IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 24 March 2025, accepted 26 May 2025, date of publication 11 June 2025, date of current version 23 June 2025.

Digital Object Identifier 10.1109/ACCESS.2025.3578757

TOPICAL REVIEW

A Proposal for Future Research Agenda on Automated Disruption Management in Intralogistic Systems

IMANOL OLAIZOLA-ARREGUI[1,2], MIGUEL MEDIAVILLA[3], AND ENRIQUE ONIEVA[1]
[1]Faculty of Engineering, University of Deusto, 48007 Bilbao, Spain
[2]NEST Innovation and Talent Centre, 20700 Urretxu, Spain
[3]Departamento de Operaciones Logístico-Productivas, Mondragon Unibertsitatea, 20500 Arrasate, Spain

Corresponding author: Imanol Olaizola-Arregui (imanol.olaizola@opendeusto.es)

ABSTRACT This paper presents a systematic literature review on Automated Disruption Management (ADM) in intralogistic systems, analyzing 1.406 papers between 2018 and 2024. The review examines current approaches to managing disruptions in modern intralogistic environments, focusing on system architectures, adaptation capabilities, decision-making methods, and implementation aspects. Through a structured analysis following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework, we identify several critical gaps in current research, particularly in handling multiple simultaneous disruptions, integrating predictive capabilities with real-time adaptation, and validating theoretical developments in real-world settings. Our findings reveal a significant trend toward Reinforcement Learning (RL) approaches and an observable evolution from traditional Automated Guided Vehicles (AGV) to more flexible Autonomous Mobile Robot (AMR) solutions. Also, our work revealed the need for more integrated approaches that can handle multiple disruption types simultaneously while maintaining system performance, particularly in complex industrial environments. Moreover, the analysis also shows a considerable gap between theoretical development and practical implementation, with very few papers reporting real-world testing results. This review contributes to the field by providing a comprehensive taxonomy of current approaches, identifying critical research gaps, and proposing a specific research agenda in the field for future research.

INDEX TERMS Intralogistic, automated disruption management, industry 4.0, systematic review, reinforcement learning.

I. INTRODUCTION

The fourth industrial revolution has fundamentally transformed manufacturing and logistics operations through the integration of cyber-physical systems, Internet of Things (IoT), and artificial intelligence [1], [2]. This digital transformation, coupled with the exponential growth of e-commerce and changing consumer expectations [3], has placed unprecedented demands on intralogistic systems to become more efficient, flexible, and responsive [4], [5]. Traditional intralogistics systems are increasingly unable to meet these evolving demands [6], [7]. Consequently, the need for faster order fulfillment, improved efficiency, and greater flexibility is driving the development of more advanced automation solutions [7]. The introduction of Automated Guided Vehicles (AGVs) [8] was an early step in this evolution, which has since progressed toward more flexible and intelligent systems, culminating in Autonomous Mobile Robots (AMRs) as a significant milestone [9]. AMRs offer greater flexibility, improved navigation, and better adaptation to dynamic environments than their AGV predecessors [9], [10]. Moreover, advancements in artificial intelligence and control systems have enabled the emergence of highly sophisticated intralogistics solutions [11], [12]. However, the increasing complexity of these systems also makes them vulnerable to disruptions that can degrade performance and reliability.

The associate editor coordinating the review of this manuscript and approving it for publication was Jason Gu.

Such disruptions range from robot failures and battery issues [13], [14] to demand fluctuations and system congestion [11], [15]. The dynamic nature of these issues poses serious challenges for system adaptation and recovery [13], [16], especially when multiple disruptions occur simultaneously. Modern intralogistic systems must balance high throughput and efficiency with low energy consumption and stable operation [16], [17], [18]. Furthermore, integrating human operators adds another layer of complexity, requiring careful attention to human–robot collaboration and safety [19]. Current research largely focuses on optimizing individual aspects of these systems, such as task allocation [18], [20], path planning [10], or resource management [21]. Yet the growing complexity demands simultaneous optimization of multiple objectives. Few studies address the challenge of multiple simultaneous disruptions in this new intralogistics paradigm. Notably, most proposed solutions have only been validated in simulation, with very limited real-world implementation [21], [22]. Although some works have explored energy management [18] or real-time adaptation [23], integrated approaches that combine task reallocation, path replanning, and resource optimization in response to disruptions are largely lacking. In particular, the scarcity of research on dynamic resource reallocation [15], [16] and predictive maintenance underscores the need for more comprehensive disruption management frameworks.

This systematic review contributes to both theory and practice by:

1. Providing a comprehensive analysis of current disruption management approaches in the new intralogistic paradigm.
2. Identifying key research gaps and future research directions.
3. Analyzing real-time adaptation strategies and their effectiveness.
4. Proposing a research agenda for advancing the field.

For each article, the extracted data fields included the intralogistic system components addressed, the modeling and solution approaches employed, the technologies utilized, the disruption types considered, and the paper's unique contribution to the field. This approach ensured a comprehensive analysis of the diverse methodologies and technologies employed in automated disruption management (ADM) for the new intralogistic paradigm. The included articles were investigated according to six main themes, as outlined in our taxonomy: system components and architecture, dynamic adaptation capabilities, decision-making methods, system disruptions, performance metrics, and implementation aspects. This structured analysis helps synthesize existing works and identify areas requiring further research. While substantial research exists exploring various aspects of this new intralogistic paradigm, our review will show that a comprehensive discussion addressing ADM and real-time adaptation capabilities is still lacking. Despite extensive work on individual aspects, our review reveals a lack of integrated discussion on ADM and real-time adaptation. This review differentiates itself from existing literature reviews by focusing specifically on the intersection of ADM, real-time adaptation, and the new intralogistic paradigm. While previous reviews have examined these aspects individually, our work provides a more integrated analysis of how different approaches and technologies are being combined to create more resilient and adaptive intralogistic systems. Furthermore, our analysis particularly emphasizes the practical implementation aspects and validation methods, addressing a critical gap between theoretical developments and real-world applications.

The remainder of this paper is organized as follows: Section II presents the research methodology, Section III presents the results and analysis of the systematic review, Section IV discusses the findings and the existing research gaps, and Section V summarizes the key findings and presents the conclusions.

II. METHODOLOGY

This section outlines the methodology adopted for conducting this systematic literature review, focusing on ADM in the new intralogistic paradigm from January 2018 to December 2024. Following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework [26], a research methodology that facilitates a thorough exploration of the current state of the art, details the process of searching, collecting, and screening relevant studies, alongside presenting initial statistics related to the surveyed literature.

The PRISMA framework was selected for this study due to its broad applicability and structured approach to conducting systematic literature reviews across diverse research domains. While frameworks such as ROSES (Reporting Standards for Systematic Evidence Syntheses) are tailored specifically for environmental research, and SPIDER (Sample, Phenomenon of Interest, Design, Evaluation, Research type) is more appropriate for qualitative and mixed-methods studies, PRISMA offers a well-established and widely adopted methodology that aligns with the quantitative and engineering-focused nature of this review. Given that the objective of this study was to synthesize empirical findings from peer-reviewed journal articles in the fields of intralogistics, automation, and artificial intelligence—primarily through quantitative analysis—PRISMA provided the most suitable structure for ensuring transparency, reproducibility, and methodological rigor.

A. PRISMA FRAMEWORK

This paper analyzes the state of the art in ADM for the new intralogistic systems paradigm, focusing on real-time adaptation strategies, decision-making methods, and implementation approaches suggested in the collected papers. Noticeably, despite the demonstrated benefits of ADM in improving system resilience, optimizing performance, and reducing operational costs, many organizations still rely on reactive approaches to handle disruptions in their intralogistic operations [15], [24]. This indicates a notable opportunity

