Deploying Computational Intelligence for Logistics and Supply Chain

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ABSTRACT: *The supply chain industry has used extensive computational intelligence solutions from the scientific focus where the important challenges are addressed more effectively. Computational intelligence is playing a major role in supply chain and offer better prospects for business. Thus, many academic researchers started to do good amount of research in its applications to business. The awareness and relevance of the computational intelligence for supply chain is considered by more business sector people.*

Keywords: Artificial Intelligence, AI, Logistics, Supply Chain, digitalization

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1. Introduction

As in any other industry, logistics and supply chains strive to perform their activities and business processes intelligently as much as possible. And intelligently means digital. Nowadays we are increasingly confronted with concepts such as Intelligent logistics or Supply Chain, Industry 4.0 (or even 5.0), Digital Logistics or Supply Chain, Smart Logistics or Supply Chain and similar, both in professional and scientific environments. To achieve such a level of intelligence, the major and the most important role plays the technology.

Technology has always been and will always be very important for the optimization of the operational performance and efficiency of each company. It offers many key opportunities, but it offers also some key challenges. Among the latter are high costs and requirements for the technology implementation, ethical and legal concerns, the resistance of workforces, safety issues, integration issues, and other. Therefore, it is extremely important to approach the selection and implementation of technology thoughtfully and in a mature way.

Logistics and supply chains more than ever strive to be smarter, cost-effective, more flexible, accurate, efficient, precise, faster, sustainable, transparent, customer-centric, and to be available 'as a Service'. With current advancements in technology, this is more accessible than ever before.

2. Technologies in Logistics and SC

To help logistics and supply chain players select or invest in the 'right', 'promising enough' technology, various predictions and classifications of promising technologies were prepared. In Table 1 three of them are presented. While Gartner [1] made a list of Top 10 strategically important technologies independent of the type of the industry, McKinsey [2] and DHL [3] offer classifications of technology trends dedicated for supply chains and logistics, respectively.

Gartner*	***McKinsey****	**DHL*****
Autonomous Things	Big Data and Advanced Analytics	Cloud logistics (H, <5)
Augmented Analytics	Automation	Big Data Analytics (H, <5)
AI-driven Development	Artificial Intelligence	Internet of Things (H, <5)
Digital Twins	Autonomous and smart vehicles	Robotics & Automation (H, <5)
Empowered Edge*1	Supply Chain Cloud	Artificial Intelligence (H, >5)
Immersive Technologies*2	3D printing	3D printing (H, >5)
Blockchain		Self-driving Vehicles (H, >5)
Smart Spaces (i.e. advanced digital workplace or connected factory)		Augmented Reality (M, <5)
		Low-cost Sensor Solutions (M, <5)
Digital Ethics and Privacy		Blockchain (M, >5)
		Next-generation Wireless (M, >5)
Quantum Computing		Unmanned Aerial Vehicles (M, >5)
		Virtual Reality & Digital Twins (L, >5)
		Bionic Enhancement (L, >5)

*: Top 10 Strategic Technology Trends for 2019 [1]

*1: Cloud, devices (AI chips, greater compute capabilities, more storage), 5G[1]

*2: Conversational Platforms, Augmented Reality, Mixed Reality, and Virtual Reality [1]

**: the classification was made according to their Digital Supply Chain Compass [2]

***: the classification was made according to their Logistics Trend Radar [3] – first the impact (H-high, M-medium, L-low) was taken into account, then the relevance in years (< 5, >5)

Table 1. The Most Important Technology Trends In Logistics

Inspecting these technologies it is clear that AI solutions are embedded in, or are enabling many of them. On the other hand, the rise of the power of AI will be possible just because of advances of other technologies, like radio frequency identification (RFID), big data and advanced analytics, sensor solutions, new generation communication networks, and other as well.

2.1. Artificial Intelligence

Artificial Intelligence (AI) is one of the 'hottest' technologies (already) today, and according to Costello [4], "AI adoption in organizations has tripled in the past year and is a top priority for CIOs". Following DHL [5], AI is a "trend having much greater impact on logistics than expected in the past". The fact is that many tools, products, and applications used for logistics and supply chain support today already rely on AI.

