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Machine Learning in Warehouse Management: A Survey

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Abstract

Warehouse design and planning involve complex decisions on receiving, storage, order picking and shipping products (i.e., stock-keeping units - SKUs) and can affect the performance of entire supply chains. With the advancement of Industry 4.0 and increased data availability, high-computing power, and ample storage capacity, Machine Learning (ML) has become an appealing technology to address warehouse planning challenges such as Storage Location Assignment Problems (SLAP) and Order Picking Problems (OPP) for intelligent warehousing management. This paper presents a state-of-the-art review of ML applied to Warehouse Management Systems (WMS) through the analysis of recent research application articles. A mapping to classify the scientific literature in this new research area, including ML methods, algorithms, data sources and use cases of ML-aided WMS, as well as further research perspectives and challenges, are introduced. Preliminary results suggest that the possible research areas in ML-WMS are still incipient and need to be further explored.

Keywords: Industry 4.0; Artificial Intelligence; Order Picking; Storage Location Assignment;

Nomenclature

AGVs	Automated Guided Vehicles
AI	Artificial Intelligence
AMR	Autonomous Mobile Robots
AS/RS	Automated Storage and Retrieval System
DSLAP	Dynamics Storage Location Assignment Problem
I4.0	Industry 4.0

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IIoT	Industrial Internet of Things
K-NN	K-Nearest Neighbors Algorithm
ML	Machine Learning
NLP	Natural Language Processing
OPP	Order Picking Problem
PRISMA	Preferred Reporting Items for Systematic reviews and Meta-Analyses
RFID	Radio Frequency Identification
RL	Reinforcement Learning
SKUs	Stock-keeping units
SL	Supervised Learning
SLAP	Storage Location Assignment Problem
UL	Unsupervised Learning
WMS	Warehouse Management System

1. Introduction

Warehouse management involves decisions on receiving, storage, order picking, and shipping and can affect the performance of entire supply chains. With the advancement of Industry 4.0 (I4.0) and the digital transformation of organizations, Machine Learning (ML) has become an appealing technology to address warehouse design and planning challenges, such as Storage Location Assignment Problems (SLAP) and Order Picking Problems (OPP) for intelligent warehousing and picking management [36, 33, 3, 29, 28, 48, 2].

Order-picking is the most resource-intensive process and highly depends on storage location policy [33]. SLAP involves assigning products to locations in a warehouse to minimize total handling effort. OPP refers to the order in which products are picked based on a routing strategy. These problems have a strong relationship—the SLAP solution serves as an input for OPP—since routes can only be created once the locations of the products are known. At the same time, a SLAP solution can usually only be evaluated when the strategy for solving OPP is known [36, 41, 48].

Different methods have been proposed to solve both problems—separately or in an integrated way. Model-based approaches, such as mathematical models, require a set of assumptions and special knowledge due to the complexity involved in the various instances of these problems, which makes it challenging to implement these solutions in real cases. This scenario leaves a gap filled by the use of data-driven models, where parameters or inputs are estimated based on historical data, significantly improving estimate accuracy and robustness. Also, data-driven models have been used instead of model-based approaches because they do not require as much field expert knowledge [17].

Among the ways of conducting a data-driven process, ML uses methods and the development of algorithms capable of learning from data and performing pattern recognition, which allows predictions based on data learning [24]. Some research is addressing ML initiatives in solving OPP and SLAP and benefits from the volume and diversity of data available in warehouse management systems (WMS) to recognize patterns capable of generating predictions that allow the development of operational rules to reduce order processing times [12, 23, 40].

As the volume and complexity of data generated within supply chains continue to grow, harnessing the power of ML has become essential for managing modern warehouse operations effectively to streamline order fulfillment processes and ensure timely and accurate deliveries to customers. Although there are several reviews on warehouse management practices [8, 13, 33, 41, 42], they either do not explore the use of ML, emphasizing the use of optimisation approaches, or address distinct warehouse management issues from the ones explored in this study.

Recognizing the potential contribution of ML to WMS and exploring the need to identify data-driven problem-solving methods, we conducted a systematic literature review (SLR) on using ML for WMS, especially for OPP and SLAP, in the context of I4.0. To the best of the authors' knowledge, this is the first SLR in this research area. This paper seeks to identify use cases of ML-aided WMS and the ML methods, algorithms and data sources used.

