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ORIGINAL - SURVEY OR EXPOSITION

Prescriptive analytics applications in sustainable operations research: conceptual framework and future research challenges

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Abstract
In the broad sphere of Analytics, prescriptive analytics is one of the emerging areas of interest for both academicians and practitioners. As prescriptive analytics has transitioned from its inception to an emerging topic, there is a need to review existing literature in order to ascertain development in this area. There are a very few reviews in the related field but not specifically on the applications of prescriptive analytics in sustainable operations research using content analysis. To address this gap, we performed a review of 147 articles published in peer-reviewed academic journals from 2010 to August 2021. Using content analysis, we have identified the five emerging research themes. Through this study, we aim to contribute to the literature on prescriptive analytics by identifying and proposing emerging research themes and future research directions. Based on our literature review, we propose a conceptual framework for studying the impacts of the adoption of prescriptive analytics and its impact on sustainable supply chain resilience, sustainable supply chain performance and competitive advantage. Finally, the paper acknowledges the managerial implications, theoretical contribution and the limitations of this study.

Keywords Prescriptive analytics · Systematic literature review · Content analysis · Sustainable supply chain practices · Sustainable operations research

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1 Introduction

Analytics is not a new term—it has been around since many decades (Davenport & Soulard, 2014; Zamani et al., 2022). Over this period, it has transitioned from limited number of data sources to the unlimited data being produced with every click on the website, from saving data in the repositories to using data lakes for saving Big Data. As Big Data is not only about the size, organizations began focusing on how quickly they can acquire and extract meaningful information from this data which is continuously evolving in terms of volume, velocity and veracity (Hazen et al., 2018; Hindle et al., 2020). This has led to the growth of analytics from descriptive to predictive and prescriptive (Ashrafi & Zareravasan, 2022; Larson & Chang, 2016).

Descriptive analytics is the traditional technique of data collection and classification, and also helps analysts to identify and visualize patterns in the data (Frazzetto et al., 2019). However, it lacks the ability to predict the future events. To overcome this drawback, Predictive Analytics was proposed which not only models the past events but also gives indication on what will happen in the future. Now, once the data has been collected (via descriptive analytics) and the future event has been predicted (via Predictive analytics), it become crucial to understand the possible actions that need to be taken in order to make it happen (Frazzetto et al., 2019). This last stage is achieved via Prescriptive analytics which allows decision makers to select and adapt the best possible business opportunity. Thus, it not only minimizes the associated risk by suggesting the optimal sequence of actions, but also assists the organizations in maximizing their business value (Soltanpoor & Sellis, 2016).

Although descriptive and predictive analytics have been around for years utilizing machine learning, data mining, and simulation techniques, prescriptive analytics is still in nascent stage (Gartner, 2017; Ivanov et al., 2022). It combines and integrates optimization, simulation and mathematical tools in a synergetic way so that complex real-world problems can be tackled, and better decisions can be made by relying on the accuracy of the predictions (Frazzetto et al., 2019; Šikšnys & Pedersen, 2016). This is the reason why tech giants like Microsoft, Oracle, and Google want to leverage the benefits of prescriptive analytics and achieve competitive advantage (Jiang et al., 2010; Larson & Chang, 2016; Lepenioti et al., 2020). Consequently, there has been increased interest among the research community to tackle problems related to supply chain management (Akter et al., 2016), disaster operations management (Nagarajan et al., 2012), revenue management (Besbes & Zeevi, 2009), healthcare (Nahra et al., 2009), and customer relationship management (Moon & Kamakura, 2017). More importantly, with the pressing need to create a sustainable environment, organizations are now forced to adopt procedures and practices that would not have adverse impact on the surroundings. Decision makers have recognized that sustainable operations management, encompassing green supply chain, green procurement, and reverse logistics, is the key to gain competitive advantage while safeguarding the natural resources for future generations, and thus, achieve long term success (Kamble et al., 2020; Seuring and Müller, 2008; Srivastava, 2008; Gunasekaran & Irani, 2014). In this situation, prescriptive analytics is extremely beneficial to decision makers as it would help them in selecting the best possible option while planning for waste management, evaluating strategies for water resource management, finding the optimal location for setting up the waste treatment plant, ranking the alternatives in a vendor selection process, and so on (Achillas et al., 2010a, b; Montazer et al., 2009; Mysiak, 2006). Thus, prescriptive analytics is an important asset and poses a number of novel questions to decision makers and researchers that are relevant amid the growing demand to create a sustainable environment.

