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Environmental Supply Chain Risk Management for Industry 4.0: A Data Mining Framework and Research Agenda

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Abstract: AbstractSmart technologies have dramatically improved environmental risk perception and altered the way organizations share knowledge and communicate. As a result of the increasing amount of data, there is a need for using business intelligence and data mining (DM) approaches to supply chain risk management. This paper proposes a novel environmental supply chain risk management (ESCRM) framework for Industry 4.0, supported by data mining (DM), to identify, assess, and mitigate environmental risks. Through a systematic literature review, this paper conceptualizes Industry 4.0 ESCRM using a DM framework by providing taxonomies for environmental risks, levels, consequences, and strategies to address them. This study proposes a comprehensive guide to systematically identify, gather, monitor, and assess environmental risk data from various sources. The DM framework helps identify environmental risk indicators, develop risk data warehouses, and elaborate a specific module for assessing environmental risks, all of which can generate useful insights for academics and practitioners.

Keywords: environmental risk management; sustainability; data mining; framework; mitigation strategies

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1. Introduction

Risk is an important issue threatening the sustainability and competitiveness of supply chains [1,2]. The frequency, severity, and variety of supply chain (SC) risks are accelerating as a result of increasing globalization of supply chains, mounting customer expectations, and shorter product life cycles [3,4]. In addition to these traditional risks, recent studies are increasingly focusing on environmental risks [5–8].

In general, environmental risks relate to threats of adverse effects on the environment resulting from waste, negative emissions, effluents, and resource depletion due to supply chain operations [9]. Abundant literature has been dedicated to the topic of environmental supply chain risk management (ESCRM) [10–13].

On a parallel track, the Industry 4.0 concept has emerged to characterize the spread of information and communication technologies and the adoption of several technologies such as the Internet of Things (IoT), cloud computing (CC), and big data analytics (BDA). Cyber physical systems (CPSs), on which the adoption of Industry 4.0 technologies depends, generate an increasing volume of data [14–17]. This extensive volume of data has prompted firms to implement business intelligence (BI) and data mining (DM) techniques to enhance real-time decision making [18,19]. DM has proven its efficiency in tackling supply chain risk factors in general [20–22] and in particular environmental risks [19]. However, despite the growing research interest in Industry 4.0 and ESCRM, a specific framework to address environmental risks within the context of Industry 4.0 is lacking. A holistic framework with the ability to integrate DM and ESCRM is necessary to more effectively and efficiently process big data generated by Industry 4.0 technologies. This paper, therefore, contributes to this line of research by developing a novel ESCRM framework for Industry 4.0 supported by DM to identify, assess and mitigate risks. Based on previous premises, this paper seeks to provide answers to the following research questions:

RQ1: What are the potential environmental risks in the context of Industry 4.0?

RQ2: How can environmental supply chain risks be mitigated through a DM approach?

To address these research questions, this paper provides first a systematic review of more than 140 peer-review papers on ESCRM in the Industry 4.0 context. Second, through a descriptive and thematic analysis of the selected papers, a DM framework that addresses environmental risks, their impact, and mitigation strategies in the context of Industry 4.0 is presented. The DM framework helps to identify environmental risks indicators, develop risk data warehouses, and elaborate a specific module for assessing environmental risks, all of which can generate useful insights for academics and practitioners.

As a theoretical contribution, the proposed framework is developed following a literature review of the relevant areas of Industry 4.0 and ESCRM. In doing so, we contribute to the recent line of research connecting sustainability with Industry 4.0 [16,17]. In addition, this study reinforces the relevance of adopting a DM approach for ESCRM in the context of Industry 4.0 [18,19]. The proposed DM framework provides a holistic view through the identification of risk threats, sources, and metrics and the potential gains stemming from a DM approach of ESCRM. Such framework can be considered as a foundation for further research on the implementation of DM algorithms in the context of Industry 4.0.

As practical implications, the present research can shed light on how decision makers might develop ESCRM practices in the context of Industry 4.0. The proposed DM framework might serve as a benchmarking tool that practitioners can employ to identify relevant environmental risks for their supply chains, as well as the related consequences and strategies used to manage and minimize such risks.

The paper is structured as follows. Section 2 describes the concepts of ESCRM and Industry 4.0. Section 3 presents the research methodology of the systematic literature review. Section 4 presents the main findings related to descriptive and thematic analysis of the literature. In Section 5 we discuss the relevance of DM as an appropriate conceptual framework resulting from adopting a holistic approach to managing environmental risks in Industry 4.0. The final section concludes with a synthesis of the theoretical framework's implications and proposes future avenues of research.

2. Theoretical Framework of Industry 4.0 and Environmental Supply Chain Risk Management

This section is dedicated to the presentation of the concepts mobilized in this study, namely the concept of Industry 4.0 and the peculiarities of environmental supply chain risk management

2.1. Industry 4.0 Conceptualization

Industry 4.0 is a set of technologies that allows digital and physical processes to interact with each other beyond geographical and organizational borders [23]. Although there are several pieces of research on the topic, a consensual definition of Industry 4.0 seems to be lacking. Industry 4.0 can be defined as a set of technological applications that allows machines and products to interact with each other without human control [17,24]. The concept of Industry 4.0 has emerged and evolved following the development of digitization, automation, manufacturing systems, and information and communication technologies [25]. The integration of these technologies has given birth to cyber physical systems that allow computers to run and monitor physical processes [23,24].

Despite the endeavors of researchers to conceptualize Industry 4.0, views on its main components seem to diverge widely. In light of previous conceptual studies and reviews of the literature [23,26,27] the conceptualization of Industry 4.0 has centered around three major concepts:

(1) The Smart Manufacturing (SM) concept which is presented as an adaptable manufacturing system where flexible lines automatically adjust production processes for various types of products in various industrial settings [28–30]. Smart manufacturing in a smart factory improves quality, productivity, and flexibility, which results in mass customization and efficient resource consumption [23,28];
(2) The Smart Supply Chain (SSC) concept that relates to integrating supply chain processes and partners through the exchange of information and coordination to mitigate undesirable bullwhip effects [16]. SSC aims to render resource use for supply chain members to be more efficient by sharing resources and coordinating activities [31,32];
(3) The Smart Products (SP) concept that provides data feedback for new product development [23] as well as new services and solutions to customers through embedded technologies [33]. Smart products allow new business models such as product-service systems, which create new opportunities for manufacturers and service providers [29,34].

