispersed in the literature (Tranfield et al., 2003). We confirm that DTs can make a solid contribution to Industry 5.0 projects. Researchers may use the DT vision, to identify precisely how they contribute to Industry 5.0 and identify lines for future research across the SA-DT framework. Both researchers and practitioners participating in the recently created Industry 5.0 Community of Practice (CoP 5.0) may find our work interesting to guide the deliverables and identify use cases. In our view, the twin transition strategy (Mäkitie et al., 2023) and DT strategy are inseparable.

Finally, companies must identify solutions to address the forthcoming requirements of European regulations and determine how to achieve corporate social innovation (Mirvis et al., 2016). DTs are a possible solution to address both supply chain and societal enhancements, but their value depends on knowledge exchange capabilities. For example, a machine DT can provide value for predicting maintenance and reducing costs and resources. Analogous to the maturity model proposed by Uhlenkamp et al. (2022) for DTs, this particular DT would be at a low level of maturity for Industry 5.0, but can evolve to address other priorities, incorporate more stages of the lifecycle in manufacturing, and expand the restricted level of analysis (a single machine) to a fleet-level exchanging knowledge with third-party organizations. DT pilot projects for Industry 5.0 must consider a societal rollout plan, which will require more collaboration with academic institutions and industry associations. For example, it would be interesting to design new DT platforms for benchmarking and provide shared services for fleet management in particular industries and supply chains. Government and certification institutions may create requirements for DTs suitable for remote monitoring and improvement of companies following specific mandatory regulations or voluntary standards certification schemas (e.g., health and safety, environmental, energy, or responsibility). Digitalization with a specific purpose (European Commission, 2022) offers new opportunities to compete with social innovation, but there is a trade-off. The industry will require more physical-digital convergence and must prepare its investments for the possibility that Industry 5.0 will become increasingly -positively- intrusive in company data and decision-making processes at a more fine-grained level than ever, putting DT deployments at the top of digital transformation priorities.

CRediT authorship contribution statement

João Barata: Writing – review & editing, Writing – original draft, Methodology, Investigation, Conceptualization. **Ina Kayser:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Conceptualization.

Declaration of competing interest

The other authors have no competing interests to declare that are relevant to the content of this article.

Data availability

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Appendix A. Supplementary data

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