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Digital Twin Applications for Intralogistics Processes: A Literature Review

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Abstract: Intralogistics manages material and information flows within facilities, and Industry 4.0 has introduced digital twin (DT) technology as a tool for managing complex systems. Despite its transformative potential, DT adoption in intralogistics remains limited. Thus, this paper reviews literature to identify trends and challenges in this domain. Findings reveal increasing interest in DT applications for intralogistics, especially in laboratory environments, while the integration of digital models, optimisation algorithms, and machine learning remains underexplored. The study seeks to enhance theoretical understanding of DT's impact on intralogistics and offer practical insights to help managers implement effective strategies for optimising internal logistics processes.

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Keywords: Digital twin, digital model, digital shadow, intralogistics, internal logistics processes, warehouse, material handling, literature review

1. INTRODUCTION

Intralogistics is a term that refers to the management, control, and optimisation of material and information flows within a facility, from the moment raw materials enter the structure to the distribution of the finished product. It encompasses a wide range of activities, including storage, handling, internal distribution, and transportation of materials (Drissi Elbouzidi et al., 2023). In the context of the Industry 4.0 revolution, which integrates advanced digital technologies into production processes, digital twins (DTs) have acquired increasing attention. The concept of DT has its origins in the 1960s, when NASA conducted experiments to determine whether it was possible to physically replicate systems on Earth in order to match those in space. DTs can be generally defined as a computerised models that represent a physical system for any given moment in time (Ivanov, 2023). In addition, DT can be seen as a simulation-based virtual counterpart of a physical system, exploiting real-time data synchronisation to optimise the actions undertaken by the physical system (Kritzinger et al., 2018). Therefore, the fundamental aim of the DT is to create a virtual copy that is as accurate as possible to the physical object it represents, and to establish a real-time connection between the two (Coelho et al., 2021). Based on the level of integration between the physical object and the digital object, the definition of digital model (DM), digital shadow (DS) and DT have been given (Kritzinger et al., 2018). Specifically, a DM is a digital representation of an existing or planned physical object without any automated data exchange between the two. In contrast, a DS features an automated one-way data flow from the physical object to its digital counterpart. Finally, a DT involves fully integrated, bidirectional data flows between the physical and digital objects. Figure 1 displays the differences between the three type of integration. From this classification, it is evident that the scope of a DT is much broader than that of a DM, as it encompasses multiple layers, including the network structure and information flows with external systems and databases (Ferrari et al., 2023).

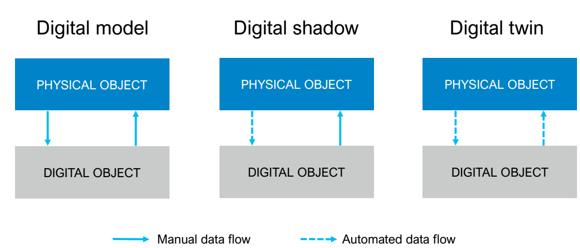

Fig. 1. Digital model, digital shadow and digital twin. Source: adapted from Kritzinger et al. (2018).

The implementation of DTs offers a range of significant advantages. Through the use of DTs, various simulations can be exploited to determine the most efficient system setups. The ability to simulate alternative scenarios provides a powerful decision-making tool to evaluate the impact of different operational strategies and mitigate the risks associated with changes and innovations (Leung et al., 2022). In this context, DT represents a suitable solution for managing smart factories, predicting future situations, and monitoring systems. Despite the evident advantages associated with the implementation of DTs and the increasing attention they have received in recent years, there has been a relatively limited research effort dedicated to the application of DTs in intralogistics processes. Currently, DTs are mostly employed in industry to optimise the modelling and analysis of product properties before manufacturing (Martínez-Gutiérrez et al., 2021), thereby leaving a significant gap in the understanding of their

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potential for optimising internal material and information flows (Braglia et al., 2019). Therefore, it is crucial to address this gap, as intralogistics plays a pivotal role in achieving seamless and efficient operations in smart factories and other complex industrial systems. To this end, this paper presents a comprehensive literature intending to answer to the following Research Questions:

(1) What is the current state-of-the-art in the application of Digital Twins for intralogistics processes, and how do these implementations differ in terms of data integration level, functionalities, and scope?
(2) What intralogistics systems have been targeted by Digital Twin applications?
(3) What are the research gaps and future directions concerning the implementation of fully integrated Digital Twins for intralogistics processes?

