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DECISION SUPPORT SYSTEMS IN PRODUCTION LOGISTICS: AN ANALYTICAL LITERATURE REVIEW

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ABSTRACT

Decision Support Systems (DSS) are a crucial component in production logistics, aiding companies in solving complex decision problems with multiple influences. This publication provides a structured review of the literature on the application of DSS in production logistics, focusing on methods for decision support, such as simulation and Artificial Intelligence (AI). The analysis considers scientific publications from 2015 to 2024, including industry use cases. Data analysis of categorizations of DSS is used. The findings highlight trends and limitations of current DSS application cases from the literature. Optimization methods, particularly heuristic and metaheuristic, are the most commonly employed decision support methods, followed by simulation. Despite the increased interest in AI technologies, their role in DSS for production logistics remains secondary. Like simulation methods, AI technologies are highly relevant when combined with optimization methods. The study provides a foundation for future research and practical advancements in decision support for manufacturing environments.

1 INTRODUCTION

Effective decision-making requires evaluating system-wide (cost) implications and their impact on customer value. This complex task requires human abilities, but can be supported by decision support systems (DSS).

Modeling and classification techniques within DSS are essential to abstract reality, identify environmental influences, and manage complexity. The granularity of the model must be sufficient to ensure the transferability and analysis of system-wide implications of solutions, yet simple enough to allow for efficient development and analysis (Schuh et al. 2012; Law 2015).

Top-level management sets key priorities, deducing further objectives for all departments. Consistent with the company's overall goals, production logistics typically aims to optimize economic objectives, such as minimizing process costs or maximizing performance under cost constraints. In addition, social and increasingly ecological goals are gaining importance and must be considered (Beckmann 2008; Kappler 1975; Gudehus 2010).

The ongoing digitization of manufacturing offers significant potential to improve the complex planning, control, and adaptability of production systems, with DSS following companies' goals (Luo et al. 2023; Koch et al. 2018; Schumacher 2023). Despite the availability of advanced methods, over 20 % of companies surveyed in 2016 and 2024 reported, for example, relying primarily on Excel for machine scheduling (Luo et al. 2023; Fuchs, C. 2024; Harjunkoski et al. 2014; Figueira et al. 2015). According to Fuchs (2024), only 50 % of the manufacturers worldwide use specialized scheduling software, such as advanced planning and scheduling systems.

To expand digitalisation, this publication aims to provide a comprehensive literature review of DSS with production logistics use cases. This publication identifies which methods are most commonly applied to which decision problem domain and which types of DSS are most frequently referenced and further developed in research publications from 2015 to 2024.

This publication is organized as follows: Section 2 provides the theoretical foundation by introducing decision support, methods of DSS, and the fundamentals of production logistics. At the end, Section 2 merges both fields and refers to related literature reviews. Section 3 outlines the research process for the literature review. Section 4 presents the main findings and discusses their implications. The publication is completed by a discussion, an outlook on future research directions, and a summary of the key observations.

2 FUNDAMENTALS OF DECISION SUPPORT IN PRODUCTION LOGISTICS AND RELATED WORK

The following section concerns the theoretical foundations for the subsequent literature review. In this regard, definitions are provided for decision support, the methods employed, and the domain of production logistics. Literature reviews in the domain are also mentioned.

2.1 Decision Support

DSS enables well-informed and transparent decisions (Sharda et al. 2021). DSS are computer-based information systems whose primary goal is to improve the quality of decisions and increase the efficiency of the decision-making process (Budde et al. 2022; Sauter 2010). However, a DSS does not replace the decision-maker, but is used as an auxiliary tool for semi-structured or unstructured problems that cannot be solved solely through algorithms (Alpar et al. 2019; Küpper 2002). DSSs differ from each other in their areas of application and functionality. The primary functions of DSS include data collection and processing, analytical capabilities, and data visualization or reporting, enabling recommendations even for complex decisions (Xu 2024). Internal and external data sources can be utilized for data collection (Power 2002). It should be noted that the data made available in this way must be prepared for further use (Alpar et al. 2019). The use of data in the analytical functions of a DSS can occur in various ways. For instance, simulation models can be used to make forecasts or supplemented with optimization techniques as the decision tool itself (Steglich et al. 2016). Users can interact with the system via a user interface (Lei and Moon 2015).

