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Towards self-organizing logistics in transportation: a literature review and typology

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Abstract

Deploying self-organizing systems is a way to cope with the logistics sector's complex, dynamic, and stochastic nature. In such systems, automated decision-making and decentralized or distributed control structures are combined. Such control structures reduce the complexity of decision-making, require less computational effort, and are therefore faster, reducing the risk that changes during decision-making render the solution invalid. These benefits of self-organizing systems are of interest to many practitioners involved in solving real-world problems in the logistics sector. This study, therefore, identifies and classifies research related to self-organizing logistics (SOL) with a focus on transportation. SOL is an interdisciplinary study across many domains and relates to other concepts, such as agent-based systems, autonomous control, and decentral systems. Yet, few papers directly identify this as self-organization. Hence, we add to the existing literature by conducting a systematic literature review that provides insight into the field of SOL. The main contribution of this paper is two-fold: (i) based on the findings from the literature review, we identify and synthesize 15 characteristics of SOL in a typology, and (ii) we present a two-dimensional SOL framework alongside the axes of autonomy and cooperativity to position and contrast the broad range of literature, thereby creating order in the field of SOL and revealing promising research directions.

Keywords: logistics; self-organization; literature review; distributed control; transportation

1. Introduction

The logistics sector faces many challenges related to its operations in dynamic, complex, and uncertain environments. These challenges include heterogeneous markets with high demand fluctuations, short product lifecycles with high product variations, and increasing pressure on logistics performance and costs, exemplified by shorter delivery times and delivery flexibility while aiming for

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high resource utilization and simultaneously achieving sustainability goals such as decarbonization (Windt and Hülsmann, 2007; Quak et al., 2018; Mes and Gerrits, 2019). To address these challenges, we typically require time-consuming arithmetic operations to solve logistics problems on an operational level (e.g., job-shop scheduling and vehicle routing), in which uncertainties and disturbances frequently occur. This often has the effect that information or the environment changes during decision-making processes, resulting in an infeasible decision even before the execution of plans commences (Windt and Hülsmann, 2007).

A way to cope with the logistics sector's complex, dynamic, and stochastic nature is to deploy self-organizing systems in which automated decision-making and decentralized or distributed control structures are combined. Such control structures reduce the complexity of decision-making, require less computational effort, and are therefore faster, reducing the probability that changes during decision-making render the solution invalid. This requires a shift from manual to automated decision-making and from central-oriented control structures to decentralized or distributed control structures. While central control structures and global optimization methods may still be efficient in more stable environments—as from a systems perspective, they can (theoretically) make better decisions by utilizing all available information—they are less suitable for dynamic and complex environments. This is because central control (i) typically requires a large amount of information in advance, (ii) is sensitive to information updates, (iii) is not able to respond in a timely manner, and (iv) is not flexible enough to deal with changing environments and settings with multiple autonomous actors (Mes et al., 2007).

In a decentralized control structure, automated decision-making is delegated to lower levels in the hierarchy, resulting in a system that is less prone to a single point of failure and can quickly respond to changes and disturbances through local decision-making. Such systems can inhabit certain *self-organizing* properties requiring limited or no supervisory control. However, the absence of supervisory control may also lead to unintended or chaotic behavior when relying solely on local decision-making and interactions. A system should thus be tweaked and steered toward a desired configuration (Gershenson, 2012), which is also underlined by Choi et al. (2001, p. 351), who state that "*imposing too much control in a complex system detracts from innovation and flexibility; conversely, allowing too much emergence can undermine managerial predictability and work routes*."

Examples of self-organizing systems from nature include flocks of birds, schools of fish, herds, and crowds (Camazine et al., 2003). Such self-organizing systems are able to achieve a global function or behavior (Gershenson, 2005) through cooperative behavior and show a form of optimization through learning and by adapting to the environment. The prevailing elements of self-organization in biological systems are: (i) the absence of external or central control (i.e., autonomy) and (ii) local interactions that induce global behavior (i.e., cooperative behavior). As such, biological systems provide inspiration for designing logistics control systems, where external control is limited and decision-making is initiated through local interactions between autonomous actors or assets, which is denoted by self-organizing logistics (SOL).

This paper addresses the notion of SOL through a systematic literature review (SLR) with a focus on transportation. A notion related to SOL is that of agent-based systems, which are widely applied in logistics through an abundant stream of literature, for example, see Caridi and Cavalieri (2004) and Lee and Kim (2008). However, we are more broadly interested in the concept of SOL and aim to explore all types of self-organization in logistics and expose its characteristics. Therefore, we review the logistics literature in a broad sense and do not focus solely on a specific solution method (e.g., agent-based systems) and provide a detailed classification to catalog SOL papers on several relevant characteristics. We utilize the SLR methodology of Durach et al. (2017) to assess the state of the art, identify promising research areas, and address the logistics sector's challenges. The contributions of this paper are as follows. First, we provide a universally applicable definition of SOL, as there is currently limited insight into what qualifies as SOL. Second, we provide an overview of SOL with a SLR. Third, based on the findings of the review, we establish a comprehensive typology, identifying 15 characteristics of SOL. Last, we unify the review's findings in a two-dimensional SOL framework alongside the notions of autonomy (i.e., degree of external control) and cooperativeness (i.e., degree of useful interactions), allowing researchers to position and compare works related to SOL.

Before conducting the literature review, we elaborate on the notion of SOL and related literature in Section 2. In Section 3, we present the SLR process and present the acquired insights in Section 4. Based on the review, we present an SOL typology in Section 5 and present a two-dimensional SOL framework in Section 6. We close with conclusions and directions for further research in Section 7.

2. Related literature and research context

Despite the lack of a structural review and analysis of SOL, the need and potential to shift from conventional logistics decision-making approaches (e.g., global optimization) to methods leaning toward autonomy and self-organization is underlined throughout the literature. For example, Windt and Hülsmann (2007) mention that the logistics sector faces increasing complexity in decision-making processes and simultaneously faces high customer expectations, such that centralized planning and control systems are no longer adequate to manage this complexity in a feasible manner. According to the authors, this characterizes a "paradigm shift" from centralized control of "non-intelligent" items to decentralized control of "intelligent" items. Moreover, "decentralized autonomous control" intends to improve performance by coping with such complexity in a distributed and flexible fashion (Scholz-Reiter et al., 2011). This aim is also underlined by Wagner and Kontny (2017, p. 255), who state that "*the main drivers for the development and implementation of self-organizing adaptive operation processes are the increase of flexibility while lowering costs in times of growing consumer demand*" and present a use case on automated and self-organizing data analysis to establish an adaptive supply chain. Moreover, the abovementioned elements are included in the work of Serugendo et al. (2005), who state that the absence of external control, decentralized control, and dynamic operations are important properties of self-organizing systems. Also, they provide some characteristics of self-organizing systems, including endogenous global order, emergent behavior, simple local rules, instability, adaptivity, and complexity. Last, Gershenson (2007, p. 34) notes that self-organization is not the only approach for designing and controlling systems, but it "*can be very useful in complex systems where the observer cannot a priori conceive all possible configurations, purposes, or problems that the system may be confronted with*" and mentions traffic control, distributed robotics, and complex software systems as examples of such systems. Despite these early advocates of SOL, systematic analyses of SOL seem to be missing so far.

As discussed in the previous section, the notion of self-organization originates from natural systems. In particular, the field of complex (adaptive) systems studies self-organization and related emergent phenomena in both natural and artificial systems (Camazine et al., 2003; Bar-Yam, 2020). However, given the scope of this paper, the discussion of the related literature will be limited to self-organization in logistics (see Section 2.1). Moreover, based on the analysis of the related literature, we provide a definition of SOL in Section 2.2.

2.1. Self-organization in logistics

One of the first papers that specifically uses the term "self-organizing logistics" is the work of Bartholdi et al. (2010), who identify the advantages and disadvantages of SOL and provide a practical application for assembly lines. The authors denote logistics systems as self-organizing when they "*can function without significant intervention by managers, engineers or software control"* and view self-organization as a promising way to solve problems in logistics due to its ease of implementation, adaptivity, and minimal data requirements. In their approach to control assembly lines, the authors propose a simple rule stipulating that workers are not assigned to a single work station but are numbered. Each worker carries work forward from station to station until they are finished or when another worker takes over. In those cases, the worker walks back upstream and takes over the work of the first worker with a lower number. Under the assumption that worker productivity can be modeled as a (walking) velocity and that the work effort is spread continuously and uniformly along the line, the authors show that such an assembly line balances itself when workers are sequenced from slowest to fastest. Their approach provides a robust solution when configured properly but may also show chaotic behavior when this is not the case. The authors show that the decision-making processes of handovers to other workers, according to the principle described above, result in a self-organizing assembly line, where faster workers are eventually allocated more work. Moreover, in the work of Bartholdi and Eisenstein (2012), the same authors propose a "self-equalizing" method of coordinating buses on a circular route such that they spontaneously equalize headways, without external control by managers or by the awareness of the bus driver. In an earlier paper, Bartholdi and Platzman (1989) address decentralized control of automated guided vehicles (AGVs) on a simple loop, focusing on elements such as incomplete knowledge and autonomous decision-making, but the authors do not yet use the notion of self-organization.

Pan et al. (2017) further specify SOL, using the notions of openness, intelligence, and decentralized control, but do not provide a practical application. In the view of these authors, an SOL system needs to (i) be open, such that actors or assets can freely join or leave the system; (ii) be intelligent, such that individuals in the system are able to make decisions autonomously; and (iii) have rule-based decentralized control with a system-wide common goal and individual-wide protocols. Similarly to Bartholdi et al. (2010), they view SOL as a system "*without significant intervention of humans and without central control by software*." Interestingly, these authors explicitly add the absence of centralized control to the definition of SOL. Moreover, Pan et al. (2017) expect SOL to have the following advantages: effective, efficient, agile, flexible, resilient, and sustainable.

Several authors discuss specific examples of SOL without addressing its definition, with examples including transportation (Hongler et al., 2010), order fulfillment (Reaidy et al., 2015), and Physical Internet (PI) (Sallez et al., 2016), as well as emergent behavior in supply networks (Choi et al.,

2001) and parcel distribution (Quak et al., 2019). The latter adopts the same definition as Pan et al. (2017) and is one of the few papers combining autonomous robots with SOL but lacks a general approach to extrapolate within the broader domain of logistics. More general approaches focus on other areas, such as cyber-physical systems (Gershenson, 2020), reverse logistics (Jaaron and Backhouse, 2015), and city planning (Rauws et al., 2020). To the best of our knowledge, the literature lacks an endeavor to structure the multitude of attempts to use various forms of control delegation within logistics, being it denoted by agent-based systems, decentralized control, distributed systems, holonic systems, self-organization, or others. This paper aims to fill that void.

2.2. Definition of SOL

For the sake of this review, we adopt a practical definition of SOL to classify and review the available literature. Our definition builds upon the descriptive definition of SOL presented in Bartholdi et al. (2010) and the notions presented in Pan et al. (2017) and is as follows:

> Self-organizing logistics is a logistics control system in which decision latitudes are—at least partially—delegated to intelligent, autonomous assets through decentralization to achieve some form of optimization.

Note that we use the somewhat loaded term *optimization*. By this, we do not necessarily mean optimization from a mathematical point-of-view (i.e., explore a solution space to find an optimum of a given objective function) but rather take a practical angle and use the term to denote preferable, non-trivial behavior of the system. From our definition, we distill three notions on which SOL is built—logistics, decentralization, and intelligence—providing a starting point for our SLR.

2.2.1. Logistics

The self-organizing properties of the control system should relate to decision-making for (complex) problems in the logistics sector. The decision-making capabilities should (at least partially) rest at autonomous actors or assets within the logistics domain. These include, among others, transportation resources (e.g., trucks, ships, autonomous vehicles), transportation units (e.g., containers, pallets), storage locations, robots, or entire organizations.

2.2.2. Decentralization

Unlike Pan et al. (2017), we do not rule out (partial) central control. More specifically, we use the term *decentralization* to denote the process of establishing a certain *degree* of control delegation, as opposed to decentral control, as the latter hints at a fully decentralized system without any central elements. In a *distributed* control system, some or all (i.e., a fully decentralized system) of the decision-making capabilities are distributed throughout the control hierarchy, typically to lower levels in the hierarchy. We thus denote the process of delegating control throughout the control hierarchy by the concept of decentralization. Hence, SOL may inhabit central or supervisory elements. Autonomous assets may benefit from some degree of centralized control, for example, when (i) decentral units are not able to reach a mutual understanding, (ii) the established self-organization shows unintended or chaotic behavior, or (iii) the system reaches a scenario in which the decision-making capabilities of the decentral units are no longer sufficient. More generally, we may see SOL systems in which decentralized decisions are based on centralized information or centralized decisions are based on decentral information (e.g., decentral assets share part of their data). However, we exclude fully centralized decision-making (i.e., central information and central decision-making), as in that case all decision-making logic and power resides with a single stakeholder, deploying global optimization, which does not exhibit self-organizing behavior.

2.2.3. Intelligence

To establish autonomous behavior and reach some form of optimization, autonomous assets must have a certain level of intelligence to make decisions autonomously. This behavior may range from basic rule-based logic to self-learning units that adapt to their environment. Note that decision-making by autonomous assets is a characteristic of self-organizing systems. Thus, in our view, self-organization goes a step further than *autonomous control*, for example, by being able to show emergent or unexpected behavior.

2.3. Research context and demarcation

Before performing the SLR based on the methodology proposed by Durach et al. (2017), we first need to identify a useful demarcation. As a pre-processing step of our review (see also Fig. 2 in Section 3.4), we first need to find keywords related to “self-organization,” “logistics,” and “decision-making” to establish a useful and bias-free scope for the review.

First, to find keywords related to “self-organization,” we consulted review articles on self-organization using Scopus. We visualized the top keywords of the literature found by this strategy using *VOSViewer* (see Section 3.4 for details) and included these keywords in the search. We found that relevant papers are often connected to the following keywords: “distributed control,” “decentralized control,” “decision,” “multi-agent,” “agent-based,” and “holonic.” In our next step, we included the abovementioned relevant keywords using the OR operator and limited the search results to relevant domains, resulting in over 192,000 papers of which roughly 2000 were reviews. Although the number of results is too large to review manually, we identified useful keywords related to self-organization during this step.

Second, we aimed to find useful keywords related to “logistics.” We found more than 2600 reviews solely on logistics in the last five years. From the keyword visualization tool, we found that the logistics domain is simply too broad for a comprehensible SLR on self-organization. Therefore, we limited our scope and decided to focus on the transportation domain.

Last, we aimed to find keywords related to “decision-making.” We searched for papers with at least one keyword from both sets: (i) intelligent, adaptive, optimization, or autonomous and (ii) planning, routing, scheduling, algorithm, decision support, decision-making, or problem-solving. After limiting this query to the transportation domain, we found 516 review articles. We again visualized the top keywords from these articles.

Using this step-wise approach, we tried to obtain a search strategy free from bias and to balance the workload of reviewing the papers without limiting our focus too much. The keyword analysis and final search query are further discussed in Section 3.4.

3. SLR

The goal of this paper is to provide a state-of-the-art overview of SOL. We specifically focus on intelligent decision-making to control or optimize operations by analyzing and synthesizing the extant literature and proposing promising directions for future research. This review adopts the SLR methodology proposed by Durach et al. (2017), which consists of the following six steps: (1) define the research questions, (2) determine the inclusion and exclusion criteria, (3) determine search procedures, (4) select pertinent literature based on inclusion/exclusion criteria, (5) synthesize literature, and (6) report the results. These steps are discussed in dedicated Sections 3.1 to 3.6.

3.1. Research questions and theoretical framework

The first step of the SLR methodology of Durach et al. (2017) is to define the purpose of the SLR. Our goal is to get an overview and understanding of self-organization in the extant logistics literature by addressing the following research questions:

RQ 1. How to perform a categorical analysis of the literature related to SOL?
RQ 2. How to characterize SOL in a descriptive and holistic manner?
RQ 3. How to establish a spectrum of SOL to compare research efforts and identify research directions?

RQ1 is answered using our SLR, and the categorization is presented in Section 4.1. Based on the review's findings, RQ2 is answered by presenting an SOL typology in Section 5, and RQ3 is answered in Section 6 by presenting a two-dimensional framework to compare research efforts and identify research directions.

3.2. Inclusion and exclusion criteria

The criteria to select studies, as well as the reasoning behind each criterion, are presented in Table 1. We include papers that have been published as journal articles, conference proceedings, or book chapters in the past 30 years that focus on (semi-)autonomous decision-making in logistics in relevant academic fields. Moreover, we exclude papers that do not address a (practical) application or focus solely on (offline) global optimization methods.

3.3. Search procedures

Our search procedure consists of three steps: (i) determine the scientific database that serves as a source, (ii) define a list of relevant keywords, and (iii) construct a search query. The first step of the search procedure is to locate relevant literature in the field of logistics in a well-known scientific database. For this review, we select the Scopus database, as it is one of the world's largest abstract and citation databases (see https://www.elsevier.com/solutions/scopus).