The motivation for our study stems from the current need to perform sustainable operations, along with the significant role of prescriptive analytics in attaining it. This necessitates a quick response to questions surrounding sustainable operations research and comprehend how prescriptive analytics can assist decision makers in creating a sustainable environment. Over the last decade, an enormous array of reviews, offering important insights, has been conducted on descriptive (Batrinca & Treleaven, 2015; Duan & Xiong, 2015; Sun et al., 2013; Tsai et al., 2015), predictive (Lu et al., 2017; Mishra & Silakari, 2012) and prescriptive analytics (Lepenioti et al., 2020). Moreover, separate literature reviews have been conducted in the area of sustainable operations research (Jia et al., 2021; Srivastava, 2007; Taghikhah et al., 2017; Thies et al., 2019; White & Lee, 2009). However, there is no published survey comprehensively encompassing prescriptive analytics and sustainable operations research. At present, this topic is at a nascent stage, even though it is a promising and crucial research area. Therefore, this work aims to help bridge the gap by investigating the available prescriptive analytics literature and its role in attaining a sustainable environment.

Our study is devoted to exploring the applications of prescriptive analytics through the lens of sustainable operations research and identify the avenues for future research. It thus aims to contribute in the following four ways: First, we collate state-of the-art research on prescriptive analytics and sustainable operations research and investigate the role of prescriptive analytics in carrying out sustainable operations. Second, we streamline the literature by classifying the studies in various themes and sub-themes as the existing knowledge on prescriptive analytics and sustainable operations research is multi-faceted and deserves to be thoroughly reviewed and analyzed. Third, we intend to offer a robust research agenda by investigating the past, present and future, of prescriptive analytics and sustainable operations-related field. This will assist in advancing the extant literature and, at the same time, provide decision makers significant insights while focusing on the sustainability aspect. Fourth, based on this literature analysis, we propose a conceptual framework that can be adopted by supply chain managers and decision makers to gain sustainable supply chain performance, sustainable supply chain resilience and competitive advantage by incorporating sustainable supply chain practices and prescriptive analytical capabilities.

We carefully examine 147 articles published in peer-reviewed academic journals during 2010 to August 2021. Streamlining the literature allowed us to reveal several new research themes and subthemes building connections between prescriptive analytics and sustainable operations research. To this end, our study aims to address four main research questions (RQ):

RQ1: How far prescriptive analytics has diffused in Sustainable operations research? This research question can be helpful in understanding the significance of prescriptive analytics in carrying out sustainable operations.
RQ2: What are the main themes linking prescriptive analytics and Sustainable operations? Insights from this question will make it possible to see the dominant topics and their interconnections.
RQ3: What is the past, current and future research trends for prescriptive analytics and sustainable operations? This point allows for an understanding of the research agenda, which will be useful for developing the topic further.
RQ4: Based on the current knowledge of the literature, what would be a suitable conceptual framework to study the role of prescriptive analytical capabilities in understanding sustainable supply chain performance, sustainable supply chain resilience and competitive advantage by utilizing all three pillars of sustainable supply chain practices: environmental practices, social practices, economic practices?

In particular, we see that prescriptive analytics continues to diffuse in the areas of healthcare, inventory management, revenue management, supply chain management, waste management, water management, energy conservation, disaster management and so on. We also find that the relevant literature can be classified into five main themes: applications of optimization techniques, sustainable operations management, data mining and statistical techniques, sustainable supply chain management, and disaster management. Corresponding to each theme, various sub-themes with the current and potential future research gaps and objectives are proposed and discussed. Our findings and proposed framework can be used by decision makers and researchers to propose avenues for improvements and bridge the gap between the theory and practice.

The paper is organized as follows. The next section presents the prior reviews conducted in the area; Sect. 3 shows the methodological approach to the review; Sect. 4 synthesizes the principal themes drawn from the body of research reviewed; and Sect. 5 discusses the main issues to future research on prescriptive analytics and in its application in sustainable operations research.