DSS can be categorized based on different criteria, such as knowledge base, area of application, degree of interactivity, and techniques used. DSS knowledge base:

- *Data-driven*: DSS focused on analyzing data (Alpar et al. 2019; Power 2002). In this context, databases, data warehouses, and OLAP technologies are often employed (Shim et al. 2002).
- *Model-driven*: Focus on types of models such as mathematical models, simulation models, or optimization models (Power and Sharda 2007; Power 2004).
- *Knowledge-driven*: Incorporating expert knowledge or rules into decision-making (Özbayrak and Bell 2003; Power 2002).
- *Communication-driven*: Group decisions supported through collaboration and communication (Power 2002).

DSS differ in their degree of support and interactivity. *Passive* systems merely provide information upon which decisions can be based, while *active* systems offer specific action recommendations (Hättenschwiler 2001). Cooperative systems enable *interactivity* by allowing collaboration with users through customizable suggestions they generate (Hättenschwiler 2001).

2.2 Methods for Decision Support

In this publication, all methods, techniques, and concepts used to achieve decisions are considered decision support methods. In the following, techniques and algorithms that are frequently used to distinguish them better in the subsequent, are briefly described:

Simulation: Simulation is a problem-solving method that uses models to analyze system behavior (Banks 2000). Instead of solving tasks directly on the system, a model is employed, and findings are transferred to the system (Gutenschwager et al. 2017). The specifications of simulation may vary significantly, depending on the intended application. For instance, discrete event simulation (DES) is a prevalent method in logistics (Kuhn and Wenzel 2008), though hybrid simulation are also employed.

Digital twin (DT): A very comprehensive virtual representation with possible future scenarios that are simulated using the data on the digital shadow, and which reacts to changes, new technologies, and processes similarly to the real system, is called a DT. A DT can also be created for sub-areas only. (Schumacher 2023; Weyer et al. 2016)

Optimization: Optimization methods improve a performance metric under resource constraints. Many real-world models are NP-hard and cannot be solved optimally within practical time limits. Exact methods like linear programming (LP) or non-linear programming (NLP) can prove optimality, but it often takes weeks to reach the optimum, if they can be found at all. (Meta)Heuristics offer scalable alternatives but yield iterative improvements without guarantees on optimality or solution quality gaps (Schumacher 2023). Types of combining simulation and optimization are studied by Figueira and Almada-Lobo (2014).

Visuals: Various methods are available for visualizing complex systems, with applications spanning mixed reality, virtual reality, and augmented reality, among others (Ciuffini et al. 2016; Baroroh and Chu 2022). By integrating virtual and physical components, this methods enhance analytical capabilities and provide users with a more-advanced level of insight (Ciuffini et al. 2016).

Artificial intelligence (AI): The field of Industry 4.0 has seen the integration of AI, its technologies and methodologies, particularly in the context of managing substantial, heterogeneous data sets to extract meaningful insights (Soori et al. 2024). This encompasses applications from the fields of machine learning, reinforcement learning, and deep learning (Soori et al. 2024; Voss et al. 2022; Yousefi et al. 2023), which are collectively referred to as AI in this publication.

2.3 Production Logistics

The key logistics domains and tasks of logistical nodes and networks are categorized according to procurement, production (in-house), distribution, and reverse logistics (Beckmann 2008). This publication will focus on DSS-supported production logistics use cases.

Production logistics is mainly divided into production planning and control processes, as well as internal transport (Verein Deutscher Ingenieure e.V. 2004), and fields like layout planning.

Logistical decision-making tasks and planning can be categorized based on different time horizons and hierarchical organizational responsibilities. The levels at which decisions are made are strategic, tactical, and operational (Gudehus 2010). In comparison, DSS for factory and layout design, material flow analysis, and supplier selection guide strategic decisions, DSS for production planning and control, in-house transportation, and warehousing support tactical or operational tasks.

It is essential to distinguish production planning and control from process planning, which is conducted during product design, and we do not include in our analysis. While process planning is implemented once for each product, regardless of the actual order, it determines how the product should be manufactured. Production planning and control are performed after each order and involve scheduling its production (Eversheim 1989).

An initial overview of the existing DSS is essential to systemize its application within production logistics and facilitate informed decision-making among practitioners.

Similar literature reviews concerning DSS have been conducted in other domains such as agriculture (Zhai et al. 2020) or medicine (Fernandes et al. 2020). Although there are also reviews from the field of logistics, they are either outdated concerning DSS from 1995 to 2001 (Eom and Kim 2006), focus on the integration of specific technologies like machine learning (Kramer et al. 2021; Usuga Cadavid et al. 2020), deal with DSS in other subfields of logistics such as sustainable logistics (Zarte et al. 2019; Qaiser et al. 2017), reverse logistics (Alimohammadi and Behnamian 2024) or city logistics (Bozzo et al. 2014), or cover the broad area of DSS in all logistic disciplines (Winkelhaus and Grosse 2020; Teniwut and Hasyim 2020). In the academic literature on logistics, production logistics is often not explicitly addressed, rather represents an integrated element within broader analyses. This article, therefore, closes a research gap.