Table 1
Inclusion and exclusion criteria

Inclusion criteria	Exclusion criteria
Paper published between 1991 and 2021 (available online included)	Paper does not specify a specific application
Paper published as journal article, conference proceedings, or book chapter	Paper addresses people transportation or public transit
Paper written in English	Paper addresses ride-sharing or navigation
Paper investigating (semi-)autonomous decision-making in logistics	Paper addresses only IT components
Paper's subject area should be part of one of the following domains: computer science, engineering, mathematics, decision sciences, business management, or economics	Paper addresses only (off-line) global optimization methods
Paper is an earlier version of a different paper in the review	Avoid duplicates and exclude earlier versions of a paper

Table 2
Search strategy for keyword analysis

Keyword Group	Search query
1	TITLE-ABS-KEY [transport* OR routing]
2	TITLE-ABS-KEY [Self-organising OR self-organizing OR cyber-physical OR Internet of Things OR Physical Internet OR multi-agent OR agent-based OR holonic OR distributed control OR decentralized control OR distributed decision OR decentralized decision]
3	TITLE-ABS-KEY [intelligen* OR adaptive OR optimi*ation OR autonom*]
4	TITLE-ABS-KEY [planning OR routing OR scheduling OR algorithm OR decision support OR decision-making OR problem solving]
5	NOT TITLE-ABS-KEY [biological OR biochemical OR animal OR cell OR psycho* OR drug OR clinical OR disease* OR hospital OR chemis* OR health-care OR health care OR healthcare OR thermo OR thermal OR lithium OR membranes OR graphene OR nanotechnology OR fluid dynamics]
6	LIMIT-TO [SUBJAREA, "COMP"] OR LIMIT-TO [SUBJAREA, "ENGI"] OR LIMIT-TO [SUBJAREA, "MATH"] OR LIMIT-TO [SUBJAREA, "DECI"] OR LIMIT-TO [SUBJAREA, "BUSI"] OR LIMIT-TO [SUBJAREA, "ECON"]

The second step is to define a list of keywords. As discussed in Section 2.3, we perform a bibliometric study to find related keywords not initially included by the authors. We deploy the visualization tool *VOSviewer* to analyze the relationships between keywords and identify the most frequent co-occurring keywords, comprehensively covering all aspects of our research problem. Based on this procedure and the application of multiple combinations of keywords, we aim to find an exhaustive list of relevant literature. Recall from Section 2.3 that we limited ourselves to the transportation domain. Using *VOSviewer*, we construct a bibliometric map based on the 2000 highest-cited papers from the search query shown in Table 2. All keyword groups are combined using the AND operator in the search query. The bibliographic map is shown in Fig. 1.

In the third step, we build the final search query. After analysis of the bibliographic map, we found that many papers were related to transport but not necessarily to logistics, which includes applications such as ride-sharing and public transport. Therefore, we explicitly added the keyword

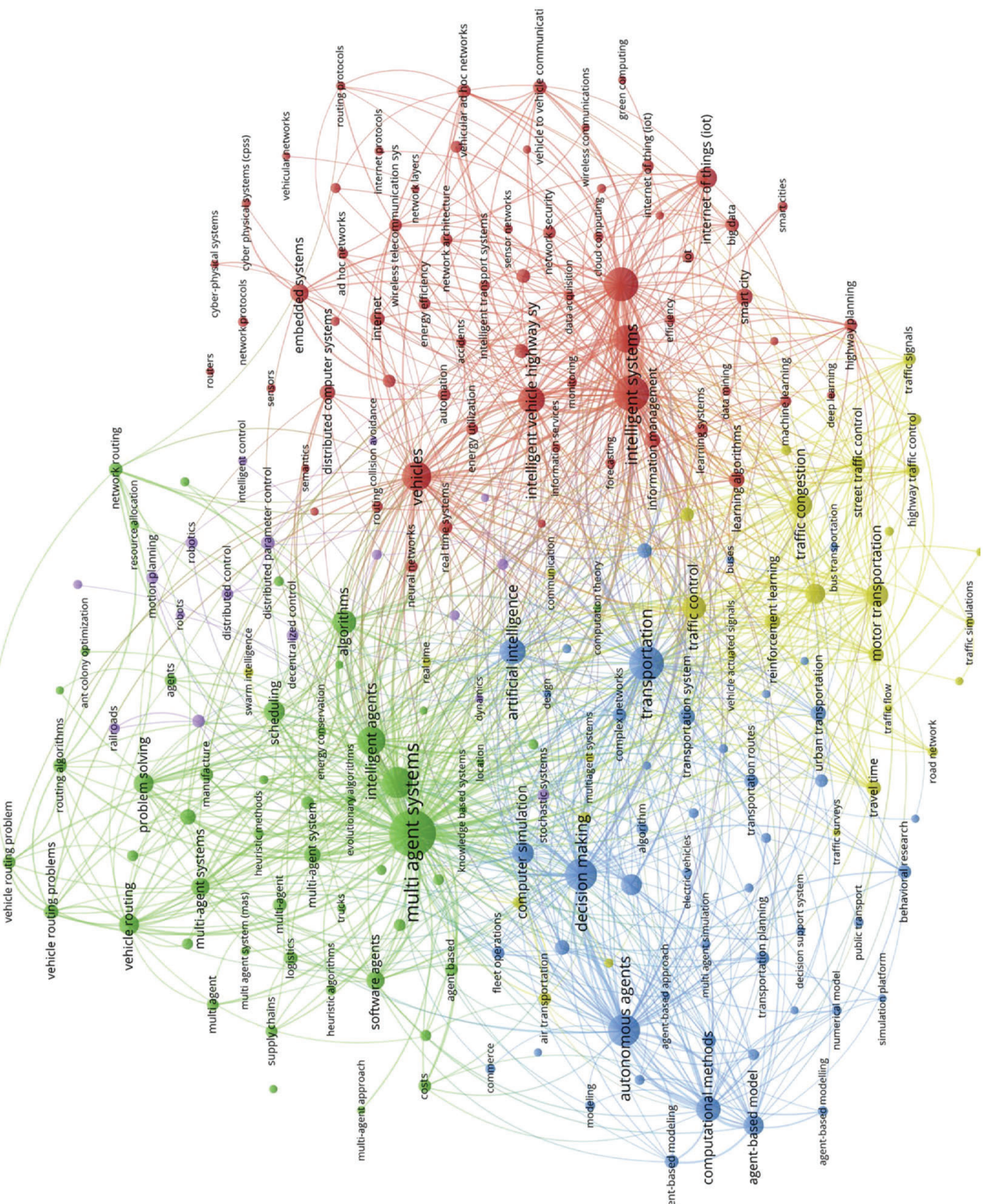

Fig. 1. Bibliographic map to identify keywords for the final search strategy.

Table 3
Final search strategy

Keyword Group	Search query
1	TITLE-ABS-KEY [logistic*]
2	TITLE-ABS-KEY [transport* OR routing]
3	TITLE-ABS-KEY [Self-organising OR self-organizing OR cyber-physical OR Internet of Things OR Physical Internet OR multi-agent OR agent-based OR holonic OR distributed control OR decentralized control OR distributed decision OR decentralized decision]
4	TITLE-ABS-KEY [intelligen* OR adaptive OR optimi*ation OR autonom*]
5	TITLE-ABS-KEY [planning OR routing OR scheduling OR algorithm OR decision support OR decision-making OR problem solving]
6	LIMIT-TO [SUBJAREA, “COMP”] OR LIMIT-TO [SUBJAREA, “ENGI”] OR LIMIT-TO [SUBJAREA, “MATH”] OR LIMIT-TO [SUBJAREA, “DECI”] OR LIMIT-TO [SUBJAREA, “BUSI”] OR LIMIT-TO [SUBJAREA, “ECON”]

“logistic” to our search strategy. As a result, we found that some exclusion criteria (i.e., Keyword Group 5 in Table 2) were no longer required, as the final search query only brought papers relevant to logistics. The final search query consists of six keyword groups as shown in Table 3. The first group limits our search to the field of logistics, while the second group narrows this down to transport or routing. The third group consists of relevant keywords for self-organization and decentralization in general. The fourth group limits our search to include only papers focusing on intelligent or autonomous optimization, and the fifth group contains the decision-making problems we are interested in. The sixth group applies our inclusion criterion regarding relevant academic fields. All groups are combined using the AND operator.

3.4. Literature selection

Based on the search query from Table 3, performed on 24 May 2023, we found 553 papers relevant to our research problem. After screening the abstracts of these papers using the criteria from Table 1 in Section 3.3, 328 papers were selected for a full-text review. When reviewing the full text, we paid specific attention to the applicability of the paper for our review and again applied the exclusion criteria presented in Table 1. This resulted in the exclusion of 159 papers, and finally 169 papers were selected for review and analysis. All the steps of the literature selection process are shown in Fig. 2.

3.5. Literature synthesis and categorization

We choose to categorize the literature on five criteria: logistics, decentralization, intelligence, validation, maturity, and degree of self-organization, each containing subcriteria selected by the authors, as shown in the classification structure in Fig. 3. How we use these criteria to classify the literature

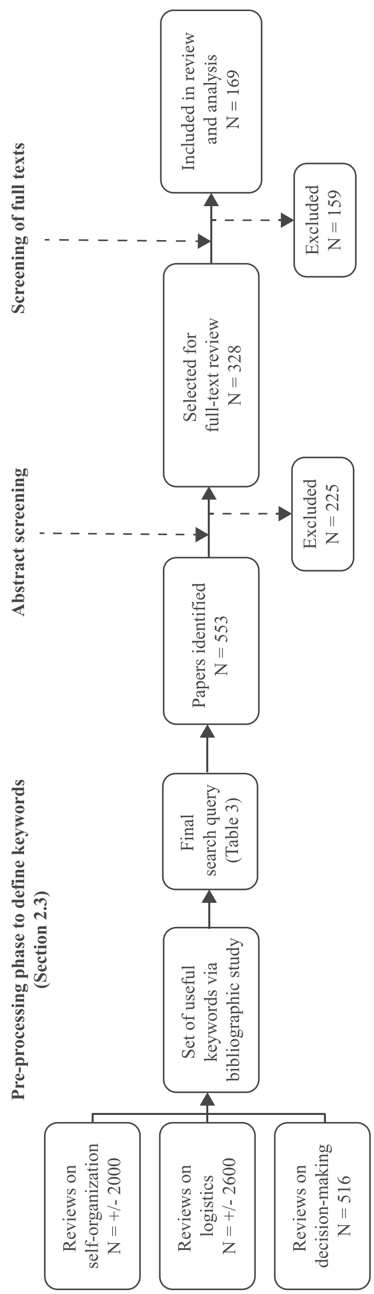

Fig. 2. Steps in the literature selection.

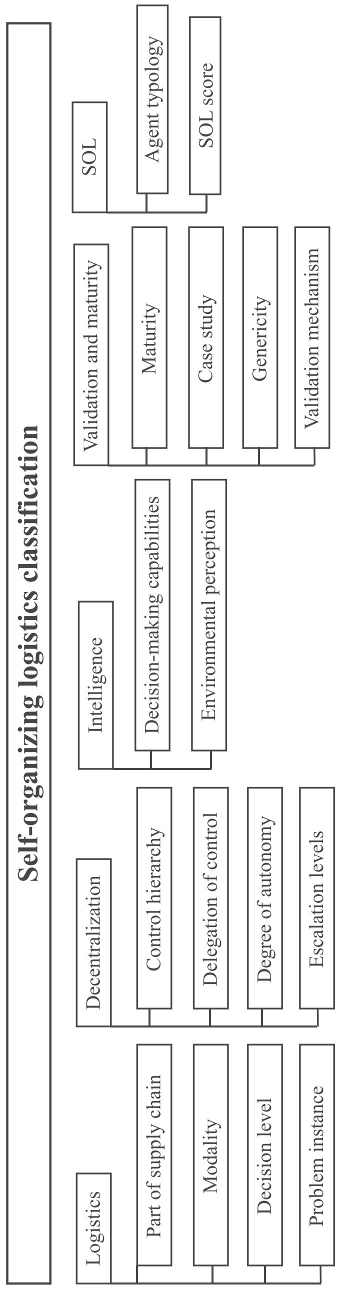

Fig. 3. Literature classification structure.

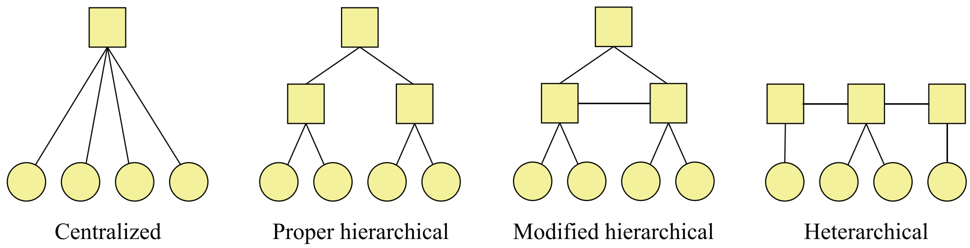

Fig. 4. Control architectures (square = decision-making entity, circle = execution only). Adopted from Mes and Gerrits (2019).

is further discussed in this section. The 169 papers identified in this review are presented alongside this structure Appendix 1.

3.5.1. Logistics

The first group focuses on logistics and contains four subcategories. First, the specific part of the supply chain is addressed. During our review, we identified many different scopes and clustered these into seven categories. For example, we found papers focusing on port logistics, container terminals, sea ports, and berth scheduling and clustered these in the category "ports and terminals." Second, the mode(s) of transport under consideration are identified and assigned to one of 12 categories (e.g., trucks, trains, aircraft, and automated vehicles). Third, we identified which type of decision-making is considered. We clustered these in a commonly used typology in logistics, that is, strategic, tactical, and operational decision-making. Last, the size of the problem instance is considered. That is, the number of entities (e.g., agents, vehicles, trucks) of the problem instance considered in a paper. To create a categorical analysis, we identified four categories, depending on how many actors or assets are included in the problem instance: small (1–10), medium (10–50), large (50–100), and very large (100+).

3.5.2. Decentralization

The group of decentralization is split into four subcategories: control hierarchy, delegation of control, autonomy location, and escalation levels. The first is used to classify the literature on control hierarchy (see Fig. 4). We use three clusters to classify the control hierarchy: central, hybrid (i.e., proper and modified hierarchical), and decentral (i.e., heterarchical). Second, the delegation of control is identified. This denotes which type of decisions are delegated for autonomous decision-making by the actors or assets under consideration. Several clusters are identified. For example, velocity control and navigation are allocated to "vehicle control," and all decisions related to the planning and control of transport are allocated to "transport planning." The third category denotes where the autonomy actually resides. For example, in a hybrid control hierarchy, decisions can be made centrally, decentrally, or a combination of both. The fourth category denotes whether any escalation mechanisms are considered; for example, in certain scenarios, a decentral autonomous asset may not be able to show useful behavior, and a central agent (or human supervisor) is asked for additional information or the decision-making is handed over to the central agent.

3.5.3. Intelligence

The intelligence group is divided into two subcategories: decision-making capabilities and environmental perception. The first subcategory denotes the type of algorithm or heuristic being deployed to solve the problem at hand (e.g., agent-based or metaheuristics). The second subcategory denotes how the paper addresses the environmental perception of the autonomous actors or assets (e.g., utilizing sensor data from Internet of Things (IoT) devices).

3.5.4. Validation and maturity

In this group, the validation and level of maturity of the literature are identified. We identify the genericity of the paper (ranging from low to high), which validation techniques are used (e.g., absent, simulation, or real life), and whether the paper includes a real-life or theoretical case study. Last, we assess the maturity of the paper in terms of the stage of the implementation process (e.g., ideation phase, conceptual model, simulation, pilot implementation, or deployed).

3.5.5. Self-organization

The last category synthesizes the findings to assess the degree of SOL. We are interested in the extent to which we can speak of SOL. We use a five-point scale to classify the literature: 0—*no autonomy or self-organizing properties* (no SOL), 1—*very limited application of SOL*, 2—*basic application of SOL*, 3—*advanced application of SOL*, 4—*best examples of SOL*. Additionally, as we will see in Section 4.1, the majority of the SOL literature uses the notion of multi-agent systems or agent-based modeling, hereafter simply referred to as MAS. During the review, we found that this notion differs significantly per paper and affects the degree of SOL. Therefore, we classify the papers considering MAS using the following typology: (i) the MAS is used as a decomposition method to break down a complex system but typically remains (highly) central; (ii) the MAS is used as a method to study the system in a simulation environment, that is, agent-based simulation; (iii) the MAS is used to model already autonomous actors in practice, for example, a collaboration between companies; and (iv) the MAS is used to delegate control to traditionally non-autonomous digital or physical assets (i.e., orders, containers, or pallets). We expect that especially the latter two categories will play a role in SOL.

3.6. Reporting of results

The final step of the methodology of Durach et al. (2017) is reporting the results. We focus on a categorical analysis, which provides insights into the key aspects of SOL alongside the elements of the classification structure presented in Fig. 4. This analysis is performed in Section 4.1.