The goal of AI is to create such a technology that gives the 'human' intelligence to the machines, - i.e., computers, computer-controlled robots, or software -, so that they can imitate humans and behave in an intelligent manner. Because the machines demonstrate intelligence, they are sometimes called also the machine intelligence.

AI solutions most often used or implemented for logistics and supply chain are machine learning approaches (through machine translation, speech recognition, image classification, and information retrieval), robotics, computer vision, natural language processing, and expert systems as the synonym of decision support system.

One of the greatest benefits of the AI solutions is the ability to learn and extract insights and knowledge from unstructured data (unstructured text, documents of various types, videos, online browsing data, conversations and posts on social media, emails, letters, photos, and other sources).

2.2. Key Applications of AI in Logistics and Supply Chain

As the supply chains and logistics itself are complex networks of product or service, information and financial flows between suppliers and customers, - i.e., physical and digital networks, which must function optimally and harmoniously, AI solutions, which are mostly network-based too, are very suitable for the problem solving in logistics and supply chain management (LSCM).

According to [2], [3], and [5], the key applications of AI in LSCM are:

Intelligent Decision Making Support

Knowledge-based decision support systems are the result of AI used for decision- making. Such systems behave like an expert, consultant that is capable to gather and analyze data, identify problems from these data, and finally find and evaluate the solutions. Decision -making with the support of knowledge-based decision support systems is much more efficient and fast.

Back-office Automation or Automation of Knowledge Work

A large amount of data-repetitive tasks could be faster, cheaper, and more accurately executed using the cognitive automation, - i.e., a combination of AI and software robots (bots) that are integrated into existing IT applications. Bots are programmed for the execution of tasks according to predefined rules and (only) structured inputs. They can provide AI tools with a waste amount of business data while using AI technology like natural language processing, the extracted data from unstructured document or source of information (invoices or contract) can be classified and given to bots as input data.

Automated Planning and Scheduling

Ad hoc and real-time planning (demand forecasting), that dynamically changes over time as a result of changed requirements or constraints, is giving to the SC much more flexibility and creates a new business models such as Supply Chain-as-a-Service. It is possible when big data and advanced analytics together with AI techniques (Bayesian networks and machine learning) are used.

Predictive Logistics

Machine learning-based tools can be used for predictions of delays, transit times, interest for a specific product/service (which and when the interest will be maximal), prospects for the global trade, (supplier) risks.

AI-powered Customer Experience with Logistics Provider - Customer Personalization Voice agent (a speaker or a software tool able to communicate via Facebook Messenger or SMS) offers a voice-based service in tracking ordered parcels and providing with the information about delivery times, locations, and other information.

Anticipatory logistics uses AI for delivering goods to customers before their effective order and maybe before they realize to need them. Anticipations are designed based on predictions made from browsing behavior, purchase history and other data.

Automation of customer interactions by voice with chatbots, playing the role of virtual assistants, allows complex dialogs with customers and therefore real-time customer assistance.

Collaborative human-machine environments (i.e. use of collaborative robots)
Collaborative robots are assisting workers while carrying out repetitive tasks, working with workers, who perform more intelligent, technically demanding tasks (so -called 'digital work'). Virtual Reality tools support workers in training and remote collaboration.

"Uberization" of Transport and New Transport Concepts
The cooperative intelligent transport systems, intelligent route optimization offering dynamic routing facilities, last-mile delivery using autonomous unmanned aerial vehicles or autonomous ground vehicles, use of autonomous trucks/fleets, truck platooning or caravanning of groups of semi-trucks, etc. are some of the most important results of AI implementation in transport.

Logistics Network Orchestration
Harmonization of physical and digital networks on which logistics companies depend, using AI technologies.

Smart Logistics assets or "Seeing, Speaking and Thinking Logistics Assets" [5]
Smart logistics is created by use of robotics (sorting robots, collaborative robots), computer vision systems (visual inspection, inventory management and execution, vision-based sorting), conversational interfaces (voice-based picking, conversation of logistics operators with IT system – i.e., system can interpret the meaning of speech/voice information and after "understanding" which product was mentioned, connects the data in ERP, WMS, or TMS about this product and allow the input, store or retrieval of data), autonomous vehicles (self-learning and self-navigating AGVs – Autonomous Guided Vehicles) as added value to the human workforce.