The structure of the paper is as follows: first, a detailed explanation of the methodology used in the literature review is detailed, accompanied by an explanation of the key pillars of intralogistics DTs. Subsequently, the primary trends and research gaps are identified and examined, thereby offering insights into the current state of the field. Finally, the paper concludes with discussions on the implications of the findings, outlining potential avenues for advancing the integration of DTs in intralogistics systems.

2. METHODOLOGICAL APPROACH

To evaluate the use of DT in the intralogistics sector, a literature review was conducted using the Scopus database. Two level of keywords were used to guide the search of papers, one regarding the DT and the other one regarding the system into analysis. Thus, keywords like *digital twin*, *warehouse*, *automated storage and retrieval system*, *distribution centre*, and *material handling* were employed to define the database queries. The time frame of the analysis was set in the range between 2017 and 2023, since the first paper in topic was published in 2017. To assess whether a document fell within the terms of the analysis, certain inclusion criteria were established. The first selection criterion regarded the type of publication and the document availability. In particular, only journal papers or conference proceedings with the whole text available written in English were considered as eligible. The second filter was placed on the type of DT developed by the authors of the publication. Specifically, only papers that clearly indicated that the DT had been implemented, and not just designed, were considered relevant and analysed. Additionally, based on the classification presented before (Kritzinger et al., 2018), only applications with at least one data flow between the physical and the digital object were taken into account. Hence, the DM must be connected to the physical system, and, consequently, a transmission of information must be observed. A DT that is not connected to the physical system can be interpreted only as a DM, i.e. a stand-alone application (Ferrari et al., 2022). Finally, greater value was given to articles that demonstrated the advancement of the research and the results obtained through the application of the developed concepts to a case study. This because some of the information tracked often included details that can only be shown through a practical case, such as input and output data from the DT.

A total number of 194 papers were selected, but based on the inclusion and exclusion criteria only 37 articles were finally included in the corpus. The articles relevant to the implementation of DT technology intralogistics were then analysed to derive the actual research results, including objectives, outcomes, methods, and other detailed concepts regarding the current applications of DTs.

3. RESEARCH TRENDS

3.1 The diffusion of DT

The first step of the analysis was studying the trend of publications over the years. From Figure 2, it is easily noticeable that research on the topic of DT has been increasingly growing. This is understandable, given that the technology in question is only of interest since relatively recent times. Despite this, it is also worth noting that in 2023, the number of articles was lower than in 2022, indicating a possible reversal of the previously increasing trend.

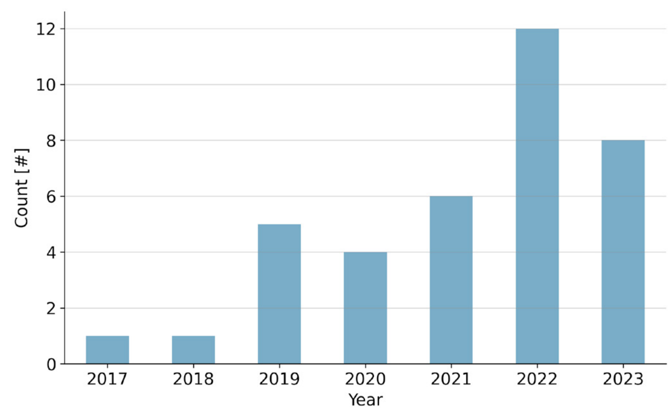

Fig. 2. Number of publication by year.

Looking at the application sector, the main areas are shown in Table 1, both in terms of absolute and percentage values. The laboratory sector was the most common application area (45.95% of publications), highlighting that the technology is still in a developmental and experimental phase. Furthermore, the lack of specified application sectors in some cases suggests that researchers may be encountering challenges when attempting to scale DT applications to real-world industrial settings. However, the few instances of DT deployment in business environments have yielded excellent results, demonstrating their potential in industrial contexts such as logistics and the food industry (24.32% in total).

