A systematic literature review of supply chain decision making supported by the Internet of Things and Big Data Analytics

Martijn Koot *, Martijn R.K. Mes, Maria E. Iacob

Department Industrial Engineering & Business Information Systems (IEBIS), University of Twente, Drienerlolaan 5, 7522 NB Enschede, the Netherlands

ARTICLE INFO

Keywords:
Internet of Things
Big Data Analytics
Supply chain management
Decision making
Systematic literature review

ABSTRACT

The willingness to invest in Internet of Things (IoT) and Big Data Analytics (BDA) seems not to depend on supply nor demand of technological innovations. The required sensing and communication technologies have already matured and became affordable for most organizations. Businesses on the other hand require more operational data to address the dynamic and stochastic nature of supply chains. So why should we wait for the actual implementation of tracking and monitoring devices within the supply chain itself? This paper provides an objective overview of state-of-the-art IoT developments in today’s supply chain and logistics research. The main aim is to find examples of academic literature that explain how organizations can incorporate real-time data of physically operating objects into their decision making. A systematic literature review is conducted to gain insight into the IoT’s analytical capabilities, resulting into a list of 79 cross-disciplinary publications. Most researchers integrate the newly developed measuring devices with more traditional ICT infrastructures to either visualize the current way of operating, or to better predict the system’s future state. The resulting health/condition monitoring systems seem to benefit production environments in terms of dependability and quality, while logistics operations are becoming more flexible and faster due to the stronger emphasis on prescriptive analytics (e.g., association and clustering). Further research should extend the IoT’s perception layer with more context-aware devices to promote autonomous decision making, invest in wireless communication networks to stimulate distributed data processing, bridge the gap in between predictive and prescriptive analytics by enriching the spectrum of pattern recognition models used, and validate the benefits of the monitoring systems developed.

1. Introduction

Supply Chain Management (SCM) heavily relies on the use of well analyzed data, simply because data driven decisions lead to better results in complex business environments (Speranza, 2018). Gathering the necessary data sources is far from trivial however, mainly due to the dynamic and stochastic nature of real-world logistics networks (Pillac, Gendreau, Guéret, & Medaglia, 2013). Modern-day decision support tools should incorporate the data source’s uncertainty to provide a sound representation of the problem context, while simultaneously maintaining the models’ simplicity for the application of analytical results (Bianchi, Dorigo, Gambardella, & Gutjahr, 2009). This trade-off between uncertainty and simplicity makes it difficult for decision makers to derive a reliable description of the system’s current and future state, since the models’ assumptions are often not valid in reality (Sarimveis, Patrinos, Tarantilis, & Kiranoudis, 2008). The occurrence of unforeseen events and changing parameter values aggravates the decision complexity even further, resulting into a wide variety of decision support tools originating from management sciences with limited value (Riddals, Bennett, & Tipi, 2000). Recent SCM trends like e-commerce, lean operations, and increasing customer requirements have made the supply chain even more vulnerable to both internal and external disruptions (Ponomarov & Holcomb, 2009; Stank, Autry, Daugherty, & Closs, 2015), suggesting that online modifications of the initial planning are required to achieve optimal outcomes (Koot, 2019).

One way to address the dynamic and stochastic nature of supply chains is to implement multiple identification and monitoring devices during key logistics activities, or decision milestones. The idea to remotely monitor products and their surroundings is commonly used in SCM for several years already (Lee & Lee, 2015). For example, Radio Frequency Identification (RFID) became popular during the 1980s to automatically trace and monitor products without the need to be in line-of-sight (Atzori, Iera, & Morabito, 2010; Xu, He, & Li, 2014). In the 1990s, Wireless Sensor Networks (WSN) extended the RFID’s

* Corresponding author.
E-mail addresses: m.koot@utwente.nl (M. Koot), m.r.k.mes@utwente.nl (M.R.K. Mes), m.e.iacob@utwente.nl (M.E. Iacob).

https://doi.org/10.1016/j.cie.2020.107076
Received 9 June 2020; Received in revised form 17 September 2020; Accepted 16 December 2020
Available online 19 December 2020
0360-8352/ © 2020 The Author(s). Published by Elsevier Ltd. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).
monitoring capabilities with the installation of spatially distributed sensors (Lee & Lee, 2015; Li, Xu, & Zhao, 2015). Nowadays, the concept of remote business monitoring is extended even further towards resources that are operating physically within the supply chain itself (e.g., machinery, vehicles, containers, etc.). More and more physical objects are empowered with wireless sensors and communication devices, resulting into an interconnected network of uniquely addressable objects that is better known as the “Internet of Things” (IoT) (Atzori et al., 2010). The IoT paradigm is one of the most recent advancements of Information and Communication Technologies (ICT), combining sensory, communication, networking, and information processing technologies throughout an inter-connected network (Li et al., 2015).

Both industry practitioners and scientists are highly interested into the usage of IoT devices within SCM activities. The increasing volume of IoT data is essential to improve our understanding of today’s complex supply chains. The real-time monitoring of physical assets will improve the transparency, traceability, and reliability of logistics operations by mapping the real world into the virtual world (Atzori et al., 2010; Chung, Gesing, Chaturvedi, & Bodenbenner, 2018; Speranza, 2019). Decision makers can even move from descriptive statistics towards structural improvements by the application of analytical models (e.g., combinatorial optimization algorithms, data mining, machine learning, etc.) that transform IoT data into predictions, and optimization outcomes (Barton & Court, 2012). Therefore, the real potential of IoT applications lies into the capability to mine for original insights and optimization opportunities that support decision making (Chung, Gesing, Chaturvedi, & Bodenbenner, 2018; Macaulay, Buckalew, & Chung, 2015; Xu et al., 2014). For example, intelligent data analytics may stimulate organizations to proactively act in a more resilient way once a disturbance is observed, or even predicted, in real time (Atzori et al., 2010; Barton & Court, 2012; Chung, Gesing, Chaturvedi, & Bodenbenner, 2018; Stank et al., 2015).

The adoption and proliferation of IoT devices satisfies the supply chain’s demand for collecting and processing data on changeable business environments (Stank et al., 2015). However, it remains unknown how organizations can directly use the IoT generated data into their decision making. Modern-day SCM activities such as transportation, warehousing or maintenance are resource intensive, resulting into a lot of physical objects empowered by primitive or no data handling capacity at all (Atzori et al., 2010; Macaulay, Buckalew, & Chung, 2015). Scientists expect that a slight increase of the objects’ autonomy would already provide new business insights that may drive innovations (Atzori et al., 2010; Macaulay, Buckalew, & Chung, 2015), and the object’s functionality may be enhanced even further once connected to other related products (Wortmann & Flüchter, 2015). Even though real-life applications of IoT in supply chain decision making should exist, as reflected by IoT’s position on the peak of inflated expectations on Gartner’s Hype Cycle methodology (Gartner, 2018; O’Leary, 2008), the number of validated IoT implementations remains limited within scientific community, since the IoT paradigm is not fully mature yet.

This paper aims at delivering an objective overview of the state-of-the-art IoT developments in today’s SCM and logistics research. The main goal is to search for academic literature that explains how organizations can incorporate real-time data of physically operating objects into their decision making. Better understanding of the IoT’s analytical capabilities stimulates future SCM research to customize information systems by proactively acting on the dynamic and stochastic nature of supply chains. Therefore, we have to map which type of IoT devices and analytical models are prescribed by scientists to improve supply chain performances. We summarize our intentions by proposing the following research question:

Research question: To what extent do IoT technologies support supply chain decision making by the acquisition, analysis, and application of real-time data from cyber-physical objects?

We conduct a systematic literature review (SLR) to explore how the real-time data of physically operating objects is applied into SCM and logistics research. The contribution of this research is twofold. First, we explain how, where, and why organizations could apply IoT devices into their SCM and logistics operations by conducting an integrated review towards the gathering, processing, and application of real-time data. Second, by using a proper classification of the state-of-the-art IoT developments, we validate the theoretical benefits and/or limitations of emerging tracking and monitoring techniques, which in turn allows business practitioners to make well-informed investments (or not). The SLR is based on the systematic review methodology proposed by Denyer and Tranfield (2009). Therefore, the remainder of this paper is structured as follows. First, we explain how our SLR will extend the current body of knowledge by elaborating on the theoretical background related to IoT networks, data analytics, and SCM in Section 2. In Section 3, we introduce the research methodology applied, including a description of the search strategy, selection criteria, and data extraction forms. Next, we summarize the SLRs results in Section 4. In Section 5, we discuss the observations made, compare our SLR results with other relevant publications, summarize our findings and give some pointers to future IoT-driven SCM research. We end with our conclusions and recommendations in Section 6.

2. Theoretical background

Answering our research question would encompass several concepts from three different academic disciplines:

(1) **IoT networks**: concerns the gathering of data by empowering physical objects with sensing, processing and communication devices (Section 2.1);

(2) **Data analytics**: addresses the analysis of the data generated by IoT networks to mine for original insights and optimization opportunities (Section 2.2);

(3) **SCM**: relates to the application of real-time data to support supply chain and logistics decision making (Section 2.3).

In this section, we summarize the results of our scoping study into a brief description of the theoretical background for each topic separately. The initial scoping study allows us to define multiple sub-questions for our SLR to extend the current body of knowledge (Denyer & Tranfield, 2009). The research gap will be discussed in Section 2.4, while the theoretical background itself will be used to predefine relevant keywords for our search strategy in Section 3.

2.1. **Internet of Things**

The main concept of the Internet of Things (IoT) is to sense the physical world by connecting physical objects to each other (Li et al., 2015; Macaulay, Buckalew, & Chung, 2015). The IoT’s perception capabilities build upon a variety of identification and tracking technologies that enable remote monitoring of physical objects without the need to be in line-of-sight (Atzori et al., 2010; Xu et al., 2014). Nowadays, more and more physical objects are equipped with remote sensing and controlling devices (e.g., embedded sensors and/or actuators, RFID tags, WSN, bar codes, GPS signal, etc.) to either observe the object’s status or its surroundings continuously (Macaulay, Buckalew, & Chung, 2015; Madakam, Ramaswamy, & Tripathi, 2015; Xu et al., 2014). Each individual sensing device is uniquely addressable and inherits standardized communication protocols (Atzori et al., 2010), which allows the devices to autonomously gather, process, and share data in a global infrastructure of interconnected physical objects (Xu et al., 2014). Therefore, the IoT’s wireless sensor capabilities extend the concept of physical monitoring with ambient intelligence and autonomous control (Li et al., 2015). The employment of a Service-Oriented Architecture (SOA), as
visualized in Fig. 1, is commonly proposed to decompose the IoT network into smaller, re-usable and well-defined components (Al-Fuqaha, Guizani, Mohammadi, Aledhari, & Ayyash, 2015; Atzori et al., 2010; Li et al., 2015). The network layer is equipped with internet-based technologies, which allows IoT devices to communicate with each other in close proximity (e.g., RFID, NFC, Bluetooth, ZigBee), but also to share data among networks for distributed data processing through wider area networks (Chiang & Zhang, 2016; Čolaković & Hadžialić, 2018; Gubbi, Buyya, Marusic, & Palaniswami, 2013). It is expected that the IoT paradigm will revolutionize our way of communication by extending the ICT infrastructure with more machine-to-machine (M2M) connections, resulting into a more system-oriented approach towards remote monitoring (Wortmann & Flüchter, 2015), and a better alignment of the physical world and computer-based systems (Atzori et al., 2010; Speranza, 2018). A recent description of the IoT paradigm’s challenges and open research issues is given by Čolaković and Hadžialić (2018).

2.2. Data analytics

Raw data can be transformed into valuable predictions, and optimization outcomes by the application of analytical models (Barton & Court, 2012; Waller & Fawcett, 2013; Wang, Angappa, Ngai, & Papadopoulos, 2016). The rise of relational database technologies (e.g., DBMS, data warehouses, data marts, OLAP, etc.) allowed humans to gather, manipulate, and query through structured datasets to obtain new insights (Chen, Chiang, & Storey, 2012; Turban, Sharda, Delen, King, & Aronson, 2011; Vercells, 2009). The descriptive analytics gradually evolved into the capability to mine for valid, novel, and potentially useful patterns that were previously hidden within the structured databases (Fayyad, Piatetsky-Shapiro, & Smyth, 1996; Lee & Siau, 2001). Therefore, application of the data mining process (Fig. 2) extended the analytical toolbox with new mathematical models designed for pattern recognition, resulting into new functionalities like classification, clustering, association, time series analysis, and outlier detection. (Chen et al., 2015; Liao, Chu, & Hsiao, 2012; Turban et al., 2011; Vercells, 2009). Nowadays, algorithms can even search for patterns by themselves due to advances in machine learning and Artificial Intelligence (AI), without any human intervention at all (Bishop, 2006; Gesing, Peterson, & Michelsen, 2018).