4. Results and key findings

The results rely on 169 articles included in the review, published between 1994 and 2023. Eighty-nine papers were part of conference proceedings (52%), 69 were published in journals (41%), and 11 were book chapters (7%). Particularly for the conference proceedings, the included papers are

Table 4
Categorization of papers regarding logistics

Logistics					
Category	Value	#	Category	Value	#
Application area	General transport	97	Decision type	Strategic	7
	Internal logistics and material flow	30		Tactical	20
	City and urban logistics	16		Operational	140
	General supply chains	9		Not specified	2
	Ports and terminals	8			
	Inter- and multi-modal transport	7			
	Agriculture	1			
	Reverse logistics and spare parts	1			
Mode of transport	Trucks	78	Problem instance size	Small	54
	Automated vehicles and robots	21		Medium	46
	Aircraft	1		Large	14
	Bikes	2		Very large	26
	Delivery vans	7		Not specified	29
	Vehicles	15			
	Barges and vessels	9			
	Internal transport	4			
	Multi-modal	7			
	Cars	2			
	Trains	5			
	Other	3			
	Not specified	15			

spread very thin over a wide range of conferences, 64 in total. Moreover, 36 different journals are included in the review. Based on our literature classification structure, we provide a categorical analysis in Section 4.1 and present the research trends and insights in Section 4.2.

4.1. Categorical analysis

This section reports the findings of the categorical analysis from the literature review. We provide an overview of the classification of the papers alongside the classification structure presented in Section 3.5. The findings are presented in the following order: logistics (Table 4); decentralization (Table 5); intelligence (Table 6); and validation, maturity, and degree of SOL (Table 7). The full categorization can be found in the Appendix 1. For every table, we briefly discuss two exemplary papers (i.e., with a high SOL score) to facilitate a discussion per category pertaining to SOL (e.g., decentralization) and to highlight the use of self-organization for the decision-making process under consideration in these papers.

From Table 4, we see that the majority of papers included in the review focus on general transport (97) and particularly on trucks (78). Thirty papers focus on internal logistics or material flow, in which automated vehicles and robots are often considered (19). Over 80% of the papers focus on operational decision-making, which can be expected given the notion of self-organizing systems,

Table 5
Classification of papers regarding decentralization

Decentralization					
Category	Value	#	Category	Value	#
Control hierarchy	Central	41	Where is the autonomy?	Central	51
	Hybrid	55		Hybrid	14
	Decentral	73		Decentral	101
				Not specified	3
Delegation of control	Transport planning	101	Escalation levels	None	165
	Routing	11		Active involvement	3
	Intralogistics	7		Additional information	1
	Vehicle control	9			
	Resource scheduling	5			
	Network design	5			
	Allocation	2			
	Manage processes	2			
	Multiple decisions	2			
	Other	6			
	No delegation	13			
	Not specified	6			

where decision-making typically involves real-time or online problems. Moreover, the size of the problem instance is often not specified (29 papers). These are typically papers that have a low maturity (e.g., ideation phase) or do not provide a case study. Interestingly, many papers have a small or medium problem instance size. Given the decentralization aspect of SOL, it would be expected that particularly large problem instances benefit from SOL, yet such instances are rarely observed in the analyzed papers. Further analysis shows that of the papers that deploy a central control hierarchy, 73% have a small or medium problem instance. For the other control hierarchies under consideration, the size of the problem instances is roughly evenly distributed (i.e., 50% small or medium and 50% large or very large). How self-organization can aid decision-making in logistics is illustrated using two examples below.

First, to illustrate self-organizing decision-making in supplier/customer relationships, Berndt (2013) focuses on tactical decision-making in general supply networks and uses a self-organizing mechanism to aid decision-making regarding the order/delivery processes. The author models the supply network actors as autonomous agents and models the business relations between entities as either the role of a supplier or the role of a customer. Each agent has a different objective according to its role and is represented by a utility function and a selection method. The supplier aims to fulfill orders; if not all orders can be fulfilled, a supplier prefers regular customers due to their predictability. A customer agent has two objectives: (i) maximize the number of fulfilled orders and (ii) minimize the number of receivers per message to ensure low communication efforts. The author shows through simulation that the approach autonomously decides upon relationships between

Table 6
Classification of papers regarding intelligence

Intelligence					
Category	Value	#	Category	Value	#
Decision-making capabilities	Agent-based	79	Environmental perception	IoT	27
	Exact method	22		Traditional IT (Information Technology)	5
	Metaheuristics	25		GPS (Global Positioning System)	2
	Other heuristics	18		Geo-data	3
	Artificial Intelligence	11		Sensors	2
	Simulation heuristics	1		Physical Internet (PI)	8
	Not specified	13		Wireless networks	2
				RFID (Radio Frequency Identification) and barcodes	6
				Not specified	114

Table 7
Classification of papers regarding validation, maturity, self-organizing logistics (SOL) score, and multi-agent systems (MAS) typology

Validation and maturity					
Category	Value	#	Category	Value	#
Maturity	Simulation	115	Genericity	Low	27
	Conceptual model	13		Semi-generic	77
	Numerical experiment	18		High	59
	Ideation	1		Very high	6
	Deployed	5			
	Prototype	10			
	Development phase	1			
	Design phase	4			
Case study	Yes (real life)	64	Validation	Yes (simulation)	92
	Yes (hypothetical)	40		Yes (real world)	13
	No	61		Partially	5
	Not specified	4		No	59
SOL score and MAS typology					
Category	Value	#	Category	Value	#
SOL score	No autonomy (0)	10	MAS typology	Not applicable	45
	Very limited application (1)	31		Decomposition method	44
	Basic application (2)	60		Agent-based simulation	17
	Advanced application (3)	47		Modeling already autonomous actors or assets	27
	"Best of breed" application (4)	21		Delegation of control to physical or digital actors/assets	36

suppliers and customers, without a priori assumptions about agent characteristics or negotiations, with near-optimal performance regarding customer satisfaction and fulfillment rates.

Second, to support interdependent task planning, Ter Mors et al. (2004) present a framework for coordinating autonomous planning agents. They propose a coordination method that guarantees a solution to a joint planning problem, whatever plans agents may have constructed independently, while respecting the autonomy of each agent and using limited information sharing. They apply their approach to a multi-modal planning problem with stand-alone planners that require joint efforts of several planners who are dependent on each other. They compare their approach to other (centralized) planning systems, finding that their coordination method only requires a fraction of computation time and outperforms the other systems concerning plan quality.

From Table 5, we see that roughly half of the papers (73) included in the review focus on a decentral control hierarchy, which aligns with the notion of self-organization. Moreover, many papers have a hybrid control hierarchy (55), combining central and decentral elements. In self-organizing biological systems, central control is fully absent, but from this analysis, it can be concluded that artificial self-organizing systems may contain some central elements. Nevertheless, in roughly 60% of the papers (101), the (decision-making) autonomy resides fully at the decentral level. Furthermore, the decisions that are delegated are mostly related to transport planning, which is in line with the part of the supply chain most papers focus on. Interestingly, only four papers include some form of escalation (e.g., human involvement). The remainder of the papers fails to identify that the autonomous control system deployed may not adequately solve the problem at hand or may result in unintended or chaotic behavior. From our perspective, this can be explained in three ways: (i) the authors simply do not consider the possibility of this behavior, (ii) the delegation of control is merely used as a decomposition method, or (iii) the decentral actors or assets are strictly bounded in their autonomous decision-making by (rule-based) heuristics with predictable outcomes. In the latter two situations, it is unlikely that emergent or unexpected behavior will arise.

An example of the aspect of decentralization is presented by Jaaron and Backhouse (2015). The authors focus on reducing costs resulting from reverse logistics, caused by forward logistics inefficiencies, by empowering employees to learn from and interact with customers to create informal learning on the causes of failures or unsatisfied customers. The authors recognize the added value of self-organization when encountering random events and failures. The added value is achieved through decentralized, team-based informal structures that enable knowledge sharing and learning emergence. Another example includes the work of Feng et al. (2017), who propose a decentralized decision-support system for hinterland transport. They argue that a centralized planning system can optimally coordinate all stakeholders regarding their schedules and resources but requires full cooperation from all stakeholders. The latter undermines the autonomy of the decision-makers and will not be a feasible solution in practice. Their decentralized approach enables every single party to preserve their autonomy and requires only limited information sharing.

From Table 6, we see that predominantly agent-based systems are used as a solution method for SOL. Further analysis shows that 95% of the agent-based systems have a decentral or hybrid control architecture. Interestingly, exact methods are also used often and in all control hierarchies. Further analysis shows that papers using an exact solution method have a low SOL score, whereas agent-based systems have a higher SOL score. This is further discussed at the end of this section.

Moreover, 111 papers do not address the environmental perception of the actors or assets. If addressed, IoT is used most often (27 papers).

As an example of intelligence in SOL, Yu and Haisheng (2020) present a method for path planning for AGVs based on deep reinforcement learning such that the vehicles have a certain degree of self-learning abilities to cope with unknown environments and adapt to dynamic environments. Another example of intelligence in SOL is given by Van Heeswijk (2020), who presents an algorithm for smart containers to learn bidding strategies. The key notion is that bidding experiences are shared among containers, enabling them to jointly learn policies while retaining autonomous bidding capacity and safeguarding sensitive information. The study indicates that decentralized learning can yield high-quality negotiation policies, even in the case of rudimentary IoT intelligence.

The maturity level of most papers (68%) is limited to simulation. Only a few papers are matured to the prototype phase (10) or deployed systems (5). Moreover, 13 papers (8%) only present a conceptual model. In addition, roughly half of the papers include a real-life or hypothetical case study to illustrate or evaluate their self-organizing approach. Ninety-two papers validate their approach using simulation, and only nine papers have a real-world validation. In terms of genericity, most papers have a semi-generic approach (77) or a highly generic approach (59).

While reviewing the literature, we noticed that the agent paradigm is used in different ways, which leads to confusion concerning the specific meaning. Therefore, we introduce a MAS typology based on different meanings of agent-based systems we found throughout the literature and classify the literature accordingly. Obviously, when no agents are used, this typology is not applicable. Forty-four papers use the agent paradigm as a decomposition method, in which a large problem is broken down and allocated to different agents to solve specific parts of a global problem, but the system remains mostly central. In 17 papers, agents are used as a method to study systems in a simulation environment, that is, agent-based simulation. Moreover, 27 papers use agents to model the autonomous behavior of actors or assets that are already autonomous in the real world (e.g., a collaboration between different companies). Real autonomous decision-making by actors or assets, which in real life typically do not have decision-making capabilities (e.g., orders, containers, or vehicles), is addressed in 36 papers.

Moreover, we scored the papers based on our view of how well the paper fits the characteristics of SOL, ranging from no self-organizing or autonomous control to fully self-organizing and autonomous control (i.e., closely mimicking biological self-organizing systems). We found that 10 papers do not consider any form of local autonomy (i.e., they consider fully centralized control), and 31 papers have a very limited application of SOL, that is, only one or a few elements addressed in the paper can be considered self-organizing. Most papers have a basic application of SOL (60), but there are 47 papers containing an advanced application of SOL. Last, we classified 21 papers as "best of breed" applications of SOL, showcasing the state of the art of SOL. Interestingly, papers with a high SOL score also tend to score high on the MAS typology, and vice versa. Some of the papers with high scores include Van Belle et al. (2011), who focus on bio-inspired coordination of cross-docking operations, Sun et al. (2010) who provide a novel approach for decentralized teams of autonomous robots for intralogistics, Bartholdi et al. (2010) who deploy self-organizing assembly line workers, Feng et al. (2017) who focus on interorganizational decision-making for transportation planning in a collaborative fashion, McKelvey et al. (2009) who take an electronic auction approach to facilitate interactions between smart parts and transportation firms, Carpanzano et al. (2014) who focus on reconfigurable transport systems for inbound logistics, and Berndt (2013) who shows that coordination based on mutual cooperation of autonomous agents in supply chain networks can lead to self-organizing and near-optimal performance.

4.2. Research trends and insights

This section addresses the main insights of this review.

1. Decision-making in logistics can be supported by the notion of self-organization and can benefit from autonomous decision-making, limited information sharing, and adaptability.

Throughout the literature, we found that self-organizing properties and self-organization, in general, can aid decision-making in logistics in a wide variety of applications. Through the notions of decentralization and intelligence, logistics systems can become (more) self-organizing (Pan et al., 2017), resulting in comparable performance to centralized systems (Van Heeswijk and La Poutré, 2019) while benefiting from autonomous decision-making (Wooldridge, 2009), respecting stakeholder integrity (Serna-Urán et al., 2018), limited data sharing, improved scalability, increased adaptability, and ease of implementation (Bartholdi et al., 2010). On the other hand, self-organizing systems can inhabit emergent behavior (Van Belle et al., 2011), which can limit predictability and thus may limit acceptance from a managerial perspective.

2. Few papers address SOL directly or compare multiple approaches.

Although many papers address an autonomous control system, where (autonomous) actors or assets perform intelligent decision-making, only a few address this as a self-organizing system. This may be caused by the interdisciplinarity of self-organization, combining elements from agent-based systems, decentralized control, and autonomous decision-making. Researchers may be more familiar with these latter notions and thus prefer to use them. Nevertheless, self-organization is a broad notion that can be helpful in structuring and comparing research efforts in logistics as we will see in Section 5. Moreover, with a few exceptions, the current literature fails to compare non-self-organizing and self-organizing systems in terms of logistics KPIs (Key Performance Indicators) or other qualitative measures. This void needs to be filled to support practitioners considering adopting SOL.

3. SOL is most often applied at the operational decision-making level by using decentral or hybrid control architectures.

When control regarding autonomous decision-making in logistics is delegated to lower levels in the control hierarchy, this is typically done on an operational decision-making level. This can be explained by the fact that self-organizing/decentral systems are useful in stochastic environments where fast and short-term decision-making is crucial for operational efficiency. To avoid the mathematical complexity of global optimization for operational decision-making, decentral or hybrid control hierarchies are often used. This is in line with self-organization in nature, where local decision-making and mutual cooperation induce global behavior. The use of hybrid control hierarchies can be explained by the fact that intervening from a central level (e.g., based on the state of the entire system) may be beneficial for system performance, especially in single-stakeholder environments, since there is only one problem owner. Moreover, as SOL is an *artificial* self-organizing system, central elements are often used to avoid full decentralized control (i.e., not having any influence on the decision-making process or being unable to intervene when undesirable behavior occurs). From a practical point of view, this seems realistic.

4. SOL systems have a semi-generic to highly generic nature.

Throughout the literature, most papers design self-organizing systems with a semi-generic to highly generic scope. This is promising for the wide applicability of self-organizing properties in the logistics sector but may lack the details and specifics required to adopt SOL in real-life situations.

5. SOL applications are often basic and lack maturity and case studies, which has not changed in recent years.

Although 40 papers are classified as considering an "advanced" application of SOL, the majority of the papers only have a very limited or basic application of SOL. It seems most authors only use a basic concept of self-organization or autonomous decision-making, which is also exemplified by the lack of case studies considered in the literature and that the maturity of SOL is currently mainly on a simulation level. Moreover, this has not changed throughout the years. Therefore, to advance the field of SOL, more advanced SOL applications—based on real-world case studies—are required, ultimately leading to adoption in practice. Especially, the real-world case studies are vital to demonstrate the usability, readiness, and business case of SOL.

6. The majority of papers use agent-based modeling, but this is often merely used as a decomposition method.

Throughout the review of the literature, we found that often the terminology agent-based or MAS is used. However, the term MAS is often used with different meanings, and therefore we introduced a MAS typology as discussed in Section 3.6. Although agent-based systems are often associated with decision-making by autonomous actors/assets, it is often merely used as a decomposition method. That is, a complex (central) problem is broken down into smaller problem-solving units (i.e., agents) to reduce the complexity of the system. However, these types of decomposition methods are often used in single-stakeholder environments where the necessity of decentral control systems—apart from reducing mathematical complexity—is limited, as all information used for decision-making is available and in the hands of a single (central) entity. Nevertheless, it may still be useful to delegate control to physical or digital assets in a single-stakeholder environment and thus be able to speak of a "proper" implementation of the agent paradigm. However, in our view, self-organizing systems *especially* thrive in dynamic environments with multiple stakeholders and with limited access to global information. In such systems, decisions are made by autonomous agents through interactions based on local information to reach a state where all stakeholders are satisfied (e.g., sharing of resources between [competing] stakeholders).

7. The IT component, the human role, and escalation levels are neglected in the SOL literature.

An important aspect of self-organizing systems is the ability of local actors/assets to obtain and process information from their (local) environment. However, how this is handled in SOL is seldom addressed in the current literature. The same holds for the role of humans (e.g., planners) and when and how they should intervene in the autonomous decision-making process by the local actors or assets (this is particularly relevant in hybrid control architectures).