2 Prior reviews

To synthesize the literature and gain insights, it is important to conduct literature review-based studies (Kazemi et al., 2019). It accelerates the development of the research area by providing quick access to related issues and exploring the major contributions (Creswell, 2013; Machi & McEvoy, 2012). Owing to the significant interest in the areas of prescriptive analytics and sustainable operations research, various literature reviews have been conducted which target one of these two areas. In the direction of analytics (descriptive, predictive, and prescriptive analytics), social media tools and techniques were comprehensively reviewed by Batrinca and Treleaven (2015), big data and business analytics captured the attention of Duan and Xiong (2015), Tsai et al. (2015), Mikalef et al. (2018), and Ajah and Nweke (2019), visual analytics techniques and applications were surveyed by Sun et al. (2013), predictive visual analytics recent trends and developments were explored by Mishra and Silakari (2012) and Lu et al. (2017), and more recently, the literature on prescriptive analytics was reviewed by Lepenioti et al. (2020) to identify the research and implementation challenges. In the direction of SOR, Srivastava (2007) reviewed the literature on green supply chain management, White and Lee (2009) discussed the potential of operations research in the area of sustainable development, Gunasekaran and Irani (2014) gave a call for papers on sustainable operations management in order to understand the strategies, tactics and implementation processes, Thies et al. (2019) reviewed 142 articles that use Operations Research methods for assessing the environmental and social impacts of the products, and Jia et al. (2021) systematically reviewed 83 articles on sustainability-oriented supplier development and adopted contingency theory to understand how these initiatives can be incorporated in the supply chains. However, to the best of our knowledge, no review study has appeared which conjoins prescriptive analytics and sustainable operations research areas together. Thus, we aim to fill this gap in the literature by providing a comprehensive review of the applications of prescriptive analytics in the area of sustainable operations research.

Table 1 Research protocol

Research protocol	Details description
Research database	Scopus database
Publication type	Peer-review journals (indexed by Scopus)
Language	English
Data Range	The period for consideration was 2010–2021 (August)
Search fields	Titles, abstracts, and keywords
Search fields	Prescriptive analytics OR Mathematical programming OR machine learning OR Data mining AND Sustainable operations research OR Operations research
Criteria for inclusion	Papers that presented prescriptive analytics and applications in sustainable operations research context
Criteria for exclusion	Papers that purely presented analytics discussion, without having any sustainability context and grey literature (books, conferences and newspaper articles)
Data extraction	We used a bibliometrics and visualization tool Gephi
Data analysis and synthesis	Supported by content analysis, we performed a content analysis approach

3 Research design

In this section, we describe the research methodology adopted in this study. We begin with the systematic literature review methodology framework, then define the search terms and database, followed by the search results, while describing the inclusion and exclusion criteria of this refinement and finally, discuss about the literature review analysis, conceptual framework and future research directions.

3.1 Step 1: Selecting systematic literature review methodology

The aim of a Systematic Literature Review (SLR) is to examine the body of literature, highlight the major gaps and underline the boundaries of knowledge (Tranfield et al., 2003; Ambilkar et al., 2022; Dohale et al., 2022; Paul & Criado, 2020). SLR has been considered as one of the most rigorous methods for conducting the literature reviews as its applications can be seen in various fields, including the recent works in the area of supply chain (Sawyerr & Harrison, 2022; Suryawanshi & Dutta, 2022).

In this study, we adopted a research protocol highlighted in Table 1 from Queiroz et al. (2020). Research background is first established for prescriptive analytics applications in sustainable operations research and then the search terms are defined for the data collection. For data extraction, we used bibliometric software Bib Excel and, using Endnote, the data is further cleaned by removing any duplicated and invalid documents. Next, the content analysis is presented to discuss the major themes, followed by the avenues for future research.

3.2 Step 2: Defining the appropriate search terms and database

This research is conducted to explore the applications of prescriptive analytics in sustainable operations research. The topic consists of two terms: prescriptive analytics and sustainable

operations research. To ensure that both aspects are fully captured by the keywords, we included two search strings, which are shown in Table 2. The first string is related to prescriptive analytics, including machine learning and data analytics. The second search string contains "sustainable operations research" and "operations research". The selection of keywords was based on previous literature reviews on similar topics and the authors' own research experience.

The data used in this research was collected from the well-established academic database, Scopus, to ensure no major relevant works are missed out as it has been considered one of the largest bibliographic databases. It provides seamless access to articles published since 1996 and covers approximately 58 + million records. Even though there are other databases like Web of Science, EBSCO, we considered only Scopus database because it includes all sort of journals with or without an impact factor, thus fulfilling our objective to identify maximum number of articles for the literature review. However, the debate on which database is better is outside the scope of this study. Also, the user-friendly search engine of Scopus facilitated the article refinement process because it enabled us to incorporate specific search conditions.