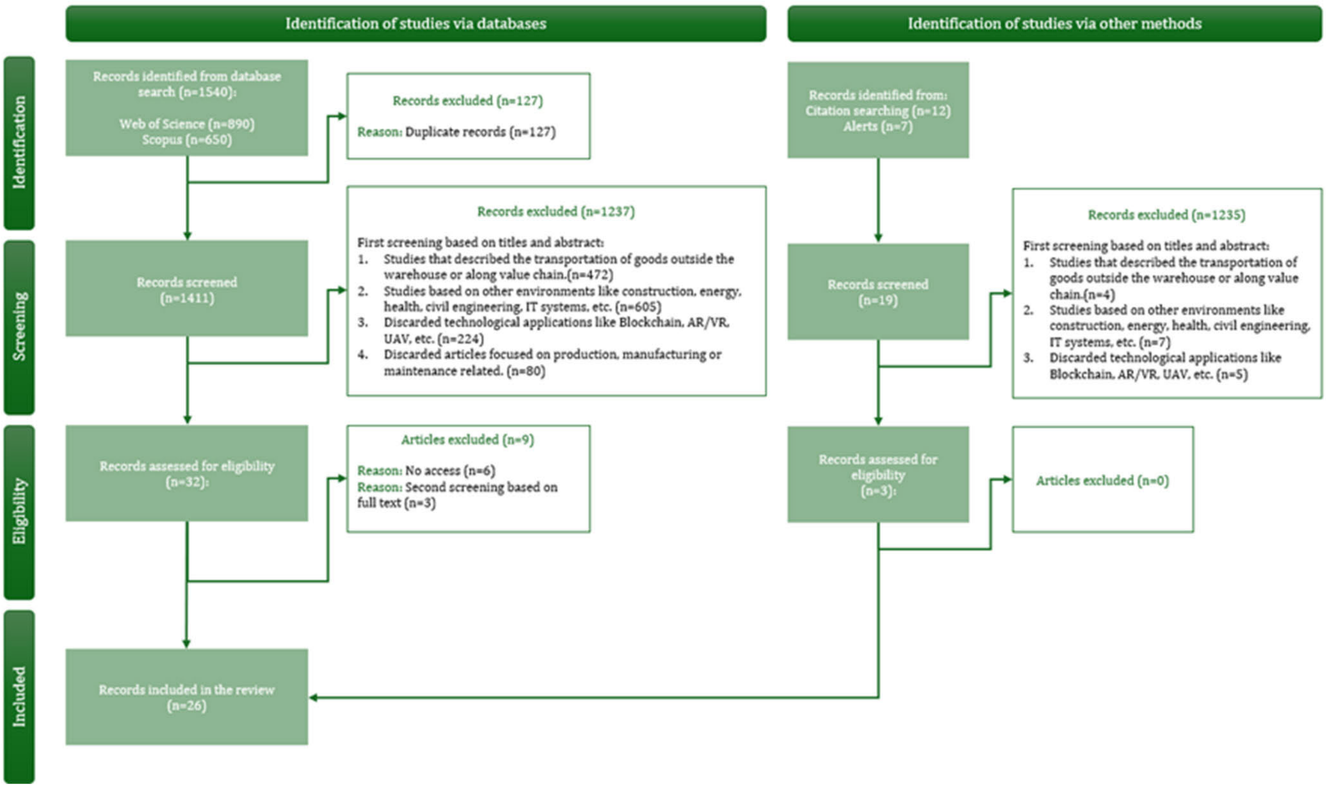

FIGURE 1. **PRISMA search framework.**

for advancing the practical implementation of automated solutions in this new intralogistic system paradigm [25]. With a systematic literature review approach, this research consolidates and analyzes present literature on the strategies employed for ADM in new intralogistic environments. The search encompassed Web of Science and Scopus databases using specific keywords to find English-language publications from the target time period. Following the process shown in Fig. 1, the systematic review identified, screened, evaluated, and selected the most relevant articles for analysis.

B. DOCUMENT SEARCH PROCESS

As part of the identification process, keywords were chosen and designed their relationship to create the following query: (intralogist* OR logist* OR smart production logist* OR ''autonomous mobile'') AND (((((((synchronisation) OR real-time) OR adaptative) OR smart) OR intelligent) OR dynamic) OR prescriptive). The selection of keywords was guided by the objective of capturing a broad yet relevant spectrum of literature related to automation and adaptability in intralogistic systems. The terms ''intralogist*'', ''logist*'', and ''smart production logist*'' were chosen to encompass both general and domain-specific terminology used in the field of internal logistics. The inclusion of ''autonomous mobile'' was intended to capture literature focused on mobile robotic systems, particularly AMRs, which are central to current ADM developments. The second part of the query—comprising terms such as ''synchronisation'', ''real-time'', ''adaptative'', ''smart'', ''intelligent'', ''dynamic'', and ''prescriptive''—was selected to reflect the core attributes of modern ADM systems, including responsiveness, intelligence, and adaptability. These keywords were refined through preliminary scoping searches and were found to be consistently present in high-impact publications within the target research areas.

Regarding time period, some preliminary research without any time constraints showed an increasing trend beginning to emerge after 2019, leading to becoming a starting point for our research. Also reviews, conference papers and book chapters were filtered, solely acquiring journal articles. Regarding research areas, Computer Science and Engineering were chosen as the prior ones. Hence, this search strategy, spanning from 2018 to 2024, originally identified 1,540 articles published in English. After detecting the duplicates, the number of relevant articles was reduced to 1,413.

To ensure methodological rigor and minimize potential bias, a structured evaluation framework was developed. The framework was established through the following steps. First, a comprehensive codebook was developed based on intralogistics and real-time adaptation literature, defining explicit evaluation criteria for article selection. The codebook included classification parameters covering general metadata, research characteristics, content focus, and application context. To validate the evaluation framework and assess inter-rater reliability, two independent researchers were engaged in a validation process. Each researcher independently evaluated a sample of 10 articles from the dataset using the established codebook. The results were then compared to assess consistency in classification and identify potential discrepancies. The reliability achieved was 94.3%, calculated as the number of fields coded in the same way by both researchers over the total number of fields in the codebook. Any disagreements were discussed openly, leading to refinements in the codebook definitions and evaluation criteria. Regular self-audit protocols were established, with previously evaluated articles randomly selected for re-evaluation to ensure consistency. Screening decisions were recorded in a standardized matrix, including reasons for inclusion/exclusion, classifications, and relevance.

Initial filtering based on titles and abstracts removed articles unrelated to intralogistics, such as those focused on transport outside the warehouse or across the supply chain. Studies on real-time adaptation in unrelated sectors (e.g., construction, health, civil engineering) were also excluded. Likewise, papers centered on technologies like Blockchain, or UAVs were discarded for lacking alignment with the review's scope. Articles focused on production or maintenance rather than internal warehouse tasks (e.g., unloading, picking) were also excluded. This process narrowed the pool to 34 relevant articles. Many exclusions stemmed from the broadness of the keywords; filtering terms like health, COVID, disaster, last mile, urban, and maritime could have prevented noise and reduced initial records. Final eligibility was confirmed through a quick full-text review. Three articles were excluded due to unsuitable methodologies, and six more were discarded due to lack of access, resulting in 25 included articles.

Additional papers were identified via citation searching and database alerts. Of 19 extra articles screened, only 3 met the eligibility criteria, applying the same filters as before. Ultimately, 26 articles were selected as suitable for this review. A comprehensive analysis was conducted to address the key research questions.

C. YEARLY PUBLICATION TRENDS

Fig. 3 shows the publication trend in ADM research within the new intralogistic paradigm by year. Research activity has grown notably since 2020, peaking in 2023 with 9 publications, highlighting increasing interest in automated disruption management. The progression goes from 0 papers in 2018, 1 in 2019, 2 in 2020, 3 in 2021, and 4 in 2022, culminating in the 2023 surge. The slight drop to 8 papers in 2024 and 1 in 2025 reflects the review's time frame, not reduced interest.

The 2025 paper by Ma et al. [58] was included via early access. Overall, the trend confirms growing attention to ADM as industries face complex, multi-disruption challenges.

D. CITATION IMPACT

Fig. 4 presents a citation analysis reflecting the influence of ADM research in the new intralogistic paradigm. Several papers stand out for shaping the field. Hu et al. [36] leads with 152 citations for their work on Deep Reinforcement Learning (DRL) in AGV scheduling. Zhang et al. [17] follows with 65 citations for dynamic prioritization in robotic warehouses. Bolu and Korcak [20] received 56 citations for adaptive task planning, and Zhao et al. [21] gained 50 for integrating digital twins and knowledge graphs. Other notable works include Li and Huang [24] with 47 citations (production-intralogistics synchronization), Fernandes et al. [12] with 41 (trajectory

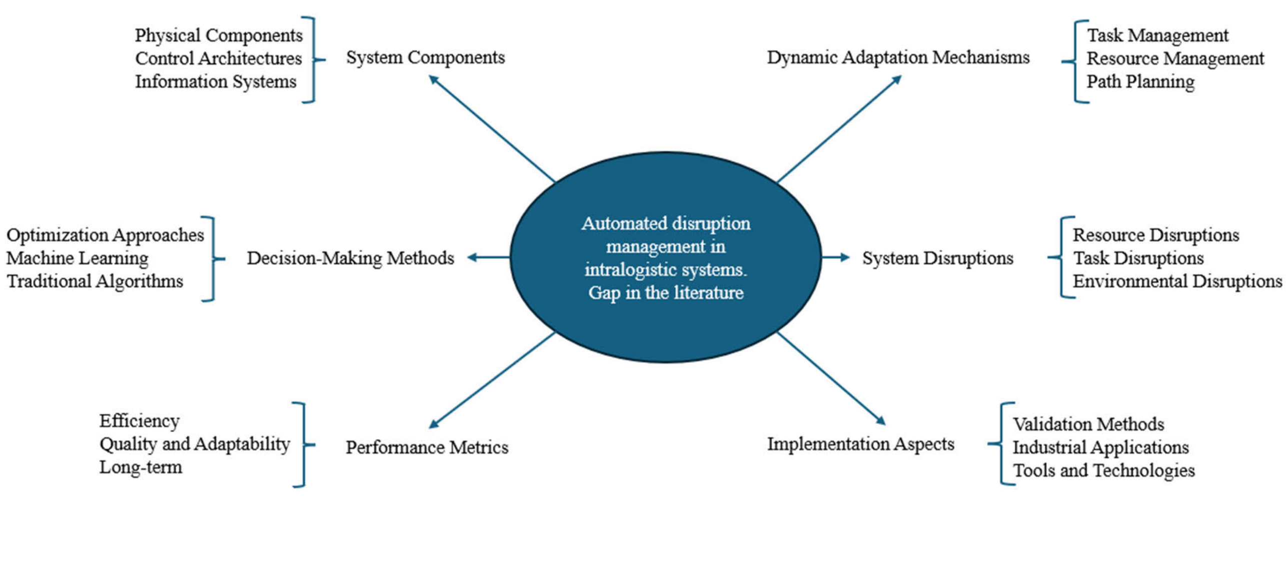

FIGURE 2. Taxonomy graphical representation.