The structured literature review has provided valuable insights into the topic of SOL. Through an extensive analysis of the extant literature, it has become clear that SOL is a promising yet difficult notion to identify and characterize, complicating the task of positioning and comparing research efforts. This insight will be the focus of the remainder of this paper. Specifically, we create an SOL typology in Section 5, such that authors in the field of SOL can meticulously express their designs of (partially) self-organizing systems. From this detailed SOL typology, we distill a visual representation of SOL—in the form of a two-dimensional framework—that allows for a quick comparison of different systems in Section 6.

5. SOL typology

In this section, we tackle one of the issues identified by our literature review: the current difficulty to clearly delineate and compare research efforts in the field of SOL. To this end, we propose an SOL typology. Based on characteristics found during our review of the extant literature, we synthesize 15 characteristics into an SOL typology. Section 5.1 discusses the 15 characteristics with a high degree of abstraction to enable universal application within the logistics domain. We present the resulting SOL typology in Section 5.2.

5.1. Characteristics of SOL

Based on the review results presented in Section 4, we find that classifying and comparing literature is often difficult in light of SOL. As self-organization is an interdisciplinary study across many domains and relates to many other concepts—such as agent-based systems, autonomous control, and decentral systems—it is difficult to get a systematic view on what a paper specifically addresses, which control methods are deployed, and how it compares to other studies. Therefore, we propose a typology that affords an approximate analysis of SOL. This typology is based on the review's findings presented in Section 4 and aims to provide a holistic view of SOL. We identified a total of 15 characteristics of SOL during our review, of which the majority relate to characteristics listed by early advocates of SOL. Specifically, the works of Bartholdi et al. (2010), Pan et al. (2017), and Böse and Windt (2007) all list several useful (and sometimes similar) characteristics of autonomous control systems and self-organization in logistics. We include the notions "ease of implementation," "adaptability," and "data requirements" identified by Bartholdi et al. (2010) and "openness" and "intelligence" identified by Pan et al. (2017). Moreover, the notions related to autonomous control, as introduced by Böse and Windt (2007), are included. These are: "control hierarchy," "decision-making method," "location of decision-making," and "data source." Last, notions related to (biological) self-organization, such as "the micro–macro effect," "interactions," "level of order," and "dynamism," are included based on the work of De Wolf and Holvoet (2005).

These 13 characteristics are complemented by two characteristics we often encountered during our review: the degree of control delegation and predictability.

For each characteristic, we provide multiple values, indicating a broad range of values that a characteristic can take and covering the findings from our review. Note that these values are context-specific, that is, when using the SOL typology to describe a certain system, the scope and demarcation of the system must first be determined. To exemplify, one of the characteristics in the typology is "control hierarchy." Consider an example of a routing problem for AGVs in a warehouse. When a decision-making system is deployed in which AGVs autonomously decide upon their routing, possibly through cooperation with other AGVs, one may characterize such a control system as decentral. However, when considering the warehouse as a whole, the (autonomous) routing function of the AGVs is only a small part of all the logistics processes that take place in a warehouse. Therefore, when the other processes are taken into account and are controlled in a rather centralized manner, one may classify such a system as mostly central. For the typology to be useful in describing a system in relation to SOL, one thus has to take into account a relevant scope and demarcation and evaluate the system from this perspective. The 15 characteristics and their respective values are further discussed below.

5.1.1. Control hierarchy

The control hierarchy describes the interrelatedness of all actors and assets in the system, as well as the hierarchical relations between them. The control hierarchy is explicitly stated in virtually all papers from our review. Recall that in Section 3.5, we identified four types of control hierarchies: centralized, proper hierarchical, modified hierarchical, and heterarchical (decentralized). Thus, the values of this characteristic are based on these four control hierarchies. The hybrid control architectures are expected to be either proper hierarchical or modified hierarchical, depending on the degree of decentralization.

5.1.2. Decision-making method

In every SOL system, decisions are made to achieve some sort of optimization or preferred behavior. We isolate three decision-making methods: (i) (approximate) optimization techniques, (ii) rule-based, and (iii) learning. The first is the classic approach in mathematics and operation research and aims to maximize (or minimize) an objective function. Although one can distinguish between different types of optimization techniques, for example, see the taxonomy of Roni et al. (2022), we cluster them in a single category. Examples within this category include exact methods such as branch-and-bound and dynamic programming (which solve to optimality), heuristics (which are typically problem-specific and use a fixed search rule to produce good solutions), and metaheuristics like evolutionary algorithms and swarm intelligence (which are problem-independent and use an adaptive search rule based on feedback from previous decisions, also to produce good solutions).

The second method consists of deploying (simple) rules to make decisions without referencing an objective function. Typically, these are priority rules or decision rules. Note that heuristic rules, such as nearest neighbor, can also be seen as a simple rule. However, we distinguish between these two (simple) approaches, as heuristics are typically defined as efficient procedures to convert complex problems into simpler ones (Hey, 2016) to find a solution to a pre-defined optimization problem.

We view a rule-based approach as a simple rule or procedure without (explicit) reference to a global optimization problem (i.e., not searching for a solution to a problem).

The third method relevant to SOL is learning. In such a decision-making method, an intelligent agent tries to learn which decisions are favorable to achieve a goal by interacting with its environment. The agent can thus change its behavior over time when better courses of actions are learned or when the environment changes. As discussed in Section 4.1, the majority of the papers specifies the decision-making method, and all three types of decision-making methods are represented in our review.

5.1.3. Location of decision-making

This characteristic denotes on which level in the hierarchy the (majority of) decisions are executed. For simplicity, we assume that any information processing (if required before decisions can be made) is also done at this level. Depending on the size, scope, and demarcation of the system under consideration, decisions can be made on different levels of the hierarchy. This characteristic gives a simple and overall view of where decisions are made in the control hierarchy. This can be further detailed by deploying diagrams or schemes. For the location of the decision-making, we distinguish between: (i) central, (ii) mostly central, (iii) mostly decentral, and (iv) decentral. From our review, we found that in the vast majority of papers, the decisions are executed "mostly decentral" or "decentral."

5.1.4. Location of data

This characteristic denotes where the (majority of) data are obtained in the control hierarchy, for example, data from IoT sensors (decentral) or data from an ERP (Enterprise Resource Planning) system (central). We again distinguish between: (i) central, (ii) mostly central, (iii) mostly decentral, and (iv) decentral. This characteristic, combined with the previous, corresponds to the axes of the framework on logistics control structures introduced by Hopman et al. (2022). From our review, we found that this characteristic is often underexposed, and data structures are typically not specified.

5.1.5. Interactions

This characteristic describes how the actors and assets in the system interact with each other and the environment. First of all, there simply can be no interaction in the system. In the second variant, information is exchanged between (some of) the assets in the system. The third variant deploys cooperation via direct communication. That is, assets are actively working together explicitly. The fourth variant is an indirect form of cooperation through the environment, also known as stigmergy (Theraulaz and Bonabeau, 1999). When the actions of a specific agent influence the environment, which also contains other agents, these actions may also indirectly influence the other agents, as these agents may respond to changes in the environment.

5.1.6. Openness

Openness denotes to which extent a system is opened to external influences. That is, the system boundary may be unset and open such that individuals or other parties (e.g., actors, assets, companies, supply chains) can easily join and leave the system (Ballot et al., 2012). By that, SOL systems become extendable and reducible to offer a certain degree of flexibility (Pan et al., 2017). We distinguish between four degrees of openness: (i) closed, (ii) open to data, (iii) open to other actors/assets, and (iv) fully reconfigurable. First, the system can be closed where all actors and assets are more or less pre-defined. Second, the system can be open to external data, that is, during run time, the system can benefit from external information to make better-informed decisions (e.g., traffic information). Third, the system can also be open for other actors or assets to join (or leave) the system. Fourth, once the system is open to other actors and assets, the system can be fully reconfigurable, that is, an extreme form in which the system is open to any kind of change and may result in a completely different configured system than originally defined. Reconfigurability may be particularly important to cope with disruptions, that is, the system self-reconfigures (Ren et al., 2015). Moreover, it can lead to the rise and fall of systems through competition or natural selection.

5.1.7. The degree of control delegation

The degree of control delegation refers to the amount of decision-making power delegated to lower levels in the control hierarchy. This depends on the scope and boundary of the system under consideration. We distinguish between: (i) none, (ii) some, (iii) many, and (iv) all.

5.1.8. Level of order

The level of order denotes an aspect of self-organization that captures to which extent decision-making is based on historical memory. A system becomes less ordered when it loses historical memory (De Wolf and Holvoet, 2005). A system with no order cannot be expected to show useful behavior. Still, a system with too much order (i.e., decision-making relies on full historical memory) can organize itself into conditions so complex that no useful functionality can be expected. We distinguish between four levels of order: (i) no order (chaos), (ii) lowly ordered (chaotic), (iii) highly ordered (structured), and (iv) too much order (complex).

5.1.9. Micro–macro effect

The micro–macro effect refers to properties, behaviors, structures, or patterns on a global (macro) level arising from interactions at a lower (micro) system level. Such properties are also called emergents (De Wolf and Holvoet, 2005). This characteristic denotes whether such a micro–macro effect is present, and, if so, how well it is understood. We distinguish between four variants of this effect relevant for SOL: (i) not present, (ii) not understood, (iii) ill-understood, and (iv) well-understood.

5.1.10. Dynamism

The notion of dynamism denotes the degree to which the system is prone to changes, either internally or externally caused. In rapidly changing environments, there needs to be a continuous dynamic to adjust system behavior to maintain operational efficiency. De Wolf and Holvoet (2005) denote this by a *far-from-equilibrium* system. A far-from-equilibrium system is more fragile and sensitive to changes in the environment but also more dynamic and capable to react than a system in equilibrium (De Wolf and Holvoet, 2005). We distinguish between four types of dynamism: (i) static, (ii) mostly static, (iii) mostly dynamic, and (iv) dynamic.

5.1.11. Intelligence

Intelligence is not used as a measure of how intelligent a system is but rather where the intelligence emerges. System intelligence is defined as intelligence that emerges from global decision-making, and collective intelligence is defined as intelligence that emerges from a group of (simple) agents that cooperate. We, therefore, distinguish between four types: (i) system intelligence, (ii) mostly system, (iii) mostly collective, and (iv) collective intelligence.

5.1.12. Predictability

The predictability of a system refers to the extent to which the system behaves as expected from the given situation it is in, that is, whether actors and assets act in a manner that is expected when confronted with a certain situation. During our review, we found that predictability is often discussed in the light of SOL, as increased autonomy of decentral assets may lead to a less predictable system. Hence, we view predictability as an important characteristic of SOL, and we distinguish between four levels of predictability: (i) low, (ii) medium, (iii) high, and (iv) very high.

5.1.13. Adaptability

The adaptability of a system refers to its capacity to react and adjust to both internal and external changes efficiently. Internal changes include events such as equipment failures, while external changes involve events such as surges in demand. Adaptability can also be synonymous with flexibility. Essentially, a system with a high level of adaptability or flexibility tends to be more robust and resilient. In other words, when a system has a high degree of adaptability or flexibility, it tends to be more robust or resilient. We distinguish between four degrees of adaptability: (i) low, (ii) medium, (iii) high, and (iv) very high.

5.1.14. Data requirements

This characteristic refers to how much data are required for the system to be able to make decisions. For example, when a centralized system requires (up-to-date) information from all subordinate levels to deploy some sort of global optimization technique, we may classify this as (very) high data requirements. On the other hand, when an agent makes decisions based on limited domain knowledge and local data only, we may classify this as low data requirements. We thus again distinguish between four levels of data requirements: (i) low, (ii) medium, (iii) high, and (iv) very high.

5.1.15. Ease of technological implementation

This characteristic refers to the technological ease of implementation of the (proposed) system. Hence, we do not refer to implementation issues like regulatory issues and managerial acceptance. Rather, we take the perspective of Bartholdi et al. (2010), who state that the ease of implementation only relates to establishing a process without paying much attention to the configuration of the system itself. When a system subsequently fine-tunes itself due to self-organization, a system is easily implemented. On the other hand, when every actor and asset in the system needs to be rigorously defined, modeled, and maintained, as well as their interactions and inner workings, the system can be viewed as difficult to implement. Again, we distinguish between four levels: (i) low (i.e., difficult), (ii) medium, (iii) high, and (iv) very high (i.e., very easy). Easily implemented systems are perceived as favorable for practitioners, yet very few papers from our review discuss the implementation process.

As discussed in Section 5.1, no single configuration (i.e., selection of values on all 15 characteristics) can be viewed as superior, nor is it expected to outperform other configurations. That said, some configurations are more suitable than others either for certain applications or from a logical or practical point of view. For example, a closed centralized system that adopts global optimization in a rather static environment tends to be highly predictable and shows no self-organizing behavior. Also, deciding whether or not a system is self-organizing highly depends on the system's boundaries, as these determine what can be seen as external control and what is not. Last, we acknowledge that some discussion may occur when applying our SOL typology to a certain use case or system. For example, there may be a difference of opinion on classifying the predictability of a system or whether a system is denoted as mostly decentral or fully decentral. Although there may not be a scientific procedure to resolve such discussions for every characteristic, this is also not the purpose of our descriptive typology. Instead, we aim to provide a tool for researchers and practitioners to think about and describe their work in relation to SOL, using the 15 characteristics presented. The values presented for each characteristic serve as guidelines to expose the breadth of each characteristic. When researchers use the SOL typology to describe their work and feel that their system does not (precisely) relate to one of the mentioned values of a characteristic, we invite them to interpolate (e.g., medium-to-high in terms of predictability).

5.2. SOL typology

The typology shown in Table 8 synthesizes the 15 characteristics discussed in the previous section and helps researchers to position their work and simultaneously helps practitioners to properly design complex systems, such that the system is configured to the needs of the user. For example, a configuration may be expressed in the ability to show self-organizing behavior, system predictability, data requirements, location of decisions, and adaptability. As mentioned, we do not argue that one configuration prevails over the other but rather provide insight into how systems can be configured to suit their intended purposes. Moreover, the outcome of a system configuration (e.g., global system behavior) is a complex function of its inputs. Therefore, there seems to be no simple function that adequately maps the inputs of a system (e.g., control hierarchy, level of autonomy, and the number of interactions) to an output that indicates the self-organizing behavior of a system. Most definitely, different configurations may eventually lead to similar system behavior, and likewise, similarly configured systems may yield different (global) outcomes. Similarly to self-organization itself, in which global behavior cannot be easily deduced by the behavior of its components, the degree of SOL is a complex, ill-understood function of the design and configuration of the system. The characteristics in the typology are divided across four groups: (i) system architecture (related to control hierarchy, decision-making, and data structure), (ii) cooperativeness (related to local interactions and system openness), (iii) autonomy (related to autonomous control), and (iv) features (related to system outcomes such as predictability and ease of implementation).

From Section 4, we found that many authors only include information on a few of the elements we propose in our typology. For future works, we invite authors to use this typology to position their work, compared to the literature on SOL. Moreover, the utilization of this typology allows readers

Table 8
An SOL typology

Group	#	Elements	Values			
System architecture	1	Control hierarchy	Hierarchical (central)	Mostly hierarchical (hybrid)	Mostly heterarchical (hybrid)	Heterarchical (decentral)*
	2	Decision-making method	(Approximate) optimization techniques	Rule-based*		Learning
	3	Location of decision-making	Central	Mostly central	Mostly decentral	Decentral*
	4	Location of data	Central	Mostly central	Mostly decentral	Decentral*
Cooperativeness	5	Interactions	None	Exchange of information	Cooperation via direct communication*	Cooperation through stigmergy
	6	Openness	Closed	Open to data*	Open to other actors/assets	Fully reconfigurable
Autonomy	7	Degree of control delegation	None	Some	Many*	All
	8	Level of order	No order (chaos)	Lowly order (chaotic)	Highly ordered (structured)*	Too much order (complex)
	9	Micro–macro effect	Absent	Well-understood*	Ill-understood	Not understood
	10	Dynamism	Static (in equilibrium)	Mostly static	Mostly dynamic*	Dynamic (far from equilibrium)
Features	11	Intelligence	System intelligence	Mostly system	Mostly collective	Collective intelligence*
	12	Predictability	Low	Medium	High*	Very high
	13	Adaptability	Low	Medium	High	Very high*
	14	Data requirements	Low*	Medium	High	Very high
	15	Ease of technological implementation	Low	Low-med	Med-high	High*

Note: As an example, we classify Bartholdi et al. (2010) using asterisks.