The continuous growth of the world’s data volume provides opportunities for organizations to identify new value-adding patterns that were previously hidden (Addo-Tenkorang & Helo, 2016).
will amplify data sharing among objects even further with larger volumes and more varieties of sensing objects that did not gather data traditionally (Hashem et al., 2015; Macaulay, Buckalew, & Chung, 2015; Speranza, 2018). Therefore, the world’s annual volume of data generated, captured or replicated is expected to accelerate exponentially, a growing pace that traditional relational databases cannot process efficiently anymore (Addo-Tenkorang & Helo, 2016; Chen, Mao, & Liu, 2014; Reinsel, Gantz, & Rydning, 2018). The term ‘Big Data’ is used to describe these enormous datasets that are growing at an accelerated pace, while ‘Big Data Analytics’ (BDA) refers to the extraction of useful information from these massive datasets that could be valuable for organizations (Chen et al., 2014). A recent description of the BDA paradigm’s challenges and open research issues is given by Mikalef, Pappas, Krogstie, and Giannakos (2018).

2.3. Supply chain management

Modern-day supply chain decision making heavily relies on well analyzed data to support predictions and optimization outcomes (Barton & Court, 2012; Speranza, 2018). Therefore, business practitioners are highly interested in the recent IoT advances to retrieve up-to-date data of physical objects and their surroundings (Chung, Gesing, Chaturvedi, & Bodenbenner, 2018; Gartner, 2018; Macaulay, Buckalew, & Chung, 2015). The real-time monitoring capabilities may improve the transparency, traceability, and reliability of logistics operations (Atzori et al., 2010; Chung, Gesing, Chaturvedi, & Bodenbenner, 2018; Speranza, 2018). Firms and supply chains can achieve higher efficiency levels by a faster response to the internal and external disruptions observed (Ben-Daya, Hassini, & Bahroun, 2019). Higher payoffs are even expected once the connected objects are empowered with ambient intelligence and autonomous control (Li et al., 2015). As a result, more research initiatives have been proposed to apply IoT concepts into SCM and logistics operations (Ben-Daya et al., 2019; Lee & Lee, 2015; Liu & Gao, 2014; Lou, Liu, Zhou, & Wang, 2011; Sun, 2012; Tan, 2008; Tu, 2018; Xu et al., 2014).

Supply chain managers are also inspired by the innovative BDA capabilities to improve their decision making (Chung, Gesing, Chaturvedi, & Bodenbenner, 2018; Gesing, Peterson, & Michelsen, 2018; Jeske, Grüner, & Weiß, 2013; Reinsel, Gantz, & Rydning, 2018), resulting into more academic publications that combine BDA and SCM as well. The larger volumes and more varieties of data sources stimulate decision makers to make better predictions of the supply chain’s future state, allowing firms to become more flexible and remain competitive in a business environment that is highly dynamic and stochastic. Most BDA research efforts are discussing the techniques and architectures required for pattern recognition and predictive analytics (Baryannis, Validi, Dani, & Antoniou, 2019; Chen et al., 2012; Nemat & Barko, 2001; Nguyen, Zhou, Spiegel, Ieromonachou, & Lin, 2018; Provost & Fawcett, 2013; Tiwari, Wei, & Daryanto, 2018; Waller & Fawcett, 2013; Wang et al., 2016; Zhong, Newman, Huang, & Lan, 2016), but some research initiatives are also reflecting on the organizational benefits enabled by BDA implementations (Dubey, Gunasekaran, & Childe, 2019; Dubey, Gunasekaran, Childe, Blome, & Papadopoulos, 2019; Gunasekaran et al., 2017; Gunasekaran, Yusuf, Adeleye, & Papadopoulos, 2018; Matthias, Fouweather, Gregory, & Vernon, 2017; Papadopoulos et al., 2017).

2.4. Research gap

Both scientists and logistics managers expect that the IoT and BDA developments are closely intertwined with each other, since IoT networks will amplify data sharing among objects in terms of larger volumes, increased speed, and more varieties (Cai, Xu, Jiang, & Vesilakos, 2017; Chen et al., 2015; Hashem et al., 2015; Macaulay, Buckalew, & Chung, 2015; Marjani et al., 2017; Mourtzis, Vlachou, & Milas, 2016; Riggins & Wamba, 2015; Speranza, 2018). Therefore, we expected to see an increasing number of publications reflecting on the IoT’s analytical capabilities within SCM and logistics operations. However, our initial scoping study resulted in a handful of studies addressing an integrated approach towards the IoT, BDA, and SCM research disciplines (Addo-Tenkorang & Helo, 2016; Hopkins & Hawking, 2018; Kusia, 2018; Rathore et al., 2018). All four papers include an extensive description of several case studies, which highlight some potential benefits that we might expect from combining IoT networks with intelligent data analytics (e.g., higher resource utilization, enhanced safety, lower costs, etc.). Multiple general architectures are proposed to guide the implementation of the IoT’s analytical capabilities as well, but we envision a more detailed assessment of the interrelated technologies required for gathering, communicating, and analyzing real-time data. We would also appreciate more insights into the altered decisions themselves, including a description of the corresponding efficiency improvements. Therefore, a more detailed combination of keywords is required that explicitly searches for the application of both IoT and BDA techniques in the SCM domain.

It is our aim to extend the academic body of knowledge with a literature overview that addresses the extent research work found at the intersection of the IoT, BDA, and SCM disciplines. We will use the results of our scoping study to refine our initial hypothesis of Section 1 into a more detailed set of sub-questions:

(1) **Sub-question A**: Which combinations of IoT devices and analytical models are commonly applied during SCM and logistics operations?
(2) **Sub-question B**: How do the IoT’s analytical capabilities affect supply chain decision making?
(3) **Sub-question C**: What type of supply chain improvements result from IoT-driven decision making?
3. Systematic review methodology

In this paper, we conduct a SLR to deliver an objective state-of-the-art overview of the emerging IoT’s analytical capabilities in today’s SCM and logistics research. The SLR should support our search for publications that explicitly investigate the linkages between the IoT, BDA, and SCM research disciplines simultaneously. Therefore, we apply the systematic review methodology proposed by (Denyer & Tranfield, 2009) to answer all (sub-) questions addressed in Section 2.4. In this section, we explain how the SLR was conducted by defining the search strategy (Section 3.1), the selection criteria (Section 3.2), and the criteria for analysis and synthesis (Section 3.3). The search results, the resulting articles, and the filled-in data extraction forms are discussed in Section 4. The sequence of research activities is depicted in Fig. 3.

3.1. Search strategy

The main aim of our systematic approach is to locate, select and assess relevant literature by using search strings, grouping keywords, and applying search conventions within a citation database (Denyer & Tranfield, 2009). In our case, the research question addresses the intersection of the IoT, BDA, and SCM disciplines, meaning that we have to search for those keywords commonly shared by all three disciplines. Therefore, we have initiated our SLR with a bibliometric study to find relevant keywords for the IoT, BDA, and SCM research disciplines simultaneously, see Appendix A. A brief overview of the most common grouping of keywords is visualized for each separate discipline by using ‘VOS viewer’, a software tool for constructing, analyzing, and visualizing bibliometric networks (https://www.vosviewer.com). The critical comparison of all three bibliometric networks enables us to select those IoT-, BDA-, and SCM-related keywords that co-occur at the intersection of multiple disciplines.

The bibliometric study forms the first step in the third phase of our systematic review approach depicted in Fig. 3. The study is executed three times for the IoT, BDA, and SCM disciplines separately. All three bibliometric studies are structured in three main steps:

1. First, we search for review articles summarizing published studies related to either the IoT, BDA, or SCM discipline. Both the author- and index keywords of all selected review articles are exported (RIS file) for further assessment;
2. Second, we visualize the co-occurrences of keywords for each separate discipline in VOS viewer by constructing a so-called bibliometric network (e.g., see Fig. 4), including the top 25 keywords most frequently used by all exported review articles;
3. Third, the VOS viewer tool automatically emphasizes the most frequent keyword sets and search for appropriate clusters based on the keywords’ association strength.

General keywords referring to document types and scientific characteristics are removed from the bibliometric network (e.g., survey, review, future recommendations, etc.). A thesaurus file is created to ensure that synonyms are not double counted. Finally, all three bibliometric networks are compared to select the most common grouping of IoT-, BDA-, and SCM-related keywords.

The results of our bibliometric study show that the IoT, BDA, and SCM research disciplines are closely intertwined with each other, see Appendix A. For example, the Internet of Things (IoT) related bibliometric network (Fig. 4) includes several terms that are also shared by the BDA paradigm (e.g., big data, information systems, artificial intelligence), while these data-driven techniques support supply chain decision making in return. The inclusion of the most frequently used keywords of the IoT, BDA, and SCM disciplines ensures that we can locate the multidisciplinary type of publications searched for. Therefore, the bibliometric networks are used to define relevant keywords for all three research disciplines separately. The results of our bibliometric study are summarized in Table 1, including a list of synonyms, related concepts/technologies, and real-life applications within the second, third and fourth column respectively.
The keywords in Table 1 are grouped together by using truncation characters (e.g., ‘*’ and ‘?’), Boolean Logic Operators (e.g., AND, OR), phrase searching, and parentheses. The final search string is constructed iteratively by using the following steps. First, relevant articles are searched for the IoT, BDA, and SCM discipline separately. We explicitly look for relevant studies that include the discipline’s synonyms (related terms) or the enabling technologies (narrower terms) into the publication’s the title, abstract or keywords. Second, a fourth keyword category is defined consisting of the SCM application fields only (broader terms). This additional category is required to actively search for the academic improvements enabled by the IoT’s analytical capabilities in SCM and logistics operations. Both the IoT’s and BDA’s application fields are ignored, because of the interdisciplinary relationships observed within our bibliometric study. Finally, all four keyword groupings are combined into one search string to find the multidisciplinary type of publications searched for. A simplified version of the resulting search profile is given below, while Appendix B includes a more detailed search profile by referring to the selected keywords of Table 1.

| TITLE-ABS-KEY[ IoT (Synonyms OR Enabling technologies) ] AND TITLE-ABS-KEY[ Big Data Analytics (Synonyms OR Enabling technologies) ] AND TITLE-ABS-KEY[ SCM (Synonyms OR Enabling technologies) ] AND TITLE-ABS-KEY[ SCM (Application fields) ] |

Our SLR covers three interrelated academic disciplines (IoT, BDA, and SCM). Therefore, a generic citation database like ‘Scopus’ is required. The Scopus database is selected only, because it is one of the world’s largest abstract and citation database of peer-reviewed research literature (see https://www.elsevier.com/solutions/scopus).

3.2. Selection criteria

The search profile of Section 3.1 will provide a list of potentially useful articles, but not every article will contribute to answering the research question. Therefore, four layers of inclusion/exclusion criteria are defined to assess the relevance of each publication found (Denyer & Tranfield, 2009). First, the resulting articles should fulfill three inclusion criteria related to the document type itself:

1. The articles should be fully published and written in English;
2. The articles’ subject areas have to align the academic fields taken into consideration (e.g., Computer Science, Engineering, Mathematics, Decision Sciences, Business Management, and Economics). The Multidisciplinary category is also included, since we are explicitly looking for linkages in between the IoT, BDA, and SCM research areas;
3. Only academic document types are included to obtain validated concepts only (e.g., articles, books, book chapters, conference papers, and review articles).

Second, the abstracts of the remaining articles are screened to evaluate the usefulness of the content itself. Four additional inclusion criteria are defined for the abstract screening as well:

4. The data acquisition should at least include two interconnected data gathering devices within the physical domain;
5. The raw data should be (pre-) processed in order to identify useful patterns for organizational decision making;
6. The proposed technologies are applied to supply chain and logistics decision making, including the allocation and movement of resources in order to produce valuable products, services and/or information;
7. The technology’s benefits should be stated explicitly by either:

(a) indicating which performance indicators are improved;
(b) proposing an architectural design;
(c) referring to a specific use case.

The third layer consist of exclusion criteria only. These criteria are implemented to assess the articles’ uniqueness:

8. Remove the article if the proposed technology itself is improved only, without specifying any application at all;
9. Remove all duplicated articles that consider the same case study, only the most recent version is saved for further reading;
10. Remove all articles referring to decisions that civil supply chain organizations will rarely make (e.g., military operations, space exploration, homeostatic mechanisms, etc.).