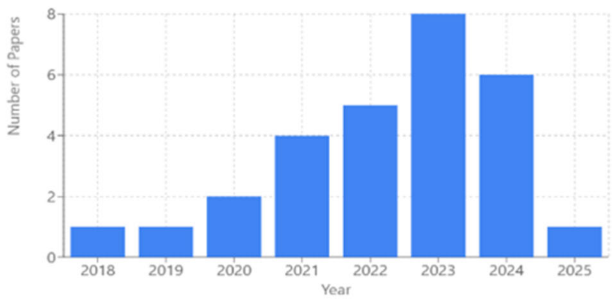

FIGURE 3. Publication trend from 2018 to 2025.

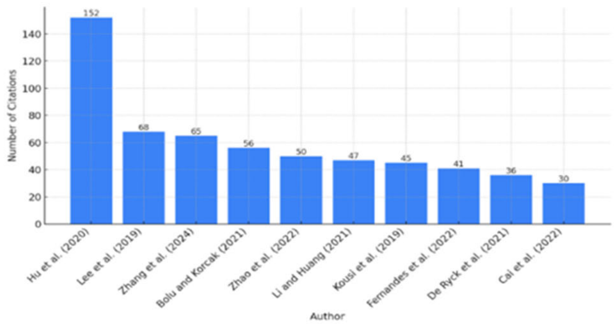

FIGURE 4. Top influencing authors.

planning), and De Ryck et al. [34] with 36 (decentralized task allocation). These citation figures underscore the growing relevance and technical maturity of ADM research in modern intralogistics.

III. LITERATURE ANALYSIS AND RESULTS

The taxonomy in this review emerged from an iterative analysis of the literature, identifying six core categories: System Components, Dynamic Adaptation Mechanisms, Decision-Making Methods, System Disruptions, Performance Metrics, and Implementation Aspects. As shown in Fig. 3, this structure aligns with the layered architecture of cyber-physical systems [33], where physical/logical elements (e.g., AGVs, sensors, control software) form the base, followed by adaptive decision layers. Dynamic Adaptation Mechanisms were included as a distinct category based on studies highlighting the need for real-time reconfiguration in automated warehouses [9], [27]. Decision-Making Methods were classified into optimization, machine learning, and heuristics, following established operations research and AI frameworks [28], [29]. System Disruptions were prioritized due to findings in supply chain risk literature emphasizing obstacle dynamics and demand volatility [30], [31]. Performance Metrics include KPIs like throughput time and collision frequency [31], (Thrun et al. [59]), while Implementation Aspects address challenges in operationalizing theoretical models [32]. Subcategories were defined to reflect methodological and technological granularity, offering a comprehensive view of current research. This framework helps visualize research concentrations and gaps and provides a foundation for future classification efforts.

A. DISTRIBUTION AND TRENDS ANALYSIS

This review covers 26 papers published between 2018 and 2024. As shown in Fig. 2, research activity has increased, especially from 2022 onward, reflecting growing interest in ADM amid rising demands for efficient, resilient intralogistics. Fig. 5 shows sectoral distribution, aligned with automation needs driven by e-commerce and Industry 4.0. Fig. 6 highlights methodological trends, indicating a shift toward intelligent, adaptive solutions alongside continued use of traditional optimization techniques.

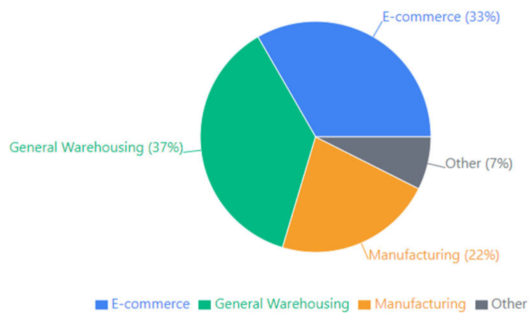

FIGURE 5. Distribution of research focus areas.

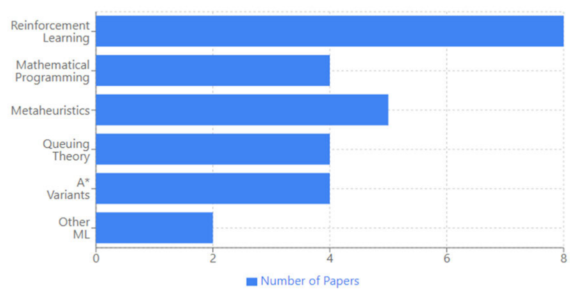

FIGURE 6. Most used methodological approaches.

B. EVOLUTION OF SYSTEM COMPONENTS

The analysis of system components and architecture highlights key changes in modern intralogistics design [34]. Three main elements define these systems: physical components, control architecture, and information systems [32], [33].

Physical setups have shifted from static conveyors to modular, robot-driven infrastructures, with AMRs and IoT-enabled devices enabling reconfigurability [9]. Control architectures now favor decentralized models for real-time responsiveness [16]. Information systems leverage digital twins and cloud computing to integrate sensor data with predictive analytics [16]. This section reviews recent contributions and evaluates their effectiveness in addressing intralogistic challenges.

1) PHYSICAL COMPONENTS

Research shows a shift from AGVs (7 papers) to AMRs (9 papers), reflecting a preference for more flexible, autonomous solutions. Zhang et al. [17] and Low et al. [10] highlight AMRs' superior adaptability to dynamic disruptions. However, infrastructure such as charging stations (2 papers) remains underexplored, despite its importance for ensuring system efficiency and autonomy [14].

2) CONTROL ARCHITECTURES

The literature contrasts centralized (2 papers) and decentralized (3 papers) control. [34], [34] support decentralization for resilience, while Li and Huang [24] show efficiency gains from centralized models. Hybrid architecture is scarcely addressed, marking a clear research gap.

3) INFORMATION SYSTEMS

Digital twins and IoT integration are equally represented (4 papers each). Zhao et al. [21] show digital twins improve disruption prediction. Li et al. [16] emphasize IoT's role in real-time monitoring. The mention of knowledge graphs (1 paper) signals potential for advancing system intelligence.

C. DYNAMIC ADAPTATION MECHANISMS

The analysis reveals varying levels of advancement in adaptation capabilities across different aspects of the new intralogistic systems paradigm. These mechanisms represent critical components in system resilience and efficiency, particularly in responding to disruptions and maintaining operational continuity.

1) TASK MANAGEMENT

Task management in intralogistics involves assigning and scheduling operations efficiently, balancing objectives like minimizing delays, completion time, and optimizing resource use. Dynamic adaptation is key to handling disruptions such as breakdowns, urgent orders, or delays [36]. Task allocation is addressed in six papers, from auction-based methods [34] to AI-driven approaches [20]. De Ryck et al. [34] improve scalability and robustness in AGV systems via auctions, while Bolu and Korcak [20] propose an adaptive heuristic system using digital twins for real-time decision-making. Task scheduling, covered in seven papers, includes real-time adaptation [14] and energy efficiency [36]. Zhang et al. introduced a DRL method that enhances battery use while maintaining service levels. Hu et al. develop a flexible scheduler that improves makespan and reduces delays under shop floor variability. Real-time replanning, explored in three papers, shows promise for dynamic environments. Maw et al. [23] propose the iADA* algorithm, achieving 2–3.7× faster computation than existing methods—crucial for fast-changing contexts. Cai et al. [13] extend this with a scheduling mechanism that uses continuous data analytics to handle system deviations and uncertainties.

2) RESOURCE MANAGEMENT

Resource management deals with optimal use of system assets—robots, operators, storage, and equipment—requiring continuous adaptation to disruptions, workloads, and changing conditions [16]. Effective strategies support resilience and performance [15], reflecting the complexity of intralogistics. Five papers address resource allocation, showing a shift from traditional optimization to AI-based methods. Zhao et al. [21] propose an innovative approach combining digital twins with spatial-temporal knowledge graphs, enhancing precision in production logistics. Their real-world implementation offers insights into the benefits and challenges of advanced systems. Energy management, covered in six papers, reflects industry focus on sustainability and efficiency. Yang et al. [18] present a maximin-based multi-objective algorithm that balances energy use and task allocation, improving utilization without compromising performance. Zhang et al. [14] add battery replacement to scheduling, tackling a key practical issue often overlooked in theory. Capacity management, addressed in three papers, shows growing interest in scalability. Li and Huang [24] propose a framework for heterogeneous AGV fleets that consider capacity constraints while optimizing tasks—highlighting real-world relevance in mixed-fleet environments.

3) PATH PLANNING

Path planning focuses on determining optimal routes for mobile resources in dynamic environments, avoiding obstacles and conflicts [14]. Key innovations center on real-time adaptation and obstacle avoidance [10], [36]. Real-time algorithms, covered in eight papers, move beyond A* toward reinforcement learning. Low et al. [10] propose an improved Q-learning method using distortion concepts and optimization modes, achieving better obstacle avoidance with efficient computation. Obstacle avoidance appears in six papers, emphasizing dynamic environment handling. Zhang et al. [17] introduce the Bi-AM-RRT* algorithm, outperforming standard RRT variants in complex settings—crucial for dense warehouse scenarios. Fernandes et al. [12] complement this with Enhanced Diversity Particle Swarm Optimization, yielding smoother, more adaptive paths. Congestion management, explored in three papers, shows promise for system-level optimization. Kobayashi et al. [11] present a Q-learning–enhanced Dynamic Window Approach that adapts to congestion, improving path efficiency and reducing collisions. Li and Huang [24] extend this by integrating congestion and task planning into a unified traffic optimization framework.