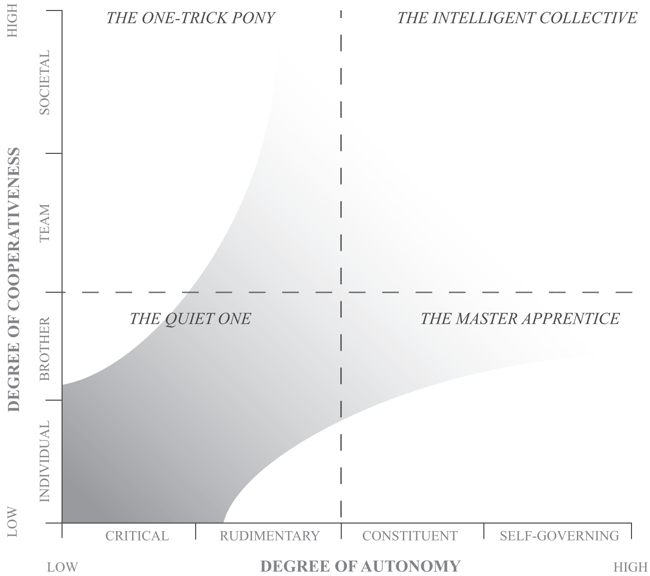

Fig. 5. Self-organizing logistics (SOL) framework alongside the axes of the degree of autonomy and the degree of cooperativeness, identifying several degrees of self-organization.

to promptly discern the specific setting on which a paper concentrates. To illustrate the application of our typology, we take the work of Bartholdi et al. (2010) and indicate the applicable value for each element using an asterisk in Table 8 (e.g., Bartholdi et al., 2010, have a decentral control hierarchy and a rule-based decision-making system). Note that the typology consists of generic characteristics and values, not necessarily pertaining to SOL in transportation. We hypothesize that the typology presented in Table 8 is also applicable, or at least useful, to the broader context of SOL.

6. A unifying framework for SOL

In the previous section, we presented an SOL typology such that authors in the field of SOL can meticulously express their design of (partially) self-organizing systems. To facilitate a quick comparison of different systems (or papers), we provide a visual representation classifying SOL in a two-dimensional framework. Given the prevailing elements of the SOL typology, we present this framework alongside the axes "degree of autonomy" and "degree of cooperativeness" in Section 6.1, revealing four quadrants that are further discussed in Section 6.2. In Section 6.3, we illustrate the use of the framework by positioning several state-of-the-art papers from our review.

6.1. A two-dimensional SOL framework

The two-dimensional SOL framework is presented in Fig. 5. We present this framework along two axes (autonomy and cooperativeness) for the following reasons. First, these two aspects of SOL are the prevailing aspects of the typology presented in Section 5.1 specifically pertaining to SOL, whereas the other groups are more generic. The "system architecture" group of the typology is related to design decisions (i.e., input), and the "features" group is related to the system's outcomes, depending on how the system is designed and configured. Second, autonomy and cooperativeness are the prevailing aspects when talking about (artificial) self-organizing systems, see Section 1. This framework provides a basic understanding of the degree of SOL, as "autonomy" and "cooperativeness" are at the core of SOL. We expect lowly self-organizing systems to score low on both "autonomy" and "cooperativeness," whereas highly self-organizing systems are expected to score high on both elements. This expectation is substantiated by the positioned literature in Section 6.3. Certainly, to fully understand the self-organizing abilities of a logistics system, one requires additional axes (e.g., elements from the SOL typology). However, as discussed in Section 5.2, only a few authors provide information on these elements. Nevertheless, we illustrate how to integrate additional axes in Section 6.3 using the "control hierarchy" characteristic from the SOL typology. This additional third dimension retains the visual interpretability of the framework while enriching its SOL representation.

We selected the descriptions alongside the axes of the framework to provide general categorizations, as such, applying to a broad spectrum of logistics applications (e.g., transport, warehousing, purchasing). Moreover, the framework identifies four areas to classify research in the field of SOL. The boundaries between these areas are far from rigid. Still, they provide researchers and practitioners with a common ground and vocabulary to guide the discussion on SOL and to identify directions to enhance (the degree of) SOL. The shaded area represents our view on the path toward SOL, having clearly demarcated, lowly self-organizing systems near the origin and loosely coupled, highly self-organizing systems when approaching the top right.

We divide the degree of autonomy into four levels: (i) critical, (ii) rudimentary, (iii) constituent, and (iv) self-governing. Let us illustrate these levels with a use case focusing on automated transport. The first level (critical) comprises systems where the only autonomy is focused on critical or safety-related tasks (e.g., avoiding imminent danger or collisions). Within the second level (rudimentary), some additional, rudimentary tasks can be decided upon (e.g., following a pre-defined route or returning to a base station). Within the third level (constituent), the majority of the tasks can be performed autonomously, but human supervisory control may be required in some scenarios. One may think of determining a route based on real-time congestion information or rerouting to a charging station. However, the most difficult tasks are not performed autonomously but by a human or external software. The last level (self-governing) consists of systems where all, or close to all, tasks are performed autonomously, and the responsibility (or decision latitude) resides fully in the autonomous system. It goes without saying that typically in such self-governing systems, the human role is not fully absent. In some situations, human control may still benefit the system (or be required) as discussed in Section 3.5.

The degree of cooperativeness is also divided into four levels: (i) individual, (ii) brother, (iii) team, and (iv) societal. The first level (individual) consists of systems where the autonomy (any degree of it) resides with only a single actor or multiple actors/assets but without cooperation. Within the second level (brother), there is some level of cooperation but only within a set of (like-minded) homogeneous actors/assets. Within the third level (team), the degree of cooperativeness is extended and includes cooperation between other systems or system functionalities (e.g., cooperation between routing, scheduling, and battery replenishment of electric vehicles to determine effective routes and simultaneously taking into account energy levels of the vehicles and the capacity of charging stations). Such a team typically operates within the boundaries of a single company or a small set of stakeholders (e.g., a fleet of automated vehicles at a container terminal). Within the last level (societal), the cooperation goes beyond the boundaries of a single company/stakeholder. That is, within a certain logistics system, the entire (or large part) of the society (e.g., stakeholders or processes) cooperatively manages the logistics system. An example is a fleet of autonomous trucks cooperating with traffic lights to optimize traffic flow. One may also view this as a set of subunits working together to manage the entire logistics chain (i.e., horizontal collaboration). Again, the interpretation of the levels may be case-specific.

In the next section, we introduce the four categories of the SOL framework based on different combinations of degrees of autonomy and cooperativeness. Moreover, we provide insight into the state of the art in relation to the SOL framework.

6.2. Four categories of SOL

In this section, we introduce the four categories of SOL based on different combinations of degrees of autonomy and cooperativeness. The categories are assigned colloquial names to avoid technical or application-specific interpretations.

6.2.1. The Quiet One

In the lower-left quadrant of Fig. 5, we identify both the degrees of cooperativeness and autonomy as low and denote this category by *The Quiet One*. This denotation comes from the fact that the systems classified in this quadrant typically perform their tasks in relative solitude with no to little communication with others. These systems show no form of autonomy or only for safety-critical or rudimentary tasks. Examples include automated warehouses where pallets are moved around using robots or reconnaissance drones that map pre-programmed areas. All decisions within these logistics processes (e.g., what to do when) are determined, not by the actors/assets themselves but by either a human controller or a centralized system. In these systems, the decision latitude is very low to low, with no to little cooperation between the actors/assets or with external systems. The intelligence then emerges from a system level in a more-or-less centralized fashion (see also Table 9). These systems are typically highly coupled and clearly demarcated, which are preferred properties for stability and predictability, but show no to little emergent behavior nor contain many self-organizing properties. An example from our review includes the work of Xiong et al. (2018), who deploy a global optimization method for milk-run logistics, in which all decision-making takes place at the central level, with no autonomous decision-making by the actors (i.e., suppliers) and assets (i.e., vehicles) involved.

6.2.2. The Master Apprentice

In the lower-right quadrant of Fig. 5, we find lowly cooperative but medium to highly autonomous systems and denote these by *The Master Apprentice*. Like the previous category, the degree of cooperativeness is low to medium, but the actors/assets have substantial autonomy. This ranges from partly delegated control to fully self-governing control. These systems show some form of

Table 9
Selection of papers positioned in the SOL framework in Fig. 6

ID	Reference	SOL score	Control hierarchy
1	Di Febrarro et al. (2018)	1	Central
2	Fikar et al. (2018)	1	Central
3	Omelianenko et al. (2019)	1	Central
4	Poeting et al. (2019)	1	Central
5	Yao et al. (2020)	1	Central
6	Dimitriou and Stathopoulos (2011)	2	Decentral
7	Levchenkov and Gorobetz (2005)	2	Hybrid
8	Otto and Bannenberg (2010)	2	Decentral
9	Śniezyński et al. (2010)	2	Decentral
10	Sprenger and Mönch (2011)	2	Central
11	Arendt et al. (2016)	3	Hybrid
12	Baykasoglu and Kaplanoglu (2011)	3	Decentral
13	Feng et al. (2014)	3	Hybrid
14	Mes et al. (2013)	3	Decentral
15	Weyns et al. (2005)	3	Hybrid
16	Bartholdi et al. (2010)	4	Decentral
17	Berndt (2013)	4	Decentral
18	Malus et al. (2020)	4	Decentral
19	Mes et al. (2008)	4	Decentral
20	Van Belle et al. (2011)	4	Decentral

self-organization, mainly due to their autonomous nature, but typically within a limited scope or application area. There is no connection or cooperation with external systems or awareness of the broader impact of their actions. However, within their limited domain of cooperation, these systems perform well with no to little (human) supervisory control required. As the degree of control delegation increases, the intelligence moves from a system level to the autonomous actors/assets (i.e., collective intelligence). An example from our review is the work of Bartholdi et al. (2010), in which a set of workers autonomously balances a production line. In our view, this falls within this category with a high degree of autonomy (i.e., self-governing level) and a limited degree of cooperativity (i.e., brother level).

6.2.3. *The One-Trick Pony*

In the upper-left quadrant of the SOL framework, we identify lowly autonomous and medium to highly cooperative systems and denote these by *The One-Trick Pony*. This designation is motivated by the fact that the logistics systems in this quadrant typically have limited decision-making capabilities. They score low on autonomy, which is confined to safety-critical or rudimentary tasks. Their degree of cooperativeness, however, is high. The latter enables them to communicate with their environment, for example, with external logistics systems. Opposed to the previous two categories, these systems cooperate beyond the borders of their own span of control to form collaborations. As system boundaries become increasingly ambiguous when cooperating with other parties or (IT-)systems, the predictability may decrease when moving away from closed systems. Moreover, notions such as trust, vulnerability, and responsibility come into play, as existing cooperative partners may change their minds, leave the system, or be replaced by other partners with different interests. However, as the decision latitude is low for this category, the impact on these notions is expected to be small and thus may provide a safe haven as a step toward SOL for systems currently identified as *The Quiet One*. An example from our review is the work of Van Heeswijk (2020), who presents an autonomous bidding approach for transport services in a spot market (i.e., a specific part of the entire transport planning process, and thus positioned on the boundary of rudimentary and constituent). By sharing information between (competing) agents, they jointly learn good bidding policies (i.e., team/societal level).

6.2.4. The Intelligent Collective

In the top-right quadrant, both the degree of cooperativeness and autonomy are medium to high. Self-governing autonomous systems that cooperate with external systems fall within this category. Decisions are made autonomously, and tasks are performed via mutual cooperation and coordination. Therefore, we denote this category by *The Intelligent Collective*. In this category, there is a high delegation of control that spans beyond the boundaries of a closed domain by cooperating with external actors or systems. The top-right corner of this category includes extreme forms of SOL and shows similar self-organizing properties and emergent behavior as biological systems, like ant colonies and beehives. An artificial example is the PI, an ambitious concept toward efficiency and sustainability in transport logistics. PI aims to achieve full consolidation of logistics flows from independent shippers through extended pooling of resources and assets in open, connected, and shared networks to achieve seamless integration throughout the logistics network (ALICE-ETP, 2020). Other, less extreme examples of systems within *The Intelligent Collective i*nclude coordination between manually operated and autonomous vehicles in mixed-traffic applications and real-time collaborative transport planning. Examples from our review include: (i) Feng et al. (2017), who present an approach for autonomous decision-making for transport planning (i.e., self-governing or at least constituent) while deploying collaboration between competing actors (i.e., societal level), and (ii) Van Belle et al. (2011), who introduce self-organizing behavior at a cross-docking facility by autonomous decision-making for all cross-docking operations (i.e., self-governing) and by collaboration between resource ants and product ants (i.e., team level).

6.3. State of the art

To illustrate the application of our SOL framework presented in Section 6.1, we revisit the literature review presented in Section 4. Recall that one of the elements of the literature classification structure from Fig. 3 focuses on determining to which extent we can speak of SOL. For this purpose, we introduced an SOL score ranging between 0 (no autonomy or self-organizing properties) and 4 (best example of SOL). In this section, we connect the findings of this classification to the SOL framework. To this end, we position part of the reviewed literature in the SOL framework. For each SOL score (except for an SOL score of 0), we select five representative papers (so a total of

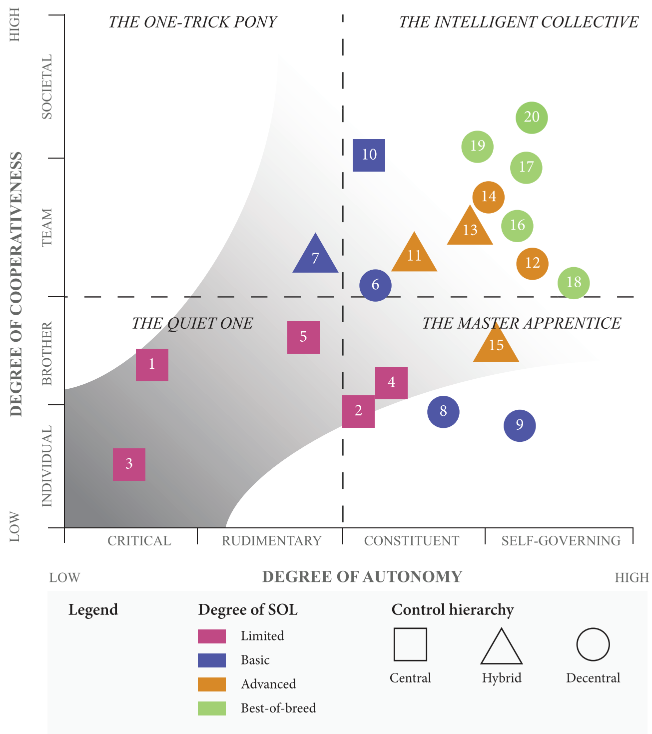

Fig. 6. A selection of papers from the literature review positioned in the SOL framework.

20). We carefully evaluate both the degree of autonomy and cooperativeness for each selected paper. This evaluation is based on the scope and demarcation presented in each paper, as this context is important to justify the degree of autonomy and cooperativeness. As a third dimension, we focus on the “control hierarchy” characteristic of the SOL typology, as virtually all authors include this characteristic. Figure 6 positions the 20 selected papers in the SOL framework. The numbers in the figure coincide with the papers listed in Table 9 at the end of this section. The colors indicate the degree of SOL, and the shapes indicate the control hierarchy as a third dimension.

Figure 6 shows that the current state-of-the-art applications (i.e., the best examples of SOL, shown in green) are concentrated in the top-right quadrant of the SOL framework, indicating a high degree of autonomy and cooperativeness. The majority of the papers in this quadrant have a high SOL score (3 or higher). Most of the reviewed papers focus mainly on delegating decision-making capabilities (i.e., autonomy) to lower-level assets, with limited attention to cooperativeness. These are typically papers focusing on (functional) agent-based systems. These papers can be found on the middle right-hand side of the framework. An interesting research direction is to augment the autonomy aspect of agent-based systems with collaborative capabilities, ultimately beyond their own sphere of influence, to move toward the top-right quadrant of the SOL framework and thus closer to the best-of-breed examples. Moreover, not seldom we found papers that address agent-based systems or decentral control hierarchies, where the decision-making capabilities reside at the central level, where, for example, global optimization techniques are used. These are often papers where the agent typology is merely used as a decomposition method, and they are typically positioned in the lower-left quadrant of the SOL framework. These papers also tend to have a low SOL score. For the decision-making processes discussed in these kinds of papers to become more self-organizing, future research should focus on increasing the cooperativeness or autonomy of the assets under consideration. Ultimately, both directions can be addressed to move toward *The Intelligent Collective*, and a step-wise approach is likely useful for both researchers and practitioners to increase the self-organizing behavior of their systems in an ordered fashion.

As an illustration, we reflect on the findings of the literature review with respect to a third dimension of the SOL framework: *control hierarchy*. We observe that lowly self-organizing systems typically have a central control hierarchy, and highly self-organizing systems typically have a decentral or hybrid control hierarchy. We do not argue that the SOL framework inhabits a clear cut-off value that would indicate either central or decentral systems. Rather, we observe a tendency to move from centralized to hybrid and ultimately to decentral control hierarchies when the degree of autonomy and cooperativeness increases. A similar analysis can be made for other third dimensions (e.g., using other elements from the SOL typology), given that the authors of the papers address these elements.

Our view on the path toward SOL, represented by the shaded area in Fig. 6, seems to align with the SOL score assigned to the reviewed papers. Near the origin of the framework, we observe lowly self-organizing systems, and we observe highly self-organizing systems in the top-right, with middle-of-the-road systems somewhere in between. Based on the findings from the review, the expected benefits of increasing the self-organizing abilities of logistics control systems can be summarized as follows: (i) greater flexibility to adapt to changes and unforeseen events and hence a more robust system, (ii) improved scalability and adaptability due to a more decentralized approach, (iii) better real-time decision-making with lower latencies and fewer data requirements, (iv) better representation of the (competing) interest of multiple stakeholders in open and cooperative environments, and (v) easier implementation as the system is able to fine-tune itself as it self-organizes.