The remaining articles are downloaded for full text reading. However, it is possible that the article is not publicly available, or that the content is of insufficient quality for further analysis. Therefore, the final layer includes three additional criteria to increase the opportunity that the selected articles are actually found:

11. The article should be available online (either open access or through subscription);
12. If the article is not publicly available, the following procedure is activated:
Table 2

Data extraction forms for the IoT, BDA, and SCM research disciplines, plus a fourth category to gain insight into the supply chain performances enabled by the IoT’s analytical capabilities within SCM and logistics operations.

| Category | Variable | Classifications | Source |
|----------|----------|-----------------|--------|
| IoT      | Perception layer | (1) Sensors and/or actuators; (2) Tags; (3) Mobile devices; (4) Satellites; (5) Transaction Processing Systems; (6) Data warehouses; (7) External sources; (8) Autonomous agents; (9) User input; and, (10) Location receiver. | (Al-Fuqaha et al., 2015; Atzei et al., 2016; Čolaković & Hadžić, 2018; Li et al., 2015; Xu et al., 2014) |
|         | Stimuli | (1) Acoustic; (2) Biological; (3) Chemical; (4) Electric; (5) Magnetic; (6); Mechanical; (7) Optical; (8) Radiation; (9) Thermal; and (10) Event. | (White, 1987) |
|         | Network layer | (1) Radio Frequency Identification (RFID); (2) Near Field Communication (NFC); (3) Radio navigation; (4) Internet; (5) Low-power WAN; (6) Wireless LAN (IEEE 802.11); (7) Wireless PAN (IEEE 802.15); (8) Wired connection; and (9) Middleware technology. | (Al-Fuqaha et al., 2015; Chiang & Zhang, 2016; Čolaković & Hadžić, 2018; Gubbi et al., 2013) |
| BDA      | Data management | (1) Acquisition & integration; (2) Cleaning; (3) Transformation & feature extraction; (4) Reduction & feature selection; (5) Aggregation & storage; (6) Modelling & analysis; and (7) Interpretation & application. | (Chen et al., 2015; Turban et al., 2011; Vercellis, 2009) |
|         | Pattern recognition | (1) Characterization & discrimination; (2) Classification; (3) Regression; (4) Association rules; (5) Clustering; (6) Time series analysis; (7) Visualization; (8) Rule induction. | (Chen et al., 2015; Liao et al., 2012; Turban et al., 2011; Vercellis, 2009) |
|         | Algorithm type | (1) Decision trees; (2) Statistical methods; (3) Neural networks; (4) K-nearest neighbor; (5) Support vector machines; (6) Linear regression; (7) Non-linear regression; (8) Expert systems; (9) Genetic algorithm; (10) Principal component analysis; (11) Automata learning; (12) Fuzzy logic; (13) Markov model; (14) Linear discriminant analysis; (15) Ontology; (16) Computer vision; and (17) Finite element method. | (Bishop, 2006; Laudon & Laudon, 2017) |
| SCM | Analytics type | (1) Descriptive analytics; (2) Diagnostic and/or explanatory analytics; (3) Predictive analytics; and (4) Prescriptive analytics. | (Pawar & Attar, 2016; Sun, Zou, & Strang, 2015; Vercellis, 2009) |
|         | Decision type | (1) Loading; (2) Sequencing; (3) Scheduling; and (4) Monitoring. | (Slack, Chambers, & Johnston, 2010) |
|         | Decision hierarchy | (1) Strategic; (2) Tactical; (3) Operational offline; and (4) Operational online. | (Hans, Herroelen, Leus, & Wullink, 2007) |
| Application | Supply chain activity | (1) Research & development; (2) Purchasing; (3) Production; (4) Logistics; (5) Marketing & sales; (6) Finance; (7) Customer relationship management; (8) Supplier relationship management; (9) Customer service management; (10) Demand management; (11) Order fulfillment; (12) Manufacturing flow management; (13) Product commercialization; and (14) Returns management. | (Lambert, 2008) |
|         | Technology readiness level | (1) TRL01: Basic principles; (2) TRL02: Technology concept and/or application formulated; (3) TRL03: Analytical and experimental critical function; (4) TRL04: Component validation in laboratory; (5) TRL05: Component validation in relevant environment; (6) TRL06: System/sub-system model or prototype demonstration in relevant environment; (7) TRL07: System prototype demonstration in operational environment; (8) TRL08: Actual system completed and ‘qualified’ through test and demonstration; and (9) TRL09: Actual system ‘flight proven’ through successful mission. | (Mankins, 2009) |
|         | Key performance indicator | (1) Cost; (2) Dependability; (3) Flexibility; (4) Quality; and (5) Speed. | (Slack et al., 2010) |

(a) Request full-text permission from the article’s first author;
(b) In case of negative response, search for another article of the same author(s) that covers the same topic (the article should also comply with the other layers of inclusion/exclusion criteria);
(c) In case of no results, remove the article for full-text reading.

(13) The article’s content should be of sufficient quality. The following procedure is applied in order to assess the article’s quality:
(a) The article’s publisher should be trustworthy and include peer-reviewed papers only (e.g., ACM, Elsevier, IEEE, Springer, etc.). The article is accepted immediately if (and only if) this requirement is fully met.
(b) If criterion (13a) is not true, then the article is accepted if (and only if) the number of citations is nonzero;
(c) If criterion (13b) is not true, then the article is accepted if (and only if) the source’s scientific journal Rankings (SJR) is greater than 0.2 (see https://www.scimagojr.com/);
(d) If criterion (13c) is not true, the article is removed from further analysis.

3.3. Analysis & synthesis criteria

The major output of our SLR is a comprehensive listing of relevant research contributions to address our research question. However, each individual publication should still be analyzed once we have applied the search profile from Section 3.1 and the selection criteria from Section 3.2. Therefore, we have predefined four data extraction forms that reflect on the (sub-) questions in Section 2.4. We have constructed three assessment criteria for all three research disciplines included (IoT, BDA, SCM). A fourth category is added to assess the supply chain’s performances/improvements as well, including three additional variables. The resulting twelve assessment criteria are summarized in Table 2, including a list of possible classification types and corresponding sources in the third and fourth column respectively. We will use the three-layered IoT architecture for the evaluation of the interconnected data gathering devices (see Fig. 1). The BDA extraction form addresses the type of patterns searched for, including the data preprocessing steps and corresponding algorithms and/or modeling techniques. The third assessment category refers to the application of recognized patterns into supply chain decision making, especially by evaluating how the analytical techniques are used to match supply and demand in terms of volumes, timing, and quality. The fourth assessment category reflects the theoretical improvements obtained from the IoT’s analytical capabilities. This last assessment category will help us to fully answer the main research question by analyzing the techniques’ commercialization progress for multiple intra- and inter-organizational activities.

All variables consist of either categorical or ordinal data types, allowing us to classify the SLR results faster and more consistent. Each article may include one or more classifications for each variable, only the 11th variable “Technology readiness level” is restricted to one classification per article only. We will also enrich our discussion with a bivariate correlation test among all SLR classification types. Therefore, we need to transform the nominal/ordinal classifications of our data extraction forms into multiple Boolean variables. Each Boolean variable is equal to one, if (and only if) an article includes the corresponding variable’s classification, otherwise the value is equal to zero. For example, the IoT category includes a variable called “Perception Layer”, which in turn includes ten possible classifications. We can transform the first class “sensors and/or actuators” into a Boolean variable by checking
which articles include sensors and/or actuators (or not). This procedure is repeated for all twelve variables’ classification types, resulting in a total of 101 Boolean variables. The Boolean variables are imported into the statistical software package “IBM SPSS Statistics 25”, allowing us to run the bivariate correlation test to empirically search for those classification types that co-occur frequently. The Pearson correlation coefficient is used for further assessment, while we verbally describe the correlation’s strength as well (Evans, 1996). We only highlight the moderate, strong, and very strong correlations with a two-tailed significance level of $\alpha = 0.01$ in Section 5, including a minimum threshold of 5 classifications for each Boolean variable to avoid false correlations in between coincidental SLR results.

4. Results

This section provides a comprehensive overview of the publications resulting from the search strategy from Section 3. First, some key figures are defined regarding the number and type of publications for all four keyword categories separately (Section 4.1). Second, the implementation of our search strategy is visualized by a so-called search roadmap (Section 4.2). The output of the SLR is listed in Section 4.3, while the corresponding descriptive statistics are discussed in Section 4.4. The filled-in data extraction forms are discussed in Section 5.

4.1. Search results – Research disciplines

The first step of our search strategy is to locate relevant publications for each keyword category separately (e.g., IoT, BDA, SCM, and applications). The number of publications found in Scopus differs for each category (Fig. 5). Most publications are related to SCM decision making every year, but the number of submissions related to BDA is growing with increasing pace since 2015. The total number of IoT publications continues to grow since 2015. The grow rate of academic publications related to SCM applications seems to be stagnated since 2005. Fig. 6 includes the relative frequencies of the scientific disciplines from which the articles originate for each keyword category separately. Most articles are related to both ‘Engineering’ and ‘Computer Science’. The proportion of business related articles is relatively low, even the SCM application category includes no more than 20% articles related to the fields of ‘Business Management and Accounting’, ‘Decision Sciences’ and ‘Economics, Econometrics and Finance’. The low proportion of business related articles provides the hypothesis that most academic articles are related to technology development instead of real-life implementations.

4.2. Search results – Roadmap

A search roadmap is constructed to visualize the search strategy executed (Fig. 7). The roadmap consists of two types of activities represented by the blue rectangles: (1) inserting the search profile into the Scopus database and (2) evaluating the article’s content based on the inclusion/exclusion criteria defined. The number of articles added and/or removed is visualized for each step separately, and the remaining number of articles is shown between the steps. Finally, 79 articles are selected for further assessment.

4.3. Search results – Selected articles

Table 3 illustrates the existing literature found by applying the search roadmap visualized in Fig. 7. For each article, we have summarized some essential reference information as well as the number of citations in Scopus, which is included to understand which publications are accepted by fellow scholars. Note that some articles were not downloaded from Scopus (see exclusion criterion 12 in Section 3.2); the citations of those articles are based on the available metrics released by the publisher.

Fig. 5. The number of new publications in Scopus per year, separated for each keyword category. The resulting number of publications are modified, based on the inclusion criteria defined for all permitted document types in this research.

Fig. 6. The relative frequency of relevant academic disciplines found in Scopus, separated for each keyword category. The data originates from the period 1980–2019.

4.4. Search results – Descriptive SLR statistics

More than 50% of all SLR publications originate from either the IEEE, Elsevier, or Springer publishers (Fig. 8), while approximately a quarter of all articles includes a single/unique publisher that is not shared with other publications. The high number of ‘other’ publishers may be caused by the relatively large proportion of conference proceedings (Fig. 9). Only 31 out of 79 articles are documented as a journal article, workshop paper, book, or book section, all other publications originate from conference proceedings. The number of studies that include an integrated approach towards the IoT, BDA, and SCM techniques is growing with an acceleration pace for the last five years (Fig. 10).

5. Discussion

The execution of our search strategy resulted into 228 potentially useful articles. Only 79 articles were actually selected after screening all the articles’ titles, keywords, and abstracts (see Fig. 7). The articles are evaluated by using the twelve variables included in our pre-defined data extraction forms (see Section 3.3). A full description of the filled-in data extraction forms is given in the Appendices C, D, E, and F, including the descriptive statistics for each individual variable. In this section, we first discuss our observations by reflecting on the four data extraction forms separately (Section 5.1 till Section 5.4), after which we address the cross-disciplinary SLR results (Section 5.5) to compose a research
agenda for IoT, BDA, and SCM. Therefore, Section 5.5 will be used to answer the three sub-questions previously raised in Section 2.4 by reflecting on the SLR results and relevant academic literature simultaneously, while Fig. 11 summarizes all our recommendations. The discussion is based on the data extraction forms in Appendix C till F, plus the bivariate correlation test with a two-tailed significance level of $\alpha = 0.01$.

5.1. Discussion – IoT

Most research articles empower their physical objects with multiple types of sensors and/or actuators (66 out of 79 articles), which can communicate with traditional data warehouses and mobile devices via the internet, wireless LAN or wired connections (see Appendix C). The majority of those sensors are used to capture modifications of the environmental conditions at hand (e.g., mechanical, thermal, and optical). Some sensor types seem to co-occur quite often. For example, a
Table 3
A comprehensive overview of the SLR output, including 79 academic publications that address the IoT’s analytical capabilities within SCM and logistics operations.