D. DECISION-MAKING METHODS

Decision-making in modern intralogistics requires advanced methods to manage operational complexity and disruptions [33]. The literature identifies three primary approaches: optimization techniques for solving constrained problems, machine learning for managing uncertainty and dynamics [41], and traditional algorithms for routing and allocation [42], consistent with recent classifications [32]. This section reviews these methods and their effectiveness in intralogistic applications.

1) OPTIMIZATION APPROACHES

Decision-making often involves balancing multiple objectives under complex constraints and evolving conditions [16]. Mathematical programming transforms operational problems into models with objective functions and constraints, making it suitable for well-defined scenarios (Hillier & Lieberman, 1968), though its computational cost can rise with problem scale [49]. Metaheuristics, inspired by natural processes, offer near-optimal solutions efficiently and adapt well to dynamic environments [48]. Techniques such as genetic algorithms [47] and ant colony optimization (Dorigo & Stützle, 2004) are commonly applied. Queuing theory provides mathematical tools to analyze system behavior under variable demand and service conditions, useful for resource allocation and performance prediction [45], [46].

Four papers demonstrate the applicability of mathematical programming. Jiang and Huang [56] optimize robotic warehouse synchronization using mixed-integer models, achieving improved makespan and operational efficiency. Boysen et al. [4] propose a two-step optimization for robotized sorting, maintaining near-optimal performance even with limited foresight. Khoei et al. [57] and Tutam and De Koster [19] apply similar models to energy minimization and order picking, respectively. Metaheuristics appear in five papers, addressing problems where exact solutions are infeasible. Zhu et al. [37] combine genetic algorithms and ant colony optimization to reduce shelf movements and processing time in robotic mobile fulfillment systems. Fernandes et al. [12] apply enhanced particle swarm optimization to improve trajectory planning in dynamic environments. Further contributions by Jiang and Huang [56] and Khoei et al. [57] explore metaheuristic variants tailored to specific challenges.

Queuing models are used in four papers to predict system behavior and optimize configuration. Lamballais et al. [15] apply semi-open networks for resource reallocation in robotic systems under varying demand. Kumar et al. [5] extend this to parts-to-picker systems, incorporating human factors and workload. Ma et al. [58] propose closed queuing networks for cellular warehouses, improving throughput prediction accuracy.

2) MACHINE LEARNING TECHNIQUES

Machine learning techniques have become essential for solving complex decision-making problems in intralogistics, offering strong capabilities for managing dynamic environments and uncertainty. Current research highlights three main categories: supervised learning for predictive modeling, reinforcement learning (RL) for adaptive decision-making, and unsupervised learning for pattern recognition [39], [40]. RL, in particular, is well suited for tasks such as AGV control and resource allocation, where systems must learn from interaction and adapt to evolving conditions [29], [35]. Deep Q-learning (DQN) extends traditional RL by integrating deep neural networks (DNN), enabling decision-making in complex environments [38]. DNNs, inspired by the human brain, are composed of multiple interconnected layers capable of learning complex spatial-temporal patterns, making them valuable for prediction and optimization tasks in intralogistics. Additional machine learning methods—such as time series clustering, self-organizing maps, and dynamic time warping—provide tailored solutions for pattern recognition and temporal analysis in specific logistics problems. RL dominates machine learning applications in this field, appearing in eight papers for tasks in dynamic, uncertain environments. Zhang et al. [14] apply DQN for AGV scheduling, achieving a 9.8% reduction in makespan and a 10.9% improvement in delay ratio over traditional approaches. Low et al. [10] contribute an enhanced Q-learning algorithm for path planning that improves obstacle avoidance and computational efficiency. Further implementations by Kobayashi et al. [11] and Lamballais et al. [15] confirm RL's adaptability across use cases. Although DNNs appear in only one paper, Zhao et al. [21] successfully use them for spatial-temporal analysis in a knowledge graph-based resource allocation system, improving efficiency through better pattern recognition. Another specialized approach by Kalkha et al. [54] combines time series clustering, self-organizing maps, and dynamic time warping for storage location optimization, achieving 61–69% efficiency gains across various picking strategies. These results highlight the potential of machine learning—particularly RL—for advancing decision-making in intralogistics.

3) TRADITIONAL ALGORITHMS

Path planning and resource allocation in intralogistics rely on specialized algorithms. Three main approaches stand out: A* and its variants, Dijkstra's algorithm, and heuristic methods. A* combines completeness and heuristic guidance, making it effective for warehouse navigation. Its variants adapt to dynamic obstacles and time constraints. Dijkstra's algorithm, while more computationally demanding, guarantees shortest-path solutions without relying on heuristics, useful when optimal paths are not evident. Heuristic methods, based on domain knowledge and simplified rules [44], offer fast, practical solutions, often used alongside formal algorithms for tasks like multi-robot coordination [43]. A* and its variants appear in four papers. Bolu and Korcak [20] and De Ryck et al. [34] validate their use in real-time scenarios, while Li and Huang [24] adapt A* for heterogeneous AGV fleets, improving performance in complex layouts. Dijkstra's algorithm is applied in one paper—Zhao et al. [21]—as part of a broader resource allocation framework. Auction-based methods are also explored once, with De Ryck et al. [34] applying them to decentralized task allocation. Heuristic methods appear in four papers. Bolu and Korcak [20] combine heuristics with A* for improved planning, and Khoei et al. [57] develop heuristics for energy-efficient routing. These methods prove valuable for quick, effective solutions in complex environments.

E. DISRUPTION MANAGEMENT APPROACHES

Our literature review addresses three main categories of disruptions, each presenting unique challenges and solutions. Our analysis reveals an increasing trend toward integrated approaches that can handle multiple disruption types simultaneously, though such comprehensive solutions remain relatively rare.

1) RESOURCE DISRUPTIONS

Resource-related disruptions receive balanced attention, particularly in predictive management and recovery. Battery and energy issues are covered in three papers. Zhang et al. [14] propose a DRL-based framework integrating battery replacement, achieving 9.8% makespan and 10.9% delay reductions while managing energy constraints. Equipment failures, also addressed in three papers, focus on detection and recovery. Li et al. [16] introduce the Operation Twins framework, combining real-time monitoring and predictive maintenance to improve system stability. Cai et al. [13] complement this with a scheduling mechanism that incorporates equipment status and failure prediction into decision-making. Capacity constraints, examined in four papers, reflect growing interest in system limitation management. De Ryck et al. [34] contribute a decentralized control architecture that adapts to resource constraints while maintaining efficiency, showing strong performance under fluctuating availability. Lamballais et al. [15] extend this by developing dynamic reallocation policies, achieving up to 52% cost reduction in variable capacity conditions.

2) TASK DISRUPTIONS

Task-related disruptions have attracted considerable attention, especially regarding workload management and demand adaptation in automated systems [52], [53]. Six papers focus on dynamic handling of order and task arrivals. Zhang et al. [14] propose a DRL-based system that adapts to real-time fluctuations while maintaining energy efficiency, showing strong performance under variable conditions. Demand fluctuations, addressed in three papers, are notably explored by Lamballais et al. [15], who use a Markov Decision Process for dynamic resource reallocation, achieving up to 52% cost reduction during peak demand. Kalkha et al. [54] complement this with a storage location strategy that adapts to demand changes, yielding 61–69% efficiency improvements across picking strategies. Priority changes and task rescheduling are also critical in dynamic environments. Zhang et al. [17] introduce a dynamic priority queuing network that improves fairness and throughput over static systems, particularly benefiting low-priority orders. Cai et al. [13] support this with a real-time priority calculation mechanism that adapts to system conditions, helping balance competing demands while maintaining stability and performance.

3) ENVIRONMENTAL DISRUPTIONS

Environmental disruptions have gained attention, especially in dynamic obstacle management [4]. These disruptions—such as moving personnel, misplaced goods, or equipment failures—can degrade system performance by increasing latency or collision risk (Thrun et al. [59]). Dynamic obstacles are the most studied factor, with seven papers developing detection and avoidance strategies. Zhang et al. [17] contribute a multi-agent policy learning approach that performs well in complex environments, reducing navigation failures by 52% and energy use by 12%. Congestion management, addressed in three papers, focuses on traffic optimization. Kobayashi et al. [11] propose a Q-learning-based Dynamic Weight Coefficient method (DQDWA), achieving the shortest completion times and lowest path deviation by adapting to congestion. Li and Huang [24] enhance this by integrating congestion control with task allocation for system-wide optimization. Multi-robot coordination, though less explored in disruption management, shows promise. Low et al. [10] offer a reinforcement learning-based path planning method that improves collision avoidance and path efficiency in high-density robot environments.

F. PERFORMANCE EVALUATION

Our literature review reveals diverse approaches to performance measurement, reflecting the multifaceted nature of intralogistic systems. Our analysis shows an evolution from simple efficiency metrics toward more comprehensive evaluation frameworks that consider multiple performance dimensions.