For some scholars, all digital technologies can be included among Industry 4.0 tools, whereas other researchers focus on flexibility and customization resulting from technological applications in manufacturing processes [16,17]. In this research, we adopt an integrative approach by basing our conceptualization on two main categories of technologies:

(1) '*Smart technologies*' aiming to achieve radical transformation of the manufacturing activities based on emerging technologies (Smart Manufacturing) and the way products are designed and marketed (Smart Products) [23]. Those technologies relate to the way raw materials and products are delivered (Smart Supply Chain) [29,35] and the new ways workers perform their activities based on the support of emerging technologies (Smart Working) [36,37]. The combination of these smart technologies creates an integrated network or supply chain that processes various types of flows to address operational and market needs [17,23];
(2) '*Base technologies*' which include technologies providing connectivity and real-time data for front-end technologies, thus enabling the complete integration of the manufacturing system [38–40]. These technologies constitute the foundations of Industry 4.0 dimensions by making interconnectivity possible between manufacturing systems and other processes [40]. The deployment of such technologies is what constitutes the peculiarity of Industry 4.0, differentiating the latter from previous industrial revolutions [38].

Concerning base technologies, abundant literature underlines the role of several tools such as:

(i). IoT resulting from wireless communication between sensors and computing through the internet [41]. Technological advancement made the implementation of IoT possible. Thus, the decreasing cost of sensors along with the expansion of internet networks have allowed the use of this technology to spread among companies [30,42];
(ii). Likewise, cloud technology has benefited from enhancing internet services and computing to provide remote access to stored data in servers [29,39]. In addition, this technology enables the integration of various devices to share data and coordinate activities [39,43];
(iii). Both cloud and IoT technologies can be combined with different types of equipment to share data, which results in a huge amount of data called Big Data [29,44,45]. The big data collected from equipment, objects, and systems necessitates processing tools/analytics such as data mining and machine learning [33,46]. It is expected that the combination of big data with analytics can make industrial plants and warehouses self-managed and able to optimize their capacity by identifying glitches in the system before their occurrence [30,40,47];

(iv). Additive manufacturing and 3D printing constitute a different approach to manufacturing by generating successive layers of materials through a digital model that contributes to the creation of the final product [48], thus avoiding the need for parts and component assembly. Additive manufacturing and 3D printing techniques can help companies to produce small batches of customized products with complex, lightweight designs [49] which will reduce transport costs and stock on hand [50];

(v). Robotic systems in a smart factory can take charge of various tasks without needing reprogramming [40,51]. Robotic systems can reduce costs, provide a wide range of capabilities (surpassing traditional assembly lines or existing automated guided vehicle) and perform several operations in smart factories [52,53] including tasks too dangerous for human operators;

(vi). Simulations and prototyping can allow organizations to study CPS dynamic behavior through real-time data on machine operations, manufacturing cost, connectivity, and movements [54,55]. In that way, firms can test machine settings to increase quality, reduce setup times, and mitigate risks such as cyber threats [43]. Moreover, simulation and prototyping techniques are used for real-time tracking of manufacturing cost [56], and advanced optimization for planning and scheduling [47].

Literature on Industry 4.0 has highlighted the existence of several risks that threaten business continuity and operations in supply chains [24,28]. In particular, environmental risk management has become relevant for Industry 4.0 implementation as highlighted by several studies [16,17,24,28].

2.2. Environmental Supply Chain Risk Management

A review of studies investigating ESCRM was conducted using the Scopus database. This enabled us to delineate the main environmental supply chain risks and the strategies to mitigate them. Accordingly, two main categories of environmental risks exist:

(i) Endogenous risks which result from company supply chain operations including pollution and harmful emissions, as well as accidents caused by the firm's staff, operations, and machines [57]. Endogenous risks include inefficient resource consumption, waste, and scrap generation [58]. Further, other scholars consider non-compliance with regulations related to personnel safety, ecology, and social responsibility as an endogenous risk [6];

(ii) Exogenous risks which emerge from the interaction of firms with their external environment [6,59]. Thus, exogenous environmental risks relate to natural disasters (e.g., earthquakes, hurricanes, and pandemics) and man-made disasters such as terrorist attacks, wars, and military conflicts [60,61]. Numerous scholars [6,10], have prioritized endogenous risks over exogenous risks since the latter are mostly unpredictable and hard to control. In contrast, endogenous risks result from the actions of firms and their supply chain partners, hence the possibility to assign responsibility of mitigating these risks [62].

Overall, environmental supply chain risks are linked to firms' activities, processes, and relationships. Thus, endogenous environmental risks affect the external environment while the latter also yields exogenous environmental risks that affect supply chain activities. Drawing on prior studies [6,10,59] we synthesized the ESCRM categories as in Figure 1.

Uncontrolled, exogenous, and endogenous risks can have severe impacts on firms, including:

– Reputational damage that affects the company's reputational capital [63,64];
– Financial consequences in the form of decreased gains, augmented costs, and liquidity shortage due to penalties [5,65,66];
– Legal actions of governmental and institutional actors in the case of firm's non-compliance with laws and regulations [66,67].