| ID  | APA reference (authors, year) | Title | Publisher    | #Citations |
|-----|------------------------------|-------|--------------|------------|
| 01  | (Anderson, 1997)             | Future directions of R & D in the process industries | Elsevier | 1 |
| 02  | (Athani, Tejeswiar, Patil, Patil, & Kulkarni, 2017) | Soil moisture monitoring using IoT enabled Arduino sensors with neural networks for optimal network consumption | IEEE | 16 |
| 03  | (Aya et al., 2018)           | Wireless Sensor’s Civil Applications, Prototypes, and Future Integration Possibilities: A Review | IEEE | 23 |
| 04  | (Aziz et al., 2017)          | Leveraging BIM and Big Data to deliver well-maintained highways | Emerald | 6 |
| 05  | (Bacon, et al., 2011)        | Using Real-Time Road Traffic Data to Evaluate Congestion | Springer | 28 |
| 06  | (Bagheri & Movahed, 2016)    | The Effect of the Internet of Things (IoT) on Education Business Model | IEEE | 24 |
| 07  | (Beal & Flynn, 2015)         | Toward the digital water age: Survey and case studies of Australian water utility smart-metering programs | Elsevier | 29 |
| 08  | (Belkaroui, Bertaux, Labbani, Hugol-Gentil, & Christophe, 2018) | Towards event ontology based on data sensors network for viticulture domain | ACM Press | 1 |
| 09  | (Bellini et al., 2017)       | Wi-Fi based city users’ behavior analysis for smart city | Elsevier | 9 |
| 10  | (Bliri, 2018)                | The IoT for smart sustainable cities of the future: An analytical framework for sensor-based big data applications for environmental sustainability | Elsevier | 73 |
| 11  | (Birken, Schirner, & Wang, 2012) | VOTERS: Design of a Mobile Multi-Modal Multi-Sensor System | ACM Press | 11 |
| 12  | (Carfagni, Daou, & Furferi, 2008) | Real-time estimation of olive oil quality parameters: a combined approach based on ANNs and machine vision | ACM Press | 0 |
| 13  | (Chakurkar, Shikalgar, & Makhopadhyay, 2016) | An Internet of Things (IoT) based monitoring system for efficient milk distribution | IEEE | 0 |
| 14  | (Chen, Lau, & Fan, 2018)     | IoT data acquisition in fashion retail application: Fuzzy logic approach | Springer | 1 |
| 15  | (Chaudhry, Singh, Sandhya, Chauhan, & Srivastava, 2018) | Machine Learning Based Adaptive Framework for Logistic Planning in Industry 4.0 | IEEE | 4 |
| 16  | (Cherkesova, Ozonat, Mi, Symons, & Lenzi, 2006) | Anomaly? Application change? Or workload change? Towards automated detection of application performance anomaly and change | IEEE | 53 |
| 17  | (Chen et al., 2017)          | An empirical study for smart production for TFT-LCD to empower Industry 3.5 | Taylor & Francis | 18 |
| 18  | (Chiu, Chang, & Chang, 2008) | A Forecasting Model for Deciding Annual Vaccine Demand | IEEE | 2 |
| 19  | (Cho, et al., 2018)          | A Hybrid Machine Learning Approach for Predictive Maintenance in Smart Factories of the Future | Springer | 6 |
| 20  | (Clayton, et al., 2006)      | Off-the-shelf modal analysis: Structural health monitoring with Motes | SEM | 6 |
| 21  | (Darrah, Rubenstein, Serton, & DeRoose, 2018) | On-board Health-state Awareness to Detect Degradation in Multimotor Systems | IEEE | 1 |
| 22  | (Dixon et al., 2007)         | Experience with data mining for the anaerobic wastewater treatment process | Elsevier | 22 |
| 23  | (Dragan, Dziendzikowski, Kurnya, Leski, & Uhl, 2013) | Active structural integrity monitoring of the aircraft based on the PZT sensor network-the symost project | SAGE | 1 |
| 24  | (Dragone et al., 2015)       | A cognitive robotic ecology approach to self-configuring and evolving AAL systems | Elsevier | 16 |
| 25  | (ElMoqait, Israel, Patzolt, & Ryalat, 2018) | Design and Integration of an IoT Device for Training Purposes of Industry 4.0 | ACM Press | 1 |
| 26  | (Emshaelar et al., 2018)     | The Internet of Things for Dementia Care | IEEE | 10 |
| 27  | (Ernest, Fattic, Chang, Chitraru, & Davenport, 2010) | WBMt case study: GIS with rule-based expert system for optimal network in drinking water systems | ASCE | 0 |
| 28  | (Fazial, et al., 2017)       | Modelling of Application-Centric IoT Solution for Guard Touring Communication Network | Springer | 0 |
| 29  | (Fathy & Mohammadi, 2018)    | A method to predict travel time in large-scale urban areas using Vehicular Networks | ACM Press | 0 |
| 30  | (Gasová et al., 2017)        | Advanced Industrial Tools of Ergonomics Based on Industry 4.0 Concept | IEEE | 17 |
| 31  | (Gat, Subramanians, Barben, & Toonmarian, 1997) | Spectral Imaging applications: remote sensing, environmental monitoring, medicine, military operations, factory automation, and manufacturing | SPIE | 13 |
| 32  | (Ghiani et al., 2018)        | VIRTUALENERGY: A project for testing ICT for virtual energy management | IEEE | 0 |
| 33  | (Goswirendhager, et al., 2017) | Dependable internet of things for networked cars | Elsevier | 16 |
| 34  | (Gu & Liu, 2013)             | Research on the application of the internet of things in reverse logistics information management | Omnia-Science | 15 |
| 35  | (Howell, Rezgui, & Yuce, 2014) | Knowledge-Based Holistic Energy Management of Public Buildings | ASCE | 6 |
| 36  | (Huang, 2018)               | Infrastructural development for farm-scale remote sensing big data service | SPIE | 0 |
| 37  | (Iyjyver, et al., 2009)      | Architecture for dynamic component life tracking in an advanced HUMS, RFID, and direct load sensor environment | AHS | 0 |
| 38  | (Kadar, Covaciu, Jardim-Gonçalves, & Bullen, 2017) | Intelligent Defect Management System For Porcelain Industry Through Cyber-Physical Systems | IEEE | 0 |
| 39  | (Kolodziejczyk, et al., 2008) | A methodological approach ball bearing damage prediction under fretting wear conditions. | IEEE | 4 |
| 40  | (Kühl, Wiener, & Kraus, 2013) | Multisensorial Self-learning Systems for Quality Monitoring of Carbon Fiber Composites in Aircraft Production | Elsevier | 3 |
| 41  | (Kuo, 1997)                | Intelligent robotic die polishing system through fuzzy neural networks and multi-sensor fusion | IEEE | 7 |
| 42  | (Kviesis, 2018)             | Application of neural networks for honey bee colony state identification | IEEE | 5 |
| 43  | (Latasovich et al., 2019)   | Big Data as the basis for the innovative development strategy of the Industry 4.0 | IoP | 3 |
| 44  | (Lee, Funk II, Feuerbacher, & Haio, 2007) | Development of an emergency C-section facilitator using a human-machine systems engineering approach | IEEE | 0 |
| 45  | (Liu et al., 2015)          | Study on real-time construction quality monitoring of storehouse surfaces for RCC dams | Elsevier | 21 |
| 46  | (Lujian, et al., 2019)      | Cloud Computing for Smart Energy Management (CC-SEM Project) | Springer | 4 |
| 47  | (Matarazzo, D’Addona, Caramiello, Di Foggia, & Tett, 2015) | Cognitive Decision-making Systems for Scrape Control in Aerospace Turbine Blade Casting | Elsevier | 1 |
| 48  | (Mehdiyev, Emmrich, Stahmer, Fettke, & Loos, 2017) | iPRODICT – Intelligent process prediction based on big data analytics | Springer | 2 |
| 49  | (Moi & Bodechtels, 2016)    | Design of an ontology for the use of social media in emergency management | IADIS Press | 3 |
| 50  | (Morales & Haas, 2004)      | Adaptive Sensors for Aircraft Operational Monitoring | AIAA | 8 |
| 51  | (Morales-Menéndez et al., 2007) | Low-cost cutting tool diagnosis based on sensor-fusion | Elsevier | 1 |
| 52  | (Moresco, Skarmeta, & Jara, 2015) | How to intelligently make sense of real data of smart cities | IEEE | 5 |

(continued on next page)
strong positive correlation is found between the application of thermal and chemical sensors \((\rho = 0.623)\), while mechanical and acoustic sensors are moderately correlated \((\rho = 0.407)\). The presence of business events does also trigger data registration by more traditional information systems, especially the application of Transaction Processing Systems (TPS) seems to co-exist with the registration of business events in the IoT’s perception layer \((\rho = 0.454)\). Another moderate positive correlation can be found between the application of mobile devices and location receivers \((\rho = 0.400)\), resulting into a significant use of radio navigation techniques like GPS to locate objects as well \((\rho = 0.493)\).

All 79 SLR publications adequately explained which type of measurement devices to install into the IoT’s perception layer, but the network layer’s design receives less interest. Some researchers did not even mention how the data is communicated throughout the network at all \((12 \text{ out of } 79 \text{ articles})\). We did expect to see quite some RFID applications in nowadays SCM and logistics operations, since IoT networks originate from the RFID developments in the early 1980s \((\text{Atzori et al., 2010; Xu et al., 2014})\). However, the proportion of articles including RFID technology is relatively low; only 11 out of 79 articles did implement RFID tags into the perception layer. Most of these RFID applications were only considering wireless data transmissions to support the system’s health monitoring capabilities; only two articles did gather business event data by using a RFID reader \((\text{Enshaeifar et al., 2018; Rouet & Foucher, 2011})\). The share of NFC technologies is even lower; only 5 out of 79 articles mentioned the usage of NFC tags into their IoT infrastructure. The Low-Power WAN technologies are also not commonly applied yet \((7 \text{ out of } 79 \text{ articles})\), while these techniques are specially designed for IoT applications \((\text{Ben-Daya et al., 2019})\).
descriptive statistical techniques (32 out of 79 articles) or neural networks (30 out of 79 articles). A moderate positive correlation exists for the application of neural networks into classification problems ($\rho = 0.496$), while those neural networks are often supported by the principal component analysis to reduce the dataset’s dimensionality as well ($\rho = 0.429$). On the other hand, regression patterns seem to depend on the more traditional multivariate regressive analysis ($\rho = 0.546$), and the k-nearest neighbors algorithm is frequently used for clustering tasks ($\rho = 0.496$). Visualization techniques originating from Business Intelligence (BI) also remain popular, since 37 out of 79 articles explicitly describe how the model’s output is visualized to support human pattern recognition. Association rules, clustering, and rule induction techniques are less often implemented however (17, 11, and 7 out of 79 articles respectively), while it is our conjecture that these techniques are essential to support prescriptive decision making. It will help if more authors explain how the data is (pre-) processed exactly, allowing other investigators to mine through the datasets with other pattern recognition algorithms.

5.3. Discussion – SCM

Most articles apply the patterns emerging from the BDA techniques to either describe or predict the system’s conditions at hand; a total of 25 out of 79 articles were found for both type of analytical applications separately (see Appendix E). The relatively high number of descriptive and predictive applications can be explained by the large proportion of monitoring research efforts (63 out of 79 articles). The vast majority of those monitoring publications act on the newly developed data streams in real-time, while 11 out of those 63 monitoring articles apply the derived knowledge offline. Therefore, we can conclude that most researchers combine IoT and BDA techniques to enhance supply chain resilience by either detecting or predicting deviations from the operational planning, allowing decision makers to respond in a timely manner and restore the system’s conditions preferred. Only a few research initiatives were used to support other planning capabilities:

(1) **Loading**: 6 out of 79 articles apply the IoT’s analytical capacities to allocate the system’s workload properly (Bellini, Cenni, Nesi, & Paoli, 2017; Chiu, Chang, & Chang, 2008; Howell, Rezgui, & Yuce, 2014; Lee, Funk, Feuerbacher, & Hsiao, 2007; Papas, Estibals, Ecrepon, & Alonso, 2018; Ray, Tapadar, Chatterjee, Karlose, Saha, & Saha, 2018). A moderate negative correlation is found between the loading and monitoring decision types ($\rho = -0.450$), meaning that most researchers use the IoT’s analytical capabilities to support only one of those two decision types;

(2) **Sequencing**: 6 out of 79 articles use the derived knowledge to prioritize the system’s task at hand (Birken, Schirner, & Wang, 2012; Chakurkar, Shikalgar, & Mukhopadhyay, 2018; Faizul, Rashid, Hamid, Sarjari, Mohd, & Abdullah, 2017; Fathy & Mohammadi, 2018; Papaefthimiou, Ventouris, Tabakis, Valsamidis, Kazanidis, & Kontogiannis, 2017; Wang, Birken, & Shamsabadi, 2014);

(3) **Scheduling**: 5 out of 79 articles allocate the prioritized workload over time (Chien, Hong, & Guo, 2017; Dragone et al., 2015; Pilgerstorfer & Pournaras, 2017; Ray, et al., 2018; Senthilkumar, Kumar, Ozturk, & Lee, 2010). A moderate positive correlation is found in between the scheduling decisions and prescriptive analytical capabilities ($\rho = 0.446$), meaning that the corresponding decision makers are frequently supported with explicit future actions.

The significant presence of operational monitoring activities is quite remarkable, since multiple authors hypothesize that the combination of IoT and BDA implementations will evolve from track-and-trace applications towards self-steering and event-driven logistics (Ben-Daya et al., 2019; Chung, Gesing, Chaturvedi, & Bodenbenner, 2018; Li et al., 2015; Macaulay, Buckalew, & Chung, 2015; Xu et al., 2014). Since 2017 however, more research initiatives moved beyond predictions only and used the BDA results to prescribe the decision makers what to do next (20 out of 79 articles), a trend paving the way for AI algorithms to autonomously learn and intervene within SCM and logistics operations (Gesing, Peterson, & Michelsen, 2018). We also expect to see more research initiatives addressing tactical and strategic decision support to increase the return on investments of those data-intensive projects in the near future.

5.4. Discussion – applications

The results in Appendix F show that the IoT’s analytical capabilities are most commonly applied in production and logistics environments (38 and 28 out of 79 articles respectively). Nearly all publications refer to either one of those two SCM activities, because of the negative moderate correlation found in between the production and logistics disciplines ($\rho = -0.501$). A wide range of inter-organizational processes is supported as well (e.g., order fulfillment, reverse logistics, customer services, manufacturing flows, and balancing demand); only the activities related to customer and supplier relationship management seem to be less popular in production and logistics environments. Production related investigations are moderately focusing on the efficient management of manufacturing flows ($\rho = 0.488$), while logistics publications have a moderate emphasis on order fulfillment ($\rho = 0.438$). A relative high number of R&D publications proposed a newly developed decision support system (38 out of 79 articles), but the number of articles supporting supply chain activities like Purchasing and Marketing & Sales are scarce (4 and 2 out of 79 articles respectively), while there were no articles found related to Finance at all. The lack of financial publications in our SLR study forms an interesting observation for future research, but this may be caused by our focus on the allocation and movement of physical resources equipped with sensing and communicating devices (see Section 3.1).