Table 2 Summary of review articles on prescriptive and sustainable operations research

Author	Type of review	Theory/framework	Focus topic/area
Mishra and Silakari (2012)	General review	Theory	Predictive visual analytics
Sun et al. (2013)	Broad survey	Theory	Visual analytics techniques
Batrinca and Treleaven (2015)	Sentiment analysis/Opinion mining	Theory	Social media analytics
Duan and Xiong (2015)	General report	Theory	Big data analytics and business analytics
Tsai et al. (2015)	Systematic literature review	Framework	Big data analytics
Mikalef et al. (2018)	Systematic literature review	Framework	Big data analytics capabilities
Ajah and Nweke (2019)	General review	Theory	Trends in Big data and business analytics
Lu et al. (2017)	Survey method	Framework	Predictive visual analytics
Lepenioti et al. (2020)	Systematic literature review	Theory	Prescriptive analytics
Srivastava (2007)	General review	Theory	Green supply chain management
White and Lee (2009)	Case study	Framework	Operations research in the area of sustainable development
Gunasekaran and Irani (2014)	Editorial	Modelling	Sustainable operations management
Thies et al. (2019)	Systematic literature review	Framework	Operations Research methods for assessing the environmental and social impacts
Jia et al. (2021)	Systematic literature review	Framework	Sustainability-oriented supplier development

3.3 Step 3: Data search results

The initial search attempts identified 3089 titles (see Fig. 1). Next, the data is cleaned by focusing on articles and reviews published between 2010 and August 2021 and removing all the articles not written in English. The reason for selecting the above timeline is that post-2010 only, the area of prescriptive analytics actually gained the popularity and most of the seminal articles appeared after that. This screening resulted in 250 papers. Next, the articles which did not mainly focus on the role of prescriptive analytics in sustainable operations research were excluded. To facilitate this, a team of co-authors prepared a table with all 250 papers and a column to decide 'include' or 'exclude' the article. This search resulted in 147 papers which were stored in CSV format to include all the essential paper information such as paper title, authors' names and affiliations, abstract, keywords and references. The inclusion and exclusion criteria can be clearly seen in Table 2.

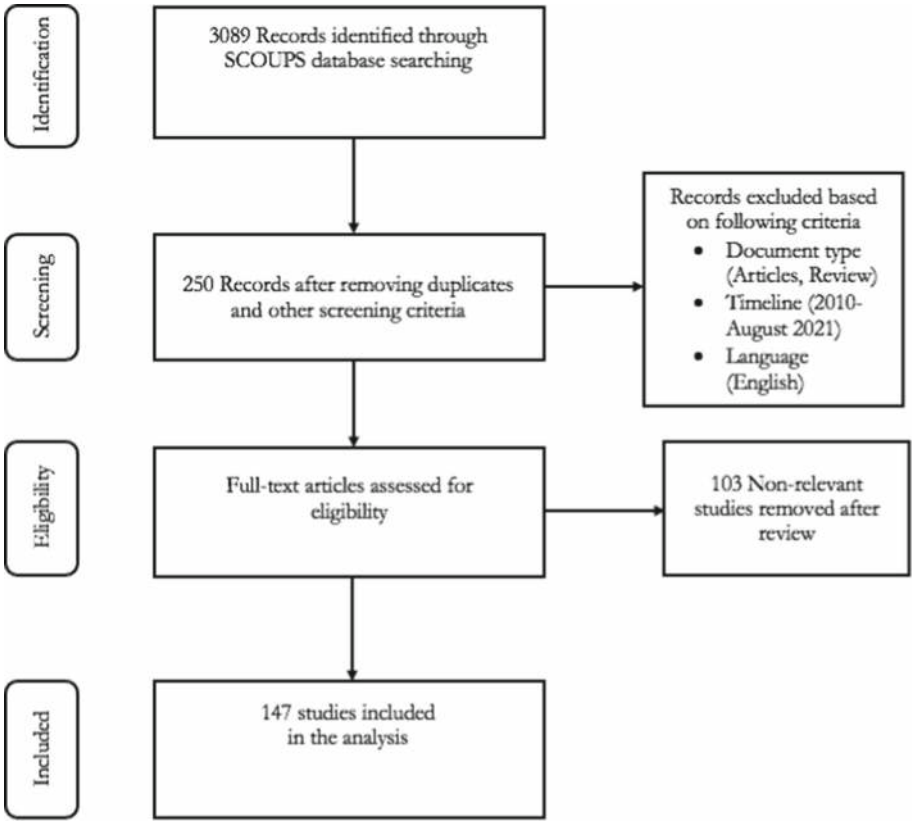

Fig. 1 Methodology framework

3.4 Step 4: Literature analysis

All the shortlisted articles are used for data analysis. We performed content analysis and identified five broad themes. We also conducted a descriptive analysis to highlight the journal publication trend, top countries and subject areas.