2.2. Results of the Literature Review and Classification
The data about the authors, title, aspect(s) studied, AI approaches used, the scope and the results of the article, as well as the publication year and journal title, were collected during the full-text reading.

3. The Scientific Literature Review of AI Applications in Logistics and SC

3.1. The Methodology of the Literature Review
The review of open-access scientific original or review papers published until now was conducted in May 2019 by browsing the two of the most important and largest scientific databases, ScienceDirect and Scopus. As the purpose of the review was to found out how frequently the researchers have studied the application of Artificial Intelligence tools and approaches in the field of logistics and/or supply chain and which AI tools or approaches were studied, the search of databases was performed using keywords such as Logistics AND ("Artificial Intelligence" OR "Intelligence" OR "AI") and "Supply Chain" AND ("Artificial Intelligence" OR "intelligence" OR "AI"). The search was focused on titles, abstracts, and keywords for English-written full-text free-available scientific journal papers resulting in 95 papers found. After the initial reading of titles, abstracts, and keywords, 23 papers were excluded because the techniques used were not from the AI field, and 5 because they were duplicates. Remaining 67 papers were considered relevant after full-text reading and they entered the classification process. The overall search process is shown in Figure 1.

3.2. Results of the Literature Review and Classification
The data about the authors, title, aspect(s) studied, AI approaches used, the scope and the results of the article, as well as the publication year and journal title, were collected during the full-text reading.

As expected, the most often AI approaches were used for the optimization purposes (11), planning and scheduling problem solving (11), and forecasting and predicting (8). The review of other aspects of logistics and supply chain, as well as some short details about the reviewed articles are given in Table 2. The empty cell in the column AI approach means that the literature review of was performed.

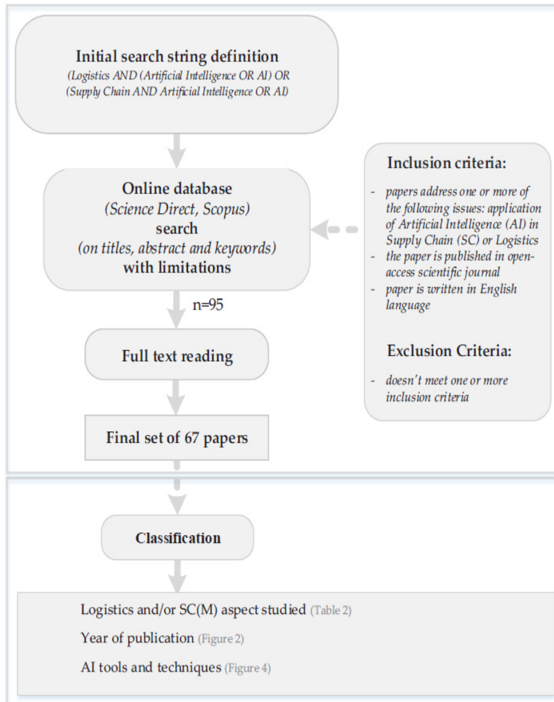

Figure 1. The overall search process

Aspect studied	**Ref.**	**AI approach**	**Year**	**Summary**
Allocation	[6]	Tabu search, path relinking	2012	A hybrid metaheuristic for dynamic berth alloca tion problem (port logistics) with the goal to mini mize the total time the vessels stay at the port
Automation and Control	[7]	A rule-based system, machine learning	2018	Approach for proactive management of raw milk quality with a high level of accuracy
	[8]	Machine learning	2014	New detection and avoidance mechanisms of all counterfeit parts and forged documentation for electronic component SC
	[9]	Distributed AI, multi-agent system, real-time decision making	2009	Forecast of the use of radio frequency identifica tion (RFID) technologies integrated into ICT framework in a cooperative intelligent logistics systems
	[10]	Fuzzy logic, genetic algorithms	2016	A proposal for a combined application to control the procurement process in the enterprise (inven tory control under uncertain conditions)
	[11]	Deep learning	2018	3D object recognition and autonomization of logistics