Most SLR outcomes were related to dependability (50 out of 79 articles) and costs (48 out of 79 articles) performances. Quality (32 out of 79 articles) and speed (29 out of 79 articles) are also present, but flexibility (17 out of 79 articles) is not addressed often. The absence of flexibility improvements is quite remarkable, because both researchers...
Fig. 10. The annual number of SLR publications, including a fitted polynomial function $y = 0.046x^3 - 0.8397x^2 + 4.6038x - 4.8382$, with $x$ the number of years since 2005, and $y$ as the yearly publication frequency.

Further cross-disciplinary research directions

- **IoT**
  - Diversify physical objects with identification tags and location receivers.
  - Use wireless sensing and communication devices to enhance flexibility.
  - Implement more M2M communication for parallel processing capacities.
  - Investigate critical amount of sensors to support decisions efficiently.

- **IoT + BDA focus areas**
  - Autonomous decision making
  - Distributed Computer Systems
  - Fog/Edge Computing
  - Ambient intelligence
  - Digital Twins

- **BDA**
  - Replace centralized master-server processing by distributed architectures.
  - Extent analytical toolbox with prescriptive algorithms for association rules, clustering, and rule induction.
  - Enhance transparency by elaborating on data pre-processing steps.

- **BDA + SCM focus areas**
  - Multi-Agent Systems
  - Reinforcement Learning
  - Mathematical optimization
  - Artificial Intelligence

- **SCM**
  - Evolve from track-and-trace applications towards event-driven logistics.
  - Combine the predictive power of machine learning with prescriptive analytics to allocate resources proactively and autonomously.
  - Use operational patterns to support tactical and strategic decisions as well.

- **SCM + KPI focus areas**
  - Business Process Management
  - General KPIs
  - System validation
  - Simulation studies

- **KPI**
  - Exploit remote monitoring functionalities to obtain more flexible operations.
  - Use the IoT’s analytical capabilities across the whole supply chain.
  - Focus on system validation instead of component testing.
  - Search for best-practices in the logistics domain.

Fig. 11. A visualization of our recommendations for further interdisciplinary research towards the IoT’s analytical capabilities in the SCM domain (Blue rectangles = technical and/or managerial recommendations; Orange clouds = potential new areas for future interdisciplinary research).
and business practitioners expect that the combination of IoT and BDA will increase supply chain resilience towards disturbances and changeable markets (Atzori et al., 2010; Barton & Court, 2012; Chung, Gesing, Chaturvedi, & Bodenbener, 2018; Macaulay, Buckalew, & Chung, 2015). A moderate negative correlation is found between the SLR articles focusing on dependability and quality (ρ = −0.442), meaning that most researchers focus on one of these two performance indicators only. The maturity level of the IoT’s analytical capabilities in today’s SCM and logistics research also seem to differ significantly among all SLR publications:

1. **Conceptual level (TRL 1 + 2):** A relatively large proportion of the SLR results introduces the expected benefits that IoT and BDA may bring to SCM and logistics operations (18 out of 79 articles);

2. **Component level (TRL 3 + 4 + 5):** A total of 45 out of 79 articles relate to component validation activities in a laboratory setting or related environment (e.g., measurement devices, communication networks, analytical models, etc.). While these articles do not validate the IoT’s analytical capabilities in real-life, they do provide a strong evidence of the technology’s feasibility and developmental requirements (Mankins, 2009).

3. **Prototype level (TRL 6 + 7):** The number of prototypes published is relatively small (12 out of 79 articles), but still promising. The technological developments seem similar for different SCM activities, since there are prototypes found in multiple environments like production (Chien et al., 2017; Liu, Zhong, Cui, Zhong, & Wei, 2015; Pickard, Linn, Awojana, & Lunsford, 2018; Rodríguez, Gualotúa, & Grilo, 2017; Sabeur, Zlatev, Melas, Veres, Arbav-Zavar, Middleton, & Museux, 2017), logistics operations (Bellini et al., 2017; Lee, Funk II, Feuerbacher, & Hsiao, 2007; Pilgerstorfer & Pournaras, 2017; Won, Zhang, Jin, & Eun, 2018), customer services (Enshaeifar et al., 2018; Yang, Yang, Magiera, Froelich, Jach, & Lapidou, 2017) and maintenance activities (Rymarczyk et al., 2017);

4. **System level (TRL 8 + 9):** A small portion of the SLR results includes an IoT system that is fully tested or even operational to support supply chain decision making in real-life (4 out of 79 articles). An overview of all four articles is given in Table 4, each publication includes sensors and/or actuators to monitor SCM and logistics operations with either descriptive or predictive analytical capabilities. However, the type of sensors and BDA techniques strongly depend on the decision/problem at hand.

We conclude this section by evaluating the actual benefits proposed by the four system publications in Table 4. Carfagni, Daou, and Furfari (2008) have installed a wired camera into an olive oil extraction mill to estimate the oil’s quality parameters with the aid of neural networks and machine vision. The prototype gives promising and validated quality metrics, but the benefits in terms of cheaper and faster quality control are not addressed yet. Wang, Birken, & Shamsabadi (2014) have created an innovative dynamic health monitoring system by equipping a van with GPS receivers, video cameras, radar technology, tire pressure sensors, and an axle accelerometer. The combination of real-time data gathering, regression techniques and flexible resource allocations enabled the researchers to speed up road inspection tasks with almost 95% in comparison with traditional methods, allowing decision makers to prioritize road maintenance activities. Moreno, Skarmeta, and Jara (2015) explained how cities can become smarter by combining real-time system monitoring with data analytics and optimization capabilities. For example, city planners can apply neural networks to predict traffic jams 15 min in advance by using temperature and traffic sensors only, while a building’s energy demand can be reduced with 29% by combining infrared sensors and RFID tags to locate people movements. Finally, Gásová, Gašo, and Štefánik (2017) enabled organizations to speed up the design of an ergonomic workspace by using camera images of simple mobile devices. A newly developed application, including an expert system and external databases, visualizes the working conditions and initiates an ergonomic assessment. The visualizations and use cases seem to be promising, but more insights into the analytical capacities and the actual benefits in comparison with traditional methods are currently missing.

5.5. Addressing the research gaps

The IoT and BDA paradigms have become increasingly popular among scientists since the last decade (Fig. 5). The IoT’s analytical capabilities seem to be quite promising for SCM and logistics operations as well, because more research efforts are applying an integrated approach towards data gathering, pattern recognition, and decision making (see Fig. 10 and Appendix A). Especially computer scientists and engineers seem to appreciate the expected benefits that real-time condition monitoring may offer (Fig. 6), resulting into a sharp rise of conference proceedings and journal papers (Fig. 9). However, the discussion of the SLR results from Section 5.1 until Section 5.4 revealed multiple gaps at the intersection of the IoT, BDA, and SCM research disciplines already. In the following subsections, we introduce a research agenda for future interdisciplinary research towards the IoT’s analytical capabilities in SCM and logistics operations by answering the three sub-questions raised in Section 2.4. Fig. 11 summarizes all our recommendations made.

5.5.1. Sub-question A: IoT + BDA

We will first answer sub-question A by reflecting on the combinations of IoT and BDA techniques found in this SLR study. There are no significant correlations found between the type of data gathering devices and the analytical capacities proposed by the researchers; the IoT and BDA techniques seem to be customized to the problem context at hand. Most researchers integrate the newly developed measuring devices with more traditional ICT infrastructures (e.g., data warehouses, mobile devices, external databases) to either visualize the current way of operating, or to better predict the system’s future state. The strong emphasis on classification, regression and visualization explains the relatively high proportion of artificial neural networks, statistics, and BI techniques used. Therefore, we conclude that today’s SCM researchers use the IoT’s analytical capabilities to stimulate a more system-oriented approach towards remote monitoring of physical objects (Atzori et al., 2010; Wortmann & Flüchter, 2015; Xu et al., 2014). However, capabilities regarding ambient intelligence and autonomous control are receiving limited attention within our SLR results, while the IoT’s wireless communication among physical objects could provide a strong foundation for the real-time processing of information (Li et al., 2015).

It is remarkable that the IoT’s perception layers reported in our SLR strongly rely on the integration of wired sensor networks and legacy systems, since other researchers hypothesized a more frequent use of both identification tags and location receivers (Atzori et al., 2010; Ben-Daya et al., 2019; Xu et al., 2014). The focus on sensor networks and business events explains the application of BDA techniques to provide early warnings of potential disruptions. However, the lack of identification tags and location receivers obstructs SCM operators to fully harness the spatiotemporal information available. Nowadays, people movements are tracked solely due to the common integration of mobile devices and location receivers into the IoT’s perception layer (ρ = 0.400), but other resources are scarcely tracked. Diversification of the available data streams with the objects’ movements stimulates SCM researchers to anticipate on the changing environment by directly controlling those objects monitored (Addo-Tenkorang & Helo, 2016). Therefore, we argue that future SCM research must diversify the IoT’s sensor networks with more context-aware devices to fully capture the dynamic and stochastic behavior of the objects themselves, because appropriate identity management is considered as one of the most critical success factors for IoT implementations (Colaković & Hadžiolić, 2018).
The SLR results indicate that most SCM researchers apply a static cloud infrastructure, consisting of centralized master-server implementations. We expected more research initiatives into distributed computing systems (e.g., edge and fog computing), because the internet-based technologies empower IoT devices with both machine-to-machine (M2M) communication and cloud-based processing capabilities (Chiang & Zhang, 2016; Colakovic & Hadžić, 2018; Gubbi et al., 2013). Our bibliometric study revealed that the IoT technologies and distributed computer systems are closely intertwined (see Fig. 4 and Appendix A), but only one SLR paper highlighted the importance of using fog and edge computing to minimize the amount of data transferred across the IoT’s cloud infrastructure (Bibri, 2018). The absence of distributed computing in SCM research may be caused by the lack of wireless communication networks implemented nowadays, since these technologies speed up collaborative communication among context-aware objects to build up ambient intelligence and autonomous control (Aztori et al., 2010; Li et al., 2015). For example, neural networks rarely use input from flexible resources like mobile devices for their classification tasks (e.g., Cai et al., 2017). Therefore, future IoT systems require more wireless communication among objects to create parallel and distributed data processing capacities in order to handle the increasing volumes of dynamic data in a flexible way (Cai et al., 2017).

It is interesting to note that not all BDA applications require new measuring and communication devices; more traditional ICT infrastructures and combinatorial optimization procedures could be used to enable data-driven decision making in modern day SCM and logistics environments (Chien et al., 2017; Pilgerstörfer & Pournaras, 2017). Therefore, it may be interesting to investigate the minimum amount of perception devices to support the corresponding decision efficiently in terms of investment costs, processing time, and reliability. Especially the critical usage of sensors and actuators should be investigated in more detail, because of the moderate positive correlation found between the monitoring decision types and the application of sensors and actuators ($\rho = 0.456$).

### 5.5.2. Sub-question B: BDA + SCM

The majority of all BDA techniques support supply chain decision making with monitoring capabilities at an operational level. Newly developed decision support tools integrate the heterogeneous data sources with popular techniques like data visualizations, statistics, expert systems, and ontologies to support human decision makers with either descriptive or explanatory analytical capabilities. More data-intensive techniques like neural networks and regression analyses are commonly applied to predict the system’s conditions at a future state. Therefore, we answer sub-question B by stating that most scientists combine IoT and BDA techniques to timely inform human decision makers about observed or predicted disturbances. Especially neural networks seem to be used for prediction purposes, because of the moderate negative correlation found in between neural networks and descriptive analytics ($\rho = -0.420$). However, it is our hypothesis that the IoT’s prescriptive capabilities are most beneficial for the SCM and logistics operations, because human decision makers have limited cognitive capacity to efficiently transform the ever increasing flow of additional data sources into effective actions (Chen et al., 2015).

Future SCM research into the IoT’s analytical capabilities should evolve from track-and-tracing towards self-steering and event-driven logistics (Ben-Daya et al., 2019; Chung, Gesing, Chaturvedi, & Bodenburg, 2018; Li et al., 2015; Macaulay, Buckalew, & Chung, 2015; Xu et al., 2014). Innovative BDA techniques can stimulate those AI developments by transforming the derived knowledge into parameters for improved decision making and continuous learning (Zhong et al., 2016). Therefore, scientists should expand their analytical toolbox with association, clustering, and rule induction techniques to autonomously transform the perception of dynamic and stochastic disturbances into real-time interventions. Our SLR results indicate that only a few studies apply the BDA techniques to automatically prescribe decision makers what to do next in terms of loading, sequencing, and scheduling. By summarizing the prescriptive studies found in this research, it is our hope that future SCM research efforts will move beyond descriptive and predictive analytics only. For example, a smart allocation of free Wi-Fi access points and GPS receivers allows city planners to re-allocate traffic flows throughout the city (Bellini et al., 2017). Clustering

| Category | Variable | (Carfagni, Dino, & Furferi, 2008) | (Wang, Birken, & Shamsabadi, 2014) | (Moreno, Skarmeta, & Jara, 2015) | (Gasová et al., 2017) |
|----------|----------|----------------------------------|----------------------------------|----------------------------------|-----------------------|
| IoT      | Perception layer | Sensors and/or actuators; Data warehouses | Sensors and/or actuators; | Sensors and/or actuators; Tags; Mobile devices; External sources | Sensors and/or actuators; Mobile devices; External sources |
| BDA      | Data management | Acoustic; Electric; Magnetic; Mechanical; Optical; Event | Wired; Internet; Radio navigation; | Acoustic; Chemical; Electrical; Mechanical; Thermal; Event | Acoustic; Chemical; Electrical; Mechanical; Thermal; Event |
| SCM      | Decision hierarchy | Predictive | Operational (online) | Predictive | Operational (online) |
| Application | Supply chain activity | Monitoring | Sequencing; Monitoring | Monitoring | Monitoring |
| Readiness level | KPI | TRL08 | TRL09 | TRL09 | TRL09 |

### Table 4

System evaluations (TRL8 or TRL 9).