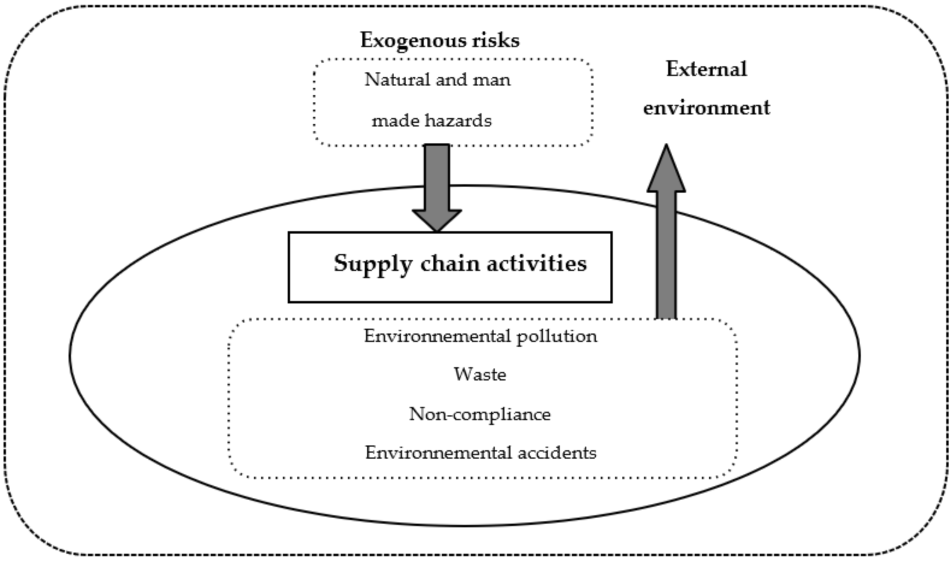

Figure 1. Environmental supply chain risk management categories.

For these reasons, firms have to develop mitigative measures to avoid these undesirable consequences. Such measures can include:

- Elaborating environmental management programs to address issues related to waste, resources management, recycling, and reuse of materials [68]. Green practices entail managing pollution, emissions, and hazardous substance storage, handling and disposal [10]. Environmental management systems can be developed to ensure the monitoring, tracking, and treatment of greenhouse gas (GHG) emissions [69];
- Developing cooperative initiatives with suppliers and customers. Focal firms can help their suppliers adopt environmental practices through ISO 14000 certification, environmental audits of suppliers' environmental management system, and providing assistance to suppliers implementing environmental practices [69]. Likewise, firms can be aided by their customers to develop environmental management based on their clients' requirements;
- Ensuring compliance with legislation related to environmental, safety, and health issues;
- Developing contingency plans in cases of disruption, emergency, and unexpected events related to exogenous risks.

On a parallel track, managing environmental risks can draw from the SCRM literature that emphasizes the identification, assessment, treatment, and monitoring of SC risks, through the internal implementation of risk tools, techniques, and strategies and the external coordination and collaboration with SC partners [4,70,71].

Both of Industry 4.0 and ESCR can be linked through the adoption of Industry 4.0 technologies that offer several possibilities to mitigate ESCR. Consequently, it is relevant to assess how environmental risks have been addressed in current research on Industry 4.0. In the following section we present our review of extant literature on the topic.

3. Research Methodology

Our review adopted a mixed methodology combining a systematic literature review (SLR) approach to select the most relevant articles to be included in the review, and content analysis to assess ESCRM in Industry 4.0 literature. The SLR is an evidence-based method to identify, select, and analyze research papers [72,73]. SLR is based on the principles of transparency and inclusivity to enhance the objective overview of the search results [74].

SLR offers a systematic and transparent way to analyze and incorporate ideas from extant studies in a way that enables replication and overcomes the limitations of single studies in terms of generalization [74]. Consistent with the suggestions made by several scholars [74,75], we conducted the literature review in two steps: Paper selection phase related to selection and retrieval of relevant papers and Data analysis phase that comprises descriptive and content analysis of the considered papers as shown in Figure 2.

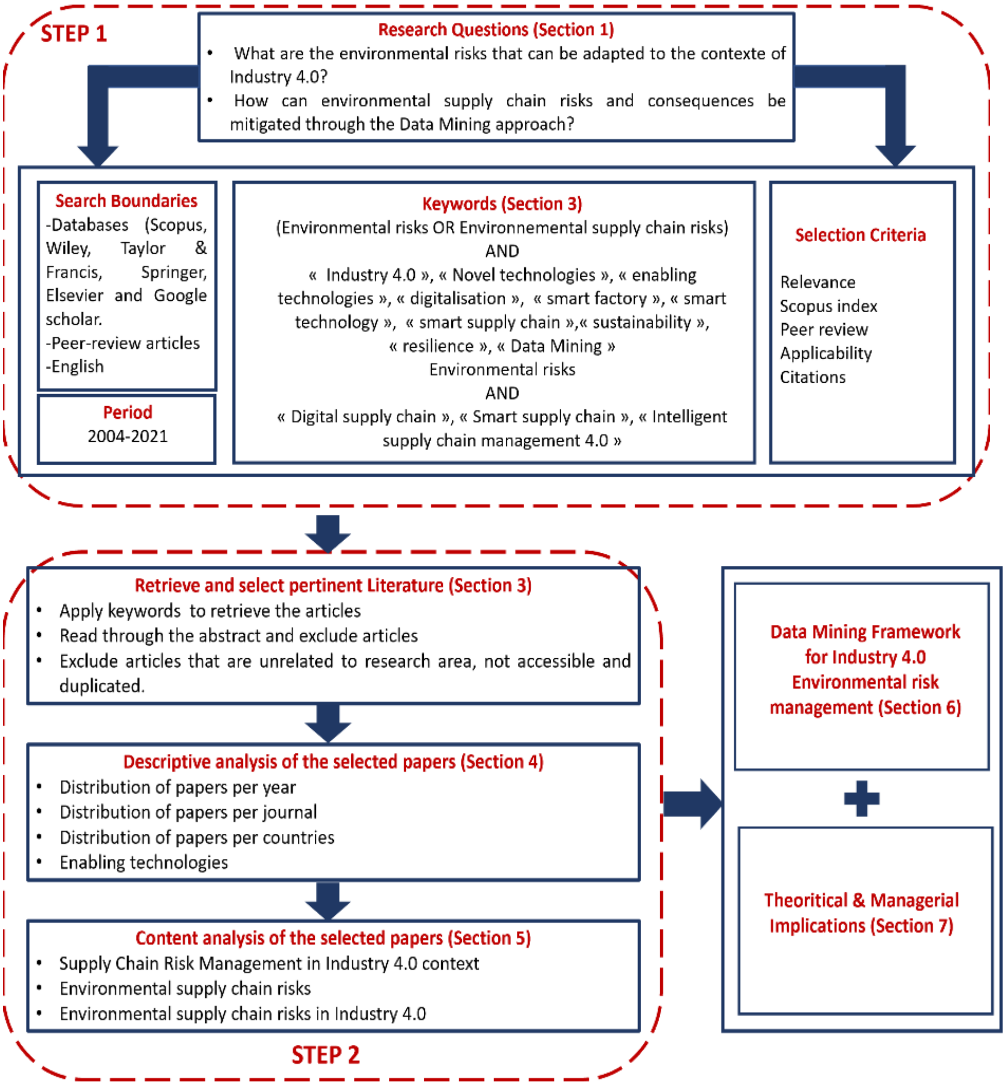

Figure 2. Research methodology process.