3.5 Step 5: Example conceptual framework

Based on the literature review analysis, we propose a research framework in Sect. 4 for studying the role of adoption of prescriptive analytics in creating a sustainable environment in terms of sustainable supply chain resilience, sustainable supply chain performance and competitive advantage.

3.6 Step 6: Future research directions

The most important aspect of any literature review is to provide future research opportunities for other scholars who are working in the same research area. For this purpose, we have provided opportunities for future research in Sect. 5.

3.6.1 Descriptive statistics

This part of the study focuses on the descriptive statistics of the reviewed literature. Figure 2 shows the distribution of the publications over the years starting from 2010 to August 2021. It is quite evident that the number of publications has increased drastically in the last 3 years thereby reflecting the actual growth in this area. It is also expected that this publication trend will continue to increase in the coming years as post COVID-19 pandemic, companies and researchers are focussing more in this area of research.

A further bibliometric analysis was performed on the subject area. It is evident from Fig. 3 that the maximum number of papers are in decision sciences, followed by computer science, mathematics, engineering and business management area. Other subject areas, such

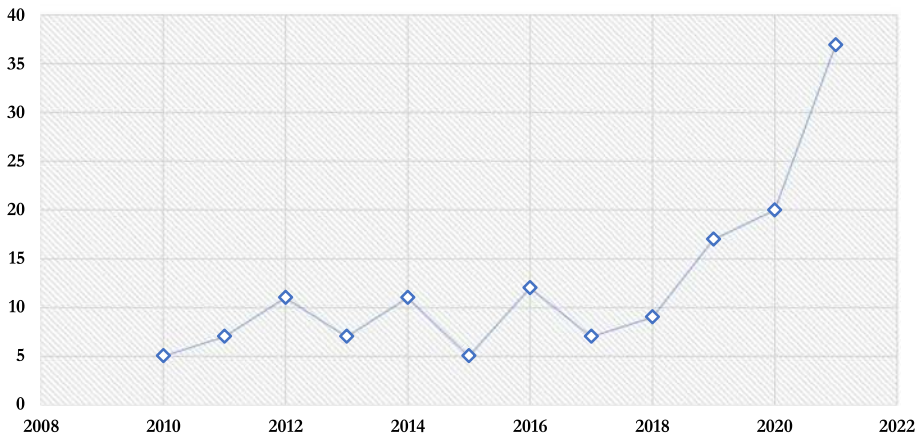

Fig. 2 Publication by year

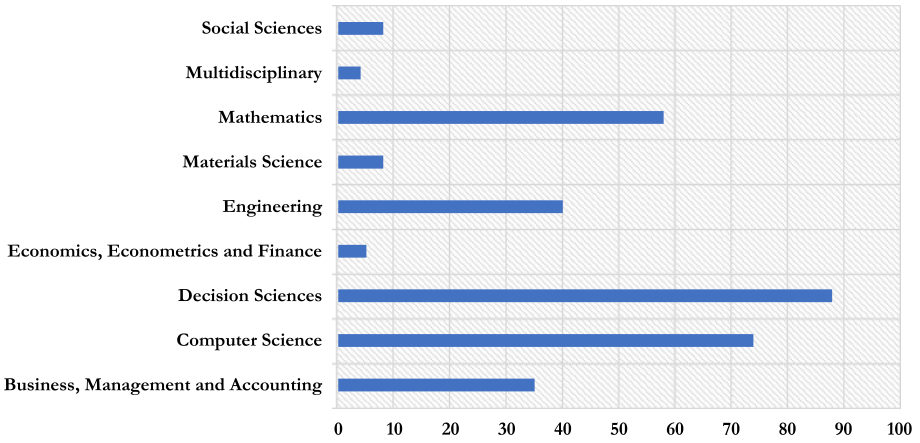

Fig. 3 Publication by subject

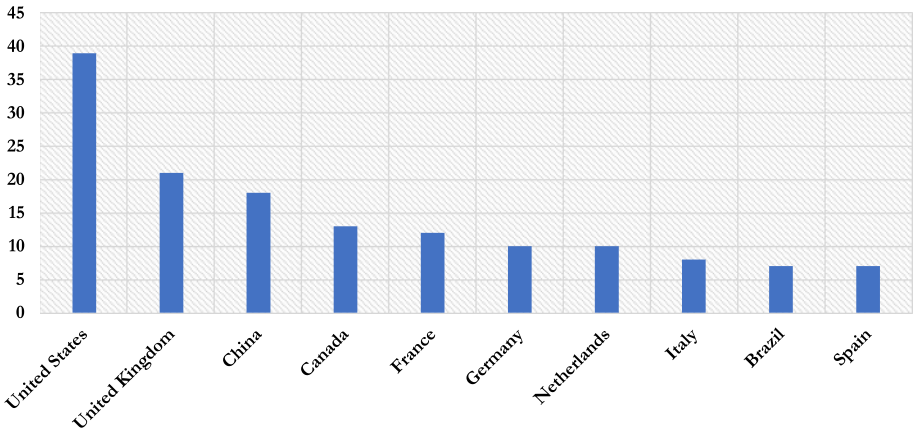

Fig. 4 Country-wise publications

as, social sciences, material science and finance are still in the nascent stage. Similarly, we used Bib Excel software to extract the country wise information for further analysis. Figure 4 highlights the top countries that have contributed maximum in this area of research. The top four countries are USA, UK, China and Canada. Nonetheless, scholars from across the world are attracted towards the area of prescriptive analytics and sustainable operations research.

4 Findings from content analysis

Content analysis is one of the most important methods for conducting literature reviews and, specifically, for generating different research themes. In content analysis, different set of information is collected in order to provide deeper insights (Krippendorff, 2004). To synthesize the content, periods, keywords, abstract, applications and methodologies for more

reliable results, it is recommended that more than one researcher should be involved in this process (Govindan & Hasanagic, 2018; Seuring & Gold, 2012). For the purpose of this study, the selected articles were segregated based on their research issues, methodologies and applications and five broad themes were developed, and within each of these themes, we identified sub-themes. The details of our research themes can be seen in the below mentioned subsections:

4.1 Theme 1: Applications of optimization techniques

There are 29 papers in this theme and these papers prominently discuss about the applications of optimization techniques in various sectors. Due to the homogeneous connections of the papers in this theme, we conduct content analysis by dividing and reviewing papers according to five subsections: (1) Optimization in Inventory Management, (2) Optimization in Revenue management, (3) Optimization in Healthcare (4) Operations Management and Operations Research.