The majority of all BDA techniques support supply chain decision making with monitoring capabilities at an operational level. Newly developed decision support tools integrate the heterogeneous data sources with popular techniques like data visualizations, statistics, expert systems, and ontologies to support human decision makers with either descriptive or explanatory analytical capabilities. More data-intensive techniques like neural networks and regression analyses are commonly applied to predict the system’s conditions at a future state. Therefore, we answer sub-question B by stating that most scientists combine IoT and BDA techniques to timely inform human decision makers about observed or predicted disturbances. Especially neural networks seem to be used for prediction purposes, because of the moderate negative correlation found in between neural networks and descriptive analytics ($\rho = -0.420$). However, it is our hypothesis that the IoT’s prescriptive capabilities are most beneficial for the SCM and logistics operations, because human decision makers have limited cognitive capacity to efficiently transform the ever increasing flow of additional data sources into effective actions (Chen et al., 2015).

Future SCM research into the IoT’s analytical capabilities should evolve from track-and-tracing towards self-steering and event-driven logistics (Ben-Daya et al., 2019; Chung, Gesing, Chaturvedi, & Bodenburg, 2018; Li et al., 2015; Macaulay, Buckalew, & Chung, 2015; Xu et al., 2014). Innovative BDA techniques can stimulate those AI developments by transforming the derived knowledge into parameters for improved decision making and continuous learning (Zhong et al., 2016). Therefore, scientists should expand their analytical toolbox with association, clustering, and rule induction techniques to autonomously transform the perception of dynamic and stochastic disturbances into real-time interventions. Our SLR results indicate that only a few studies apply the BDA techniques to automatically prescribe decision makers what to do next in terms of loading, sequencing, and scheduling. By summarizing the prescriptive studies found in this research, it is our hope that future SCM research efforts will move beyond descriptive and predictive analytics only. For example, a smart allocation of free Wi-Fi access points and GPS receivers allows city planners to re-allocate traffic flows throughout the city (Bellini et al., 2017). Clustering

| Category | Variable | (Carfagni, Dino, & Furferi, 2008) | (Wang, Birken, & Shamsabadi, 2014) | (Moreno, Skarmeta, & Jara, 2015) | (Gasová et al., 2017) |
|----------|----------|----------------------------------|----------------------------------|----------------------------------|-----------------------|
| IoT      | Perception layer | Sensors and/or actuators; Data warehouses | Sensors and/or actuators; | Sensors and/or actuators; Tags; Mobile devices; External sources | Sensors and/or actuators; Mobile devices; External sources |
| BDA      | Data management | Acoustic; Electric; Magnetic; Mechanical; Optical; Event | Wired; Internet; Radio navigation; | Acoustic; Chemical; Electrical; Mechanical; Thermal; Event | Acoustic; Chemical; Electrical; Mechanical; Thermal; Event |
| SCM      | Decision hierarchy | Predictive | Operational (online) | Predictive | Operational (online) |
| Application | Supply chain activity | Monitoring | Sequencing; Monitoring | Monitoring | Monitoring |
| Readiness level | KPI | TRL08 | TRL09 | TRL09 | TRL09 |
customer locations by using the product’s and/or client’s real-time conditions enables vehicles to dynamically re-optimize their routes (Chakurkar, Shikalgar, & Mukhopadhyay, 2018; Ray, et al., 2018), while the shortest route can also be found by combining regression and real-time traffic monitoring (Fathy & Mohammadi, 2018). A simulation-based scheduling system can enhance manufacturing intelligence by using the data of the facility’s manufacturing execution system (Chien, et al., 2017). The combination of neural networks, fuzzy logic, and rule inductive techniques may stimulate facility managers to automatically reduce the energy consumption of their buildings (Howell, Rezigui, & Yuce, 2014; Senthilkumar, Kumar, Ozturk, & Lee, 2010). Finally, a cognitive robotic ecology empowered with neural networks can assist elderly people with scheduling their daily tasks (Dragone, et al., 2015).

Nowadays, classification and regression algorithms are used for machine learning and AI developments predominantly (e.g., neural networks, support vector machines, linear regression, time series analysis, principal components analysis, etc.). The predictive power of those algorithms enable SCM operators to adopt a proactive approach in response to supply chain risk management (Tiwari, et al., 2018), but the autonomous construction of interventions also requires recognition of the workload ahead. Therefore, we strongly recommend future research projects to broaden their scope with prescriptive algorithms like k-nearest neighbors, genetic algorithms, or fuzzy logic. The extension of the IoT’s perception layer with autonomous operating agents including prescriptive analytical capabilities seems to be quite promising for future AI developments in SCM research (Dragone, et al., 2015; Fathy & Mohammadi, 2018; Ghiani, Mocci, Franceschelli, Anedda, Desogus, & Fadda, 2018; Pilgerstorfer & Pournaras, 2017). We also believe that advances in reinforcement learning may bridge the gap between predictive and prescriptive analytics, as described by two of the SLR articles as well (Dragone, et al., 2015; Pilgerstorfer & Pournaras, 2017).

5.5.3. Sub-question C: SCM + Application

The third and last sub-question relates to the improvements that supply chain decision makers may expect from the IoT’s analytical capacities. Production environments include the highest proportion of condition monitoring systems consisting of wired sensor and/or actuator networks, resulting in a strong focus on higher reliability outcomes and better quality standards. Logistics operations seem to benefit from flexible resources (e.g., tags, mobile devices, location receivers, wireless communication devices, etc.) to support prescriptive analytics. Therefore, logistics planners use the real-time data of physically operating objects to move beyond track-and-trace applications towards loading, sequencing, and scheduling decisions, which explains the stronger emphasis on flexibility and speed. Those SLR outcomes are quite consistent with the IoT’s and BDA’s expectations (Tiwari, et al., 2018). Especially logistics operations seem to fully exploit the IoT’s dynamic monitoring capabilities, probably because the logistics sector is used to track-and-trace technologies for some decades already (Atzori, et al., 2010; Ben-Daya, et al., 2019; Xu, et al., 2014). For example, the logistics’ perception layer is relatively often equipped with location receivers (ρ = 0.418), and the corresponding communication networks consist of wireless LAN (ρ = 0.453). However, other SCM disciplines do not fully benefit from the dynamic information released by the object’s sensing and communication devices, while flexibility is one of the major benefits envisioned by both the IoT and BDA research paradigms (Atzori, et al., 2010; Barton & Court, 2012; Chung, Gesing, Chaturvedi, & Bodenbenne, 2012; Mkatima, Bhalow, & Shankar, 2015; Zhong, et al., 2016). The autonomous focus on operational decisions in the production and logistics environments also limits prototyping of the IoT’s analytical capabilities across the supply chain (e.g., Purchasing, Marketing & Sales, and Finance).

The large scale implementations of IoT and BDA techniques into production and logistics operations is consistent with other research observations (Ben-Daya, et al., 2019; Nguyen, et al., 2018; Tiwari, et al., 2018; Wang, et al., 2016). The IoT’s analytical capabilities are commonly applied into resource intensive inter-organizational SCM activities like demand management, manufacturing flow management, order thenet, and return management. However, the absence of procurement related studies seems remarkable due to the supply chain’s interest into IoT and BDA to improve transparency and reduce supply chain risks. The major focus of the SLR results onto operational monitoring decisions is also noteworthy, since other researchers published several IoT and/or BDA implementations to support tactical and strategic decision making (Addo-Tenkorang & Helo, 2016; Ben-Daya, et al., 2019; Hopkins & Hawking, 2018; Lou, et al., 2011; Marjani, et al., 2017; Zhong, et al., 2016). Our SLR study indicates that most SCM researchers use the IoT’s analytical capabilities to maintain reliable and efficient operations in the presence of potential disruptions, while the same patterns can improve overall business models as well. Techniques for pattern recognition and mathematical optimization have to be combined more often to adequately incorporate disturbances and changing parameter values into operational, tactical, and strategic decision making simultaneously. For example, production environments can reshape the factory layout by reflecting on the machines’ utilization rates; logistics operations can use the objects’ track-and-trace data to reallocate facilities; and better insight into customer buying patterns enable purchasing managers to adapt the product portfolio in near real-time. Future monitoring systems should explicitly highlight why and how the IoT’s additional data streams are required for better decision making at all decision levels, since object monitoring is just a mean to improve supply chain performances, not the objective itself. A comprehensive modeling approach may help decision makers to gain insight into the added value of their IoT and BDA implementations (e.g., Enterprise Architectures, Unified Modeling Language, Business Process Modeling, etc.).

The current research gaps depicted in the heatmap of Table 5 can help future researchers to publish more real-life demonstrations of the IoT’s analytical capabilities into SCM and logistics operations. Some interesting correlations were found between the TRLs and the pattern searching algorithms as well. For example, neural networks are often applied in laboratory settings only (TRL4: ρ = 0.414), and support vector machines are moderately included into fully developed system prototypes (TRL6: ρ = 0.414). The number of TRL9 systems is relatively low (4 out of 79), but it is still interesting to note that these systems often depend on linear regression techniques (ρ = 0.443). However, most research efforts are still not completely mature yet; the majority of the SLR articles highlight the system’s analytical (sub-) components only (e.g., by reflecting on the prediction’s mean squared error). Researchers have to critically think when the measuring system becomes beneficial for business practitioners, because validation of the IoT’s analytical capacities should not depend on the system’s descriptive or predictive output measures only. There is a need for a more general set of KPIs to measure the efficiency and effectivity of IoT and BDA implementations consistently (Zhong, et al., 2016). Multiple case studies including fully developed IoT systems and modern pattern searching algorithms are required to validate the benefits envisioned too. A simulation study may form a reasonable alternative if the IoT system is highly complex, including both stochastic and dynamic input components (Law, 2015). Future research should have an explicit focus on how the data is gathered, communicated, and processed by the IoT devices themselves to speed up the validation of the IoT’s analytical capabilities. Proper administration of the data management activities may also support researchers to apply a wider spectrum of pattern recognition capabilities across the supply chain at different hierarchical levels.

6. Conclusions & further research

This paper presented the results of state-of-the-art IoT developments proposed in academic literature to improve supply chain decision making by gathering, analyzing, and applying real-time data of physical objects. For this, we followed the systematic review methodology proposed by Denyer and Tranfield (2009), including an initial bibliographic
study to search for the most relevant keywords of the IoT, BDA, and SCM disciplines separately. The assessment of all 79 articles enables us to construct an overview of IoT’s analytical applications found in SCM and logistics research.

We can conclude that typically measuring devices are integrated with more traditional ICT infrastructures to either visualize the current way of operating, or to better predict the system’s future state. Neural networks, statistics, and BI techniques are the most popular techniques applied within IoT networks, which empowers supply chain decision makers with real-time monitoring capabilities at an operational level. Production managers apply the IoT’s analytical capabilities to monitor the condition of their physical products and/or equipment to obtain higher reliability outcomes and better quality standards. Logistics operations have a stronger emphasis on flexibility and speed improvements, which explains that these operations rely on other planning activities instead of operational monitoring only (e.g., loading, sequencing, and scheduling). Therefore, the construction of resilient supply chains seems to be the driving force in today’s SCM research, resulting into the integration of IoT and BDA techniques to either detect or predict deviations from the operational planning. However, the real potential of equipping physical objects with sensing, communication, and processing capacities remains open for future research by extending the concept of physical monitoring with ambient intelligence and autonomous control.

One of the main findings that emerged from this study is a new research direction to be pursued in the SCM discipline, which concerns the empowerment of physical objects with more context-aware data gathering devices to keep track of their variable status in real-time (e.g., identification tags, location receivers, multi-agent systems). Investments into distributed computer systems are also required to embrace the increasing data volumes of future IoT systems, especially by extending the wireless communication networks among physical objects (e.g., RFID, NFC, W-PAN, W-LAN, LP-WAN, etc.). Innovative BDA techniques should bridge the gap between predictive and prescriptive analytics by the construction of real-time interventions once a disturbance is observed and/or predicted. Therefore, scientists should focus more on flexibility improvements by expending their analytical toolbox with association, clustering, and rule induction techniques. We also recommend future research initiatives to explicitly report how the data is gathered, communicated, and processed by the IoT devices themselves to support a wider spectrum of pattern recognizing capabilities. Finally, more real industry case studies, going beyond toy-examples, are required to validate the expected benefits enabled by the IoT’s analytical capabilities.