3.1. The Selection and Retrieval Phase

The research questions provide the foundation of the SLR. To avoid bias in data gathering, we adopted the following criteria in assessing and selecting publications.

(1) A search was conducted in several databases (SCOPUS, EMERALD, Taylor & Francis, Springer, Elsevier, and Google Scholar) in order to generate a comprehensive set of papers [76];
(2) The review was limited to peer-reviewed publications to guarantee quality [77]. Articles published in peer-reviewed journals are subject to a rigorous process of evaluation prior to publication [76]. Consequently, chapters in books, conference proceedings, and trade journals were excluded from the search;
(3) Conceptual and empirical research was considered in gathering as many publications as possible. The articles identified are from 2004 to 2021;
(4) Only publications in English were considered, to facilitate data analysis;
(5) Subject terms related to ESCRM and Industry 4.0 were used in screening the papers' titles, abstracts, and keywords to assess their relevance.

A total of 16 keywords were defined by the authors using a brainstorming method of commonly used keywords to define the Industry 4.0 conceptualization in managing environmental supply chain risks. The keywords were combined using basic operators and Boolean logic (AND/OR) to form a sequence of strings that could be used in database searches. The initial search yielded a total of 420 papers. The search results were saved in CSV format, which included for each paper, the title, the authors' names and affiliations, the abstract, and keywords. There were 340 papers left after the duplicates were removed. Next, we read the abstracts to see if they were relevant to the research questions, which resulted in a total of 148 articles being considered for this literature review.

3.2. Descriptive and Content Analysis of the Selected Papers

In the descriptive analysis, we present the chronological evolution of the selected papers by year, the main contributing journals, and the countries of affiliated authors. Content analysis is adopted to provide classification of the main research areas. In this review, thematic analysis followed the procedure of several scholars [78,79] regarding classification of the selected papers.

Thus, the papers were coded independently based on the abstract and the core content of the articles. A short summary of each paper was produced to help assess and interpret the data [75]. Subsequently, samples of the coded papers were swapped and discussed by members of the research team to reach agreement about their categorization [79]. As a result, the authors were able to characterize the focus of current research into the following two main areas: papers dealing with supply chain risk management (SCRM) in Industry 4.0 and papers with an ESCRM focus in Industry 4.0 context.

4. The Main Findings of the Literature Review

We present in the following section the descriptive results of the SLR and the categorization of thematic areas of the research on Industry 4.0 and ESCRM.

4.1. Chronological Evolution of Papers

Figure 3 depicts the chronological evolution of the papers. More than 78% of the publications were published between 2013 and 2020. From 2015, there was a significant increase due to the growing awareness among practitioners and researchers of ESCRM in Industry 4.0. This demonstrates that the adoption of Industry 4.0 technologies in environmental supply chain risk management is witnessing a substantial increase in terms of publication numbers.

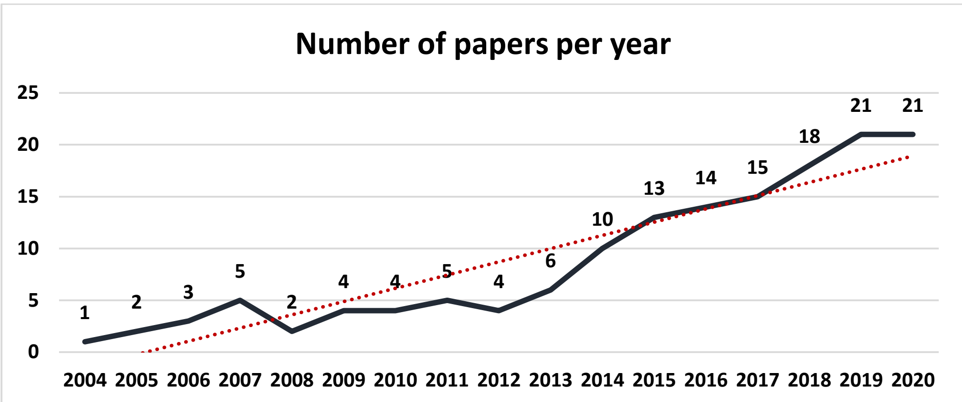

Figure 3. Distribution of the 148 selected papers per year.

4.2. Most Contributing Journals

The 148 papers selected in this review were published in more than 40 journals. Figure 4 shows the top 11 journals that published more than two papers. The journals that publish papers on ESCRM and Industry 4.0 can be categorized into: (i) journals related to

SCM/OM such as the International Journal of Production Economics (IJPE), the International Journal of Production Research (IJPR), and the International Journal of Operations & Production Management (IJOPM); (ii) journals on computers and engineering such as Computers in Industry (CI) and Computers & Industrial Engineering (CIE); and (iii) journals on environmental studies and sustainability such as Journal of Cleaner Production (JCP) and Business Strategy and the Environment (BSE).