3 RESEARCH METHODOLOGY

As part of this study, a structured literature review is conducted to gain insights into DSS in production logistics. The methodological approach is based on the five phases for a structured literature review outlined by vom Brocke et al. (2009).

Definition of review scope: The taxonomy proposed by Cooper (1988) is used to develop and classify the scope of the literature review (Table 1). Selected taxonomy characteristics of Table 1 relevant to this study are highlighted in gray. This publication aims to provide a comprehensive overview of the applications and research methods of DSS in production logistics. The focus is on theoretical foundations and practical applications. A neutral perspective integrates knowledge from various subfields within production logistics. Publications from 2015 to 2024 are considered, enabling the identification of current developments and long-term trends. Multiple scientific databases were included in the search: IEEE Xplore, ACM Digital Library, Scopus, Web of Science, and Google Scholar. The organization of this review combines conceptual and methodological approaches to address the two audiences of researchers and practitioners.

Table 1: Taxonomy for literature reviews according to Cooper (1988).

Characteristics	Categories			
Focus	Research Outcomes	Research Methods	Theories	Applications
Goal	Integration	Criticism	Identification of Central Issues	
Perspective	Neutral		Argumentative	
Coverage	Exhaustive	Exhaustive with Selective Citation	Representative	Central or Pivotal
Organization	Historical	Conceptual		Methodological
Audience	Specialized Scholars	General Scholars	Practitioners	General Public

Conceptualization of the topic: The objective of this study is to investigate production logistics and its subdomains as an application domain (see Section 2.3), DSS (see Section 2.1) as the tool to make decisions, and analyze its applied methods as well as the role of supported actors or decision-makers. Based on these considerations, the following search string was developed: *("production logistics" OR "production planning" OR "material flow" OR "information flow" OR "material handling" OR "internal transport" OR "warehousing") AND ("decision support" OR "decision-making support" OR "DSS" OR (planning AND (support OR assistance OR aid)) OR decision-guidance) AND ("method" OR "system" OR "technique" OR "algorithm" OR "process" OR "model" OR "procedure") AND ("human" OR "expert" OR "decision maker")*. This search string was consistently applied across all five databases and restricted to titles, keywords, and abstracts where possible.

Literature search: The search and filtering process is schematically illustrated in Figure 1. After searching all databases, duplicate entries were removed. Subsequently, publications were filtered based on their publication date according to Phase 1 guidelines (*Definition of review scope*). Remaining publications were preliminarily assessed based on their titles and abstracts for content relevance. Final inclusion or exclusion decisions for analysis were made after full-text examination using predefined exclusion criteria listed in Table 2. 93 publications were selected for full-text analysis (the list of considered publications can be found in Langenbach et al. (2025)).

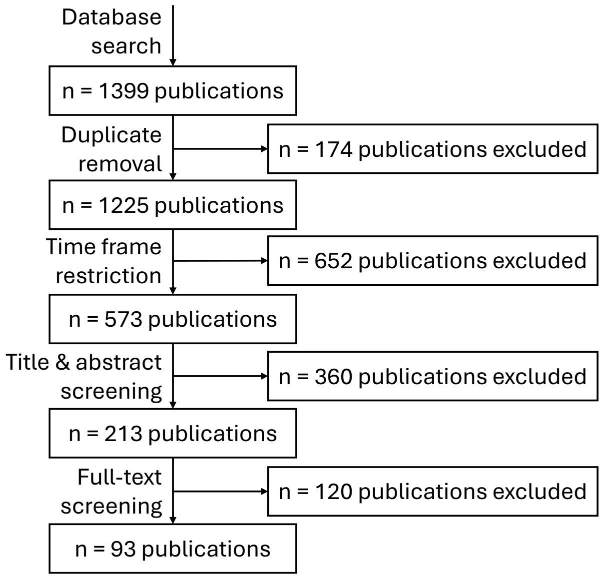

Figure 1: Screening and selection process.

Table 2: Inclusion and exclusion criteria.