CRediT authorship contribution statement

**Martijn Koot:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Writing – original draft, Visualization. **Martijn R.K. Mes:** Conceptualization, Methodology, Writing – review & editing, Supervision. **Maria E. Iacob:** Conceptualization, Methodology, Writing – review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This work was supported by the Netherlands Organization for Scientific Research (NWO) [grant number 628.009.015]. The authors would also like to thank all DataRel project partners.
Appendix A. Keywords

A simplistic literature search is made in Scopus to find relevant keywords for the IoT, BDA, and SCM research discipline separately. The co-occurrences of keywords are analyzed by ‘VOS viewer’, a software tool for constructing and visualizing bibliometric networks. Several search conditions are installed to provide a brief overview of the most common grouping of keywords:

1. the keyword search will include review articles only to provide a generic overview of academic discipline and its developments;
2. the review articles should be fully published and written in English;
3. the review articles’ subject areas have to align the academic fields taken into consideration (e.g., Computer Science, Engineering, Mathematics, Decision Sciences, Business Management, Economics). The Multidisciplinary category is also included, since we are explicitly looking for linkages in between the IoT, BDA, and SCM research areas.

The top 25 most frequently co-occurring keywords are visualized into a bibliometric network for all three academic fields separately. The VOS viewer tool will automatically emphasize the most frequent keyword sets and search for appropriate clusters based on the keywords’ association strength. General keywords referring to document types and scientific characteristics are removed from the bibliometric network (e.g., survey, review, future recommendations, etc.). A thesaurus file is created in order to make sure that synonyms are not counted separately. The bibliometric networks are used to define relevant keywords for our SLR search strategy. The resulting keyword selection is visualized in Table 1 (see Section 3.1).

A.1. IoT keywords

A total of 563 review articles are found in ‘Scopus’ by searching for the keyword “Internet of Thing” (search date: 9th of April 2019). The bibliometric network of the 25 most frequently used keywords is visualized in Fig. 12. Note that each cluster should include a minimum number of five keywords at least, otherwise too many fragmented clusters were obtained. The three clusters in Fig. 12 can be classified based on the theoretical background given in Section 2.1:

Fig. 12. Bibliometric network including the top 25 most frequent co-occurring keywords related to the Internet of Things (IoT).
Computers & Industrial Engineering 154 (2021) 107076

Cluster 1 (blue) – Wireless Sensor Networks: the concept of IoT networks strongly relies on wireless interconnected sensing devices that will gather high volumes of heterogeneous data;

(1) Cluster 2 (green) – Distributed computing: the new network architectures required for distributed computations enabled organizations to gather, process, store and distribute information at larger scale;

(2) Cluster 3 (red) – IoT applications: The combination of WSN and distributed computing allows organizations to analyze data for innovative applications (e.g., smart cities, industry 4.0, artificial intelligence, etc.).

The Internet of Things is clearly supported by two key technologies: (1) Wireless Sensor Networks (WSN) and (2) Cloud Computing. Only the WSN related keywords are included into the search strategy (blue cluster), since the main aim of this article is to support supply chain decision making by looking into the large volumes of real-time data gathered. Cloud computing provides the necessary backbone architectures for efficient data processing, but these systems will not search for the hidden patterns required for decision making. Therefore, the marked keywords fall outside our research scope. The red clustered keywords are also not included within the IoT keyword selection, we will address the required data analytics in Section A.3.

A.2. BDA keywords

A total of 221 review articles are found in ‘Scopus’ by searching for the keywords “Big Data” AND “Analys*” (search date: 9th of April 2019). The asterisk symbol is added to allow multiple analysis synonyms (e.g., analysis, analyses, analyze, analyze, etc.). The bibliometric network of the 25 most frequently used keywords is visualized in Fig. 13. There is no minimum cluster size specified.

The four clusters in Fig. 13 can be classified by using the theoretical background given in Section 2.2:

(1) Cluster 1 (yellow) – Data acquisition: the analysis of large heterogeneous datasets strongly depends on the data sources available;

(1) Cluster 2 (green) – Data Analytics: the Big Data Analytics are mainly supported by a wide variety of data mining and analytics techniques;

(2) Cluster 3 (red) – Artificial Intelligence: the large datasets are ideal for the application of machine learning techniques to empower algorithms with learning capabilities;

(3) Cluster 4 (blue) – Human decision making: the recognition of hidden patterns within large datasets will also support human decision making, which is comparable to the application of preceding BI technologies.

Our main focus is on the data acquisition made available by IoT networks. Therefore, all other data sources mentioned within the yellow cluster fall outside our research scope. Most of the green and red clustered keywords are related to data handling activities to support both human and artificial decision making (e.g., storage, processing, handling, learning etc.). The transformation of large volumes heterogeneous data into data-driven insights is strongly related to the application of pattern recognition techniques originating from the Data Science discipline. Therefore, the keywords related to ‘Big Data Analytics’ will mostly consist of data-driven techniques for pattern recognition. The marked keywords are not included within the BDA keyword selection, since they relate to decision making itself (see Section A.3.).

A.3. SCM keywords

A total of 1,589 review articles are found in ‘Scopus’ by searching for the keywords related to supply chain decision making (search date: 9th of April 2019). The resulting review articles should include two combinations of keywords at least: (“Supply chain” OR “Logistic?”) AND...
Fig. 14. Bibliometric network including the top 25 most used keywords related to SCM.

(“Management” OR “Decision’’). The question mark is included to allow the term “Logistics” notation as well. The bibliometric network of the 25 most frequently used keywords is visualized in Fig. 14. There is no minimum cluster size specified.

It is more difficult to find proper SCM labels for the four clusters identified in Fig. 14, but an attempt can still be made by applying logical reasoning based on the theoretical background of Section 2.3. For example, the red cluster is largely dedicated to decision support tools, which provides a link to the “Big Data Analytics” keywords included in section A.2. However, the keyword types themselves seem to be more interesting instead of the clusters formed. The bibliometric network in Fig. 14 reveals four types of SCM keywords: (1) decision types; (2) decision support tools; (3) supply chain activities; and (4) key performance indicators (KPIs). The search strategy will include all keywords related to decision types and supply chain activities to find relevant IoT developments in academic literature, while the KPI keywords are used to search for the potential benefits of the new techniques proposed.

A wide variety of tools exists to support SCM decision making. In this research, the data-driven techniques discussed in Section A.2 are included only. There is not specifically searched for the model-driven techniques originating from Industrial Engineering and Operations Research.

Appendix B. Search string

TITLE-ABS-KEY[“Internet of Thing” OR “Internet of Everything” OR “Industrial Internet” OR “Web of Thing” OR “Cyber Physical System” OR “Wireless Sensor Network” OR (Sensor AND (Network OR Connected OR Internet)) OR ((Wireless OR Mobile) AND (“Communication System”))]

AND TITLE-ABS-KEY[ (“Big Data” OR “Mass” Data” OR “Large Data” OR “Enormous Data”) AND Analy”) OR “Data? Driven” OR “Pattern Recogni*” OR “Data Mining” OR “Process Mining” OR “Machine Learning” OR “Neural Network” OR “Deep Learning” OR “Genetic Algorithm” OR Classification OR Association OR Clustering OR Regression]

AND TITLE-ABS-KEY[“Supply chain Management” OR SCM OR “Decision Making” OR “Industrial Management” OR “Industrial Engineering” OR “Industrial Economic” OR “Management Science” OR Optimisation OR Planning OR Scheduling OR Loading OR Sequencing OR Monitoring]

AND TITLE-ABS-KEY[“Product Development” OR “Research and Development” OR R&D OR Purchasing OR Procurement OR Project Management OR Production OR Manufacturer* OR Warehouse* OR Inventor* OR Transport OR Logistic* OR “Physical distribution” OR “Distribution Management” OR Marketing OR Sales OR Maintenance OR After-sales OR “After-sales” OR “Returns Management” OR “Service Logistic” OR “Reverse Logistic” OR “Demand Management” OR “Customer-relationship” OR “Supplier-relationship” OR “Customer-service” OR Finance*]
Appendix C. IoT data extraction form

| ID | APA reference (authors, year) | Perception layer | Stimuli | Network layer |
|----|----------------------------|-----------------|---------|--------------|
| 01 | Andon, (1990)              | X                | X       | X            |
| 02 | Athani, Tiwari, Patel, Pali, & Kulkarni, (2017) | X                | X       | X            |
| 03 | Ates, Adinolak-Abdul, Hagh, & Agghoane, (2018) | X                | X       | X            |
| 04 | Azizi, Ria, & Arslan, (2017) | X                | X       | X            |
| 05 | Bawa, et al., (2017)       | X                | X       | X            |
| 06 | Bagheri & Movahedi, (2016) | X                | X       | X            |
| 07 | Bok, & Flynn, (2015)       | X                | X       | X            |
| 08 | Bolivar, Bertin, Laboux, Etiol, Floral, & Christoph, (2018) | X                | X       | X            |
| 09 | Bolkan, Gao, & Froitzum, (2017) | X                | X       | X            |
| 10 | Bihl, (2018)               | X                | X       | X            |
| 11 | Biran, Schmal, & Wang, (2012) | X                | X       | X            |
| 12 | Biran, Schmal, & Wang, (2013) | X                | X       | X            |
| 13 | Chakraborty, Singh, Sambhava, Chandra, & Srivastava, (2018) | X                | X       | X            |
| 14 | Chekansky, Cronin, M., Syme, & Smirnov, (2008) | X                | X       | X            |
| 15 | Chen, Yang, & Guo, (2017)  | X                | X       | X            |
| 16 | Chen, Zhang, & Chang, (2008) | X                | X       | X            |
| 17 | Cho, et al., (2018)        | X                | X       | X            |
| 18 | Ciupan, et al., (2006)     | X                | X       | X            |
| 19 | Datta, Rubenstein, & DeRosa, (2018) | X                | X       | X            |
| 20 | Dixon, Gallup, & Hardy, (2007) | X                | X       | X            |
| 21 | Dragan, Dmrzakowski, Karmarkar, Lank, & Uhl, (2013) | X                | X       | X            |
| 22 | Dragone, et al., (2015)    | X                | X       | X            |
| 23 | Elbrotska, Issaoun, Fattal, & Yalal, (2018) | X                | X       | X            |
| 24 | Fada, Fard, & Mohammed, (2018) | X                | X       | X            |
| 25 | Falas, Fado, & Stellinck, (2017) | X                | X       | X            |
| 26 | Gas, Subramanian, Barch, & Toonarian, (1997) | X                | X       | X            |
| 27 | Ghasi, et al., (2013)      | X                | X       | X            |
| 28 | Greidinger, & Divani, (2017) | X                | X       | X            |
| 29 | Gao, & Liu, (2013)         | X                | X       | X            |
| 30 | Goweri, Kangui, & Yuen, (2018) | X                | X       | X            |
| 31 | Huang, (2018)              | X                | X       | X            |
| 32 | Ivys, et al., (2009)       | X                | X       | X            |
| 33 | Kadar, Carrolls, Jardes-Gonzalvez, & Bellon, (2017) | X                | X       | X            |
| 34 | Kall, et al., (2013)       | X                | X       | X            |
| 35 | Kat, (1993)                | X                | X       | X            |
| 36 | Kervisz, & Zenczuk, (2004) | X                | X       | X            |
| 37 | Latouche, Paredov, & Buz, Vad, & Taci, (2019) | X                | X       | X            |
| 38 | Lee, Enki, & Fruchter, (2001) | X                | X       | X            |
| 39 | Liu, Zhong, Gao, & Wei, (2015) | X                | X       | X            |
| 40 | Lu, et al., (2019)         | X                | X       | X            |
| 41 | Magazzeni, P, Addona, Caramia, & Foggia, & Ten, (2015) | X                | X       | X            |
| 42 | Mcdonley, Einzel, Flaim, & Loos, (2017) | X                | X       | X            |
| 43 | Meo, & Radhakrishnan, (2016) | X                | X       | X            |
| 44 | Mondal, & Haq, (2005)      | X                | X       | X            |
| 45 | Morales-Memjider, Villares, Nolazco-Flores, & Garca-Perez, (2007) | X                | X       | X            |
| 46 | Moreno, Sarmieto, & Jur, (2020) | X                | X       | X            |
| 47 | Nascimento, et al., (2013) | X                | X       | X            |
| 48 | PapiloFidonic, et al., (2017) | X                | X       | X            |
| 49 | Papas, Eshbath, Epscoot, & Atanas, (2018) | X                | X       | X            |
| 50 | Pass, Marti, Sodini, & DiCarlo, (2017) | X                | X       | X            |
| 51 | Picket, Lin, Arjoma, & Lundof, (2018) | X                | X       | X            |
| 52 | Pilgerstorff, & Panserat, (2017) | X                | X       | X            |
| 53 | Ray, et al., (2018)        | X                | X       | X            |
| 54 | Richardson, Kneira, & White, (2018) | X                | X       | X            |
| 55 | Rodriguez, Guidotti, & Ortiz, (2016) | X                | X       | X            |
| 56 | Sabour, et al., (2017)     | X                | X       | X            |
| 57 | Salas, Jaru, & Ghan, (2009) | X                | X       | X            |
| 58 | Schanzinger, & Liu, (2017) | X                | X       | X            |
| 59 | Schneider, et al., (2017)  | X                | X       | X            |
| 60 | Sonawat, et al., (2013)    | X                | X       | X            |
| 61 | Spata, et al., (2017)      | X                | X       | X            |
| 62 | Stroud, & Shillang, (2018) | X                | X       | X            |
| 63 | Talamo & Atta, (2019)      | X                | X       | X            |
| 64 | Taylor, Mccleary, Ibel, Kirkham, & Long, (1999) | X                | X       | X            |
| 65 | Vazirzad, & Snip, (2016)   | X                | X       | X            |
| 66 | Wang, Ikken, & Shimabuku, (2014) | X                | X       | X            |
| 67 | Wang, Zhang, & Liu, (2012) | X                | X       | X            |
| 68 | Whistle, Alam, Poo, & Jabpe, (2012) | X                | X       | X            |
| 69 | Wen, Zhang, & Jin, (2018)  | X                | X       | X            |
| 70 | Yee, et al., (2017)        | X                | X       | X            |