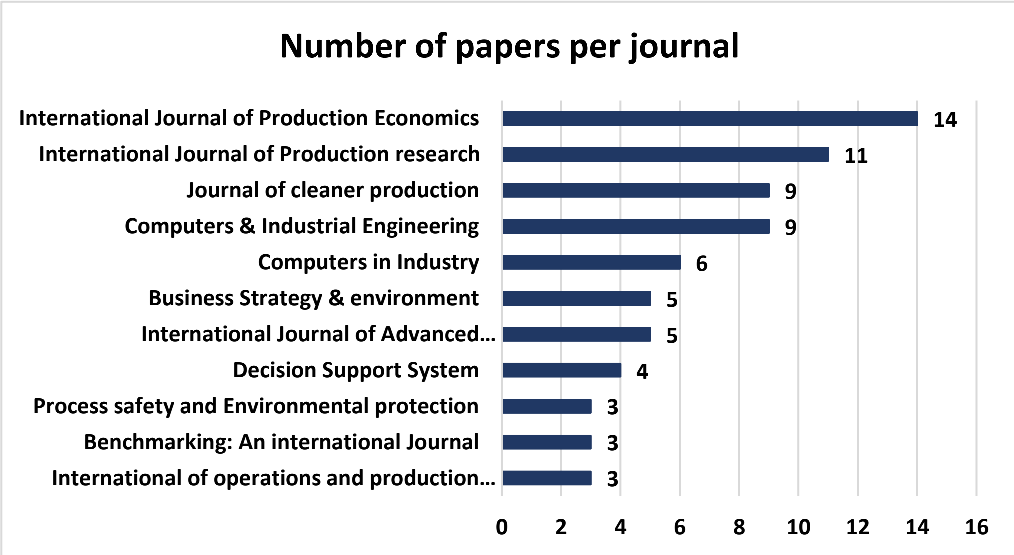

Figure 4. Distribution of the 148 selected papers per journal.

4.3. Distribution of Papers by Country

Data on the publication field study/country was retrieved and synthesized (Figure 5). Most research was conducted in developed countries such as the United States, the United Kingdom, Germany, and Italy. Data reveal also that several studies were conducted in emerging countries such as China, Mexico, and Brazil.

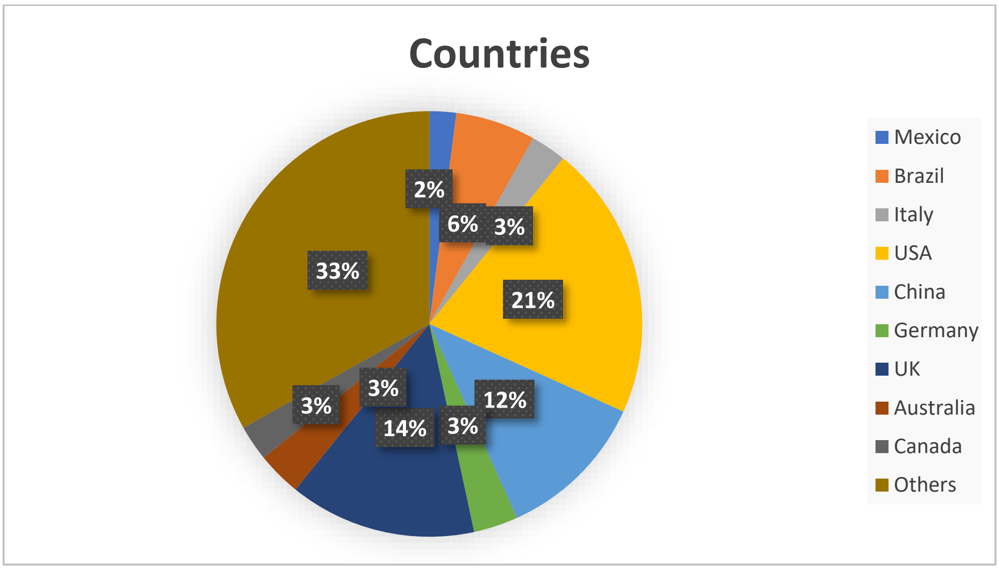

Figure 5. Distribution of the identified papers per country.

4.4. The Most Frequently Investigated Industry 4.0 Technologies

The investigated technologies in the current literature on Industry 4.0 and ESCRM are depicted in Figure 6. Accordingly, BDA is the most widely deployed technology (20 articles), followed by AI (15 articles), Blockchain (15 articles), and IoT (8 articles). The term "many" refers to articles covering many technologies. In this respect, 15 articles covered a wide range of technologies, implying that numerous emerging technologies can be deployed simultaneously to deal with environmental supply chain risks. "None" on the other hand, refers to articles that do not mention any technology which contains 18 articles.

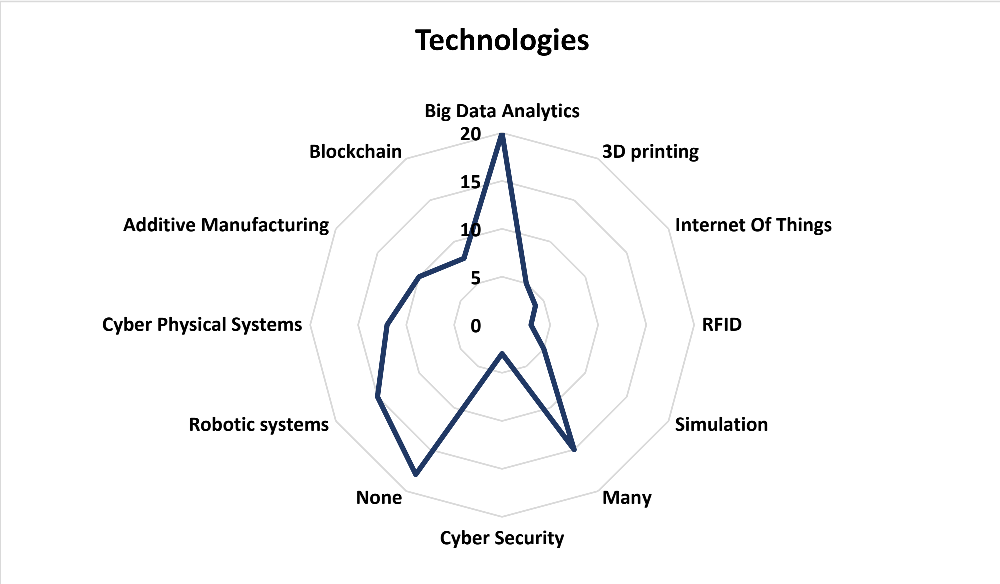

Figure 6. Enabling Technologies used in the 148 studied papers.

4.5. Content Analysis and Main Topical Areas

As a result of the content analysis process, we were able to categorize extant literature into two main clusters:

- Research highlighting supply chain risk management (SCRM) in Industry 4.0 context;
- Studies with an environmental supply chain risk management focus in Industry 4.0.