1) EFFICIENCY METRICS

Operational efficiency metrics dominate evaluation methods in literature, with strong emphasis on quantifiable indicators (Gunasekaran et al., 2004; Kaplan & Norton, 1992; Chopra & Meindl, 2016). Throughput is the most common metric, appearing in seven papers. Boysen et al. [4] analyze throughput in robotized sorting systems, achieving near-optimal results comparable to systems with full foresight. Zhu et al. [37] report processing rates of about 110 tasks/hour in their RMFS implementation. Kousi et al. [51] evaluate multiple indicators—machine utilization, MAU utilization, and production volume—achieving up to 89.17% operational machine utilization in an automotive case. Response time is addressed in six papers, reflecting interest in real-time performance. Maw et al. [23] show 2–3.7× faster computation than existing methods in dynamic settings, critical for fast adaptation. Graba et al. [22] reduce execution time by 10% without compromising path quality or safety. Energy efficiency, also covered in six papers, highlights the push toward resource optimization. Yang et al. [18] present a multi-objective evolutionary algorithm that balances energy use and task allocation, reducing overall consumption while maintaining performance. Zhang et al. [14] add battery management, improving energy utilization without affecting throughput.

2) QUALITY AND ADAPTABILITY

Beyond traditional efficiency metrics, recent studies increasingly consider system resilience and adaptability. System stability is evaluated in two papers. Li et al. [16] offer key insights with their Operation Twins framework, which improves stability under uncertainty, particularly during equipment failures and fluctuating conditions. Service level, also addressed in two papers, focuses on customer satisfaction and operational reliability. Cai et al. [13] propose a framework that integrates customer satisfaction and system performance, highlighting the need to balance objectives under disruption. Lee et al. [50] contribute by assessing system quality through conflict resolution metrics, demonstrating effectiveness in handling stay-on, head-on, and cross conflicts in Cyber-Physical Systems. Recovery metrics appear in three papers, reflecting growing interest in resilience and adaptation. Graba et al. [22] provide quantitative evaluation of recovery under disruptions, showing notable improvements in recovery time and success rates over traditional methods. Overall, the literature shows a shift toward AI-driven disruption management, though real-world validation and integrated solutions remain limited.

G. IMPLEMENTATION ASPECTS

This section examines both the validation methods employed and the specific industry applications addressed in the literature.

1) VALIDATION METHODS

Simulation is the dominant validation method, used in 23 of 26 papers. Discrete-event simulation (DES) is the most common, especially for testing performance and adaptation strategies. This reliance reflects both the complexity of intralogistic systems and the difficulty of real-world testing. Zhang et al. [14], Li and Huang [24], and Cai et al. [13] use DES via Tecnomatix to validate DRL scheduling, AGV management, and real-time scheduling, respectively. DES allows researchers to model system interactions and assess control strategies in controlled environments. Analytical validation appears in one paper. Kumar et al. [5] use mathematical models and proofs for their queuing-based parts-to-picker system, showing the value of formal analysis. Real-world testing, found in two papers, offers insights into implementation. Zhao et al. [21] report on deploying digital twins and knowledge graphs in an industrial park. Graba et al. [22] validate energy-efficient trajectory planning in real factory settings.

2) INDUSTRY APPLICATIONS

E-commerce applications appear in nine papers, reflecting rising automation needs. Bolu and Korcak [20] propose an adaptive task planning system for e-commerce fulfillment, while Lamballais et al. [15] focus on resource reallocation in robotic mobile fulfillment, addressing high-volume, variable demand. Manufacturing is covered in seven papers, emphasizing production-intralogistics synchronization and material handling. De Ryck et al. [34] tackle AGV systems with resource constraints, and Zhang et al. [14] focus on energy-efficient scheduling. Kousi et al. [51] present an implementation in automotive assembly, optimizing material supply for wheel and axle lines in a mixed-model setup. General warehousing and logistics appear in ten papers, showing the widest application range. Yang et al. [18] work on intelligent warehouses, while Li and Huang [24] address heterogeneous AGV management. These studies emphasize flexibility and adaptability more than domain-specific ones.

3) IMPLEMENTATION TOOLS AND TECHNOLOGIES

The review highlights a broad range of tools and technologies used to implement and validate new intralogistic systems. In simulation, Tecnomatix Plant Simulation is prominent for discrete-event modeling, as seen in Cai et al. [13] and Zhang et al. [14]. ROS with Gazebo is common in robotics studies, used by Kobayashi et al. [11] and Graba et al. [22] for path planning. Development tools vary, with machine learning frameworks gaining relevance. TensorFlow is widely used in RL implementations [14], [36]. For optimization, CPLEX and Python libraries are standard in studies on task and resource allocation [4], Khoei et al. [57]). Validation uses a mix of custom and commercial tools. Performance monitoring systems are key in real-world deployments, as shown by Zhao et al. [21] and Graba et al. [22]. Python-based analytics are common, while custom visualization platforms support development and performance demonstration.

IV. RESEARCH GAPS AND FURTHER RESEARCH RECOMMENDATIONS

Through our systematic review of ADM in the new intralogistic systems paradigm, manifold significant research gaps and opportunities for future research have been identified. Table 1 provides a comprehensive overview of these gaps along with supporting evidence and suggested research directions. Our analysis reveals both technological and methodological limitations that need to be addressed to advance the field further.

A fundamental gap emerges in the integration of physical components and information systems within the new intralogistic systems paradigm environments. While individual components show considerable technological advancement, their integration remains fragmented and often ad-hoc. Digital twin technology, despite its potential for system integration and optimization, has been explored in only four papers [16], [20], [21], [24], with varying degrees of implementation depth. Furthermore, only Zhao et al. [21] have investigated the potential of knowledge graphs for system intelligence, indicating a possible unexplored opportunity in advanced information integration approaches. Future research could focus on developing comprehensive frameworks that combine these technologies with real-time analytics capabilities. The management of heterogeneous robot fleets presents another significant challenge. Current research predominantly focuses on either AGVs or AMRs separately, with limited exploration of hybrid environments. While some studies, such as Li and Huang [24], have begun to address heterogeneous AGV management, comprehensive frameworks for integrating different types of autonomous vehicles remain scarce. This gap becomes particularly noticeable in the context of charging infrastructure optimization, where only two papers [14], [34] address the critical aspect of charging station management in detail.

Future work should focus on developing standardized architectures for managing mixed fleets with different capabilities and requirements. A key limitation appears to exist in the handling of multiple simultaneous disruptions. Our analysis reveals that most studies (23 out of 26) focus on addressing single disruption types in isolation, failing to capture the complexity of real-world scenarios where multiple disruptions often occur concurrently. While some papers, such as Li et al. [16] and Zhang et al. [14], acknowledge the possibility of multiple disruptions, they typically handle them sequentially rather than simultaneously. To address this, future research should explore the development of integrated control architectures that combine predictive analytics with real-time adaptation. For example, hybrid frameworks that fuse reinforcement learning with rule-based overrides could enable systems to prioritize and resolve concurrent disruptions more effectively. Additionally, simulation environments should be extended to model multi-disruption scenarios, enabling robust stress-testing of proposed solutions.

The integration of predictive capabilities with real-time adaptation strategies represents another possible research opportunity. Only three papers [13], [16], [24], address equipment failures and maintenance considerations, and their approaches primarily focus on reactive rather than predictive strategies. The scarcity of integrated approaches that combine predictive maintenance with dynamic task allocation and resource management represents a noticeable limitation in current research. Future studies could explore the development of predictive frameworks that can anticipate potential disruptions while maintaining system performance. In the domain of decision-making methods, our analysis reveals limited exploration of hybrid approaches combining multiple methodologies. While RL has shown promise, appearing in eight papers including significant works by Zhang et al. [14] and Low et al. [10], there is insufficient integration with other decision-making methods. Most papers focus on single methodologies, missing opportunities for complementary advantages. Furthermore, the scalability of current solutions remains a concern, with most implementations tested only in limited scenarios. Future research should investigate hybrid approaches that combine multiple decision-making methods while ensuring scalability for large-scale applications. The evaluation of system performance represents another area requiring significant attention. Current metrics predominantly focus on efficiency measures, with limited consideration of quality and adaptability aspects.

Only two papers address service level metrics, and just three papers present recovery metrics [10], [11], [22]. The shortage of standardized metrics for evaluating system resilience and adaptability represents a significant gap. Future research could focus on developing comprehensive evaluation frameworks that incorporate quality, reliability, and long-term performance measures. A particularly interesting gap exists in the validation and implementation of proposed solutions. Our analysis reveals that 23 out of 26 papers rely primarily on simulation-based validation, with only two papers [21], [22] reporting real-world testing results. Future research would be really benefited if it could be tested and evaluated in real-world scenarios.

Future work should prioritize the development of comprehensive validation that combines simulation with real-world testing, along with clear implementation guidelines for different industrial contexts. Human-system integration emerges as another area requiring substantial research attention. While papers such as Kumar et al. [5] and Tutam and De Koster [19] address aspects of human-robot interaction, their focus remains limited to specific operational scenarios. The insufficiency of comprehensive frameworks for managing dynamic environments where both automated and manual operations coexist, represents a possible research opportunity. Future studies should focus on developing integrated approaches that consider human factors, safety requirements, and effective interfaces for human supervision and intervention.

Looking forward, a few key priorities emerge for advancing the field of ADM in the new intralogistic systems paradigm. First, the development of integrated frameworks that can handle multiple simultaneous disruptions while considering both predictive and reactive strategies. Second, the creation of standardized architectures for managing heterogeneous robot fleets and their associated infrastructure. Third, the advancement of hybrid decision-making approaches that combine multiple methodologies while ensuring scalability and real-time performance. Fourth, the establishment of comprehensive validation frameworks that bridge the gap between theoretical development and practical implementation. Finally, we emphasize the importance of addressing these gaps through coordinated research efforts that combine theoretical advancement with practical validation. The future of the new intralogistic systems paradigm depends on our ability to develop robust, adaptable, and implementable solutions that can effectively manage the complex disruptions characteristic of modern industrial environments. As shown in Table 1, each identified gap presents specific opportunities for meaningful contributions to the field, particularly in areas where current research is limited or fragmented.