The remainder of the paper is structured as follows. Section 2 introduces the methodology. Section 3 presents the results and an overview discussion of the articles mapped. Section 4 presents avenues for future research. Lastly, Section 5 presents the conclusions.

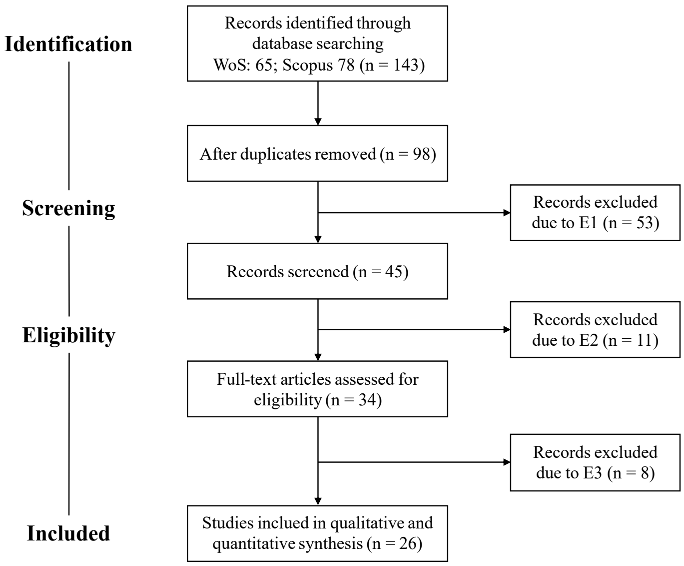
2. Materials and Methods

This study adopts the preferred reporting items for systematic review and meta-analysis (PRISMA) methodology [25], which is widely used across different research fields in conducting an SLR [27]. Table 1 presents the search protocol used to conduct the SLR.

Table 1. Search protocol

Data source:	Web of Science (WoS) and Scopus
Search string:	("machine learning" OR "reinforcement learning" OR "deep learning" OR "artificial intelligence") AND ("storage location" OR "storage assignment" OR "order picking" OR "warehouse management" OR "WMS")
Period:	From 2011 (emergence of the term Industry 4.0) to December 31, 2022
Search fields:	Title, abstract, and keywords
Language:	English
Document:	Journal articles
Subject area :	[Scopus] Engineering; Computer Science; Mathematics; Decision Sciences; Business, Management and Accounting. [WoS] Engineering; Computer Science; Operations Research; Management Science; Mathematics, Automation Control System.

The sampling process is summarized in Fig. 1. Initially, 143 articles were identified by applying the search protocol in Tab. 1 and 26 were included in the final sample for the quantitative and qualitative analyses (See Fig. 1).



Legend: E1 - elements in the string are used only as a keyword or cited expression;
E2 - study out of scope of this research; E3 - only describes a research trend/recommendation.

Fig. 1. Systematic review strategy.

The data analysis was undertaken in two stages. First, a quantitative analysis based on descriptive statistics was performed using the software VOSviewer to extract insights and identify emerging trends from the selected articles. Second, a comprehensive content analysis was conducted to assess the use cases of ML-aided WMS and categorize and classify the articles based on the problem addressed, and the ML methods, algorithms, and data sources used.

3. Results

3.1. Quantitative analysis

Fig. 2 presents the distribution of publications over time. This result allows us to infer a growth trend of scientific publications on ML applications for warehouse management (OPP and SLAP). Nevertheless, we have not perceived any publication preference since the 26 articles in the sample are spread over 23 different journals.

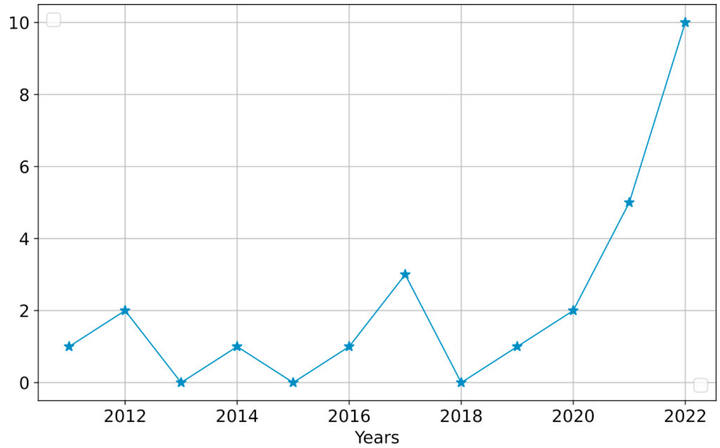


Fig. 2. Number of publications per year.