Big Data	[12]		2018	Review of Big Data Applications (BDA) in supply chain
	[13]	Support vector machine and hierarchical clustering with multiscale bootstrap resampling	2018	Proposes a big-data analytics-based approach that considers social media (Twitter) data for the identification of supply chain management issues in food industries
	[14]		2018	Review of big data analytics and applications for logistics and SCM by examining novel methods, practices, and opportunities
Cooperation	[15]	Machine learning, deep learning	2017	The concept of a research center for issues of human interaction in logistics, intralogistics, and human and machine cooperation
Decision Making	[16]	Bees algorithm, swarm intelligence	2010	A container loading support system (CLSS)
	[17]	Sequential decision making, binary decision tree, heuristic algorithms	2011	Formulation of a port of entry inspection se quencing task as a problem of finding an optimal binary decision tree for an appropriate Boolean decision function
	[18]		2014	Review and analysis of past Simulation and Mod eling efforts to support decision making in healthcare SCM
	[19]	Decision-making	2018	Design and implementation of decision support
	[20]	Approximate dynamic programming, real-time dynamic programming	2009	A real-time method for solving multistage capac ity decision problems in a manufacturing envi ronment
Forecast	[21]	Bayesian network	2019	Airline network delay propagation model devel-opment
	[22]	Machine learning, supervised models, predictive analytics, penalized regres-sion	2018	Forecast of taxi-timeout
	[23]	LSSVR model - vector regression	2017	Selection for container throughput forecasting
	[24]	Croston's method, SBA and TSB, exponential smoothing, nearest neigh-bor	2016	Forecast of sporadic demand (SCM) in the auto motive industry
	[25]	Machine learning	2014	A framework to solve the dynamic bike sharing repositioning problem
	[26]	Machine learning, neural networks, support vector machine	2009	

	[27]		2017	Review of insight into Big Data applica tions and Smart Farming
	[28]	Logistic regression, support vector machine and back-propagation neural networks	2013	Proposed novel ensemble learning ap proach for corporate financial distress forecasting in fashion and textile SC
Optimization	[29]	Multi-agent learning, deep reinforce ment learning networks combined with link-state protocol and preliminary su pervised learning, deep neural networks	2019	Optimization of the distributed packet routing system
	[30]	Least square-support vector machine, continuous general variable neighbor hood search	2017	A novel model for solving non-linear re gression problems (a case study of a sup plier selection and evaluation problem in the cosmetics industry)
	[31]	Intelligent agents, virtual reality	2017	A conceptual framework for the develop ment of real-time intelligent observa tional platform supported by advanced in telligent agents
	[32]	Self-optimization	2016	An introduction to the concept of self-optimizing production systems
	[33]	Bees algorithm, swarm-based optimiza tion	2013	Optimization method for optimum con figuration of a given supply chain problem which minimizes the total cost and the to tal lead-time
	[34]	Decision support systems, heuristics	2013	Metaheuristics for solving a complex op timization problem from logistics
	[35]	Stochastic programming, heuristic methods, simulation-based methods	2012	Modeling and optimization of SCM sys-tems
Personalized Product Sc	[36]	Deterministic and stochastic shrinking ball (DSB and SSB) approaches	2010	Presents, analyzes, and compares three ran dom search methods for solving stochas tic optimization problems with uncount able feasible regions
	[37]	Case-based reasoning, multi-agent, fuzzy logic, neural networks	2009	A multi-artificial intelligence system aimed to provide quality logistics solutions to achieve high levels of service perfor mance in the logistics industry proposed
	[38]	Machine learning, data mining, genetic algorithms, neural networks, knowledge discovery, classification, prediction, goal programming, rule induction	2006	Evolutionary/genetic algorithm (GA)-based neural approach that incorporates asymmetric Type I and Type II error costs on financial and medical data