TABLE 1. Research gaps and future directions based on the taxonomy proposed.

Taxonomy Area	Key Subcategories/Aspects	Key Papers/Authors	Identified Gaps and Limitations	Main Contributions of the State-of-the-Art	Future Research Directions
System Components	Physical Components: AGVs vs. AMRs, charging infrastructure. Control Architectures: Centralized vs. Decentralized. Information Systems: Digital Twins, IoT, Knowledge Graphs.	Zhang et al. (2024), Low et al. (2023), De Ryck et al. (2021), Li & Huang (2024), Zhao et al. (2022)	Lack of integrated frameworks that merge physical and digital layers. Limited research on managing heterogeneous fleets. Insufficient focus on charging infrastructure optimization.	Establishes a taxonomy showcasing the evolution from traditional, fixed AGVs to flexible, adaptive AMRs. Demonstrates how digital technologies (Digital Twins, IoT) enhance real-time monitoring and control in intralogistics.	Develop standardized architectures merging physical and digital systems. Create integrated frameworks that combine charging station placement, charging scheduling and task allocation. Design robust frameworks for heterogeneous fleet management and charging optimization
Dynamic Adaptation Mechanisms	Task Management: Assignment, scheduling, and real-time replanning. Resource Management: Allocation, reallocation, energy optimization and capacity management. Path Planning: Real-time algorithms (RL, A*, etc.), obstacle avoidance, congestion management.	Hu et al. (2020), Zhang et al. (2023), Bolu & Korcak (2021), Low et al. (2023)	Most solutions address disruptions in isolation, limited integration across task, resource, and routing domains. Predominantly reactive approaches. Poor handling of simultaneous disruptions.	Advanced real-time scheduling and resource optimization using RL-based techniques. Integration of reinforcement learning techniques into routing and scheduling providing improved operational flexibility and responsiveness.	Create adaptive task allocation frameworks that can handle dynamic priority changes and system constraints. Develop integrated approaches for detecting and responding to multiple simultaneous disruptions.
Decision-Making Methods	Optimization Approaches: Mathematical programming, metaheuristics, queuing theory. Machine Learning: Reinforcement Learning, Deep Neural Networks. Traditional Algorithms: A*, heuristics.	Jiang & Huang (2022), Boysen et al. (2023), Low et al. (2023), Zhao et al. (2022)	Predominant reliance on single-method approaches. Limited scalability in large-scale applications. Lack of hybrid decision-making models.	Provide a comprehensive overview of decision-making paradigms in intralogistics. Demonstrate the efficacy of RL and optimization methods. Lay the groundwork for the development of hybrid, scalable decision-making frameworks.	Develop hybrid models integrating multiple decision-making methods. Focus on scalability and real-world applicability for complex, large-scale intralogistic systems.
System Disruptions	Resource Disruptions: Battery/energy failures, equipment breakdowns, capacity constraints. Task Disruptions: Variations in order arrivals, priority shifts, rescheduling issues. Environmental Disruptions: Dynamic obstacles, congestion, multi-robot coordination challenges.	Zhang et al. (2023), Li et al. (2023), Cai et al. (2022), De Ryck et al. (2021)	Studies tend to address disruption types in isolation. Predominantly reactive strategies with limited predictive management. Lack of integrated frameworks for managing multiple, concurrent disruptions.	Establish a multi-dimensional evaluation framework that balances quantitative efficiency with qualitative aspects such as resilience and service quality. Emphasize the necessity of adaptive and integrated disruption management strategies. Links simulation results with practical operational impacts.	Develop proactive, integrated frameworks that manage multiple disruptions simultaneously. Incorporate predictive maintenance and adaptive resource allocation strategies to mitigate potential failures and delays.
Performance Metrics	Efficiency Metrics: Throughput, response time, energy consumption. Quality and Adaptability Metrics: System stability, service level, recovery measures. Long-term Performance: Sustainability and operational longevity indicators.	Boysen et al. (2023), Zhu et al. (2024), Yang et al. (2021), Graba et al. (2023)	Overemphasis on short-term efficiency metrics. Absence of standardized metrics for quality, resilience, and long-term performance. Limited evaluation of sustainability in operational environments.	Establish a multi-dimensional evaluation framework that balances quantitative efficiency with qualitative aspects such as resilience and service quality. Bridge the gap between simulation-based performance and real-world operational metrics.	Develop standardized, comprehensive evaluation frameworks that encompass both efficiency and adaptability/resilience metrics. Integrate long-term performance indicators into routine system assessments and benchmarking practices.
Implementation Aspects	Validation Methods: Predominantly simulation-based (DES) validation, limited real-world testing and theoretical analyses. Industrial Applications: E-commerce, manufacturing, warehousing implementations. Tools and Technologies: Simulation platforms (e.g., Tecnomatix), ROS, ML frameworks, custom visualization tools.	Zhao et al. (2022), Graba et al. (2023), Li & Huang (2024), Cai et al. (2022)	Heavy reliance on simulation-based validations with few real-world implementations . Fragmented practical guidelines and benchmarking standards. Limited feedback loop between theoretical models and industrial applications.	Highlight the disconnect between theoretical developments and practical applications. Demonstrate the effectiveness of simulation-based studies while underscoring the importance of real-world validations in advancing intralogistic solutions.	Promote extensive field testing and pilot studies . Develop industry-standard implementation guidelines and best practices. Establish unified benchmarking scenarios to facilitate smoother transition from simulation to real-world applications.

TABLE 2. Comparative matrix of the reviewed papers.

Author(s)	Year	Dynamic Adaptation Mechanisms	Decision-Making Method	Validation Type	Key Contribution
Hu et al.	2020	Resource Management	RL	Simulation	Deep Reinforcement Learning for AGV scheduling
Zhang et al.	2024	Path Planning	RL	Simulation	Multi-agent policy learning for AMRs
Bolu and Korcak	2021	Task Management	Heuristics	Simulation	Adaptive task planning for multi-robot systems
Zhao et al.	2022	Resource Management	Optimization	Real-world	Digital twins and knowledge graphs for resource allocation
Li and Huang	2021	Task Management	Optimization	Simulation	Production-intralogistics synchronization
Fernandes et al.	2022	Path Planning	Heuristics	Simulation	Trajectory planning with particle swarm optimization
De Ryck et al.	2021	Task Management	Heuristics	Simulation	Auction-based optimization for task allocation and resource management.
Low et al.	2023	Path Planning	RL	Simulation	Q-learning for obstacle avoidance
Kobayashi et al.	2023	Path Planning	RL	Simulation	Dynamic window approach with Q-learning for congestion management
Cai et al.	2022	Task Management	Optimization	Simulation	Real-time scheduling in production-logistics environments
Lamballais et al.	2022	Resource Management	RL	Simulation	Dynamic policies for resource reallocation in RMFS.
Yang et al.	2021	Resource Management	Heuristics	Simulation	Multi-objective evolutionary algorithm for energy management
Graba et al.	2023	Path Planning	Optimization	Real-world	Energy-efficient trajectory planning
Maw et al.	2020	Path Planning	Heuristics	Simulation	Improved anytime path planning algorithm
Li et al.	2023	Resource Management	Optimization	Simulation	Operation twins for production-intralogistics synchronization
Zhu et al.	2024	Task Management	RL	Simulation	Handling large-scale orders in RMFS while optimizing order allocation, shelf selection, and robot scheduling
Khoei et al.	2023	Task Management	Optimization	Simulation	Energy minimization in order picking
Tutam and De Koster	2024	Task Management	Optimization	Simulation	Multi-objective optimization model considering economic (travel time) and ergonomic (knee flexion) aspects
Kumar et al.	2023	Resource Management	Optimization	Analytical Modelling	Planning and coordination in parts-to-picker systems under perceived workload
Kalkha et al.	2024	Resource Management	Optimization	Simulation	Addressing the Storage Location Assignment Problem in e-commerce warehouses under dynamic demand
Boysen et al.	2023	Task Management	Optimization	Simulation	Scheduling tasks in robotized sorting systems with limited product lookahead and interdependent decisions
Jiang and Huang	2022	Task Management	Heuristics	Simulation	Mixed-integer models for robotic warehouse synchronization
Zhang et al.	2023	Resource Management	RL	Simulation	Markov Decision Process for bi-objective optimization (energy consumption and tardiness)
Li and Huang	2024	Task Management	Heuristic	Simulation	A framework combining cost computation and task assignment algorithms for heterogeneous AGVs (HATA)
Zhang et al.	2024	Task Management	Optimization	Simulation	Fair and efficient order handling in robotic warehouses with multiple order classes
Ma et al.	2025	Task Management	Optimization	Simulation	Determining optimal picking and robot-to-workstation assignment strategies in Robotic Cellular Warehousing Systems

V. CONCLUSION

This systematic review, summed up in Table 2, provides a comprehensive analysis of ADM in the new intralogistic systems paradigm, examining 26 papers published between 2018 and 2024. While substantial research exists exploring various aspects of this new intralogistic paradigm, also defined by some authors as smart intralogistics [9], our review shows that a comprehensive discussion addressing ADM and real-time adaptation capabilities is still lacking. The review reveals significant evolution in both technological approaches and methodological frameworks, while also identifying critical gaps that require further research attention. Our analysis demonstrates a perceptible trend towards more sophisticated and integrated solutions, particularly evident in the transition from traditional AGVs to more flexible AMR systems. The growing adoption of artificial intelligence, especially RL (7 papers), indicates increasing recognition of the need for adaptive and intelligent solutions. However, the predominance of simulation-based validation (24 papers) over real-world implementation (2 papers) highlights a significant gap between theoretical development and practical application.