Fig. 3 shows the density visualization by term occurrence (minimum 5) extracted from the title, abstract, and keywords of the articles included in the final sample using the VOSviewer software. It highlights three clusters related to ML with a focus on warehouse management in improving performance in the order processing process, WMS data accuracy and technological challenges.

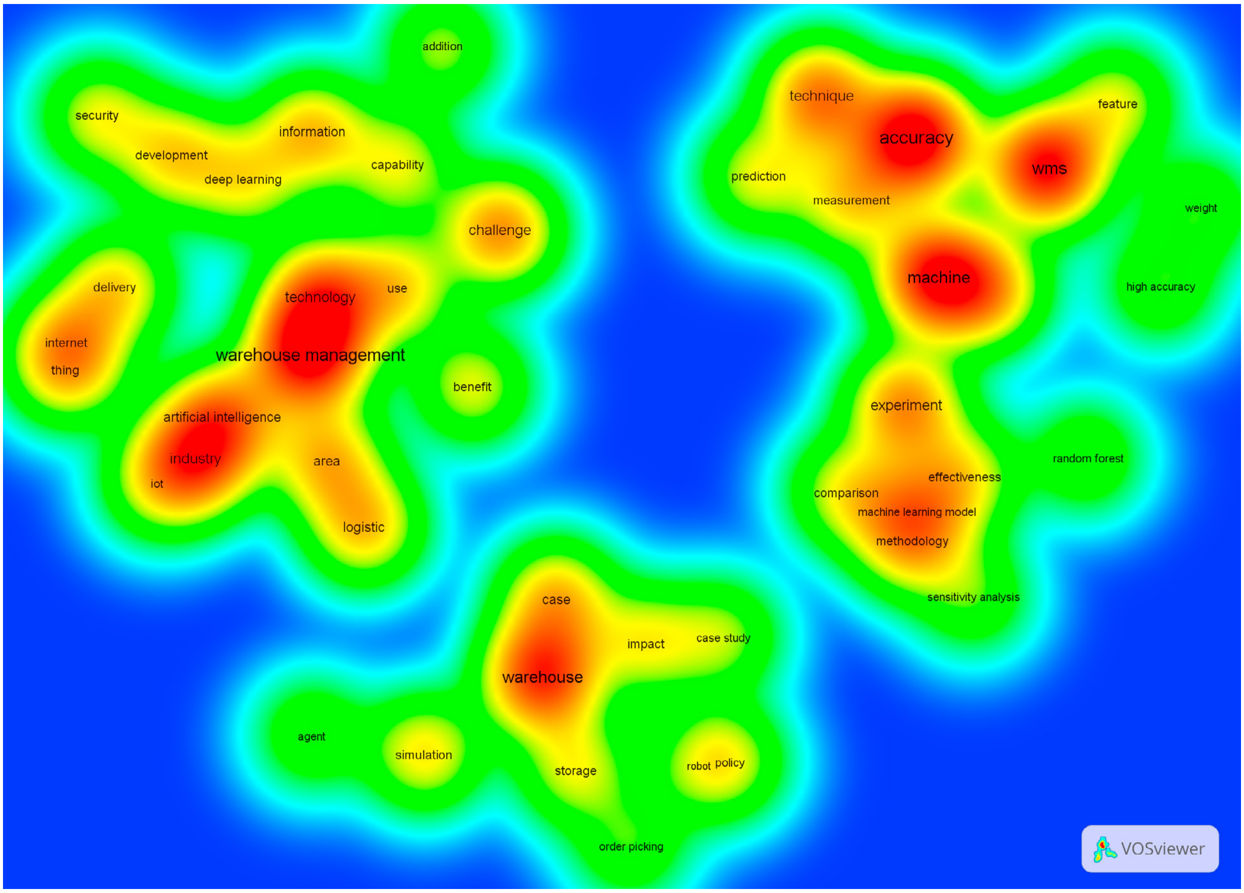


Fig. 3. Density visualization of terms by occurrence.