4.1.1 Optimization in inventory management

Overall, there are 7 papers (24.1%) in this subtheme. It is clear that the papers in the previous decade focused on application of optimization techniques in inventory management (Kök and Fisher, 2007; Dehoratius et al., 2008; Balakrishnan et al., 2008; Olsen & Parker, 2008; Pastor and Olivella, 2008; Beutel & Minner, 2012; Naseraldin & Herer, 2008).

Retailers often come across problems such as inventory record inaccuracy, assortment planning, demand uncertainty, inventory stockout. To help retailers with assortment planning, Kök and Fisher (2007) developed an algorithm to compute the best assortment of the products. Under the assumption that substitution of a product with a similar product of the same category is feasible, optimal results were obtained through the proposed iterative optimization heuristic. To tackle inventory record inaccuracy, Dehoratius et al. (2008) adopted a Bayesian approach and proposed an intelligent inventory management tool. By performing simulation, the authors showed that the proposed replenishment policy recovers the cost incurred due to record inaccuracy, and that their inventory audit policy performs better than the famous "zero balance walk" audit policy. Balakrishnan et al. (2008) highlighted the significance of maintaining higher inventories in stimulating demand. They considered profit-maximization policy for a stochastic inventory model and showed that demand stimulation can increase the service level and thereby generate higher profits. To capture the economic effect of a customer leaving the market at the time of inventory stockout, Olsen and Parker (2008) proposed models to study the stochastic demand distribution in a time-dynamic context. As manual allocation and adaptation of weekly work schedules is difficult, Pastor and Olivella (2008) proposed a mixed linear program along with a local optimization process. To check the effectiveness of their proposed method, the authors considered the two franchises of a retail clothing chain and the results were found to be satisfactory.

The traditional inventory management approaches assumed a demand distribution and a time series-based framework was used to parameterize the demand model. However, the demand may depend upon various external factors, specifically, in case of retail inventory management system. Thus, to incorporate these factors, Beutel and Minner (2012) compared regression model approach to forecast demand and linear programming approach to optimize the target inventory function. It was shown that if sample size is small, then the former method outperforms the latter, whereas, if some of the assumptions of the former method are

violated, the latter approach gives more robust inventory levels. To further assist retailers with replenishment decisions, Naseraldin and Herer (2008) integrate the number and location of each retail outlet and analyse the system using expected cost. They showed that an improved solution can be obtained by combining strategic and operational decisions and expressing in terms of the number of retail outlets.