4.5.1. Supply Chain Risk Management in Industry 4.0 Context

SCRM 4.0, i.e., managing risks in the context of Industry 4.0 is different from conventional SCRM [24]. With smart technologies, SCs become more connected and transparent with CPS, IoT, and cloud computing which enable firms to better face risks [80].

With the occurrence of supply chain disruptions, firms are increasingly facing different types of economic, supply, demand, technological, political, social, and technological risks [16–24]. The dynamic evolution of Industry 4.0 technologies has prompted firms to deploy smart technologies in dealing with SC risks in order to improve their competitiveness and protect the environment [15,81]. In addition, with the digital revolution of the Industry 4.0 era, firms are also exposed to risks related to deployment of IT in manufacturing and service industries [15,16]. For this purpose, several researchers have proposed approaches to address the key benefits, implications, and challenges in adopting Industry 4.0 when managing supply chain risks [82,83].

In the context of Industry 4.0, several scholars [2,84] define (SCRM) as an emerging cross-functional and critical approach between SCM, strategic corporate management, and enterprise risk management to achieve the aforementioned benefits. In this optic, SC risks should be assessed from the following three perspectives: risk identification, assessment, and mitigation [7]. Several studies focus on the importance of risk assessment as a systemic method that assists organizations in enhancing preparedness and developing appropriate measures to mitigate disruptions effects [83,85,86]. In particular, the implementation of CPS in risk control can improve supply chain robustness with data from digitalized supply chain processes [87]. In a digital supply chain context, risk control can be performed by addressing third-party cybersecurity threats and delivering fast operational responses to unplanned incidents [17,24]. Recent studies have emphasized the negative ripple effects resulting from SC risks [24,88–90].

4.5.2. Environmental Supply Chain Risk Management in Industry 4.0

Due to the rising diversity and scale of supply chains, environmental issues have started to constitute essential challenges to be addressed by Industry 4.0 [9,91]. Several scholars [7,92] considered environmental risks as the most critical risks in supply chains. Hence, several frameworks were suggested to define a range of problems and consequences for applying Industry 4.0 for environmental risk management [83,93–97].

Under the umbrella of sustainability, numerous scholars categorized environmental risks into endogenous and exogenous risks [36,95,98,99]. In the modern age of Industry 4.0, Li et al. [100] used information management theory to investigate how emerging technology influences environmental efficiency. Yiannakoulias et al. [8] used a serious game approach to better understand environmental risk management decisions. Oliveira et al. [99] found that using simulation-based optimization (S&O) models to handle SC risk can help with the decision-making process. By taking into account the unpredictable environment, Shojaei and Haeri [101] suggested a systematic supply chain risk management method for construction projects based on fuzzy cognitive map (FCM) and grounded theory (GT). MCDM methods were also considered by several authors to deal with environmental supply chain risk management [80,92].

4.5.3. Identified Gaps and the Necessity of a Holistic Approach to Supply Chain Risk Management in Industry 4.0

Despite the contributions of extant literature, Fagundes et al. [102] advocated for more studies and business models that focus on environmental issues in the context of Industry 4.0. To define, analyze, and minimize the threat of environmental risks in the context of Industry 4.0, an approach that makes intelligent, reliable, and timely decisions is required. This necessitates dealing with a large number of dispersed data/information sources [16,24]. Several frameworks depict how Industry 4.0 technologies can be deployed, but there is a need to provide an integrative and holistic view of how such technologies interact with environmental risks. In numerous studies, Industry 4.0 technologies that enable customized assembly systems with flexible manufacturing process design [26,103,104] are often represented as a smart networking chain [23]. Hence, Industry 4.0 can be considered as a collaborative cyber physical system that has the attributes of a supply chain in which information and material subsystems are integrated and decisions in them are cohesive [16,105]. Smart factories are akin to a supply chain with a dynamic evolving structure [16]. Therefore, adopting an ESCRM perspective of Industry 4.0 becomes relevant to delineate environmental risks, consequences, and mitigation strategies. Along the same lines, Industry 4.0 would be subjected to endogenous and exogenous environmental risks that need to be addressed through a holistic approach. Consequently, the DM approach seems to be an appropriate approach to ESCRM in the context of Industry 4.0.

5. Environmental Risk Management of Industry 4.0: A Data Mining Framework

We present the relevance of DM for managing ESCRM in the context of Industry 4.0 and the different steps towards adopting a DM approach in order to mitigate and control environmental risks.

5.1. Data Mining Relevance for Managing Supply Chain Risks in Industry 4.0 Context

Many scholars have cited DM as a key strategy for creating a business intelligence ecosystem capable of discovering hidden facts and trends from large amounts of data while mitigating supply chain risks [19,21,86,106,107]. DM is a powerful tool in identifying SC risk factors, their sources, consequences, and interconnections [107]. DM methods can also be used at different levels of the SCRM process to create reactive and proactive processes [19,21,22,108].

Risk identification is an intricate and costly process due to the high uncertainty of event occurrence and the difficulty in collecting and analyzing data. Hence, risk management for organizations is essentially a data and information/knowledge issue [70,109]. Numerous organizations have started to use automated risk management frameworks to compete in today's knowledge-driven business environment [110,111].

DM techniques constitute a powerful tool to extract useful metrics from data on risks and ESCRM. DM tools can provide an efficient approach to detect, identify, and assess risk sources which can be further analyzed by categories to predict, mitigate, and react to real time events [108,112,113]. Such features make DM a relevant approach to deal with ESCRM in the Industry 4.0 context.

The recent developments in information and communication technologies (ICT) offer wide possibilities of data gathering, storage, and assessment of different types of risks from various sources [114,115]. The combination of such tools helps create "Risk Intelligence (RI)" [116]. RI is the ability of an organization to detect, measure, process and predict various threats based on prior experience [117]. In this respect, DM is an essential tool of RI development [107,118,119]. By deploying various types of algorithms, DM is able to process huge data sets and identify hidden patterns which shed new light on the investigated phenomenon [120–122]. Hence, DM is frequently deployed in order scheduling and demand forecasting as well as risk management of volatile markets and early detection of threats [108,123,124].