The systematic categorization of the literature through our proposed taxonomy has revealed several key patterns. First, while individual components and technologies show considerable advancement, their integration remains fragmented, particularly in handling multiple simultaneous disruptions. Second, despite the growing sophistication of decision-making methods, there is limited exploration of hybrid approaches that combine multiple methodologies. Third, while performance metrics predominantly focus on efficiency, there is insufficient attention to quality and adaptability measures.

Through this comprehensive analysis, many critical research questions have emerged that need to be addressed to advance the field:

1. How to automatically detect and handle multiple simultaneous disruptions in smart intralogistic environments? This question arises from our finding that current approaches often handle disruptions in isolation, lacking integrated solutions for multiple concurrent disruptions.
2. How to dynamically reallocate tasks and resources when disruptions occur? This emerges from our observation of limited research in real-time adaptation strategies, particularly in complex operational scenarios.
3. How to implement predictive strategies to anticipate and mitigate potential disruptions? This question reflects the identified need for proactive approaches, moving beyond reactive disruption management.
4. How to validate the developed frameworks in operational environments? This crucial question stems from the significant gap between simulation-based studies and real-world implementations identified in our review.

This review makes several important contributions to the field. It provides a structured analysis of current approaches to ADM, offering researchers and practitioners a comprehensive overview of the state of the art. It identifies critical research gaps and provides specific recommendations for future research directions, as detailed in Table 1.

It also highlights the need for more integrated approaches that can handle the complexity of real-world disruptions while maintaining system performance. For researchers, this review offers a foundation for future studies by identifying promising areas for investigation, particularly in developing integrated frameworks for handling multiple disruptions, hybrid decision-making models, and standardized validation methodologies. For practitioners, it offers insights into current technological capabilities and limitations, helping inform implementation decisions, investment strategies, and workforce readiness planning. Moreover, the scarcity of empirical studies conducted in real-world warehouse environments represents a critical gap in literature. Unlike controlled simulations, real operational settings often involve complex and overlapping disruptions, making them essential for validating the robustness and adaptability of proposed ADM frameworks under realistic conditions.

Looking forward, the field of ADM in smart intralogistic systems presents numerous opportunities for meaningful contribution. Future research should prioritize the development of comprehensive frameworks that can handle multiple simultaneous disruptions, integrate predictive capabilities with real-time adaptation, and bridge the gap between theoretical development and practical implementation. Additionally, increased attention should be paid to human-system integration and the development of standardized performance metrics that consider both efficiency and adaptability. Finally, this review underscores the dynamic nature of the field and the continuous need for research that addresses emerging challenges. As smart intralogistic systems become increasingly complex and integral to modern industry, the ability to effectively manage disruptions while maintaining system performance becomes ever more critical. The gaps and opportunities identified in this review provide a roadmap for advancing the field toward more robust, adaptable, and practical solutions.

ACKNOWLEDGMENT

Claude 3.5 Haiku, a generative AI tool developed by Anthropic, was utilized during manuscript preparation to assist with refining language clarity and coherence followed by a careful author revision to verify accuracy and maintain original scientific rigor.

REFERENCES

[1] J. Lee, H. Davari, J. Singh, and V. Pandhare, "Industrial artificial intelligence for industry 4.0-based manufacturing systems," *Manuf. Lett.*, vol. 18, pp. 20–23, Oct. 2018.

[2] H. Lasi, P. Fettke, H.-G. Kemper, T. Feld, and M. Hoffmann, "Industry 4.0," *Bus. Inf. Syst. Eng.*, vol. 6, no. 4, pp. 239–242, Jun. 2014.

[3] S. Chevalier, "Global retail e-commerce market size 2014–2023," Statista, Hamburg, Germany, Tech. Rep., 2022.

[4] N. Boysen, S. Schwerdfeger, and M. W. Ulmer, "Robotized sorting systems: Large-scale scheduling under real-time conditions with limited lookahead," *Eur. J. Oper. Res.*, vol. 310, no. 2, pp. 582–596, Oct. 2023.

[5] S. Kumar, J.-B. Sheu, and T. Kundu, "Planning a parts-to-picker order picking system with consideration of the impact of perceived workload," *Transp. Res. E, Logistics Transp. Rev.*, vol. 173, May 2023, Art. no. 103088, doi: 10.1016/j.tre.2023.103088.

[6] T. Albrecht, M.-S. Baier, H. Gimpel, S. Meierhöfer, M. Röglinger, J. Schlüchtermann, and L. Will, "Leveraging digital technologies in logistics 4.0: Insights on affordances from intralogistics processes," *Inf. Syst. Frontiers*, vol. 26, no. 2, pp. 755–774, Apr. 2024.

[7] A. Cabornero, "Logística profesional," Logística Profesional, Madrid, Spain, Tech. Rep. 297, pp. 66–86, Nov. 2024.

[8] I. F. A. Vis, "Survey of research in the design and control of automated guided vehicle systems," *Eur. J. Oper. Res.*, vol. 170, no. 3, pp. 677–709, May 2006.

[9] G. Fragapane, R. de Koster, F. Sgarbossa, and J. O. Strandhagen, "Planning and control of autonomous mobile robots for intralogistics: Literature review and research agenda," *Eur. J. Oper. Res.*, vol. 294, no. 2, pp. 405–426, Oct. 2021.

[10] E. S. Low, P. Ong, and C. Y. Low, "A modified Q-learning path planning approach using distortion concept and optimization in dynamic environment for autonomous mobile robot," *Comput. Ind. Eng.*, vol. 181, Jul. 2023, Art. no. 109338.

[11] M. Kobayashi, H. Zushi, T. Nakamura, and N. Motoi, "Local path planning: Dynamic window approach with Q-learning considering congestion environments for mobile robot," *IEEE Access*, vol. 11, pp. 96733–96742, 2023.

[12] P. B. Fernandes, R. C. L. Oliveira, and J. V. Fonseca Neto, "Trajectory planning of autonomous mobile robots applying a particle swarm optimization algorithm with peaks of diversity," *Appl. Soft Comput.*, vol. 116, Feb. 2022, Art. no. 108108.

[13] L. Cai, W. Li, Y. Luo, and L. He, "Real-time scheduling simulation optimisation of job shop in a production-logistics collaborative environment," *Int. J. Prod. Res.*, vol. 61, no. 5, pp. 1373–1393, Mar. 2023.

[14] L. Zhang, Y. Yan, and Y. Hu, "Deep reinforcement learning for dynamic scheduling of energy-efficient automated guided vehicles," *J. Intell. Manuf.*, vol. 35, no. 8, pp. 3875–3888, Dec. 2024.

[15] T. Lamballais, M. Merschformann, D. Roy, M. B. M. de Koster, K. Azadeh, and L. Suhl, "Dynamic policies for resource reallocation in a robotic mobile fulfillment system with time-varying demand," *Eur. J. Oper. Res.*, vol. 300, no. 3, pp. 937–952, Aug. 2022.

[16] M. Li, D. Guo, M. Li, T. Qu, and G. Q. Huang, "Operation twins: Production-intralogistics synchronisation in industry 4.0," *Int. J. Prod. Res.*, vol. 61, no. 15, pp. 5193–5211, Aug. 2023.

[17] Z. Zhang, Y. Gong, Z. Yuan, and W. Chen, "Robotic warehouse systems considering dynamic priority," *Transp. Res. E, Logistics Transp. Rev.*, vol. 192, Dec. 2024, Art. no. 103779.

[18] S. Yang, Y. Zhang, L. Ma, Y. Song, P. Zhou, G. Shi, and H. Chen, "A novel maximin-based multi-objective evolutionary algorithm using one-by-one update scheme for multi-robot scheduling optimization," *IEEE Access*, vol. 9, pp. 121316–121328, 2021.

[19] M. Tutam and R. De Koster, "To walk or not to walk? Designing intelligent order picking warehouses with collaborative robots," *Transp. Res. E, Logistics Transp. Rev.*, vol. 190, Oct. 2024, Art. no. 103696.

[20] A. Bolu and Ö. Korçak, "Adaptive task planning for multi-robot smart warehouse," *IEEE Access*, vol. 9, pp. 27346–27358, 2021.

[21] Z. Zhao, M. Zhang, J. Chen, T. Qu, and G. Q. Huang, "Digital twin-enabled dynamic spatial–temporal knowledge graph for production logistics resource allocation," *Comput. Ind. Eng.*, vol. 171, Sep. 2022, Art. no. 108454.

[22] M. Graba, A. Amamou, S. Kelouwani, B. Allani, L. Zeghmi, K. Agbossou, and M. Mohammadpour, "Toward safer and energy efficient global trajectory planning of self-guided vehicles for material handling system in dynamic environment," *IEEE Access*, vol. 11, pp. 30753–30767, 2023.