The subsequent analysis was conducted to identify the main intralogistics systems studied with the application of a DT. Warehouses were differentiated into automated warehouses, e.g. automated storage and retrieval systems (AS/RS), traditional warehouses, e.g. served by forklifts or operators, and robotic warehouses with automated guided vehicles (AGVs), autonomous mobile robots (AMRs) or unmanned aerial vehicles (UAVs). The classification also included smart factory, as several publications holistically analysed systems encompassing production processes, material handling equipment (such as conveyors, AMRs, and

Table 1. Publications by industrial sector

Sector	Count	Percentage
Laboratory	17	45.95%
Logistics	5	13.51%
Food	4	10.81%
Metallurgical	1	2.70%
Paper	1	2.70%
Tobacco	1	2.70%
Medicine	1	2.70%
Mining	1	2.70%
Marine	1	2.70%
Unspecified	5	13.51%

robotic arms), as well as warehouses. The results of this analysis are shown in Table 2. Most of the publications referred to robotic systems, followed by AS/RS, and traditional warehouses. Smart factory was the system with less occurrences.

Table 2. Publication by intralogistics system

Intralogistics system	Count	Percentage
Robotic warehouse	12	32.43%
AS/RS	10	27.03%
Traditional warehouse	8	21.62%
Smart factory	7	18.92%

The literature can also be classified according to the DT objectives. Figure 3 shows the number of publications in relation to the objective of the DT. It can be noted that in most cases (27.03%), the article's objective was to optimise warehouse performance, which can be expected given that the primary application of DTs is to provide tools that ensure system improvements. The second most cited objective (10.81%) was ergonomics, meaning that DTs are often applied to limit the risk of injuries for operators and improve productivity and quality or work. Other two significant category were learning through innovative technologies (8.11%), which pertains to the use of a DT to teach operators or students how to operate a system using augmented reality devices or joysticks, and route optimisation (8.11%), which is a clearly defined performance metrics as opposed to the more general warehouse optimization DTs. Finally, all DTs that did not share any of the previous objectives were aggregated under the category other. Examples of these DT include the identification of breakdowns or the creation of decision-making support tool.

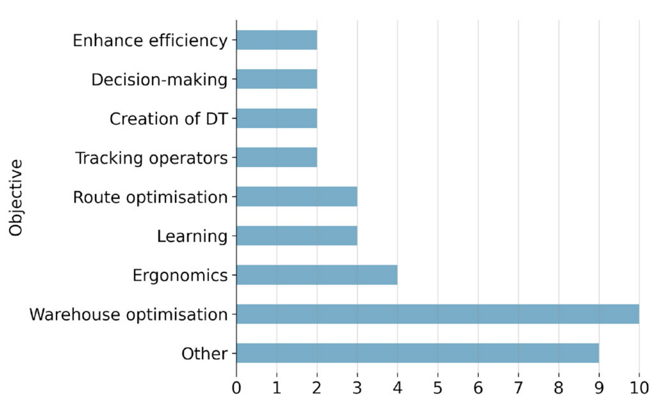

Fig. 3. Number of publication by digital twin objective

3.2 The DT digital object configuration

Three fundamental pillars define the digital object of a DT: the type of DM, the optimisation algorithm used, and the AI and ML techniques implemented. A core component of a Digital Twin (DT) is its virtual counterpart, the Digital Model (DM), which enables simulation of various scenarios (Kritzinger et al., 2018). The integration of optimisation algorithms within DTs leverages extensive data from the physical object to enhance system performance and refine simulation results (Leng et al., 2021). Furthermore, the concept of a cognitive DT extends traditional DTs by incorporating cognitive capabilities, such as self-learning, reasoning, and real-time decision adaptation, which employ Artificial Intelligence (AI) and Machine Learning (ML) algorithms (Zhang et al., 2022).