This proposed path toward SOL and the expected benefits poses interesting research directions. For example, evaluating how different degrees of SOL (i.e., by altering the degree of cooperativeness and autonomy) influence the expected benefits of SOL is a worthwhile research direction. Moreover, given the complex nature of SOL, it is interesting to further study how different degrees of SOL influence the 15 elements identified in the SOL typology and whether general insights can be formulated for various disciplines within logistics or whether insights are limited to specific domains.

7. Conclusion and future research

This paper presented the developments regarding SOL in academic literature. We deployed a SLR, including an initial bibliographic study, to identify the most relevant keywords related to SOL. We identified 169 papers related to SOL and classified these papers alongside the following notions: logistics application, decentralization, intelligence, maturity and validation, and the level of self-organization. Our review provided the following main insights:

1. SOL is an interdisciplinary study across many domains and relates to adjacent concepts, such as agent-based systems, autonomous control, and decentral systems. In general, SOL is an artificial self-organizing system inspired by biological self-organizing systems and founded on autonomous decision-making by actors or assets (i.e., absence or limited external control) and the ability of lower-level components to cooperate (i.e., establishing useful local interactions).
2. Self-organization aids system design and decision-making in a wide variety of applications in logistics. Currently, most papers focus on applications of operational decision-making.
3. Only a few papers address SOL directly or compare multiple degrees of SOL.
4. SOL applications are often basic and lack maturity and case studies, which has not changed in recent years.
5. Classifying and comparing literature related to SOL is often difficult due to its interdisciplinary nature and the different terminologies used.

To resolve the latter, we proposed a typology containing 15 elements related to SOL, allowing an approximate analysis of SOL. This typology is useful for practitioners to untangle and understand the notion of SOL, and we invite authors in the domain of SOL to use this typology to position their work explicitly. Last, we proposed a two-dimensional framework to position literature regarding SOL alongside two key dimensions: the degree of autonomy and the degree of cooperativity. This framework provides four categories of SOL and reveals a path toward highly self-organizing systems. After positioning several papers from our review, we find that highly self-organizing systems typically have high degrees of autonomy and cooperativeness. Moreover, these systems tend to be more decentral than lowly self-organizing systems. As further research, we aim to study how the four identified categories of SOL influence the 15 elements from the SOL typology (i.e., potential other dimensions of the framework) for a wide variety of logistics systems, to be able to measure and quantify the impact of increasing the degree of SOL for real-world applications.

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Appendix 1: Classification of literature

This appendix contains two tables categorizing all 169 papers included in the review. Table A1 contains the categorization regarding the categories *Logistics* and *Decentralization*. Table A2 contains the categorization regarding the categories *Intelligence, Validation, Maturity*, and *SOL*.

Table A1
Classification of literature (logistics and decentralization)

ID	APA reference (authors, year)	Application area	Problem instance size	Mode of transport	Decision	Level of delegation of control	Control hierarchy	Where is the autonomy?	Escalation levels
1	Abu-Monshar and Al-Bazi, 2022	Transport	Small	Vehicles	Operational	Routing	Central	Central	No escalation
2	Agrawal et al., 2016	City and urban logistics	Very large	Trucks	Operational	Transport planning	Hybrid	Decentral	No escalation
3	Ahamuda et al., 2020	Transport	Very large	Trucks	Operational	Transport planning	Decentral	Decentral	No escalation
4	Akkad et al., 2022	Transport	Medium	Trucks	Operational	Transport planning	Central	Central	No escalation
5	Arendt et al., 2016	Transport	Large	Trucks	Operational	Transport planning	Hybrid	Decentral	No escalation
6	Bădică et al., 2020	Transport	Medium	Trucks	Operational	Transport planning	Central	Central	No escalation
7	Bae et al., 2022	Transport	Medium	Trucks	Tactical	Transport planning	Hybrid	Decentral	No escalation
8	Barenji et al., 2019	Internal logistics and material flow	Medium	Automated vehicles and robots	Tactical	Intralogistics	Hybrid	Hybrid	No escalation
9	Bartholdi, et al., 2010	Internal logistics and material flow	Very large	Other	Operational	Intralogistics	Decentral	Decentral	No escalation
10	Baykasoglu and Kaplanoglu, 2011	Transport	Large	Trucks	Operational	Transport planning	Decentral	Decentral	No escalation
11	Baykasoglu et al., 2011	Transport	Not specified	Trucks	Operational	Multiple decisions	Decentral	Decentral	No escalation
12	Baykasoglu and Kaplanoglu, 2015	Transport	Medium	Trucks	Operational	Transport planning	Hybrid	Decentral	No escalation
13	M. Becker et al., 2006	Ports and terminals	Very large	Passenger cars	Operational	Not specified	Not specified	Not specified	No escalation

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Table A1
(Continued)

ID	APA reference (authors, year)	Application area	Problem instance size	Mode of transport	Decision	Level of delegation of control	Control hierarchy	Where is the autonomy?	Escalation levels
14	T. Becker et al., 2016	General Supply Chains	Not specified	Not specified	Operational	Transport planning	Decentral	Decentral	No Escalation
15	Bernaer et al., 2006	Inter- and multi-modal transport	Not specified	Multi-modal	Operational	Transport planning	Decentral	Decentral	No escalation
16	Berndt, 2013	General supply chains	Small	Not specified	Tactical	Manage processes	Decentral	Decentral	No escalation
17	Besselink et al., 2016	Transport	Very large	Trucks	Operational	Vehicle control	Hybrid	Central	No escalation
18	Blom et al., 2020	Internal logistics and material flow	Medium	Trucks	Tactical	Transport planning	Decentral	Decentral	No escalation
19	Boussier et al., 2009	City and urban logistics	Not specified	Delivery vans	Operational	Not specified	Not specified	Not specified	No escalation
20	Calabrò et al., 2020	Transport	Medium	Vehicles	Operational	Transport planning	Central	Central	No escalation
21	Carpanzano et al., 2014	Internal logistics and material flow	Medium	Internal transport	Operational	Transport planning	Decentral	Decentral	No escalation
22	Carpanzano et al., 2016	Internal logistics and material flow	Medium	Automated vehicles and robots	Operational	Transport planning	Decentral	Decentral	No escalation
23	Chatterjee et al., 2016	City and urban logistics	Not specified	Bikes	Operational	No delegation	Central	Central	No escalation
24	Chen et al., 2022	Internal logistics and material flow	Medium	Automated vehicles and robots	Operational	Vehicle control	Hybrid	Decentral	No escalation
25	Cheng and Qi, 2011	Transport	Large	Trucks	Tactical	Transport planning	Decentral	Decentral	No escalation
26	Danchuk et al., 2023	Transport	Small	Vehicles	Operational	Transport planning	Central	Central	No escalation
27	Dangelmaier et al., 2004	Transport	Not specified	Not specified	Operational	Transport planning	Decentral	Decentral	No escalation

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Table A1
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ID	APA reference (authors, year)	Application area	Problem instance size	Mode of transport	Decision	Level of delegation of control	Control hierarchy	Where is the autonomy?	Escalation levels
28	De Jonge et al., 2021	Transport	Small	Vehicles	Operational	Transport planning	Decentral	Decentral	No escalation
29	De Sousa and De Oliveira, 2020	Internal logistics and material flow	Small	Automated vehicles and robots	Operational	Production planning	Hybrid	Hybrid	No escalation
30	Demirag and Swann, 2007	Ports and terminals	Medium	Barges and vessels	Tactical	Transport planning	Hybrid	Hybrid	No escalation
31	Di Febbraro et al., 2018	City and urban logistics	Medium	Passenger cars	Operational	No delegation	Central	Central	No escalation
32	Di Febbraro et al., 2016	Inter- and multi-modal transport	Small	Trucks	Tactical	Transport planning	Hybrid	Decentral	No escalation
33	Dimitriou and Stathopoulos, 2011	Inter- and multi-modal transport	Medium	Trucks	Strategic	Network design	Decentral	Decentral	No escalation
34	Dimitriou and Stathopoulos, 2009	Ports and terminals	Small	Trucks	Strategic	Transport planning	Decentral	Decentral	No escalation
35	Dorer and Calisti, 2005	Transport	Not specified	Trucks	Operational	Transport planning	Hybrid	Decentral	No escalation
36	Draganjac et al., 2020	Internal logistics and material flow	Medium	Automated vehicles and robots	Operational	Transport planning	Decentral	Decentral	No escalation
37	Ebel and Eberhard, 2019	Internal logistics and material flow	Small	Automated vehicles and robots	Operational	Vehicle control	Decentral	Decentral	No escalation
38	Ebel et al., 2021	Internal logistics and material flow	Small	Automated vehicles and robots	Operational	Vehicle control	Decentral	Decentral	No escalation
39	Edelkamp and Gath, 2013	Transport	Very large	Trucks	Operational	Transport planning	Decentral	Decentral	No escalation
40	Erdmann et al., 2020	Internal logistics and material flow	Small	Automated vehicles and robots	Operational	No delegation	Central	Central	No escalation

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Table A1
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ID	APA reference (authors, year)	Application area	Problem instance size	Mode of transport	Decision	Level of delegation of control	Control hierarchy	Where is the autonomy?	Escalation levels
41	Espejo-Díaz and Guerrero 2021.	Transport	Small	Vehicles	Operational	Transport planning	Central	Central	No escalation
42	Fan et al., 2021	General supply chains	Small	Barges and vessels	Strategic	Vehicle control	Central	Central	No escalation
43	Fazili et al., 2017	Transport	Medium	Trucks	Operational	No delegation	Central	Central	No escalation
44	Feljan et al., 2017	Transport	Not specified	Trains	Operational	Not specified	Hybrid	Central	No escalation
45	Feng et al., 2014	Transport	Not specified	Barges and vessels	Operational	Information passing	Hybrid	Central	No escalation
46	Feng et al., 2015	Transport	Medium	Barges and vessels	Operational	Resource scheduling	Hybrid	Decentral	No escalation
47	Feng et al., 2017	Transport	Small	Barges and vessels	Operational	Resource scheduling	Hybrid	Decentral	No escalation
48	Fikar et al., 2015	Transport	Large	Trucks	Operational	Transport planning	Hybrid	Decentral	No escalation
49	Fikar et al., 2018	City and urban logistics	Very large	Delivery vans	Operational	Transport planning	Central	Central	No escalation
50	Filippi et a., 2022	Transport	Medium	Automated vehicles and robots	Operational	Transport planning	Central	Central	No escalation
51	Firdausiyah et al., 2019	City and urban logistics	Medium	Trucks	Tactical	Multiple decisions	Decentral	Decentral	No escalation
52	Fischer et al., 1994	Transport	Not specified	Trucks	Operational	Transport planning	Decentral	Decentral	No escalation
53	Franke et al., 2004	Transport	Very large	Not specified	Operational	Transport planning	Decentral	Decentral	No escalation
54	Gath et al., 2014	Transport	Medium	Generic vehicles	Operational	Transport planning	Decentral	Decentral	No escalation
55	Gath et al., 2013	Transport	Large	Trucks	Operational	Transport planning	Decentral	Decentral	No escalation
56	Gath et al., 2015	Transport	Very large	Trucks	Operational	Transport planning	Decentral	Decentral	no escalation
57	Gath et al., 2012	City and urban logistics	Very large	Bikes	Operational	Transport planning	Decentral	Decentral	No escalation

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Table A1
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ID	APA reference (authors, year)	Application area	Problem instance size	Mode of transport	Decision	Level of delegation of control	Control hierarchy	Where is the autonomy?	Escalation levels
58	Gerrits et al., 2017	Internal logistics and material flow	Small	Trucks	Operational	Transport planning	Decentral	Decentral	No escalation
59	Glicoes and Huhns, 1996	Transport	Not specified	Multi-modal	Operational	Transport planning	Decentral	Decentral	No escalation
60	Gontara et al., 2019	Transport	Medium	Trucks	Operational	Transport planning	Central	Central	No escalation
61	Gorodetski et al., 2003	Transport	Large	Trucks	Operational	Transport planning	Hybrid	Hybrid	No escalation
62	Gorodetsky et al., 2012	Transport	Not specified	Trucks	Operational	Transport planning	Decentral	Decentral	No escalation
63	Gronalt and Schindlbacher, 2015	Inter- and multi-modal transport	Medium	Trains	Tactical	Transport planning	Hybrid	Decentral	No escalation
64	Guo et al., 2021	Transport	Large	Vehicles	Operational	Transport planning	Hybrid	Central	No escalation
65	Haass et al., 2015	Transport	Small	Multi-modal	Operational	Transport planning	Hybrid	Decentral	No escalation
66	Hiari et al., 2017	Transport	Not specified	Trucks	Operational	Transport planning	Decentral	Decentral	No escalation
67	Hildmann and Martin, 2015	Transport	Medium	Not specified	Operational	Transport planning	Decentral	Decentral	No escalation
68	Himoff et al., 2006	Transport	Very large	Trucks	Operational	Transport planning	Hybrid	Decentral	No escalation
69	Hongler et al., 2010	Transport	Not specified	Not specified	Operational	Vehicle control	Decentral	Decentral	No escalation
70	Indrayadi et al., 2002	Internal logistics and material flow	Not specified	Automated vehicles and robots	Operational	Resource scheduling	Decentral	Decentral	No escalation
71	Irannezhad et al., 2020	Transport	Not specified	Trucks	Operational	Collaboration	Decentral	Decentral	No escalation
72	Ivaschenko et al., 2011	Transport	Very large	Trucks	Operational	Transport planning	Hybrid	Decentral	No escalation

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Table A1
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ID	APA reference (authors, year)	Application area	Problem instance size	Mode of transport	Decision	Level of delegation of control	Control hierarchy	Where is the autonomy?	Escalation levels
73	Jaaron and Backhouse, 2015	Reverse logistics and spare parts	Not specified	Not specified	Not specified	Not specified	Decentral	Not specified	Active human involvement
74	Jedermann and Lang, 2008	Transport	Not specified	Trucks	Operational	Transport planning	Decentral	Decentral	No escalation
75	Joubert, 2017	Transport	Medium	Trucks	Operational	Routing	Decentral	Decentral	No escalation
76	Kaddoussi et al., 2013	Transport	Small	Trucks	Operational	Allocation	Hybrid	Hybrid	No escalation
77	Kaddoussi et al., 2011	Transport	Small	Multi-modal	Operational	Transport planning	Hybrid	Decentral	No escalation
78	Kalina et al., 2013b	Transport	Very large	Trucks	Operational	Transport planning	Hybrid	Decentral	No escalation
79	Kalina et al., 2013a	Transport	Very large	Trucks	Operational	Transport planning	Decentral	Decentral	No escalation
80	Karageorgos et al., 2003	Internal logistics and material flow	Small	Not specified	Operational	Production planning	Decentral	Decentral	No escalation
81	Karouani and Elgarej, 2022	Transport	Medium	Trucks	Operational	Transport planning	Hybrid	Central	No escalation
82	Klumpp and Sandhaus, 2021	Transport	Large	Trucks	Operational	No delegation	Hybrid	Decentral	Active human involvement
83	Kundu and Dutta, 2017	Transport	Medium	Trains	Operational	Vehicle control	Decentral	Decentral	No escalation
84	Lang et al., 2011	Transport	Small	Other	Strategic	Transport planning	Decentral	Decentral	No Escalation
85	Lao and Leong, 2002	Transport	Very large	Trucks	Operational	Transport planning	Decentral	Decentral	No escalation
86	Lee et al., 2023	Transport	Medium	Trucks	Operational	Transport planning	Central	Central	No escalation
87	Lehner and Elbert, 2022	Transport	Medium	Trucks	Operational	Transport planning	Central	Central	No escalation
88	Leon-Blanco, et al., 2022	Transport	Large	Trucks	Operational	Routing	Hybrid	Decentral	No escalation