[23] A. A. Maw, M. Tyan, and J.-W. Lee, "IADA*: Improved anytime path planning and replanning algorithm for autonomous vehicle," *J. Intell. Robotic Syst.*, vol. 100, nos. 3–4, pp. 1005–1013, Dec. 2020.

[24] M. Li and G. Q. Huang, "Production-intralogistics synchronization of industry 4.0 flexible assembly lines under graduation intelligent manufacturing system," *Int. J. Prod. Econ.*, vol. 241, Nov. 2021, Art. no. 108272.

[25] U. Venkatadri and A. Murrenhoff, "Towards a framework for AI applications in intralogistics," *IFAC-PapersOnLine*, vol. 58, no. 19, pp. 37–42, 2024.

[26] D. Moher, A. Liberati, J. Tetzlaff, and D. G. Altman, "Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement," *PLoS Med.*, vol. 6, no. 7, Jul. 2009, Art. no. e1000097.

[27] D. Ivanov, A. Pavlov, A. Dolgui, D. Pavlov, and B. Sokolov, "Disruption-driven supply chain (re)-planning and performance impact assessment with consideration of pro-active and recovery policies," *Transp. Res. E, Logistics Transp. Rev.*, vol. 90, pp. 7–24, Jun. 2016.

[28] D. Bertsekas, *Nonlinear Programming*, 2nd ed. Belmont, MA, USA: Athena Scientific, 1999.
[29] R. S. Sutton and Y. A. Barto, *Reinforcement Learning: An Introduction*, 2nd ed., Cambridge, MA, USA: MIT Press, 2018.
[30] D. Simchi-Levi, *Operations Rules: Delivering Customer Value Through Flexibility*. Cambridge, MA, USA: MIT Press, 2010.
[31] P. R. Wurman, R. D'Andrea, and Y. M. Mountz, "Coordinating hundreds of cooperative, autonomous vehicles in warehouses," *AIMag*, vol. 29, no. 1, p. 9, Mar. 2008. [Online]. Available: https://ojs.aaai.org/aimagazine/index.php/aimagazine/article/view/2082
[32] A. Rushton, P. Croucher, and Y. P. Baker, *The Handbook of Logistics and Distribution Management*, 5th ed. London, U.K.: Kogan, 2017.
[33] J. Lee, B. Bagheri, and H.-A. Kao, "A cyber-physical systems architecture for industry 4.0-based manufacturing systems," *Manuf. Lett.*, vol. 3, pp. 18–23, Jan. 2015.
[34] M. De Ryck, D. Pissoort, T. Holvoet, and E. Demeester, "Decentral task allocation for industrial AGV-systems with resource constraints," *J. Manuf. Syst.*, vol. 59, pp. 310–319, Apr. 2021.
[35] Y. Li and H. Huang, "Efficient task planning for heterogeneous AGVs in warehouses," *IEEE Trans. Intell. Transp. Syst.*, vol. 25, no. 8, pp. 10005–10019, Aug. 2024.
[36] H. Hu, X. Jia, Q. He, S. Fu, and K. Liu, "Deep reinforcement learning based AGVs real-time scheduling with mixed rule for flexible shop floor in industry 4.0," *Comput. Ind. Eng.*, vol. 149, Nov. 2020, Art. no. 106749.
[37] Z. Zhu, S. Wang, and T. Wang, "Optimizing robotic mobile fulfillment systems for order picking based on deep reinforcement learning," *Sensors*, vol. 24, no. 14, p. 4713, Jul. 2024.
[38] V. Mnih, K. Kavukcuoglu, D. Silver, A. A. Rusu, and Y. Otros, "Human-level control through deep reinforcement learning," *Nature*, vol. 518, no. 7540, pp. 529–533, 2015.
[39] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, 2015.
[40] M. Woschank, E. Rauch, and H. Zsifkovits, "A review of further directions for artificial intelligence, machine learning, and deep learning in smart logistics," *Sustainability*, vol. 12, no. 9, p. 3760, May 2020.
[41] I. Goodfellow, Y. Bengio, and Y. A. Courville, *Deep Learning*. Cambridge, MA, USA: MIT Press, 2016.
[42] P. Toth and D. Vigo, *Vehicle Routing: Problems, Methods, and Applications*, 2nd ed. Philadelphia, PA, USA: SIAM (Society for Industrial and Applied Mathematics), 2014.
[43] S. S. Heragu, *Facilities Design*. Boca Raton, FL, USA: CRC Press, 2008.
[44] J. Pearl, *Heuristics: Intelligent Search Strategies for Computer Problem Solving*. Reading, MA, USA: Addison-Wesley, 1984.
[45] D. Gross and C. M. Harris, *Fundamentals of Queueing Theory*. Hoboken, NJ, USA: Wiley, 1998.
[46] L. Kleinrock, *Queueing Systems: Volume I—Theory*. New York, NY, USA: Wiley, 1975.
[47] D. E. Goldberg, *Genetic Algorithms in Search, Optimization, and Machine Learning*. Reading, MA, USA: Addison-Wesley, 1989.
[48] K. Sörensen and F. Glover, "Metaheuristics," in *Encyclopedia of Operations Research and Management Science*, S. I. Gass and M. C. Fu, Eds., New York, NY, USA: Springer, 2013, pp. 960–970.
[49] W. L. Winston and J. B. Goldberg, *Operations Research: Applications and Algorithms*, 4th ed. Pacific Grove, CA, USA: Brooks/Cole, 2004.
[50] C. K. M. Lee, B. Lin, K. K. H. Ng, Y. Lv, and W. C. Tai, "Smart robotic mobile fulfillment system with dynamic conflict-free strategies considering cyber-physical integration," *Adv. Eng. Informat.*, vol. 42, Oct. 2019, Art. no. 100998.
[51] N. Kousi, S. Koukas, G. Michalos, and S. Makris, "Scheduling of smart intra–factory material supply operations using mobile robots," *Int. J. Prod. Res.*, vol. 57, no. 3, pp. 801–814, Feb. 2019.
[52] R. de Koster, T. Le-Duc, and K. J. Roodbergen, "Design and control of warehouse order picking: A literature review," *Eur. J. Oper. Res.*, vol. 182, no. 2, pp. 481–501, Oct. 2007.
[53] G. Ghiani, G. Laporte, and R. Musmanno, *Introduction To Logistics Systems Management*, 2nd ed. Chichester, U.K.: Wiley, 2013.
[54] H. Kalkha, A. Khiat, A. Bahnasse, and H. Ouajji, "Enhancing warehouse efficiency with time series clustering: A hybrid storage location assignment strategy," *IEEE Access*, vol. 12, pp. 52110–52126, 2024.
[55] G. Fragapane, D. Ivanov, M. Peron, F. Sgarbossa, and J. O. Strandhagen, "Increasing flexibility and productivity in industry 4.0 production networks with autonomous mobile robots and smart intralogistics," *Ann. Operations Res.*, vol. 308, nos. 1–2, pp. 125–143, Jan. 2022.
[56] M. Jiang and G. Q. Huang, "Intralogistics synchronization in robotic forward-reserve warehouses for e-commerce last-mile delivery," *Transp. Res. E, Logistics Transp. Rev.*, vol. 158, 2022, Art. no. 102619.
[57] A. A. Khoei, H. Süral, and M. K. Tural, "Energy minimizing order picker forklift routing problem," *Eur. J. Oper. Res.*, vol. 307, pp. 604–626, Feb. 2023.
[58] B. J. Ma, S. Pan, B. Zou, Y. Kuo, and G. Q. Huang, "Operating policies for robotic cellular warehousing systems," *Transp. Res. E, Logistics Transp. Rev.*, vol. 194, 2025, Art. no. 103875.
[59] S. Thrun, W. Burgard, and D. Fox, *Probabilistic Robotics*, The MIT Press, 2005.

IMANOL OLAIZOLA-ARREGUI received the M.Eng. degree from the Barcelona School of Industrial Engineering, Polytechnic University of Barcelona. He is currently pursuing the Ph.D. degree with the University of Deusto, Bilbao, Spain. His research interests include intralogistics, reinforcement learning, discrete event simulation, and warehouse management.

MIGUEL MEDIAVILLA has a PhD in Engineering as well as a PhD in Economics. He is the Managing Director of OPERATIONS Management Engineers, a research and consulting company. Previously, Miguel worked for 20 years as executive in the industry. Additionally, Miguel is Associate Professor at the University of Mondragon (Spain). His research interest is focused on procurement, negotiation, supply chain management and international operations networks. He has over 40 publications in academic journals, book chapters and conference proceedings.

ENRIQUE ONIEVA received the B.E. degree in computer science engineering, the M.E. degree in soft computing and intelligent systems, and the Ph.D. degree in computer science from the University of Granada, Spain, in 2006, 2008, and 2011, respectively. From 2007 to 2012, he has been with the AUTOPIA Program, Centre of Automation and Robotics, Consejo Superior de Investigaciones Científicas, Madrid, Spain. In 2012, he was with the Models of Decision and Optimization Group, University of Granada. Since 2013, he has been a Professor of artificial intelligence with the University of Deusto and a Researcher of intelligent transportation systems applications with the Deusto Smart Mobility Research Unit. He has participated in more than 40 research projects and authored more than 100 scientific articles. From then, he more than 40 are published in journals of the highest level. His research interests include the application of artificial intelligence to intelligent transportation systems, including fuzzy-logic based decision, evolutionary optimization, and machine learning.