Inclusion Criteria	Exclusion Criteria
Publications available in German or English	Publications unrelated to DSS
Publications are online accessible using our university licences	Publications presenting only theoretical propositions without validation
Focus on (parts of) production logistics	Exclusive focus on software engineering
Methodological approaches addressing decision support	Pure data processing methods without connection to decision-making
Human-centered support for decision-making processes	Publications limited to technical machine settings

Literature Analysis and Synthesis: For full-text analysis, a concept matrix was employed following Webster and Watson (2002). Initially, central analytical themes were identified: areas within production logistics, classifications of DSS, and applied methods. After analyzing the first 10 % of publications, these concepts were further refined based on insights from Section 2 and findings from initial full-text analyses. The final results are presented below.

Derivation of a Research Agenda: Based on the analysis results, recommendations for future research are formulated to advance understanding of DSS within production logistics contexts.

4 FINDINGS

The literature review of 93 full-text publications indicates an increase in application-oriented DSS publications in production logistics (Figure 2). While 33 publications were extracted for the full-text analysis from 2015–2019, this number rose to 60 between 2020–2024 – almost doubling. This growth reflects the rising importance of DSS, likely driven by the push around Industry 4.0 technologies (Bundesministerium für Bildung und Forschung 2012), and supported by faster data transmission and expanded storage capacities (Schuh et al. 2016).

Across the 93 publications, active DSS are mentioned 45 times, passive DSS 50 times, and interactive DSS 26 times. The total exceeds the number of publications because active and passive classifications are not exclusive; some publications describe multi-stage DSS processes with stages assigned to different categories.

In decreasing importance, Table 3 shows that most publications for DSS in production logistics during the analysis period focus on production planning and control, in-house transport, and warehousing, with a strong focus on production planning and control. All represent the tactical or operational level of DSS. In contrast, strategic areas such as factory and layout design, material flow analysis, or supplier selection are less frequently addressed.

Table 3 and Table 4 show that approaches subsumed with the term model-driven dominate the analyzed publications. Nevertheless, a considerable difference between modeling techniques exists, which are utilized for different methods. The further analysis in Table 4 shows that model-driven DSS often appear

Table 3: Decision support methods and drivers for parts of production logistics.

	Model-driven	Data-driven	Knowledge-driven	Communication-driven	Optimization	Simulation	AI	DT	Fuzzy	Visuals
Production planning & control (72)	49	31	15	1	48	31	14	6	6	2
In-house transport (13)	7	4	4	1	8	8	3	0	0	4
Warehousing (13)	9	4	3	0	7	3	2	1	1	0
Factory and layout design (12)	9	4	3	1	7	7	2	0	0	2
Material flow analysis (4)	2	2	1	0	2	3	1	0	0	1
Supplier selction (2)	2	0	0	0	2	0	0	0	0	0
Others (5)	2	4	0	0	1	2	1	0	0	0

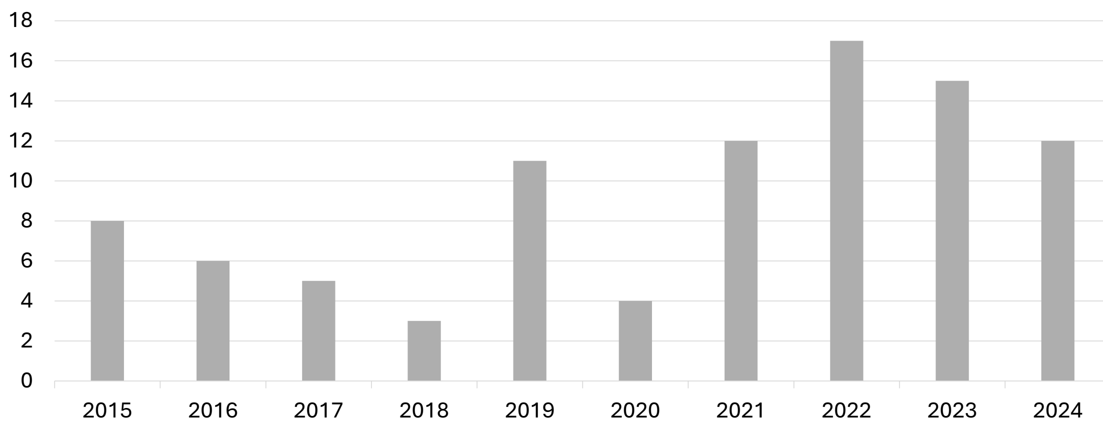

Figure 2: Number of publications per year.

in combination with data-driven (33 %) and knowledge-driven (19 %) components, reflecting a tendency to hybrid designs. Communication-driven DSS are rare and occur in only two cases.