3.2. Content analysis

The articles were evaluated based on the problem addressed, ML methods, algorithms and data sources used to solve the identified issues (see Table 2). ML methods are guides that assist in running models from available data types. An ML algorithm uses precise and probabilistic techniques that empower computers to capture past reference points and perceive patterns in data sets [32].

Table 2. Key publications are combining Machine learning with OPP and SLAP.

ML method	Algorithm	Data source	Problem	Reference
Supervised learning	Artificial Neural Network	Management	OPP	[11]
	Support vector machines	Equipment	OPP	[46]
	Decision trees	Artificial	OPP	[19]
	Quantum machine learning	Equipment	OPP	[4]
	Bayesian neural network	Artificial	OPP	[37]
	Naive Bayes / Decision Tree	Equipment	SLAP	[1]
	Artificial Neural Network	Equipment	SLAP	[21]
	Artificial Neural Network	Management	SLAP	[22]
	Random Forest trees	Equipment	SLAP	[47]
	Artificial Neural Network	Management	SLAP	[7]
	Regression methods	Artificial	OPP / SLAP	[35]
	YOLO / Artificial Neural Network	Management	OPP / SLAP	[5]
Unsupervised learning	K-means / Clustering	Artificial	OPP	[15]
	Large neighborhood search algorithm / K-NN	Artificial	OPP	[14]
	K-means	Artificial	SLAP	[44]
	Clustering	Management	SLAP	[39]
	Clustering	Equipment	SLAP	[6]
	Association rules	Management	SLAP	[26]
	Clustering	Artificial	SLAP	[18]
	Clustering	Artificial	OPP / SLAP	[20]
	K-means / K-NN	Management	OPP / SLAP	[40]
Reinforcement learning	Timed Colored Petri Nets / Q-learning	Artificial	OPP	[9]
	Actor-critic learning	Artificial	OPP	[10]
	Q-learning	Equipment	OPP	[45]
	Learning algorithm embedding mechanism	Management	OPP	[43]
	Q-learning	Management	SLAP	[31]

Legend: OPP - Order Picking Problem; SLAP - Storage Location Assignment Problem.

Regarding the WMS problem, given the definition of the strings, the proposal was to map the articles with the primary objective of solving problems linked to OPP and SLAP using ML. During the detailed reading of the articles, it was noticed in some cases that the issues are addressed simultaneously.

To identify and classify the adopted ML methods, we used definitions based on the work of Jordan et al. [16], which establishes three main types of learning: (1) Supervised Learning (SL): ML paradigm produces outputs based on a learned mapping function, producing outputs for each input, or a probability distribution over each output given the relationship with the input (labeled data); (2) Unsupervised Learning (UL): ML paradigm in which classifications and clusters can be generated from the analysis of unlabelled data; (3) Reinforcement Learning (RL): ML paradigm in which routine training data is mediated between supervised and unsupervised learning, and indicates only whether an action is correct; if an action is incorrect, the problem becomes finding the correct action.

To facilitate the analysis of algorithms results, we grouped into families as proposed by Pedregosa et al. [30], which defines the algorithms used in supervised learning, unsupervised learning and reinforcement learning. It must be noted that the "Algorithms" column in Table 2 is not an exhaustive list and is limited to the algorithms identified in the SLR.

For Sharp et al. [34], ML uses data as raw material to develop autonomous knowledge. Consequently, choosing the data source is an important dimension to be analyzed. In Table 2, the data source category was adapted from Tao et al. [38], classifying data sources into two main categories: (1) Management data: historical data from company information systems; and (2) Equipment data: data from Industrial Internet of Things (IIoT) technologies. The analysis of the 26 articles indicated that some did not fit the data sources in [38], defined in this study as category (3) Artificial data: data generated randomly according to business rules or generated data set used to evaluate ML applications.

Regarding the ML methods, the findings identify a greater concentration on the individual use of supervised learning in 12 mapped articles. In 9 articles, the benefit is directed towards unsupervised learning, and the remainder (5) deals with reinforcement learning. The identified articles present frameworks that use specialized deep learning libraries, such as TensorFlow, Keras, PyTorch, etc., which facilitate deployment of the proposed approaches.