4.1.2 Optimization in revenue management

There are four papers (13.8%) in this subtheme and mainly focus on revenue management through the use of optimization techniques (Besbes & Zeevi, 2009; Liu & van Ryzin, 2008; Mukhopadhyay et al., 2007; Netessine et al., 2006).

In e-commerce industry, dynamic cross-selling of products and services has become increasingly common. Selection of the complimentary product and it's pricing are the two major issues faced by a company. To formulate this problem of revenue management, Netessine et al. (2006) propose a stochastic dynamic program with combinatorial optimization and subsequently, suggest various pricing and packaging heuristics. Another aspect of maximizing revenue can be seen in Mukhopadhyay et al. (2007) where the focus is on airline revenue management. As revenue can be improved by making accurate passenger demand forecasts, the authors propose a method to adjust system forecast by taking into account the unseen demand and evaluate the performance using forecast monitoring system. While studying network revenue management, Liu and van Ryzin (2008) included the concept of efficiency for determining the optimal policy in the choice-based revenue management problem. To further improve the performance of the static linear programming solution, the authors proposed a practical decomposition heuristic for converting the static choice-based deterministic linear programming model solution into a dynamic control policy. In order to maximize the expected revenue, Besbes and Zeevi (2009) studied single-product revenue management problem where the demand function is unknown. On measuring the efficiency of the proposed algorithms in terms of regret, it was found to be very close to the lower bound for any admissible pricing policy.

4.1.3 Optimization in healthcare

Also, in this theme, we review 13 papers (44.8%) addressing the healthcare sector where a few have focused on sustainable ways to improve healthcare system (Jagesar et al., 2021; Kohno et al., 2019; Zolbanin et al., 2020).

Appointment scheduling has come at the forefront of the healthcare sector as it not only provides access to service providers but also to clinics for scheduling the surgeries (Gupta & Denton, 2008). For instance, a clinic scheduler might use it to schedule the appointments for outpatients. This can be formulated using a stochastic overbooking model with the idea that patient no-show will be compensated by overbooking (Muthuraman & Lawley, 2008). Another study on outpatients which employs optimization techniques is Nahra et al. (2009). The authors highlight the drawback of the traditional methodology and propose a super efficiency Data envelopment analysis to treat outpatients dealing with substance abuse. Zolbanin et al. (2020) suggested that one way in which hospitals can utilize the resources sustainably is by predicting patient's duration of stay at the hospital using deep learning neural network. To optimize the outcome of patients suffering from brain trauma, Kunene and Weistroffer (2008) modelled various factors affecting the outcome using multicriteria decision making. The results suggested that better prediction can be made if a priori information is available

when using data mining tools. To identify the application of Analytic hierarchy process (AHP) in healthcare, Liberatore and Nydick (2008) conducted a literature review and identified that the number of articles has increased significantly in the recent years. They also pointed that AHP has been used in doctor-patient decision making, selection of correct medical treatment, and evaluation of the related technologies and policies. To reduce the problem of nurse rerostering in hospitals, Moz and Pato (2004) proposed two integer multicommodity flow models. These models were tested on real data from a public hospital in Portugal and it was found that the second outperformed the first in terms of solution quality and computational time. Jagesar et al. (2021) presented requirements and guidelines to achieve a secure and sustainable digital phenotyping. To further benefit the healthcare system, Kohno et al. (2019) integrated big data analytics and information and communication technology, and proposed a medical healthcare platform that regulates sustainable operations.

Time is a critical factor in any healthcare setting, and hence, transportation needs of patients should be given utmost priority. To address this issue, Melachrinoudis et al. (2007) propose a double request dial-a-ride model where coordination and central dispatching system eases the process and also minimizes the transportation cost and inconvenience time. Further, a decision support tool was designed by Ahmed and Alkhamis (2009) to enhance the service efficiency of an emergency unit in a hospital. For this purpose, they integrated simulation and optimization and proposed an optimal allocation which would maximize patient throughput and also reduce their waiting time. As the location of nomads keeps changing seasonally, it is a challenge for health care units to provide them with the proper medical facilities. To determine the optimal number and location of health care units in such a situation, Ndiaye and Alfares (2008) formulated a binary integer programming model. The model gave efficient solution when applied to nomadic groups in Middle East. Nicholson et al. (2004) highlighted the benefit of inventory management in healthcare systems. They compared inventory cost and service level of an in-house three-echelon distribution network with that of an outsourced one and showed that outsourcing non-critical inventory items is a better choice.