Digital Model One of the main elements of a DT is the virtual replica of the real system, that is the DM. Different types of DM were identified in the corpus of papers. Control models (CM) can be defined as interactive environment where actions can be taken on the physical system, facilitating real-time interactions and optimisations, whilst not predicting the future state of a system (Balla et al., 2023). Simulation approaches such as discrete event simulation (DES) (Bertolini et al., 2019) or agent-based modelling (ABM) (Bermpohl et al., 2023) are used study the behaviour and performance of a complex system over discontinuous time. Hybrid modelling (HMO) integrates these two simulation approaches to enhance their effectiveness (Ferrari et al., 2022). Semi-physical simulation (SPS) DM are based on higher levels of simulation where physical parameters are incorporated to make the results more realistic (Leng et al., 2021). On the contrary, analytical models (AM) use established mathematical principles and theories to understand, analyse, and make predictions (Zaragoza et al., 2023). Among these, Markov decision processes (MDP) are adopted to represent decisions in a stochastic environment (Shen et al., 2023). Finally, artifact-centric business process model (ACBPM) is an approach that focuses on artifacts, i.e., data objects that are created, manipulated, and used during the process. (Zhou and Liu, 2023).

Optimisation Model With the DT, it is possible to optimise and simulate different scenarios, assessing their feasibility, identifying potential issues, or advantages of changes made to the system. The presence of an optimisation model within the DT is crucial, as it allows for the use of the extensive data collected from the physical object to optimise the system (Leng et al., 2021). Optimisation models implemented range from more common optimisation models such as joint optimisation model (JOM) (Leng et al., 2021; Leung et al., 2022; Gao et al., 2022), genetic algorithm (GA) (Liu et al., 2022), tabu search (TAS) (Latsou et al., 2023), simulated annealing (SA) (Bertolini et al., 2019), and scatter search (SS) (Latsou et al., 2023), to lesser-known ones. Among the latter group, Jonker–Volgenant algorithm (JVA) can be found (Bermpohl et al., 2023), which is an optimisation model used to solve the quadratic assignment problem with linear costs.

Machine Learning and Artificial Intelligence The next characteristic of interest for the research was the use of machine learning (ML) and artificial intelligence (AI). Reinforcement learning (RL) teaches an agent to maximise long-term rewards through trial and error, using feedback from actions to find the optimal solution (Shen et al., 2023). Adaptive network-based fuzzy inference system (ANFIS) merges neural networks and fuzzy systems, using the former to optimise fuzzy system parameters for handling uncertainty (Leung et al., 2022). An auto-encoder (AE) is an unsupervised learning model for dimensionality reduction, aiming to minimise the difference between the input and its reconstruction, retaining key data features (Zhan et al., 2022). Deep reinforcement learning (DRL) integrates deep neural networks with RL, enabling an agent to make sequential decisions by interacting with an environment, using rewards or penalties, and approximating value functions with deep neural networks (Latsou et al., 2023). Multiple linear regression and time series analysis (TSA) allow to make specific future predictions through statistical and temporal analysis (Wang et al., 2020).