Results concerning the algorithms are diversified, with a greater concentration in artificial neural network (5) in supervised learning, clustering (5) for unsupervised learning, and Q-learning (3) for reinforcement learning.

The most used data sources were management data (9), artificial data (10) and equipment (7). This allows us to make two inferences. First, researchers use mainly historical data stored in enterprise information systems (e.g., WMS). Secondly, issues are still related to the complexity of WMS problems and the types of data available. This forces researchers to establish several levels of simplifications necessary in using artificial data. These issues are mainly related to the difficulties in collecting data.

3.3. Use cases

According to the typology proposed in De Koster et al. [8], the use cases were classified according to problem (e.g., OPP, SLAP), mechanisation level and dimensionality. Gu et al. [13] defines a framework for classifying warehouse design and operation planning problems, where OPP is organised into three categories: (1) Batching - refers to partitioning the set orders into batches. Each batch will be separated and accumulated for packing and shipping during a specific time window or pick wave; (2) Routing and sequencing - determine the best sequence and route for picking items in a given order; (3) Sorting - establishes a material handling system to classify items according to their destination. SLAP is also classified into three categories: (4) SKU-department assignment - defines the dynamics of stocking products between departments, in what quantities, and what the corresponding interdepartmental movements are; (5) Zoning specifies different storage zones within a department and assigns products to the specified zones; (6) Storage location assignment is to assign incoming products to storage locations in storage departments/zones to reduce material handling costs and improve space utilization.

On dimensionality, the categories are: (7) one-dimensional warehouse is a carousel storage system with only one vertical level or a round-robin conveyor; (8) two-dimensional storage is an automated single-aisle, multi-level automated storage and retrieval system (AS/RS); (9) three-dimensional warehouse has many aisles with several vertical levels and many horizontal columns. For the level of mechanisation: (10) manual: implies that workers provide both power and control; (11) mechanised: machines provide energy, but a worker provides managing; (12) semi-automated: engines provide power and some authority; and (13) automated: devices give all power and control [8].

Table 3 summarizes the use cases for OPP and SLAP and presents the function objective of each identified paper.

No articles were identified that addressed the SKU-department concept or mechanized warehouses. There is a predominance of articles that address OPP in the context of route definition and picking sequencing, as well as the definition of product locations for SLAP. Most of the cases take place in semi-automated three-level warehouses.

Gaast and Weidinger [11] provides a support framework for designing an order-picking system using different techniques and control mechanisms (based on fixed-path systems and warehouse conveyors) that were compared in an artificial neural networks framework. After training, it can select an appropriate picking system for a given order structure and design parameters to implement the best picking systems. Zadgaonkar and Chandak [47] explores Bluetooth technology, and Weichert et al. [46] presents an actuator coupling system to collect packaging identification data and group them using image processing in automated picking systems. Alfian et al. [1] also uses RFID readings to identify product movements in warehouses, using the mapped paths as training data for a classification model capable of indicating the shortest routes. It is worth highlighting in Chen [5] the clustering technique used to identify similarities of specific product features based on the YOLO algorithm. In Lam et al. [19], an order-picking planning system from structured data is proposed based on a series of reports on movements carried out within the warehouse. Atchade-Adelomou et al. [4] optimised the automated picking process and defined the lot sizes based on historical demand characteristics and warehouse structure. Suemitsu et al. [37] developed a training model to identify the best sequences of activities considering an automated vehicle-picking system. Leung et al. [21] proposes a set of eight models to improve order demand forecasting accuracy using an order history platform in a high-level warehouse.