	[39]	Proactive uncertainty management tech niques, simulated annealing	2004	Techniques for proactive uncertainty man age ment determine the release dates of dif ferent jobs based (just-in-time job shop environment)
Personalized product SC	[40]	Multi-agent, negotiating mechanisms, mod els, and tactics	2018	Model for personalized product SC
Planning and Scheduling	[41]	Machine learning	2016 tics	An approach for predictive inbound logis-
	[42]	Review of classical and probabilistic plan ning algorithms	2013	Planning
	[43]	Agent-based system, decision support systems, genetic algorithm, tabu search, simulated annealing	2008	2 scenarios for solving Production-Distribu tion Planning Problem in a DSS framework
	[44]	Machine learning, decision theory, and distributed AI	2016	A novel real-time path planning system for SC of road construction
	[45]	Deep reinforcement learning, neural networks, a continuous-variable feedback control algorithm	2019	A learning-based logistics planning and scheduling (LLPS) algorithm that controls the admission of order requests and sched ules the routes of multiple vehicles alto gether
	[46]	Multiobjective swarm intelligence algorithm, multiobjective gravitational search algorithm	2013	Model for strategic planning and optimiz ing cost and CO2 emissions in an environmen tally friendly automotive sup ply chain
	[47]	Stroke graphs	2013	An algorithm that solves the supply network configuration and operations scheduling problem in a mass automization company that faces alternative operations for one spe cific tool machine order in a multiplant con text
	[48]	Genetic algorithm, neighborhood search	2011	Algorithm for the resource-constrained project scheduling problem
	[49]	Constraint logic programming	2000	An algorithm which will allow the creation of partial schedules for reducing the search space and their combining to obtain the glo bal schedule
	[50]	Genetic algorithm (random keys, Bernoulli crossover, immigration type mutation)	1999	An algorithm that considers the scheduling problem to minimize total tardiness given multiple machines, ready times, sequence dependent setups, machine downtime, and scarce tools
	[51]	Genetic algorithms	1998	An algorithm for the resource-constrained

				project scheduling problem
	[52]	Ant colony optimization	2001	An application of ant colony optimization to address a production- sequencing problem when two objectives are present
Production	[53]	Multi-objective optimization,Decision support systems	2017	An efficient multi-objective archived simu lated annealing approach and a visualization technique for the multi-objective inter-ter minal truck routing problem by specifically considering truck emissions
Routing	[54]	Denetic algorithm, beam search algorithm	2002	A method of routing yard-side equipment dur ing loading operations in container terminals
	[55]	Genetic algorithm	2014	The integrated design and planning of bioenergy supply chains problem
	[56]	Neural networks, backpropagation algo rithm	2011	A combination of advanced technologies to form an integrated system that helps achieve lean and agile logistics workflow
SCM improve-ment	[57]	Expert systems - knowledge engineering	2017	System for measuring the necessities of pro fessional contracts regarding insurance cov erage and improve the supply chain manage ment using IT
	[58]	Data-driven modeling, constraint logic, and mathematical programming	2017	A novel approach that would allow the flexible modeling and solving of food supply chain man agement (FSCM) problems
	[59]	Case-based and rule-based reasoning, infer ence method, neural networks, Delphi method, data mining	2014	Third-party (3PL) selection problem - review on criteria and methods
Selection	[60]	Neural network, locally linear neuro- fuzzy model, locally linear model tree learning al gorithm. multi-layer perceptron, radial ba sis function neural network, least square-support vector machine	2011	An effective AI approach to improve the sup plier selection (cosmetics industry)
	[61]		2017	A general overview of the present and future trends in sustainable SC
Technology	[62]		2019	Review of freight transport modeling tech niques
Transporta-tion	[63]	Deep belief, vector regression network method	2019	Method for flight delay prediction
	[64]	Machine learning, Bayesian classification	2019	Approach for shipment size choice in strate gic interregional freight transport models

	[65]	Fuzzy logic, genetic algorithms	2018	A new model for in-plant transportation control with the AGV
	[66]	Naive Bayesian, Bayesian network, lo gistic regression, multilayer perceptron, support vector machine, decision table, and C4.5 algorithms	2016	Comparison of the relative performance of different algorithms for the detection of transportation modes and activity episodes
	[67]	Multi-agent	2013	A structure model for military container transportation in campaigns logistics
	[68]	Combination of operational research techniques with AI search methods	2013	A new hybrid approach for intermodal transportation problem solving
	[69]		2019	Review of Artificial Intelligence (AI) adoption-within warehouses
Warehouse	[70]	Tabu search	2014	Algorithm for resource-constrained project scheduling problem optimization of truck-dock assignment in the cross-dock management system
	[71]	Least squares temporal difference learn ing method	2012	Algorithm for a vehicle-dispatching problem-solv ing in warehouse management
	[72]	Object recognition methods, convolu tional neural network	2016	A novel system to support order pickers in ware houses (using smartwatch and low-cost camera)