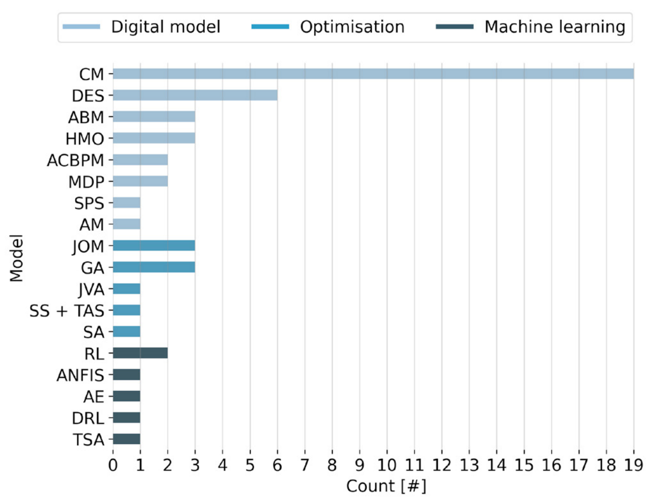

Fig. 4. Number of publication by digital twin model

Figure 4 shows the occurrences of each digital, optimisation and AI/ML model in the corpus of papers. Focusing on the DM, the majority of publications used the CM (47.5%), mainly for ergonomics and learning objectives. The other main important DMs were DES and ABM, or the combination of them, which accounted for a 22.5% of the total of publications. The papers using these approaches were focused mainly on the warehouse optimisation objective. Regarding the optimisation model, it is evident that only a small portion of the papers introduced optimisation algorithm in their DT (22.5%). The most common optimisation model was JOM, present in 3 articles, as it allows for the optimisation of multiple decision variables in aggregate. GAs were the second most common optimisation model, appearing in 3 articles of the corpus. Similarly, the use of AI/ML is still scant, given that it was found in 15% of the articles. The most frequently employed methodology was RL, although it was utilised in only two papers.

3.3 Information flow and data sharing

The subsequent analysis focused on evaluating the presence of real-time communication between the physical and digital object. According to the inclusion and exclusion criteria, all the selected articles featured at least a unidirectional real-time communication between the two parts. The concept of real-time communication was also extended to articles where there was not a continuous flow of information between the two objects, provided that the communication occurred at least at fixed time intervals. For instance, Braglia et al. (2019) studied a traditional warehouse served by forklifts, in which data collection occurred every 30 minutes, with the aim of generating new optimised routes for operators. Focusing more specifically on the communication between the physical and digital twins, bidirectional data exchange was found in 17 out of 37 articles (45.95%), which is just under half of the cases. This result highlights how integrating a DT into an existing system can be particularly complex and how difficult is to directly control the physical object based on the results of the simulation and analysis conducted with the digital object.

Data flows were also analysed based on the type of data shared between the two environments. When the input data were explicitly defined, they were classified accordingly. The position of the robotic assets belonging to the physical system was present in 7 publications. Then, 6 papers out of the total considered the position of the intralogistics operators within the system, while 3 articles used the inputs of the operators in the physical system as data source for the digital object. A further category named system state was created to include articles in which the type of data transferred was not clearly specified. The majority of publications (37.83%) focused on DTs with an exchange of this type of data. Regarding the data transmitted from the digital object, the main type of data used to control the physical object fall in the category of routes (9 papers), meaning that the definition of the optimal route for robots or operators is analysed in the digital object and then sent as feedback to the physical one. Finally, 6 articles were included in the task sequence category. In these category were included the cases in which the digital object provided the physical one with instructions to perform actions (e.g. picking or retrieving an item from an automated warehouse).

The results of this analysis are presented in Table 3, which shows the type of flow and the data shared based on the type of DM. The values in the table correspond to the number of publications. It is worth noting that only 26.32% of CM provided bidirectionality in the data flow. This observation probably relied in the fact that generally a CM tends to have the purpose of representing the physical object behaviour but it is rarely used also to optimise the system. In the case of DES, ABS and HMO, bidirectionality was more recurrent. This results is not surprising as simulation results are used to optimise the system.

3.4 Gaps

From the literature about the use of DT, several gaps can be identified. In particular, the results demonstrated that

Table 3. Data flow

Type of flow	Data	CM	DES	ABM	HMO	ACBPM	MDP	SPS	AM	Total
Physical ⟶ digital	System state	5	2		3	2	1	1		14
Physical ⟶ digital	Robot position	3	1	2			1			7
Physical ⟶ digital	Operator position	6								6
Physical ⟶ digital	Operator input	3								3
Physical ⟶ digital	Object position	1	1							2
Physical ⟶ digital	Forklift position		2							2
Physical ⟶ digital	Environment parameters	1							1	2
Physical ⟶ digital	Resource availability and demand			1						1
	Total	19	6	3	3	2	2	1	1	37
Digital ⟶ physical	Routes	2	3	1	1		2			9
Digital ⟶ physical	Task sequence	1	1	1		2		1		6
Digital ⟶ physical	Robot command	2								2
	Total	5	4	2	1	2	2	1	0	17