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Table A1
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ID	APA reference (authors, year)	Application area	Problem instance size	Mode of transport	Decision	Level of delegation of control	Control hierarchy	Where is the autonomy?	Escalation levels
89	Leung et al., 2016	Internal logistics and material flow	Very large	Internal transport	Operational	Intralogistics	Hybrid	Central	No escalation
90	Levchenkov and Gorobetz, 2005	Inter- and multi-modal transport	Small	Trucks	Operational	Transport planning	Hybrid	Hybrid	No Escalation
91	Li et al., 2014	Inter- and multi-modal transport	Small	Multi-modal	Operational	Transport planning	Central or Decen-tral	Central or Decen-tral	No escalation
92	Li et al., 2022	Transport	Small	Trucks	Operational	Transport planning	Hybrid	Central	No escalation
93	Liang et al., 2023	Transport	Small	Vehicles	Operational	Routing	Hybrid	Hybrid	No escalation
94	Lieberoth-Leden et al., 2018	Internal logistics and material flow	Medium	Generic vehicles	Operational	Intralogistics	Hybrid	Central	No escalation
95	Lokuge et al., 2004a	Ports and terminals	Not specified	Barges and vessels	Operational	Resource scheduling	Hybrid	Decentral	No escalation
96	Lokuge et al., 2004b	Ports and terminals	Small	Barges and vessels	Operational	Transport planning	Hybrid	Hybrid	No Escalation
97	Madani and Ndiaye, 2019	City and urban logistics	Small	Trucks	Operational	Transport planning	Central	Central	No escalation
98	Máhr et al., 2009	Transport	Small	Trucks	Operational	Transport planning	Decentral	Decentral	No escalation
99	Malus et al., 2020	Internal logistics and material flow	Small	Automated vehicles and robots	Operational	Transport planning	Decentral	Decentral	No escalation
100	Mangina et al., 2020	Transport	Very large	Trucks	Strategic	Transport planning	Central	Central	No escalation
101	McKelvey et al., 2009	Transport	Not specified	Multi-modal	Operational	Transport planning	Decentral	Decentral	No escalation
102	Mehmann and Teuteberg, 2014	Transport	Very large	Trucks	Operational	Transport planning	Central	Central	No escalation

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Table A1
(Continued)

ID	APA reference (authors, year)	Application area	Problem instance size	Mode of transport	Decision	Level of delegation of control	Control hierarchy	Where is the autonomy?	Escalation levels
103	Mejjaouli and Babiceanu, 2018	General supply chains	Small	Trucks	Operational	Transport planning	Decentral	Decentral	No escalation
104	Mepparambath et al., 2023	Transport	Medium	Not specified	Tactical	Transport planning	Hybrid	Central	No escalation
105	Mes et al., 2013	Internal logistics and material flow	Small	Automated vehicles and robots	Operational	Transport planning	Decentral	Decentral	No escalation
106	Mes et al., 2008	Transport	Small	Trucks	Operational	Transport planning	Decentral	Decentral	No escalation
107	Mukhutdinov et al., 2019	Internal logistics and material flow	Small	Internal transport	Operational	Transport planning	Decentral	Decentral	No escalation
108	Neagu et al., 2006	Transport	Very large	Trucks	Operational	Transport planning	Hybrid	Decentral	No escalation
109	Nechifor et al., 2015	City and urban logistics	Not specified	Delivery vans	Operational	No delegation	Central	Central	No escalation
110	Ngu et al., 2022	Transport	Small	Vehicles	Operations	Transport planning	Decentral	Decentral	No escalation
111	Omelianenko et al., 2019	Transport	Not specified	Trucks	Operational	No delegation	Central	Central	No escalation
112	Otto and Bannenberg, 2010	General supply chains	Large	Not specified	Tactical	Network design	Decentral	Decentral	No escalation
113	Otto and Kirn, 2006	General supply chains	Medium	Not specified	Tactical	Pricing	Decentral	Decentral	No escalation
114	Oucheikh et al., 2021	Ports and terminals	Small	Not specified	Operational	Vehicle control	Decentral	Decentral	No escalation
115	Pashchenko et al., 2015	Transport	Not specified	Trains	Operational	Transport planning	Decentral	Decentral	No escalation
116	Poeting et al., 2019	City and urban logistics	Large	Automated vehicles and robots	Tactical	Transport planning	Central	Central	No escalation

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Table A1
(Continued)

ID	APA reference (authors, year)	Application area	Problem instance size	Mode of transport	Decision	Level of delegation of control	Control hierarchy	Where is the autonomy?	Escalation levels
117	Qiao et al., 2020	Transport	Small	Trucks	Operational	Transport planning	Decentral	Decentral	No escalation
118	Qu et al., 2015	Transport	Medium	Trucks	Operational	Transport planning	Central	Central	No escalation
119	Quindt et al., 2011	Agriculture	Not specified	Other	Operational	Transport planning	Hybrid	Central	No escalation
120	Raba et al., 2019	Transport	Medium	Trucks	Operational	Not specified	Central	Central	No escalation
121	Rehák et al., 2006	Transport	Not specified	Generic vehicles	Operational	Transport planning	Hybrid	Hybrid	No escalation
122	Reis, 2014	Transport	Small	Trucks	Tactical	Transport planning	Central	Central	No escalation
123	Ren et al., 2022	Transport	Small	Automated vehicles and robots	Operational	Transport planning	Central	Central	No escalation
124	Rivas and Ribas-Xirgo, 2019	Internal logistics and material flow	Medium	Automated vehicles and robots	Operational	Transport planning	Decentral	Decentral	No escalation
125	Robu et al., 2011	Transport	Small	Trucks	Operational	Allocation	Decentral	Decentral	No escalation
126	de Ryck et al., 2021	Internal logistics and material flow	Small	Automated vehicles and robots	Operational	Transport planning	Hybrid	Decentral	No escalation
127	Salas et al., 2019	General supply chains	Not specified	Trucks	Tactical	Network Design	Hybrid	Decentral	No escalation
128	Sarabia-Jacome et al., 2020	Ports and terminals	Not specified	Barges and vessels	Not specified	No delegation	Hybrid	Decentral	No escalation
129	Sarvari et al., 2020	City and urban logistics	Small	Trucks	Operational	No delegation	Central	Central	No escalation
130	Scholz-Reiter et al., 2011	Transport	Medium	Trucks	Operational	Intralogistics	Decentral	Decentral	No escalation
131	Schuhmacher and Hummel, 2018	Internal logistics and material flow	Small	Internal transport	Operational	Intralogistics	Decentral	Decentral	No escalation

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Table A1
(Continued)

ID	APA reference (authors, year)	Application area	Problem instance size	Mode of transport	Decision	Level of delegation of control	Control hierarchy	Where is the autonomy?	Escalation levels
132	Senturk et al., 2018	Ports and terminals	Small	Barges and vessels	Operational	Manage processes	Decentral	Decentral	No escalation
133	Serna-Urán et al., 2018	City and urban logistics	Very large	Trucks	Tactical	Transport planning	Hybrid	Decentral	No escalation
134	Serna-Urán et al., 2021	Transport	Small	Vehicles	Operational	Routing	Hybrid	Hybrid	No escalation
135	Sha and Srinivasan, 2016	Transport	Medium	Trucks	Tactical	Network design	Decentral	Decentral	No escalation
136	Shao et al., 2019	Transport	Very large	Trucks	Operational	Routing	Central	Central	No escalation
137	Shchekutin et al., 2020	Internal logistics and material flow	Small	Not specified	Strategic	Network design	Central	Central	No escalation
138	Shi et al., 2020	City and urban logistics	Small	Delivery vans	Operational	Transport planning	Central	Central	No escalation
139	Singh et al., 2010	Transport	Medium	Trucks	Operational	Routing	Decentral	Decentral	No escalation
140	Singh et al., 2007	City and urban logistics	Very large	Trucks	Operational	Transport planning	Hybrid	Decentral	No escalation
141	Singh et al., 2008	General supply chains	Medium	Not specified	Operational	Transport planning	Decentral	Decentral	No escalation
142	Sitek et al., 2014	Transport	Small	Generic vehicles	Operational	Transport planning	Central	Central	No escalation
143	Sivamani et al., 2014	Transport	Not specified	Delivery vans	Operational	Routing	Decentral	Decentral	No escalation
144	Śniezyński et al., 2010	Transport	Small	Trucks	Operational	Routing	Decentral	Decentral	No escalation
145	Sprenger and Mönch, 2011	Transport	Small	Trucks	Strategic	Transport planning	Central	Central	No escalation
146	D. Sun et al., 2010	Internal logistics and material flow	Very large	Automated vehicles and robots	Operational	Intralogistics	Decentral	Decentral	No escalation
147	Y. Sun and Li, 2020	Transport	Very large	Multi-modal	Operational	Transport planning	Central	Hybrid	No escalation

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Table A1
(Continued)

ID	APA reference (authors, year)	Application area	Problem instance size	Mode of transport	Decision	Level of delegation of control	Control hierarchy	Where is the autonomy?	Escalation levels
148	Tapia et al., 2023	Inter- and multi-modal transport	Large	Trucks	Operational	Transport planning	Decentral	Decentral	No escalation
149	Ter Mors et al., 2004	Transport	Medium	Trucks	Operational	No delegation	Central	Central	No escalation
150	Tsang et al., 2020	Internal logistics and material flow	Not specified	Trucks	Operational	Resource scheduling	Decentral	Decentral	No escalation
151	Van Belle et al., 2011	Transport	Medium	Trucks	Operational	Transport planning	Decentral	Decentral	No escalation
152	Van Heeswijk, 2020	Transport	Medium	Not specified	Operational	Transport planning	Decentral	Decentral	No escalation
153	Van Heeswijk and La Poutré, 2019	City and urban logistics	Large	Generic vehicles	Tactical	Demand anticipation	Hybrid	Decentral	No escalation
154	Verma and Varakantham, 2019	Internal logistics and material flow	Small	Picking robots	Operational	Transport planning	Mixed	Decentral	No escalation
155	J. Wang et al., 2020	Transport	Very large	Trucks	Operational	Transport planning	Central	Central	No escalation
156	X. Wang et al., 2014	Transport	Large	Generic vehicles	Tactical	No delegation	Central	Central	No escalation
157	Y. Wang et al., 2015	Transport	Medium	Trucks	Operational	Routing	Decentral	Decentral	Additional information
158	Wenning et al., 2007	Transport	Medium	Trucks	Operational	Routing	Decentral	Decentral	No escalation
159	Wenning et al., 2006	Internal logistics and material flow	Small	Automated vehicles and robots	Operational	Transport planning	Hybrid	Decentral	No escalation
160	Weyns et al., 2005	Transport	Very large	Trucks	Operational	Transport planning	Hybrid	Decentral	No escalation
161	Wojtusiak et al., 2012	Internal logistics and material flow	Small	Automated vehicles and robots	Operational	Not specified	Hybrid	Central	Central traffic controller

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Table A1
(Continued)

ID	APA reference (authors, year)	Application area	Problem instance size	Mode of transport	Decision	Level of delegation of control	Control hierarchy	Where is the autonomy?	Escalation levels
162	Xiao et al., 2020	Transport	Medium	Trucks	Operational	No delegation	Central	Central	No escalation
163	Xiong et al., 2018	Internal logistics and material flow	Small	Automated vehicles and robots	Operational	Vehicle control	Decentral	Decentral	No escalation
164	Yang et al., 2017	General supply chains	Small	Trucks	Operational	Transport planning	Central	Central	No escalation
165	Yao et al., 2020	Internal logistics and material flow	Small	Automated vehicles and robots	Operational	Transport planning	Central	Central	No escalation
166	Q. Zhang and Li, 2014	City and urban logistics	Medium	Generic vehicles	Operational	Transport planning	Hybrid	Hybrid	No escalation
167	Y.F. Zhang et al., 2013	Transport	Medium	Trucks	Operational	No delegation	Central	Central	No escalation
168	Zhang et al., 2021	Transport	Medium	Trains	Tactical	Transport planning	Central	Central	No escalation
169	Zhu et al., 2000	Transport	Small	Aircraft	Operational	Transport planning	Hybrid	Hybrid	No escalation

Table A2
Classification of literature (intelligence, validation, maturity, and SOL).

ID	APA reference	Decision-making capabilities	Environmental perception	Maturity	Case study	Genericity	Validation	Agent typology	SOL score
1	Abu-Monshar and Al-Bazi, 2022	Agent-based	Not specified	Numerical experiment	Yes (theoretical)	Semi-generic	No	1	1
2	Agrawal et al., 2016	Agent-based	Not specified	Simulation	No	Low	Yes (simulation)	1	2
3	Ahamuda et al., 2020	Agent-based	Not specified	Simulation	Yes (real life)	Semi-generic	Yes (real world)	2	4
4	Akkad et al., 2022	Metaheuristics	IoT	Numerical experiment	Yes (real life)	High	No	0	1
5	Arendt et al., 2016	Agent-based	Not specified	Simulation	Yes (real life)	Semi-generic	Yes (simulation)	3	3
6	Bădică et al., 2020	Agent-based	N/A	Simulation	No	Low	Yes (simulation)	3	2
7	Bae et al., 2022	Agent-based	Not specified	Simulation	Yes (theoretical)	Semi-generic	No	3	2
8	Barenji et al., 2019	Agent-based	IoT	Simulation	Yes (real life)	High	Yes (simulation)	4	3
9	Bartholdi, et al., 2010	Agent-based	Not specified	Numerical experiment	No	Very high	No	4	4
10	Baykasoglu and Kaplanoglu, 2011	Agent-based	Not specified	Simulation	No	Semi-generic	Yes (simulation)	4	3
11	Baykasoglu et al., 2011	Agent-based	Not specified	Ideation	No	High	No	3	3
12	Baykasoglu and Kaplanoglu, 2015	Agent-based	Not specified	Simulation	No	High	Yes (simulation)	4	4
13	M. Becker et al., 2006	AI-based	Not specified	Simulation	Yes (real life)	Very high	No	1	1
14	T. Becker et al., 2016	Not specified	Not specified	Simulation	Yes (real life)	High	No	2	2
15	Bernaer et al., 2006	Agent-based	Not specified	Conceptual model	No	Semi-generic	No	3	3
16	Berndt, 2013	Not specified	Not specified	Simulation	No	Very high	No	4	4
17	Besselink et al., 2016	Exact method	Traditional IT (cameras, phones, ….)	Simulation	Yes (real life)	Semi-generic	No	0	1
18	Blom et al., 2020	Other heuristics	Not specified	Simulation	No	High	Yes (simulation)	4	4
19	Boussier et al., 2009	Not specified	Not specified	Simulation	Not specified	High	No	2	1
20	Calabrò et al., 2020	Metaheuristics	Not specified	Numerical experiment	Yes (real life)	High	No	1	4
21	Carpanzano et al., 2014	Agent-based	IoT	Simulation	Yes (real life)	Semi-generic	Yes (simulation)	4	4
22	Carpanzano et al., 2016	Agent-based	IoT	Simulation	Yes (real life)	Semi-generic	Yes (simulation)	4	4

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Table A2
(Continued)

ID	APA reference	Decision-making capabilities	Environmental perception	Maturity	Case study	Genericity	Validation	Agent typology	SOL score
23	Chatterjee et al., 2016	Agent-based	Not specified	Simulation	No	Semi-generic	Yes (simulation)	2	1
24	Chen et al., 2022	Agent-based	Not specified	Simulation	Yes (real life)	Semi-generic	Yes (simulation)	4	3
25	Cheng and Qi, 2011	Agent-based	Not specified	Conceptual model	No	Low	Partially	0	1
26	Danchuk et al., 2023	Metaheuristics	IoT	Simulation	Yes (real life)	High	No	0	1
27	Dangelmaier et al., 2004	Agent-based	Not specified	Simulation	Yes (theoretical)	Low	Yes (simulation)	2	2
28	De Jonge et al., 2021	Other heuristics	Not specified	Numerical experiment	Yes (real life)	High	No	1	0
29	De Sousa and De Oliveira, 2020	Agent-based	Not specified	Simulation	Yes (theoretical)	Semi-generic	No	2	4
30	Demirag and Swann, 2007	Exact method	Not specified	Conceptual model	Yes (theoretical)	High	Partially	1	0
31	Di Febbraro et al., 2018	Exact method	PI	Numerical experiment	Yes (real life)	Semi-generic	No	0	1
32	Di Febbraro et al., 2016	Exact method	Not specified	Simulation	No	Semi-generic	Yes (simulation)	1	1
33	Dimitriou and Stathopoulos, 2011	Metaheuristics	Not specified	Simulation	Yes (theoretical)	High	Yes (simulation)	3	2
34	Dimitriou and Stathopoulos, 2009	AI-based	Not specified	Simulation	Yes (theoretical)	High	Yes (simulation)	3	2
35	Dorer and Calisti, 2005	Agent-based	Not specified	Deployed	Yes (real life)	Semi-generic	Yes (simulation)	1	2
36	Draganjac et al., 2020	Agent-based	IoT	Simulation	Yes (real life)	Semi-generic	Yes (simulation)	0	3
37	Ebel and Eberhard, 2019	Exact method	IoT	Simulation	No	High	Yes (simulation)	0	3
38	Ebel et al., 2021	Agent-based	Local wireless networks	Prototype	No	Semi-generic	Yes (real world)	4	3
39	Edelkamp and Gath, 2013	Agent-based	Geo-data	Simulation	Yes (real life)	Semi-generic	Yes (simulation)	4	3
40	Erdmann et al., 2020	Metaheuristics	N/A	Prototype	Yes (real life)	Semi-generic	Yes (real world)	0	0
41	Espejo-Díaz and Guerrero 2021.	Agent-based	Not specified	Simulation	Yes (real life)	Semi-generic	No	1	2
42	Fan et al., 2021	Agent-based	IoT	Simulation	Yes (theoretical)	Low	No	2	2

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(Continued)