Table 2. Logistics and/Or SC(M) Aspect Studied

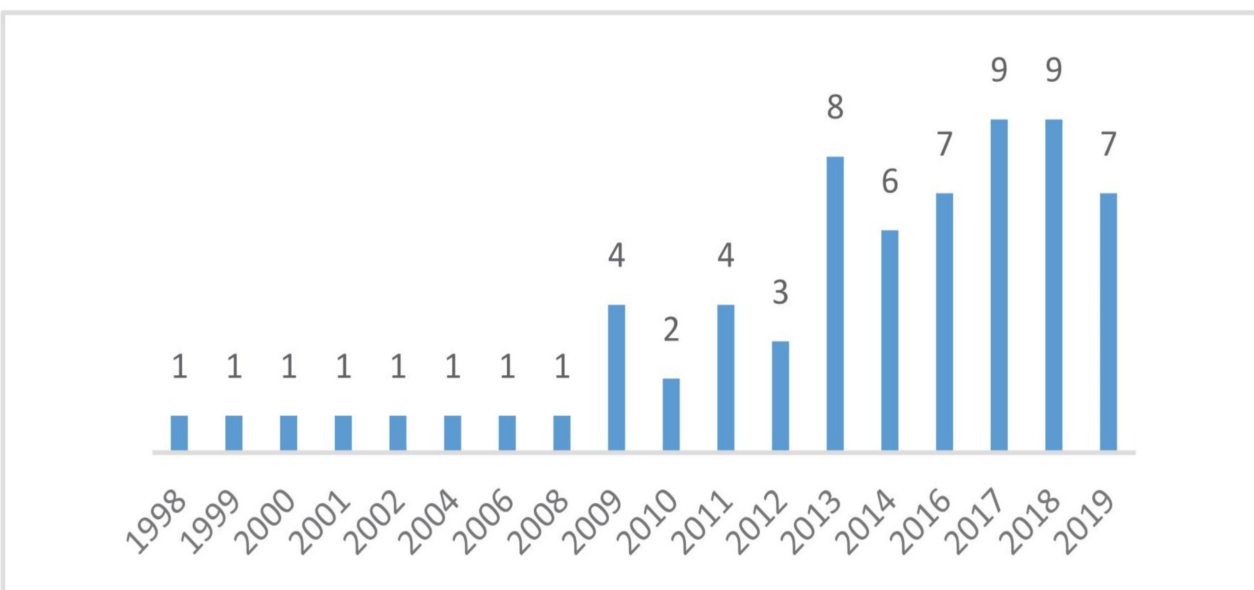

Figure 2. Publication years

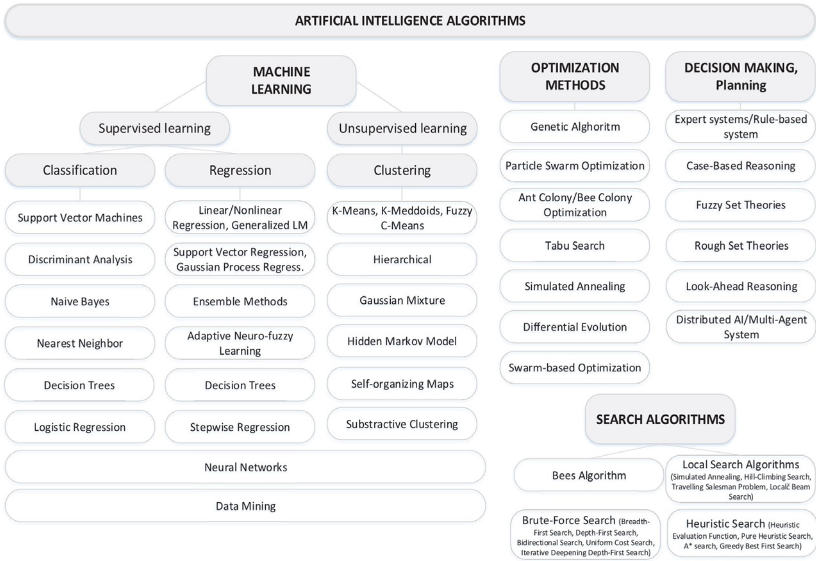

Figure 3. Most 'popular' AI algorithms [73], [74] and [75]

Figure 2 represents the number of publications by year. It could be seen that the rise of a number of papers is significant in the period of last ten years, while more than half of these papers were published in last 5 years, and that the number of publications is rising.