Table 3. Summary of uses cases

ML	Ref.	Objective	Order picking			Storage			Dimensionality			Mechanization level			
			(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	[11]	Identifies the best picking sequence			✓		✓			✓		✓			
	[46]	Identifies the best time for order picking		✓							✓				✓
	[19]	Reduces order picking planning time		✓							✓			✓	
	[4]	Minimize the total travel distance	✓	✓							✓				✓
	[37]	Minimize the makespan		✓							✓				✓
SL	[1]	Reduce product picking loading errors						✓		✓				✓	
	[21]	Improve demand forecasting accuracy					✓				✓			✓	
	[22]	Reduces the time travel						✓			✓			✓	
	[47]	Minimize the error in SKUs locating						✓		✓				✓	
	[7]	Minimizing the total distance travelled						✓		✓		✓			
	[35]	Minimizes the route length travelled		✓				✓			✓	✓			
	[5]	Enhance parcel tracking accuracy			✓			✓			✓				✓
	[15]	Improve the process of grouping orders	✓								✓	✓			
	[14]	Minimize the total travel distance		✓							✓			✓	
	[44]	Minimizes warehouse operating costs		✓							✓			✓	
	[39]	Proposed metrics for effectiveness					✓				✓			✓	
UL	[6]	Minimize material handling costs						✓			✓			✓	
	[26]	Maximizes the fitness of SKUs						✓			✓	✓			
	[18]	Minimize the total cost of travel					✓				✓				✓
	[20]	Minimize the total travel distance	✓					✓			✓	✓			
	[40]	Predict the optimal storage systems		✓				✓			✓			✓	
	[9]	Reduces the makespan		✓							✓			✓	
	[10]	Minimize cost operating vehicle		✓							✓				✓
RL	[45]	Maximizes agent (robot) collaboration		✓							✓				✓
	[43]	Balanced task allocation		✓							✓				✓
	[31]	Minimize cost operating vehicle					✓				✓			✓	

Legend: ML - Machine Learning; SL - Supervised Learning; UL - Unsupervised Learning; RL - Reinforcement Learning; (1) Batching; (2) Routing & sequence; (3) Sorting; (4) SKU-Department assignment; (5) Zoning; (6) Storage location; (7) One-dimensional; (8) Two-dimensional; (9) Three-dimensional; (10) Manual; (11) Mechanized; (12) Semi-automated; (13) Automated

When zoning is applied, additional effort is required to split the batch and consolidate items by customer order or destinations, i.e. accumulation/sorting [7, 22]. Silva et al. [35] proposes an ML model to predict the ideal sizes of product storage zones based on demand distribution data and operational policies for manual warehouses, considering layout characteristics—cross aisle width and aisle length.

Huang et al. [15] proposes that unsupervised algorithms can improve the planning of order selection lists, using them to demonstrate a clustering approach of orders with similar characteristics. Hu et al. [14] presents a set of solutions developed for Alibaba in which decisions about order-picking routes trained on neural network models are based on data related to the characteristic of the warehouse and demand variation. Wang et al. [44] explored hybrid ML models to improve in-warehouse handling during the automated picking process. Tokat et al. [39] uses an ML-assisted performance indicator to cluster products with shorter warehouse order load times. Choy et al. [6] develops an ML-based solution for a medium-sized company with a manual warehousing system based on an RFID system to collect data using clustering to define the best product position. Pang and Chan [26] develop a storage location assignment algorithm that minimizes manual efforts in storage operations, optimising the total distance travelled in both put-away and picking operations. Keung et al. [18] compared storage location strategies to group products with similar characteristics. Leung et al. [20] presents a multi-objective approach to grouping incoming orders for batch processing at distribution hubs, adjusting the maximum size of each order grouping at distribution warehouses that function as third-party logistics service providers (3PL) for large online sales platforms. Tufano et al. [40] explored the impact of the data tracking system by training classifiers that can predict the storage allocation strategy and the collection policy from a learning table whose attributes are benchmark metrics applicable to any storage system.

In Drakaki and Tzionas [9], the authors used the storage system layout measurements to define the best picking sequence for an automatic order picker, defined as an agent trained to choose the shortest distances between products.

Estanjini et al. [10] integrated a least-squares time-difference learning method, and performance was demonstrated by solving a forklift dispatch problem arising in warehouse management to reduce operating costs. Wang et al. [45] proposes an innovative approach for robot training based on feedback sharing in an automated product-picking process. Wang et al. [43] offers an order-picking model that considers the idleness of picking stations and the centre of gravity of order items to solve the picking sequencing problem for an autonomous vehicle that receives many item orders in real-time and in varying amounts. Waubert de Puiseau et al. [31] presents a case of a dynamic storage location assignment problem (DSLAP) in which a reinforcement learning algorithm was used to train an agent (robot) with historical storage and retrieval operations data to derive a suitable storage location assignment strategy to decrease transportation costs within the warehouse.