For ESCRM, DM can help detect endogenous and exogenous risks using data about the SC network and physical, financial, and information flows exchanged with SC partners [114,125]. Specifically, DM can be deployed to collect data about the firm's position and role in the SC, the risk level of the firm's activities, the volatility of the sector/market, and the different measures taken internally and externally to manage risks [126].

All of the aspects related to SCRM can be stored in risk data warehouses (RDW), i.e., a central repository that collects SC risk data from different sources (internal and external) to improve the efficiency of the decision support systems [106,127]. RDW would help develop efficient analytical processing, monitoring, and reporting tools [106,127]. Building an RDW for supply chains can require investments in time and money, hence small firms can develop data marts instead which are subject-oriented simple data repositories for a particular process/business [120]. Using RDW, the DM risk module can be developed to create an interactive data analysis platform.

5.2. Data Mining Approach for Managing Industry 4.0 Environmental Risks

The development of a DM-based ESCRM framework for Industry 4.0 necessitates an integration of numerous processes related to risk identification, data gathering, and storage, all of which would help in the conversion of risk management issues into a DM problem.

Data processing by DM algorithms and analysis of the results will define appropriate risk mitigation measures. We suggest adopting a DM based framework that integrates ESCRM and Industry 4.0, based on the DM key components (RDW, DM modules) and risk management practices (Figure 7). The suggested DM approach to ESCRM for Industry 4.0 consists of the following three main steps:

(i) Identifying environmental risks indicators. Using various metrics, measurements and indicators, organizations can identify the risk exposure of their activities [4]. Risk indicators can be obtained from internal data sources such as the organization's internal databases [128]. External sources of risk indicators are governmental and international agency reports, consultants/experts opinions, social media data, and insurance company recommendations [129–131]. Using such data, simulation models might be employed to quantify the externalities of environmental risks and their impact [132–134]. Using Industry 4.0 technologies, such as real time monitoring devices can help collect data about environmental risks [135]. For instance, using sensors, RFID tags, motion sensors, and energy monitoring systems, firms can ensure better control of cold chain products shipments and prevent waste or threats of natural or man-made disruptions. Firms can benefit from such an approach in providing better control of logistics and SC operations [129];

(ii) Developing an environmental risks data warehouse to collect risk data. RDW are built using data extracted from internal and external sources—also called supply chain database—to make data accessible [103]. Initially, a *conceptual risk data model* has to be elaborated to structure the data generated from the various entities/sources and their interaction. *Data processing* is needed to develop the appropriate format for a data warehouse [136]. A process of data cleaning, reduction, and integration is necessary [120] through smoothing, normalization, discretization, aggregation, and generalization [128]. As a result, risk metrics and indicators can be obtained by type and activity [69]. After that, risk data can be subjected to an extract transform and load (ETL) process which generates RDW by source, type, attributes, and relationships. Converted data by ETL is transformed into an analytical structure containing the risk metadata [136]. The metadata layer of the DM-based ESCRM model consists of risk indicators, metrics, sources, factors, and location in terms of activity (e.g., manufacturing, shipping) or SC network (supplier, vendor, etc.) and data collection methods [45,137]. RDW is the key to access risk data in the DM framework. Firms can specify what kind of technology can be employed according to the data and available resources. Issues related to the type of database server, software employed, ETL server, storage needs, user interface, and network type have to be discussed and clarified in detail [138]. Once a decision is made regarding such elements, the RDW can be operationalized by connecting its components (internal and external databases);

(iii) Elaborating a DM module for assessing environmental risk management. The DM module seeks to provide useful information for intelligent decision making in ESCRM. Without assessment, risk data are merely worthless information. The DM module creates risk data mart (RDM) from the RDW. RDM—also called risk problem database—is obtained through synthesizing, processing, and assessing data of the RDW according to the requirements of the DM application. Firms can assign several tasks to DM such as prediction, association, clustering, categorization, and aggregation of risk [121,127]. In such a manner, decision makers might use DM for different aims such as identifying risk triggers, predicting the impact of risks, detecting their root causes, prioritizing risks by degree, and modeling future trends [115,124].

DM is an efficient tool to predict probable risk events, identify relationships between risks and their triggering factors, synthesize risk data, and visualize the main risks [113,139]. Visual DMs are particularly helpful in interpreting the findings of risk analysis [115]. DM results can be archived for future use after identifying appropriate measures to tackle the critical risks and their triggering factors based on different scenarios related to costs, feasibility, and benefits [19].

After testing its implementation, the proposed DM framework should be developed with a dynamic approach that seeks to update and refine the results obtained with the help of DM experts and ESCRM decision makers. The findings of the DM framework can be assessed based on their accuracy, robustness, explanatory results, efficiency, agility, and ease of use [19]. In retrospect, the assessment of DM findings can be utilized to improve data analysis and risk management policies.