DT applications are still mostly related to laboratory environments. Therefore, there is still not a fully exploitation of the potential of this approach in industrial contexts. In addition it is worth noticing that in several papers the field of application was not even mentioned. In addition, another element that emerged is that researchers have been focusing mostly with internal transportation system such as AGV, AMR or UAV, while only little attention has been given to AS/RS. Another important aspect is related to the DM. The CM, which is the most adopted, is a tool with the primary purpose of providing monitoring and control of the system. The DTs based on this type of DM are generally characterised by a strong infrastructure for data exchange between the physical and the digital object, enabling them to achieve real-time communication. However, they often do not provide simulation and prediction capabilities like other DM, such as DES or ABM. In turn, the latter group of DMs may lack efficiency in terms of real-time communication and promptness of the feedback from the digital object to the real one, due to the simulation being usually computationally expensive. Ideally, the DT includes visualisation, simulation, optimisation and AI/ML (Ivanov, 2024). The combination of all these aspects is however lagging in DTs for intralogistics, highlighting another gap. A significant lack of studies integrating optimisation and AI/ML is the underlying reason for this gap. As a matter of fact only 22.5% of articles discussed optimisation, while only 15% covered AI/ML. Regarding data sharing between the physical and digital objects, a gap was found in the implementation of the bidirectionality of data flow. In fact, 54.05% of publications did not include it, especially when the CM is adopted as the DM. In this context, other types of DM could be better suited to realise interconnected systems.

4. IMPLICATIONS AND CONCLUSIONS

The objective of this study is to investigate the significance and potential applications of the DT technology to intralogistics processes. To this end, a comprehensive literature review was conducted. First it is worth noticing that based on the initial queries, several papers claimed to utilise a DT. However, upon closer examination, the actual applications often aligned more closely with the definition of a DM, as they involved creating a virtual replica of a physical system using software to analyse its behaviour. Thus, based on the definition of Kritzinger et al. (2018) and the one used in the present analysis, this kind of works cannot be defined as DTs. As a consequence, it appears that in a relevant number of works, the DT was correctly defined but then developed differently. This is the reason why, the 37 papers analysed are the result of a tight selection based on the accordance of the definition of DT considered in this work. The outcomes of the analysed papers proved that there is not a dominant industrial field of application of the DT and the majorities of studies are still referred to laboratory environments. As a consequence, this could make more difficult for practitioners the identification of potential benefits for more specific real applications. By considering the objective of the DT applications, the most relevant stream of research addressed studies related to the warehouse optimization processes, demonstrating that warehouse operations in intralogistics still captures a lot of attention. This result demonstrates that warehouse activities are more and more considered as a crucial part of companies' success, since they are the effective lever that ensure the well-synchronized flow of materials and products (Burganova et al., 2021). In addition, it is worth noticing that a quite relevant number of papers included the ergonomics issue. This result appears to be of pivotal importance, proving that ergonomics could become increasingly studied, especially considering the growing attention given to human-machine interaction. Finally, most of the papers used CMs as digital counterpart to observe the behaviour of the system under study. All the other identified categories of DMs were still scarcely explored, meaning that there is room for research exploiting different modelling approaches. Similarly, optimisation and ML algorithms were not largely adopted in DT for internal logistics processes.

Several theoretical and practical implications can be identified from this research. From a theoretical point of view, the present study could foster further research aimed at understanding the effects of DT technology in intralogistics activities, namely in terms of operations efficiency, energy consumption and human centricity. Furthermore, the results of this research can be considered as a support for the identification of the most appropriate DT approach for improving intralogistics processes, according to the system characteristics and the main objective of the DT. From a practical point of view, the present study might pave the way to a more accurate evaluation of intralogistics activities, thereby enabling the development of more effective future strategies. In particular, this work might support managers and practitioners in the identification of the most suitable approaches that can be more easily adopted to enhance their internal logistics processes.

This work can also be seen as a pillar for the future development of a framework to provide guidance for the actual implementation of DT in intralogistics and to contribute to the understanding of how DT can impact on warehouse operations. In this sense, future work will also include a comparative analysis of existing case studies in order to better map the similarities and differences between each specific DT implementation. In addition, a potential limitation of the study is the relatively small number of papers identified. Future studies will aim to expand the corpus of papers by using the snowballing technique to extend the analysis to the references of the initial corpus and those obtained by the papers.

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