In theory and in scientific research as well there are really many AI algorithms, techniques, and approaches in use. Fig. 3 presents an attempt to summarize and classify some of them from the most often used within studies, - i.e. machine learning, optimization, decision making, planning, and searching.

Many of them were used also in the reviewed studies. The most frequently used are shown in Fig. 4.

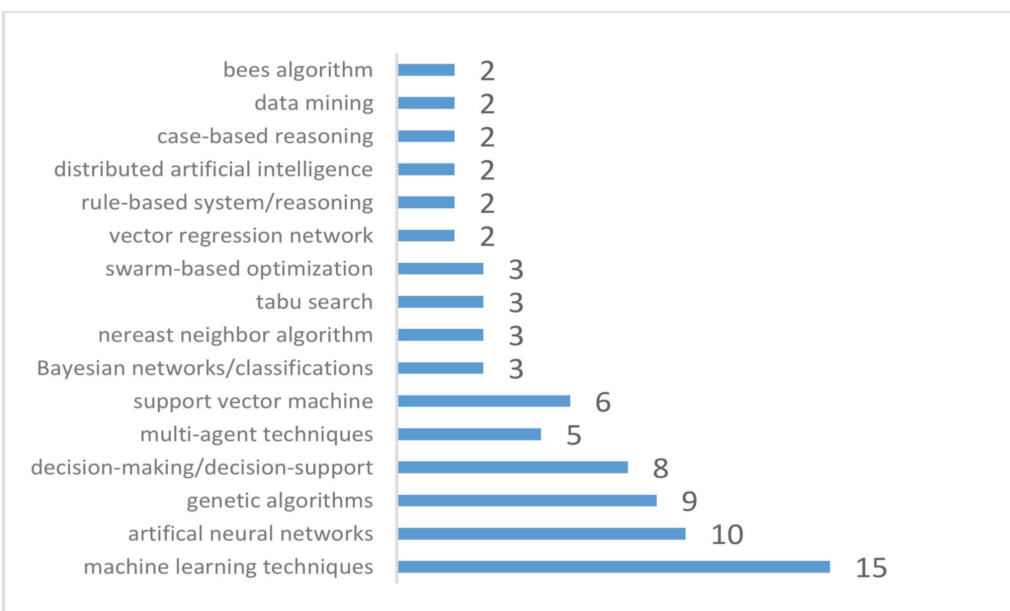

Figure 4. AI algorithms used in the reviewed studies

Exploring the last three years' studies, - i.e. from 2017 to 2019, we can conclude, that the most often studied/used AI techniques were the machine learning techniques. Machine learning indeed is becoming one of the most important AI approaches. Combined with other AI approaches, like natural language processing, object recognition, robots, and others, it's a very promising tool for many applications in logistics and supply management industry.

4. Conclusion and Discussion

There are many possibilities for the application of AI solutions across the supply chain and logistics operations. In all cases, there are some strong prerequisites that should (or better must) be fulfilled. Firstly, the 'basic' IT systems and technologies used for information (and partially) decision support must provide a large amount of data, that represent an adequate input for AI systems and tools. Secondly, the AI implementation should not be made only because it is popular and it promises 'a lot', but because there is a strong belief and awareness, that it will represent added value and substantial benefit for the business. Therefore, the business problem should be clearly defined and AI technologies appropriately selected. [76, 77] Finally, because of complexity and sometimes also the immaturity of AI technologies, for successful introduction all possible options should be carefully considered. Namely, an AI solution can be built in-house, can be bought, or outsourced. Sometimes the hybrid approach is most appropriate. [76]

Regarding the maturity of field of Logistics and Supply Chain Management (LSCM) on one side and the technology and AI maturity on the other, in next years it is therefore normal to expect higher level and stronger presence of AI in everyday logistics and supply chain operations, with the role of "accelerating the path towards a proactive, predictive, automated, and personalized future" [5] for logistics. Considering the increasing interest for AI solution from the business, the number of scientific papers offering various solutions and an insights in AI science is expecting to be much higher in the next years.

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