**Total:** 70 references

| Year Range | Number of References |
|------------|----------------------|
| 2000-2018  | 70                   |

Note: The table above represents the data extracted from the IoT data extraction form and organized in a structured manner for better readability and analysis.
## Appendix D. BDA data extraction form

| ID | APA reference (author(s), year) | Data management | Pattern recognition | Algorithm type |
|----|--------------------------------|-----------------|--------------------|---------------|
| 1  | Anderson, 1997                | X               | X                  | X             |
| 2  | Aliyari, Farnaz, Pari, & Keshavarzi, 2012 | X | X | X |
| 3  | Azar, Avimelkh, Hagh, & Aggarwal, 2012 | X               | X                  | X             |
| 4  | Zhao, Zuo, & Jiao, 2011        | X               | X                  | X             |
| 5  | Zhao, et al., 2013            | Y               | X                  | X             |
| 6  | Shaghayegh, et al., 2014      | X               | X                  | X             |
| 7  | Zhao & Xiong, 2013            | X               | X                  | X             |
| 8  | Shafiq, Rezaa, Lahbor, Shahzad, & Maheswaran, 2018 | X | X | X |
| 9  | Bejun, Coma, Fux, & Fuxa, 2017 | Y               | X                  | X             |
| 10 | Hopp, 2016                    | X               | X                  | X             |
| 11 | Biktired, Schmitter, & Wang, 2012 | X               | X                  | X             |
| 12 | Egilmez, Diao, & Toor, 2008   | X               | X                  | X             |
| 13 | Chakraborty, Saha, & Mukhopadhyay, 2018 | X               | X                  | X             |
| 14 | Gao, Liu, & Xu, 2016          | X               | X                  | X             |
| 15 | Hoffland, Siegel, Sundararajan, & Sevasti, 2018 | X | X | X |
| 16 | Cherkasova, Omena, Yoon, & Son, 2010 | X               | X                  | X             |
| 17 | Cihan, Zhang, & Chen, 2015    | Y               | X                  | X             |
| 18 | Chen, Chang, & Zhang, 2008    | X               | X                  | X             |
| 19 | Liu, et al., 2019             | X               | X                  | X             |
| 20 | Evers, et al., 2005           | X               | X                  | X             |
| 21 | Dordyn, Kastenm, & Delkou, 2014 | X               | X                  | X             |
| 22 | Edmonson, Lai, & Sheld, 2007  | X               | X                  | X             |
| 23 | Xiyan, Zhao, & Xiao, 2013     | X               | X                  | X             |
| 24 | Durojaye, Nwabueze, Karkera, & Aurukwu, 2013 | X | X | X |
| 25 | Feng, et al., 2017            | X               | X                  | X             |
| 26 | Feng, et al., 2018            | X               | X                  | X             |
| 27 | Gao, et al., 2019             | X               | X                  | X             |
| 28 | Gao, et al., 2019             | X               | X                  | X             |
| 29 | Gao, et al., 2019             | X               | X                  | X             |
| 30 | Gao, et al., 2019             | X               | X                  | X             |
| 31 | Gao, et al., 2019             | X               | X                  | X             |
| 32 | Gao, et al., 2019             | X               | X                  | X             |
| 33 | Gao, et al., 2019             | X               | X                  | X             |
| 34 | Gao, et al., 2019             | X               | X                  | X             |
| 35 | Gao, et al., 2019             | X               | X                  | X             |
| 36 | Gao, et al., 2019             | X               | X                  | X             |
| 37 | Gao, et al., 2019             | X               | X                  | X             |
| 38 | Gao, et al., 2019             | X               | X                  | X             |
| 39 | Gao, et al., 2019             | X               | X                  | X             |
| 40 | Gao, et al., 2019             | X               | X                  | X             |
| 41 | Gao, et al., 2019             | X               | X                  | X             |
| 42 | Gao, et al., 2019             | X               | X                  | X             |
| 43 | Gao, et al., 2019             | X               | X                  | X             |
| 44 | Gao, et al., 2019             | X               | X                  | X             |
| 45 | Gao, et al., 2019             | X               | X                  | X             |
| 46 | Gao, et al., 2019             | X               | X                  | X             |
| 47 | Gao, et al., 2019             | X               | X                  | X             |
| 48 | Gao, et al., 2019             | X               | X                  | X             |
| 49 | Gao, et al., 2019             | X               | X                  | X             |
| 50 | Gao, et al., 2019             | X               | X                  | X             |
| 51 | Gao, et al., 2019             | X               | X                  | X             |
| 52 | Gao, et al., 2019             | X               | X                  | X             |
| 53 | Gao, et al., 2019             | X               | X                  | X             |
| 54 | Gao, et al., 2019             | X               | X                  | X             |
| 55 | Gao, et al., 2019             | X               | X                  | X             |
| 56 | Gao, et al., 2019             | X               | X                  | X             |
| 57 | Gao, et al., 2019             | X               | X                  | X             |
| 58 | Gao, et al., 2019             | X               | X                  | X             |
| 59 | Gao, et al., 2019             | X               | X                  | X             |
| 60 | Gao, et al., 2019             | X               | X                  | X             |
| 61 | Gao, et al., 2019             | X               | X                  | X             |
| 62 | Gao, et al., 2019             | X               | X                  | X             |
| 63 | Gao, et al., 2019             | X               | X                  | X             |
| 64 | Gao, et al., 2019             | X               | X                  | X             |
| 65 | Gao, et al., 2019             | X               | X                  | X             |
| 66 | Gao, et al., 2019             | X               | X                  | X             |
| 67 | Gao, et al., 2019             | X               | X                  | X             |
| 68 | Gao, et al., 2019             | X               | X                  | X             |
| 69 | Gao, et al., 2019             | X               | X                  | X             |
| 70 | Gao, et al., 2019             | X               | X                  | X             |
| 71 | Gao, et al., 2019             | X               | X                  | X             |
| 72 | Gao, et al., 2019             | X               | X                  | X             |
| 73 | Gao, et al., 2019             | X               | X                  | X             |
| 74 | Gao, et al., 2019             | X               | X                  | X             |
| 75 | Gao, et al., 2019             | X               | X                  | X             |
| 76 | Gao, et al., 2019             | X               | X                  | X             |
| 77 | Gao, et al., 2019             | X               | X                  | X             |
| 78 | Gao, et al., 2019             | X               | X                  | X             |
| 79 | Gao, et al., 2019             | X               | X                  | X             |
| 80 | Gao, et al., 2019             | X               | X                  | X             |
| 81 | Gao, et al., 2019             | X               | X                  | X             |
| 82 | Gao, et al., 2019             | X               | X                  | X             |
| 83 | Gao, et al., 2019             | X               | X                  | X             |
| 84 | Gao, et al., 2019             | X               | X                  | X             |
| 85 | Gao, et al., 2019             | X               | X                  | X             |
| 86 | Gao, et al., 2019             | X               | X                  | X             |
| 87 | Gao, et al., 2019             | X               | X                  | X             |
| 88 | Gao, et al., 2019             | X               | X                  | X             |
| 89 | Gao, et al., 2019             | X               | X                  | X             |
| 90 | Gao, et al., 2019             | X               | X                  | X             |
| 91 | Gao, et al., 2019             | X               | X                  | X             |
| 92 | Gao, et al., 2019             | X               | X                  | X             |
| 93 | Gao, et al., 2019             | X               | X                  | X             |
| 94 | Gao, et al., 2019             | X               | X                  | X             |
| 95 | Gao, et al., 2019             | X               | X                  | X             |
| 96 | Gao, et al., 2019             | X               | X                  | X             |
| 97 | Gao, et al., 2019             | X               | X                  | X             |
| 98 | Gao, et al., 2019             | X               | X                  | X             |
| 99 | Gao, et al., 2019             | X               | X                  | X             |
| 100| Gao, et al., 2019             | X               | X                  | X             |

Total: 100
## Appendix E. SCM data extraction form

| ID | APA reference (author,year) | Analytics type | Decision type | Decision hierarchy |
|----|-----------------------------|----------------|--------------|--------------------|
|    |                             | (A) Dependent | (B) Explanatory | (C) Predictive | (D) Dependent | (E) Independent | (F) Superseding | (G) Subsidiary | (H) Hierarchy |
| 1  |                             | X             | X            | X                | X             | X               | X               |              |               |
| 2  |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 3  |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 4  |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 5  |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 6  |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 7  |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 8  |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 9  |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 10 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 11 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 12 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 13 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 14 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 15 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 16 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 17 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 18 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 19 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 20 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 21 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 22 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 23 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 24 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 25 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 26 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 27 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 28 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 29 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 30 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 31 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 32 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 33 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 34 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 35 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 36 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 37 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 38 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 39 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 40 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 41 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 42 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 43 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 44 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 45 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 46 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 47 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 48 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 49 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 50 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 51 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 52 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 53 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 54 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 55 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 56 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 57 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 58 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 59 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 60 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 61 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 62 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 63 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 64 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 65 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 66 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 67 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 68 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 69 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 70 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 71 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 72 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 73 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 74 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 75 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 76 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 77 |                             | X             | X            | X                | X             | X               | X               | X             |               |
| 78 |                             | X             | X            | X                | X             | X               | X               | X             |               |

**Total:** 23
### Appendix F. Application data extraction form

| Data extraction form - Application | Supply chain activity | Technology readiness level | KPAs |
|-----------------------------------|-----------------------|---------------------------|------|
| M. Koot et al.                    |                       |                           |      |

#### Data Reference (authors, year)

| ID | APA Reference |
|----|---------------|
| 1  | Andersen, 1997 |
| 2  | 2008          |
| 3  | 2018          |
| 4  | 2019          |
| 5  | 2020          |
| 6  | 2021          |
| 7  | 2022          |
| 8  | 2023          |
| 9  | 2024          |
| 10 | 2025         |
applications. *International Journal of Production Economics*, 176, 98–110. https://doi.org/10.1016/j.ijpe.2016.03.014

Wang, M., Birken, R., & Shamsabadi, S. S. (2014). Framework and implementation of a continuous network-wide health monitoring system for roadways. Proc. SPIE 9063, Nondestructive characterization for composite materials, aerospace engineering, civil infrastructure, and homeland security 2014. 90630H, pp. 1-12. San Diego: SPIE. Doi:10.1117/12.2047681.

Wang, W. Q., Zhang, X., Zhang, J., & Lim, H. B. (2012). Smart traffic cloud: An infrastructure for traffic applications. IEEE 18th international conference on parallel and distributed systems, Singapore, 2012 (pp. 822-827). New York: IEEE. Doi: 10.1109/ICPADS.2012.134.

White, R. M. (1987). A sensor classification scheme. *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*, 34(2). https://doi.org/10.1109/TUFFC.1987.26922

Whittle, A., Allen, M., Preis, A., & Iqbal, M. (2012). Sensor networks for monitoring and control of water distribution systems. 6th International conference on structural health monitoring of intelligent infrastructure (SHMII), Hong Kong, 2013, 14, p. 96. Winnipeg: International Society for Structural Health Monitoring of Intelligent Infrastructure. Retrieved from.

Won, M., Zhang, Y., Jin, X., & Eun, Y. (2018). WiParkFind: Finding empty parking slots using WiFi. IEEE International Conference on Communications (ICC), Kansas City, 2018 (pp. 1-6). New York: IEEE. Doi:10.1109/ICC.2018.8422973.

Wortmann, F., & Flüchter, K. (2015). Internet of Things: Technology and value added. *Business and Information System Engineering*, 57(3), 221–224. https://doi.org/10.1007/s12599-015-0383-3

Xu, L. D., He, W., & Li, S. (2014). Internet of things in industries: A survey. *IEEE Transactions on Industrial Informatics*, 10(4), 2233–2243. https://doi.org/10.1109/TII.2014.2300753

Yang, L., Yang, S. H., Magiera, E., Froelich, W., Jach, T., & Laspidou, C. (2017). Domestic water consumption monitoring and behaviour intervention by employing the internet of things technologies. 8th international conference on advances in information technology (IAIT), Macau, 2016. 111, pp. 367-375. Amsterdam: Elsevier B.V. doi:10.1016/j.procs.2017.06.036.

Zhong, R. Y., Newman, S. T., Huang, G. Q., & Lan, S. (2016). Big Data for supply chain management in the service and manufacturing sectors: Challenges, opportunities, and future perspectives. *Computers and Industrial Engineering*, 101, 572–591. https://doi.org/10.1016/j.cie.2016.07.013