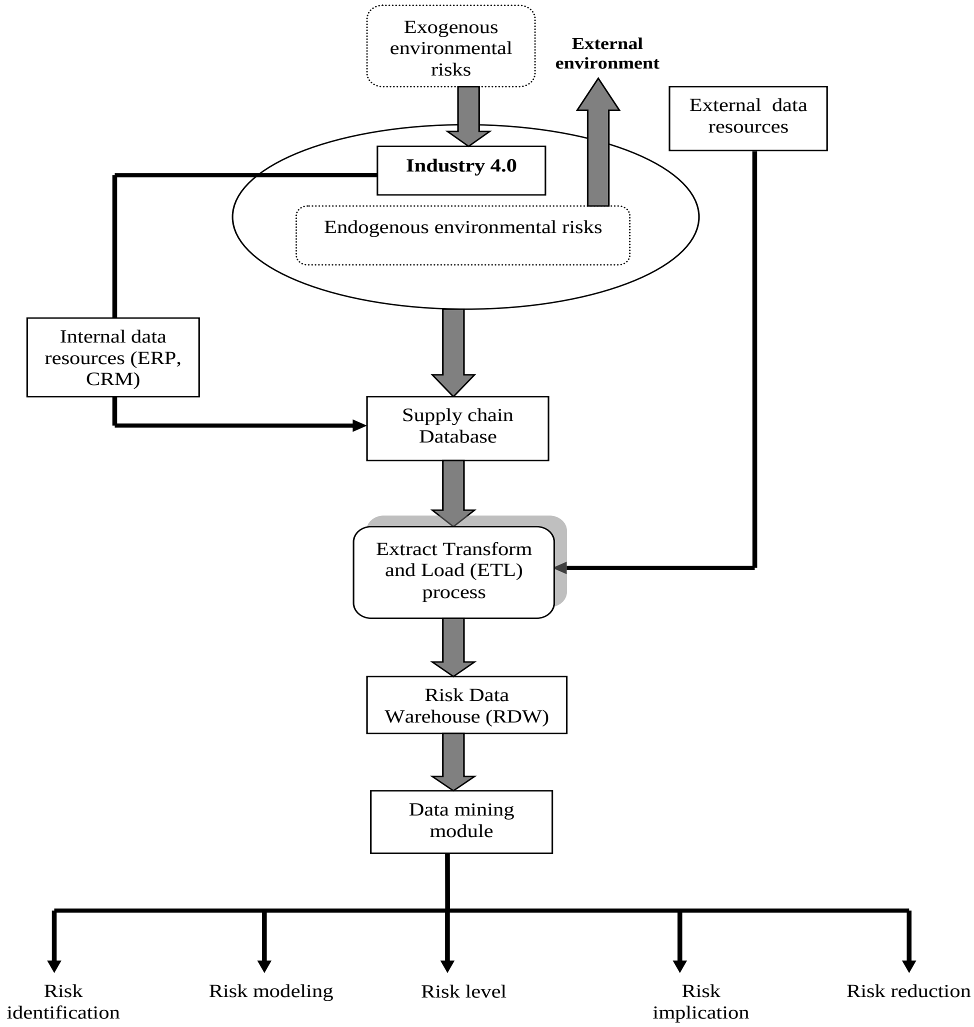

Figure 7. A DM-based framework for Industry 4.0 environmental risk management.

5.3. Further Research Directions

The proposed DM framework implies the adoption of a dynamic approach in order to follow the different evolutions of internal and external environmental risks and to accommodate the technological advances enabled by Industry 4.0. We suggest the following research avenues based on our review and DM framework:

- Further research might attempt empirical and/or experimental testing of our DM framework in specific industrial contexts. Such endeavor might pinpoint possible shortcomings or barriers hindering the adoption of DM. Such a line of research might also clarify the limits of what DM might offer to firms in terms of predictive and modeling capacity;
- Following the recent outbreak of the COVID-19 pandemic, it would be insightful to assess the potential of the DM framework regarding risk identification, risk assessment, and risk control. The disruptive nature of the pandemic can help evaluate the capacity of firms to adapt quickly to the threats of a volatile environment. Therefore, COVID-19 can constitute an adequate setting to assess the potential of the DM approach to help decision making, elaborate reactive measures, and learn from the disruption;
- A potential line of research could be related to studies connecting ESCRM and Industry 4.0 through conceptual or empirical research seeking to provide further assessment of how both concepts interact. Such a line of research would delineate how ESCRM might benefit from adopting Industry 4.0 such as IoT, CC, BDA, and others. In addition,

there is merit in elaborating further on the how Industry 4.0 implementation would require taking into consideration risk management including environmental risks.

6. Conclusions

This study targeted ESCRM and Industry 4.0, which have attracted the interest of scholars and practitioners, and the proposed framework can generate useful insights for both academics and practitioners.

6.1. Theoretical Contributions

This research can contribute to the literature on Industry 4.0 by highlighting environmental risk management aspects that have been seldom investigated in recent studies. Thus, the proposed framework offers a holistic approach to identify and mitigate endogenous and exogenous environmental risks that future studies can use for potential empirical validation or conceptual amelioration. The DM framework covers numerous risk activities and provides guidelines to convert ESCRM into a DM algorithm which can provide the foundation for prospective research in the future.

Moreover, instead of adopting an internal focus on environmental risks, we considered Industry 4.0 as a set of the interconnected cyber physical supply chain, which consolidates the approach of recent studies by several scholars [16,23,24] and points towards future avenues of research. Furthermore, our research answers the calls of several scholars for more studies (conceptual or empirical) on Industry 4.0 environmental risk issues in supply chains (e.g., [6,24,28,140]. A further contribution of this paper is the use of the DM perspective for ESCRM in the context of Industry 4.0. Our approach contributes to the literature on DM and artificial intelligence in general by providing a systematization of ESCRM in Industry 4.0 that has not been examined sufficiently in extant literature.

6.2. Managerial Contributions

The proposed DM framework can be useful for Industry 4.0 practitioners by providing a replicable approach to ESCRM, through risk identification, detection, mitigation, and control using efficient measures. The conceptual framework can also be useful to other companies which do not necessarily adopt all Industry 4.0 technologies but can be interested in developing a DM framework to manage environmental risks. Consequently, the proposed framework contributes to the development of an organizational culture of supply chain resilience in order to anticipate potential disruptive events and reinforce ESCRM. It is crucial for organizations to effectively implement risk management policies and to consider the various environmental and social issues in their supply chains. According to several studies [141–143] the presence of risk management policies acts as an enabler for resilience. Supply chain resilience offers many competitive advantages to organizations [24,142,142]. Therefore, the proposed framework can be considered by supply chain members as a way to improve their SC resilience capabilities.

6.3. Research Limitations

Conducting a literature review and adopting a conceptual approach in research is not limiting per se. However, some of the concepts provided in our research are based mostly on reviewing extant literature from Scopus and other databases, which offer comprehensive coverage of the academic literature but may not include all the publications. Further knowledge could be also found in the grey literature (reports, theses, memos, etc.). Notwithstanding, if the articles used in this study are not exhaustive, they are comprehensive enough to provide a reliable conceptualization of Industry 4.0 ESCRM. Finally, although the proposed DM framework steps were elaborated based on prior literature and following a rigorous approach, other environmental risk management mechanisms might be suggested and could provide opportunities for further additional research.

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