4. Future research avenues

Below are the main research opportunities emerging from the review that could motivate future studies:

- Current state of the extract-transform-load process from the dataset: few articles address data processing techniques and the use of data repositories.
- Development of integrated solutions for OPP and SLAP: few papers have developed ML solutions capable of solving both problems in an integrated way.
- Solutions for warehouses with manual order picking processes and random product allocation systems: few works propose ML solutions for these traditional warehouse formats.
- Cases with real applications: several articles perform reductions and simplifications of real problems, which makes it difficult to identify characteristics of the implementation process.
- Development of reinforcement learning approaches: very few articles adopted a reinforcement learning approach. This is a hot topic in the field of ML and can be applied to a wide variety of WMS problems, as it makes it possible to train system agents to learn in an interactive and dynamic environment.

Besides the perspectives of future work already presented, other areas can be explored to enhance the use of ML in WMS, including advanced ML algorithms, such as deep learning, genetic algorithm, swarm optimisation algorithms and fuzzy logic-based algorithms, and applying natural language processing (NLP) techniques to analyse unstructured data related to warehouse management. In addition, one can explore the integration of ML with other emerging technologies, such as IIoT and robotics, to improve the efficiency and accuracy of warehouse operations. The consideration of sustainability and energy efficiency aspects and the development of collaborative machine learning approaches are also promising areas for future research in the context of ML in WMS.

It is worth mentioning that other areas to be explored are related to the optimisation of resources, such as labour, equipment and physical space, using ML models. Few studies have addressed this area, and the exploration of ML approaches that consider the efficient allocation of resources in real-time can contribute to more efficient and economical warehouse management. Furthermore, research on real-time data integration is another identified gap. While many studies analyse historical data, real-time data analysis from sensors, IoT devices and monitoring systems still needs to be explored. Investigating how ML can be applied to real-time data analysis can enable more agile and accurate adaptation of storage operations. Other gaps include considering the uncertainties and variations inherent in deposit operations, besides the need to conduct comprehensive comparative studies to evaluate and compare different ML algorithms considering specific performance metrics for warehouse management problems.

5. Conclusions

This SLR contributes to identifying characteristics of ML applications to solve WMS problems (i.e., OPP, SLAP). A total of 26 articles were identified and analysed in 4 axes: ML methods, algorithms, data sources, and use cases. Regarding the type of ML methods and algorithms, results showed that papers explore supervised—with neural networks as the predominant algorithm—and unsupervised—with clustering as the principal algorithm—methods. Reinforcement learning solutions have fewer occurrences. Concerning the problem type, results show that most articles mainly deal with OPP, as it is highly complex and impacts several decisions in a warehouse. Some papers have proposed integrated ways to solve both problems (OPP and SLAP), indicating difficult situations that require step-wise learning structures. Artificial data sets are still the most used data sources. The yearly increase in publications suggests that the research topic/area grew sharply in 2023, adding crucial elements in the context of I4.0 as they present research avenues for improving warehouse operational performances.

Like other studies, this review has limitations. First, this study focused mainly on warehouse storage and order-picking processes. Other important processes (e.g., receiving and shipping) were left out of the scope of this research. Second, the search strategy only considers peer-reviewed journal articles, missing insights from other documents (e.g., conference papers). Future studies may consider expanding the scope of this research by exploring other warehouse management processes (e.g., receiving, shipping) and additional facets of intelligent warehousing related to I4.0 principles and enabling technologies, such as automated guided vehicles (AGVs), autonomous mobile robots (AMR), wearable technologies, cloud/edge/fog computing, big data analytics, ML-based digital twins, horizontal and vertical integration. Finally, despite its limitations, this systematic review contributes to both academics and practitioners striving to understand the state-of-the-art research of using ML to enhance warehouse management operations.

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Author contributions

Conceptualization, R.F.A. and W.P.F.; methodology, R.F.A. and W.P.F.; validation, R.F.A., W.P.F., A.F.F. and L.S.A.; formal analysis, R.F.A., W.P.F. and L.S.A.; investigation, R.F.A. and W.P.F.; resources, W.P.F. and V.T.; data curation, R.F.A; writing—original draft preparation, R.F.A. and W.P.F.; writing—review and editing, R.F.A., A.F.F., W.P.F., L.S.A., M.O. and V.T.; visualization, R.F.A. and W.P.F.; supervision, W.P.F and V.T.

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