ID	APA reference	Decision-making capabilities	Environmental perception	Maturity	Case study	Genericity	Validation	Agent typology	SOL score
43	Fazili et al., 2017	Other heuristics	PI	Simulation	Yes (real life)	Very high	Yes (simulation)	0	0
44	Feljan et al., 2017	Not specified	IoT	Prototype	Not specified	High	Yes (real world)	1	1
45	Feng et al., 2014	Agent-based	Traditional IT (cameras, phones, ….)	Development phase	No	Semi-generic	No	3	3
46	Feng et al., 2015	Agent-based	Not specified	Simulation	No	High	Yes (simulation)	3	4
47	Feng et al., 2017	Agent-based	Not specified	Simulation	No	High	Yes (simulation)	3	4
48	Fikar et al., 2015	Agent-based	Traditional IT (cameras, phones, ….)	Simulation	Yes (theoretical)	Low	Yes (simulation)	1	2
49	Fikar et al., 2018	Agent-based	Not specified	Simulation	Yes (real life)	High	Yes (simulation)	2	1
50	Filippi et a., 2022	Metaheuristics	Not specified	Numerical experiment	Yes (real life)	Semi-generic	No	0	2
51	Firdausiyah et al., 2019	Exact method	Not specified	Simulation	Yes (real life)	High	No	4	3
52	Fischer et al., 1994	Agent-based	Not specified	Conceptual model	No	High	No	1	2
53	Franke et al., 2004	Agent-based	Geo-data	Simulation	Yes (theoretical)	Semi-generic	Yes (simulation)	1	2
54	Gath et al., 2014	Agent-based	Not specified	Simulation	No	Semi-generic	Yes (simulation)	4	4
55	Gath et al., 2013	Exact method	Geo-data	Prototype	Yes (real life)	Semi-generic	Yes (simulation)	4	3
56	Gath et al., 2015	Agent-based	IoT	Simulation	Yes (theoretical)	Semi-generic	Yes (simulation)	4	3
57	Gath et al., 2012	Agent-based	Not specified	Simulation	Yes (real life)	High	Yes (simulation)	2	3
58	Gerrits et al., 2017	Agent-based	Not specified	Simulation	No	High	Yes (simulation)	4	3
59	Glicoes and Huhns, 1996	Metaheuristics	GPS	Conceptual model	Yes (real life)	High	No	4	3
60	Gontara et al., 2019	Other heuristics	PI	Simulation	Yes (theoretical)	Semi-generic	Yes (simulation)	0	3
61	Gorodetski et al., 2003	Agent-based	Not specified	Simulation	No	Semi-generic	Yes (simulation)	1	2
62	Gorodetsky et al., 2012	Not specified	Not specified	Not specified	No	Semi-generic	No	1	2
63	Gronalt and Schindlbacher, 2015	Other heuristics	Not specified	Simulation	Yes (real life)	Low	Yes (simulation)	2	1
64	Guo et al., 2021	Heuristics	Not specified	Simulation	Yes (theoretical)	High	Yes (simulation)	0	2
65	Haass et al., 2015	Agent-based	IoT	Simulation	Yes (real life)	Low	Yes (simulation)	4	3
66	Hiari et al., 2017	Not specified	IoT	Design phase	No	Semi-generic	No	0	3

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Table A2
(Continued)

ID	APA reference	Decision-making capabilities	Environmental perception	Maturity	Case study	Genericity	Validation	Agent typology	SOL score
67	Hildmann and Martin, 2015	Agent-based	Not specified	Simulation	Yes (theoretical)	Semi-generic	Yes (simulation)	3	2
68	Himoff et al., 2006	Agent-based	Not specified	Deployed	Yes (real life)	Semi-generic	Yes (real world)	1	2
69	Hongler et al., 2010	Other heuristics	Not specified	Numerical experiment	No	High	No	4	3
70	Indrayadi et al., 2002	Agent-based	Not specified	Design phase	No	Low	No	1	2
71	Irannezhad et al., 2020	AI-based	Not specified	Simulation	Yes (real life)	High	No	4	4
72	Ivaschenko et al., 2011	Agent-based	GPS	Deployed	Yes (real life)	Semi-generic	Yes (real world)	0	3
73	Jaaron and Backhouse, 2015	Not specified	Not specified	Conceptual model	Yes (real life)	Very high	No	0	3
74	Jedermann and Lang, 2008	Agent-based	RFID and barcodes	Not specified	No	Semi-generic	No	3	2
75	Joubert, 2017	Agent-based	Not specified	Simulation	No	High	No	2	2
76	Kaddoussi et al., 2013	Exact method	Not specified	Simulation	No	Semi-generic	Yes (simulation)	1	2
77	Kaddoussi et al., 2011	Exact method	Not specified	Simulation	Yes (real life)	Low	Yes (simulation)	1	2
78	Kalina et al., 2013b	Agent-based	Not specified	Simulation	Yes (theoretical)	Semi-generic	Yes (simulation)	1	2
79	Kalina et al., 2013a	Agent-based	Not specified	Simulation	No	High	Yes (simulation)	3	4
80	Karageorgos et al., 2003	Other heuristics	Not specified	Prototype	No	High	Partially	3	2
81	Karouani and Elgarej, 2022	Metaheuristics	IoT	Prototype	Yes (real life)	Semi-generic	Yes (real world)	1	2
82	Klumpp and Sandhaus, 2021	Not specified	Traditional IT (cameras, phones, ….)	Conceptual model	Not specified	Semi-generic	No	3	2
83	Kundu and Dutta, 2017	Agent-based	Not specified	Simulation	Yes (theoretical)	Low	Yes (simulation)	4	3
84	Lang et al., 2011	AI-based	IoT	Prototype	Yes (real life)	Semi-generic	Yes (real world)	0	1
85	Lao and Leong, 2002	Agent-based	Not specified	Simulation	Yes (theoretical)	Semi-generic	Yes (simulation)	3	2
86	Lee et al., 2023	Metaheuristics	IoT	Simulation	Yes (real life)	Very high	Yes (real world)	0	1
87	Lehner and Elbert, 2022	Exact method	Not specified	Simulation	Yes (real life)	Semi-generic	No	0	2
88	Leon-Blanco, et al., 2022	Agent-based	Not specified	Simulation	Yes (theoretical)	Semi-generic	No	4	3

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Table A2
(Continued)

ID	APA reference	Decision-making capabilities	Environmental perception	Maturity	Case study	Genericity	Validation	Agent typology	SOL score
89	Leung et al., 2016	Agent-based	RFID and barcodes	Prototype	Yes (real life)	Low	Yes (real world)	1	2
90	Levchenkov and Gorobetz, 2005	Agent-based	Not specified	Simulation	No	Semi-generic	Yes (simulation)	3	2
91	Li et al., 2014	Exact method	Not specified	Simulation	No	Semi-generic	Yes (simulation)	1	2
92	Li et al., 2022	Metaheuristics	PI	Numerical experiment	Yes (real life)	Semi-generic	No	0	3
93	Liang et al., 2023	Agent-based	Not specified	Simulation	Yes (real life)	Low	No	4	3
94	Lieberoth-Leden et al., 2018	Agent-based	RFID and barcodes	Prototype	Yes (real life)	Low	Yes (real world)	3	3
95	Lokuge et al., 2004a	AI-based	Not specified	Conceptual model	No	High	No	1	2
96	Lokuge et al., 2004b	Agent-based	Not specified	Simulation	No	Semi-generic	Yes (simulation)	3	2
97	Madani and Ndiaye, 2019	Exact method	Not specified	Simulation	No	Low	Yes (simulation)	0	2
98	Máhr et al., 2009	Agent-based	Not specified	Numerical experiment	Yes (real life)	High	No	1	2
99	Malus et al., 2020	Agent-based	Not specified	Simulation	Yes (theoretical)	High	Yes (simulation)	4	4
100	Mangina et al., 2020	Not specified	Not specified	Numerical experiment	Yes (real life)	High	No	2	0
101	McKelvey et al., 2009	Metaheuristics	RFID and barcodes	Design phase	No	Semi-generic	No	4	4
102	Mehmann and Teuteberg, 2014	Metaheuristics	Not specified	Simulation	No	Semi-generic	Yes (simulation)	1	1
103	Mejjaouli and Babiceanu, 2018	Exact method	RFID and barcodes	Simulation	Yes (real life)	Low	Yes (simulation)	0	3
104	Mepparambath et al., 2023	Agent-based	Not specified	Simulation	Yes (real life)	Semi-generic	No	3	2
105	Mes et al., 2013	Agent-based	Not specified	Simulation	Yes (real life)	High	Yes (simulation)	4	4
106	Mes et al., 2008	Agent-based	Not specified	Simulation	No	High	No	3	3
107	Mukhutdinov et al., 2019	Agent-based	Not specified	Simulation	Yes (theoretical)	Low	Yes (simulation)	4	3
108	Neagu et al., 2006	Other heuristics	Not specified	Deployed	Yes (real life)	High	Yes (real world)	1	2
109	Nechifor et al., 2015	Agent-based	Not specified	Simulation	No	Semi-generic	Yes (simulation)	1	1

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Table A2
(Continued)

ID	APA reference	Decision-making capabilities	Environmental perception	Maturity	Case study	Genericity	Validation	Agent typology	SOL score
110	Ngu et al., 2022	Agent-based	Not specified	Numerical experiment	Yes (theoretical)	High	No	0	3
111	Omelianenko et al., 2019	Other heuristics	IoT	Deployed	Yes (real life)	High	Yes (real world)	0	1
112	Otto and Bannenberg, 2010	Metaheuristics	Not specified	Simulation	No	Semi-generic	Yes (simulation)	3	2
113	Otto and Kirn, 2006	Metaheuristics	Not specified	Simulation	Yes (theoretical)	Semi-generic	No	4	3
114	Oucheikh et al., 2021	Agent-based	Not specified	Simulation	Yes (theoretical)	Semi-generic	No	4	2
115	Pashchenko et al., 2015	Agent-based	Not specified	Simulation	No	Semi-generic	Yes (simulation)	1	2
116	Poeting et al., 2019	Metaheuristics	Not specified	Simulation	Yes (real life)	High	Yes (simulation)	2	1
117	Qiao et al., 2020	Exact method	PI	Simulation	Yes (real life)	Semi-generic	Yes (simulation)	0	3
118	Qu et al., 2015	Metaheuristics	IoT	Simulation	Yes (theoretical)	Semi-generic	Yes (simulation)	0	2
119	Quindt et al., 2011	Not specified	Local wireless networks	Conceptual model	No	Low	No	1	2
120	Raba et al., 2019	Simulation heuristics	Sensors	Simulation	No	Semi-generic	Yes (simulation)	0	1
121	Rehák et al., 2006	Agent-based	Not specified	Simulation	No	High	Yes (simulation)	3	3
122	Reis, 2014	AI-based	N/A	Simulation	Yes (real life)	Semi-generic	Yes (simulation)	2	1
123	Ren et al., 2022	Exact method	Not specified	Numerical experiment	Yes (theoretical)	Low	No	0	1
124	Rivas and Ribas-Xirgo, 2019	Agent-based	Not specified	Simulation	Not specified	Semi-generic	Yes (simulation)	4	3
125	Robu et al., 2011	Agent-based	Not specified	Simulation	Yes (real life)	Semi-generic	Yes (simulation)	1	2
126	de Ryck et al., 2021	Agent-based	Not specified	Simulation	Yes (theoretical)	High	Yes (simulation)	4	2
127	Salas et al., 2019	Agent-based	Not specified	Conceptual model	No	Semi-generic	No	1	1
128	Sarabia-Jacome et al., 2020	Exact method	IoT	Design phase	Yes (real life)	Semi-generic	Partially	0	2
129	Sarvari et al., 2020	Metaheuristics	IoT	Numerical experiment	No	High	No	0	1

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Table A2
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ID	APA reference	Decision-making capabilities	Environmental perception	Maturity	Case study	Genericity	Validation	Agent typology	SOL score
130	Scholz-Reiter et al., 2011	Agent-based	Not specified	Simulation	Yes (theoretical)	Semi-generic	Yes (simulation)	0	2
131	Schuhmacher and Hummel, 2018	Not specified	Not specified	Conceptual model	Yes (real life)	High	No	0	3
132	Senturk et al., 2018	Agent-based	Not specified	Simulation	Yes (real life)	Semi-generic	No	1	1
133	Serna-Urán et al., 2018	Agent-based	Not specified	Simulation	No	High	Yes (simulation)	3	4
134	Serna-Urán et al., 2021	Agent-based	Not specified	Numerical experiment	No	Semi-generic	No	2	1
135	Sha and Srinivasan, 2016	Agent-based	Not specified	Simulation	Yes (theoretical)	Low	Yes (simulation)	1	2
136	Shao et al., 2019	Exact method	IoT	Simulation	Yes (real life)	Semi-generic	Yes (simulation)	0	3
137	Shchekutin et al., 2020	Metaheuristics	Not specified	Numerical experiment	Yes (theoretical)	High	No	1	0
138	Shi et al., 2020	Exact method	PI	Numerical experiment	Yes (real life)	High	No	1	0
139	Singh et al., 2010	Not specified	Not specified	Simulation	No	Semi-generic	Yes (simulation)	4	3
140	Singh et al., 2007	Agent-based	Not specified	Simulation	Yes (theoretical)	Semi-generic	Yes (simulation)	4	4
141	Singh et al., 2008	Other heuristics	Not specified	Conceptual model	No	High	No	1	2
142	Sitek et al., 2014	Exact method	Not specified	Simulation	Yes (theoretical)	Low	Yes (simulation)	1	1
143	Sivamani et al., 2014	Other heuristics	Traditional IT (cameras, phones, ….)	Conceptual model	No	High	No	0	2
144	Śniezyński et al., 2010	AI-based	Not specified	Simulation	No	Low	Yes (simulation)	1	2
145	Sprenger and Mönch, 2011	AI-based	Not specified	Simulation	Yes (real life)	Semi-generic	Yes (simulation)	1	2
146	D. Sun et al., 2010	Agent-based	IoT	Simulation	No	High	Yes (simulation)	4	4
147	Y. Sun and Li, 2020	Other heuristics	Not specified	Simulation	Yes (real life)	High	Yes (simulation)	0	3
148	Tapia et al., 2023	Other heuristics	Not specified	Simulation	No	High	Yes (simulation)	3	3
149	Ter Mors et al., 2004	Metaheuristics	IoT	Simulation	Yes (real life)	High	Yes (simulation)	0	1
150	Tsang et al., 2020	Not specified	Not specified	Simulation	Yes (theoretical)	Semi-generic	No	4	4
151	Van Belle et al., 2011	AI-based	PI	Simulation	No	Low	Yes (simulation)	2	3
152	Van Heeswijk, 2020	Exact method	Not specified	Simulation	No	High	Yes (simulation)	3	2

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Table A2
(Continued)

ID	APA reference	Decision-making capabilities	Environmental perception	Maturity	Case study	Genericity	Validation	Agent typology	SOL score
153	Van Heeswijk and La Poutré, 2019	Agent-based	Not specified	Simulation	Yes (theoretical)	Low	Yes (simulation)	3	2
154	Verma and Varakantham, 2019	AI-based	IoT, cloud, GPS, sensors, RFID tags	Simulation	Yes (real life)	Low	Yes (simulation)	0	3
155	J. Wang et al., 2020	Metaheuristics	Not specified	Simulation	No	Semi-generic	Partially	0	2
156	X. Wang et al., 2014	Other heuristics	Not specified	Simulation	No	Semi-generic	Yes (simulation)	1	0
157	Y. Wang et al., 2015	Other heuristics	Not specified	Simulation	Yes (real life)	High	No	1	1
158	Wenning et al., 2007	Metaheuristics	Not specified	Simulation	Yes (theoretical)	Semi-generic	Yes (simulation)	0	3
159	Wenning et al., 2006	Agent-based	IoT	Prototype	Yes (theoretical)	Semi-generic	Yes (simulation)	4	3
160	Weyns et al., 2005	Exact method	Not specified	Simulation	Yes (real life)	High	Yes (simulation)	1	2
161	Wojtusiak et al., 2012	Other heuristics	IoT	Simulation	Yes (theoretical)	High	Yes (simulation)	2	3
162	Xiao et al., 2020	Metaheuristics	Not specified	Simulation	No	Low	Yes (simulation)	0	0
163	Xiong et al., 2018	AI-based	Sensors	Simulation	No	High	Yes (simulation)	0	3
164	Yang et al., 2017	Metaheuristics	PI	Simulation	Yes (theoretical)	Semi-generic	Yes (simulation)	0	2
165	Yao et al., 2020	Metaheuristics	IoT	Simulation	Yes (real life)	High	Yes (simulation)	0	1
166	Q. Zhang and Li, 2014	Metaheuristics	Not specified	Simulation	Yes (theoretical)	Semi-generic	Yes (simulation)	0	2
167	Y.F. Zhang et al., 2013	Other heuristics	RFID and barcodes	Simulation	No	Semi-generic	Yes (simulation)	0	0
168	Zhang et al., 2021	Exact method	IoT	Numerical experiment	Yes (theoretical)	High	No	0	1
169	Zhu et al., 2000	Agent-based	Not specified	Simulation	Yes (theoretical)	Low	Yes (simulation)	1	2