Table 3 and Table 6 provide an overview of the methods employed for decision support. Optimization techniques are the most frequently used (62 %), followed by simulation approaches (42 %) and AI methods (18 %). The trend is similar, reflected for all areas of production logistics (see Table 3). Again, the total exceeds the number of publications because classifications are not exclusive; some publications describe a combination of multiple methods in use or a sequential use of methods assigned to different categories.

Table 4: Decision support drivers and their common occurrence rate (please read the percentages horizontally).

	Model-driven	Data-driven	Knowledge-driven	Communication-driven
Model-driven	63 (100 %)	21 (33.33 %)	12 (19.05 %)	2 (3.17 %)
Data-driven	21 (51.22 %)	41 (100 %)	2 (4.88 %)	0 (0 %)
Knowledge-driven	12 (60 %)	2 (10 %)	20 (100 %)	0 (0 %)
Communication-driven	2 (100 %)	0 (0 %)	0 (0 %)	2 (100 %)

Table 5: Methods and drivers of decision support (please read the percentages horizontally).

	Optimization	Simulation	AI	DT	Fuzzy	Visuals
Optimization	58 (100 %)	23 (40 %)	10 (17 %)	4 (7 %)	1 (2 %)	3 (5 %)
Simulation	23 (59 %)	39 (100 %)	10 (26 %)	6 (15 %)	3 (8 %)	4 (10 %)
AI	10 (59 %)	10 (59 %)	17 (100 %)	1 (6 %)	2 (12 %)	2 (12 %)
DT	4 (57 %)	6 (86 %)	1 (14 %)	7 (100 %)	1 (14 %)	1 (14 %)
Fuzzy	1 (17 %)	3 (50 %)	2 (33 %)	1 (17 %)	6 (100 %)	0 (0 %)
Visuals	3 (60 %)	4 (80 %)	2 (40 %)	1 (20 %)	0 (0 %)	5 (100 %)

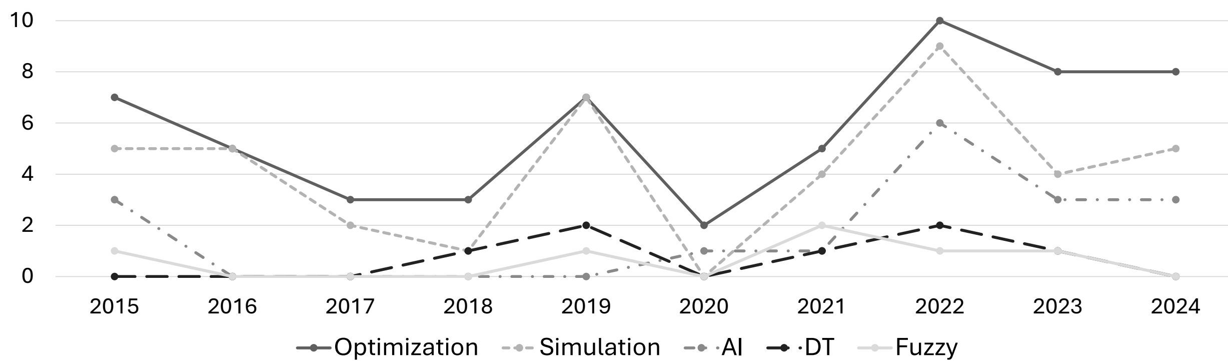

Figure 3: Published methods over time.

With regard to the combinations of methods employed, 36 DSS utilise a single method (21 employ optimization, 5 employ simulation, 10 employ other methods). It is noteworthy that the stand-alone utilisation of simulation is underrepresented in comparison to the overall proportion of simulation applications within the domain of DSSs. It is also noticeable that DSSs that use simulation as a single method are classified as passive. 57 DSS integrate multiple techniques, with up to six different methods used in a few systems. This highlights the increasing complexity and interdisciplinarity of DSS development. The cross-linkages between methods, as shown in Table 5, reveal that optimization is often combined with simulation (40 %) and with AI (17 %). In this context, the strengths and flexibility of simulation become evident when considering the areas of application of simulation in different DSS. For instance, simulation can be employed in the following ways: it can be used to consider what-if scenarios; to validate intermediate results of other methods; to generate data for other methods; and as a basis for visualisations. This facilitates the effective utilisation of alternative methods.

In detail and based on Table 6, the most frequent methods used in optimization are heuristic algorithms (heuristics and metaheuristics in 27 publications), followed by exact methods (in 18 publications). The most frequently used heuristic techniques are metaheuristics, and the most commonly used exact methods are linear programs (LPs). DES is the dominating simulation method, and simulation methods are the second category of dominating DSS methods. It can be concluded that even with the rise of AI technologies, AI is not the dominant method in the field of DSS in production logistics, neither over the whole time span under consideration nor in any of the recent years (see Figure 3). However, the number of AI studies has increased slightly over the last few years. Table 5 indicates that simulation and AI techniques, as well as other methods, except optimization, are most often used in combination with different methods, especially optimization techniques.

To sum up, the results indicated that production planning and control remain the primary application area in production logistics, typically relying on model-driven and optimization-based approaches. Other

Table 6: Classification of methods for decision support.

Decision support method		Number of publications	Percentage
Category	Specification		
Optimization		**58**	62.37 %
	LP	15	16.13 %
	NLP	3	3.23 %
	Heuristic	12	12.90 %
	Metaheuristic	15	16.13 %
	Others	20	21.51 %
Simulation		**39**	41.94 %
	DES	22	23.66 %
	Agent-based modeling	3	3.23 %
	Physics- and collision-based	3	3.23 %
	Others	16	17.20 %
AI		17	18.28 %
DT		7	7.53 %
Fuzzy		6	6.45 %
Own algorithm		6	6.45 %
Visuals		5	5.38 %
Others		36	38.71 %

fields, such as in-house transport and factory layout design, are also covered, but less extensively, with a comparable reliance on simulation and optimization.

5 DISCUSSION AND OUTLOOK

While the number of publications has increased significantly, and the analysis has become representative, our classification and interpretation of DSS approaches remain heterogeneous. The terminology employed to describe the methods of DSS is also heterogeneous, with significant variations in the level of detail used to describe DSS. Consequently, the current state poses a significant challenge to the establishment of a standardized framework for the categorization of DSS, thereby impeding the capacity to conduct meaningful comparative analyses among diverse DSS. Moreover, the growing prevalence of hybrid designs in DSS underscores the potential value of subdividing DSS into distinct levels within a framework based on their underlying methods. These methods could then be systematically assigned to a knowledge base and mapped more precisely to specific tasks within the decision-making process. Such an approach would facilitate drawing more accurate conclusions about method utilization and effectiveness. This would prove a valuable asset for a range of methods, especially simulation, which is versatile in its applications. Moreover, the results of the literature research show that modeling is crucial for decision support, but different models used in one DSS must be compatible.

To address these challenges, future research should focus on developing a comprehensive framework for structuring DSS and defining clear conceptual levels within this framework. This constructive approach could pave the way for enhanced standardization and comparability across different DSS implementations. In addition to this, however, case studies and interviews should be used to examine the extent to which research with complex DSS reflects the reality in industry.

One limitation of this literature review is the necessary subjectivity in evaluating and assigning publications to categories. Moreover, the granularity of the analysis was constrained by the available data: in some subdomains, only a few relevant publications were found, limiting the robustness of insights. Also, the quality of a few publications was limited, so the described developments were not as detailed as required for such an analysis. Encountering this, journal ranking can be incorporated as a selection criterion for publications for future literature reviews in this field. Finally, the search strategy may have led to an underrepresentation of AI-based or predictive approaches, particularly if these approaches are described using an alternative terminology in the literature. Future reviews might explore alternative search terms such as "forecasting", and "prediction" to provide further understanding of emerging DSS methods. However, an analysis of the 93 publications gives a comprehensive overview of the current state of research on DSS in the field of production logistics, which can serve as a starting point for further research.

6 CONCLUSION

Out of 1.399 publications found by the databases, 93 publications for a full-text analysis were extracted, providing a structured overview of decision support systems in production logistics between 2015 and 2024.

The results indicate that most DSS in production logistics address tactical or operational decision-making tasks, especially in production planning and control. Model-driven DSS dominate, often combined with data- or knowledge-driven elements. Optimization methods are among the most commonly employed DSS methods, particularly heuristic and metaheuristic approaches. Simulation methods are most often applied in combination with other methods. Despite the increased interest in AI technologies, their role in DSS for production logistics remains secondary, where the selection of the search string can be one reason. Like simulation techniques, AI techniques are highly relevant in combination with optimization techniques. Many publications integrate multiple methods, reflecting the interdisciplinary nature needed for research in this field. The findings indicate that the method should be chosen carefully regarding the application case and modeling specifics of the problem. So, AI is not the one-method-fits-all solution for DSS.

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