4.1.4 Operations management (OM) and operations research (OR)

There are five papers (17.3%) in this subtheme. Although OM and OR overlap in terms of the employed techniques, they differ at the conceptual level. OM is more oriented towards the management of resources which are critical to firm's growth and performance, while OR deals with modelling, problem solving and decision making (Anderson et al., 2002). In this regard, Meredith (1998) emphasized that OM should not be only studied by traditional techniques of optimization and simulation but also through case and field-based studies as they are inter-related and can offer important insights. Tranfield et al. (2003) provided step by step methodology to perform systematic review and is now being adopted by OM researchers. With the increasing usage of analytics in organizations, academicians and practitioners have shifted their attention to study the impacts and opportunities of OR. Fortun and Schweber (1993) analysed OR through the lens of World war II by studying its relation with system engineering and comparing the developments in the US and Great Britain post the world war. Kirby (2000) noted that understanding the history of OR is equally important to further expand the knowledge in this research area. With this in mind, the author connected the history of OR in Britain and United States over the span of 50 years, i.e., 1940s to 1990s. Continuing this further, Liberatore and Luo (2010) discussed the drivers of this analytic shift and also studied the opportunities and implications it offers for promoting and expanding operations research.

4.2 Theme 2: Sustainable operations management

Forty papers make theme 2 the largest theme. At the first glance, researchers mainly seek to solve sustainability related issues using MCDA, a branch of operations research, which is an efficient decision-making method to evaluate multiple criteria and find the best feasible solution, because majority of the papers (21) appear in this direction. Another direction of research which is evident from this theme is the use of Machine Learning techniques for sustainable operations management. We structure this theme as (1) MCDA and Sustainability, and (2) Machine Learning and Sustainability.

4.3 MCDA and sustainability

There are 25 papers (62.5%) in this subtheme which includes papers on MCDA, as well as ELECTRE, which is a family of MCDA techniques, and on MCDA review papers from the perspective of sustainability.

From the perspective of creating a sustainable environment, MCDA has been used in assessing eutrophication (Moriki & Karydis, 1994), evaluating water resource management strategies and selecting the best one (Nijkamp & Vos, 1977), identifying risk prone areas in mining locations (Merad et al., 2004), recognizing the optimal location for setting up electrical and electronic waste treatment plants (Achillas et al., 2010a, 2010b) and for waste management (Morrissey & Browne, 2004), developing risk assessment approach for sustainable constructions engineering projects (Marhavilas et al., 2020), for searching the optimal setpoints and the ideal gas fuel for sustainable operation of wastewater treatment plants (Heo et al., 2021; Akbaş and Bilgen, 2017). To better predict water demand, Hu et al. (2021) proposed a preprocessing framework using neural network and Balkhair et al. (2016) developed a cost-effective sustainable operation policy of the plant during the failure of any production pump. All these works emphasized on the need of cooperation between the authorities and scientists in order to create a sustainable environment. Other applications of MCDA include selection of a final solution from a set of solutions during software release planning process (Ngo-The & Ruhe, 2008), evaluation of the credibility of the credit card applicant (Matsatsinis, 2002), and in manufacturing of products as for the development of a new product, manufacturers often use old parts with similar specifications. In order to efficiently search for such parts from a database, Mun and Ramani (2011) employed MCDA and ontology, and also validated their approach by considering a case study of ejector pins.

ELECTRE belongs to the family of multi-criteria decision analysis. In recent years, evolutions of ELECTRE, such as ELECTRE III and ELECTRE Tri, have received considerable attention from the researchers and practitioners. For instance, Montazer et al. (2009) used the fuzzy version of ELECTRE III for ranking the alternatives in a vendor selection process, Mróz and Thiel (2005) employed ELECTRE III for evaluating the heating system of educational buildings. In a similar way, ELECTRE TRI was studied by Mousseau and Slowinski (1998) to assign a given alternative to some pre-defined categories. The authors proposed an interactive approach where the desired parameters (importance coefficients, weights, thresholds, category limits, etc.) are determined via assignment examples, and then this problem is solved using non-linear optimization technique. Through this approach, the decision makers have the feasibility to modify the assignment problem and draw more information for optimization. ELECTRE TRI was further modified by Mousseau et al. (2000) who proposed ELECTRE TRI Assistant method to ease the process of preference selection by the decision maker. Their method mainly targeted determination of importance coefficients by keeping

other parameters fixed and then solved the problem as linear program. Later, Moussea et al. (2001) and Ngo-The and Moussea (2002) considered subproblems to determine the weights and category limit, respectively, and formulated it as a linear programming problem. The problem of inconsistency among the constraints on these parameters was addressed by Mousseau et al. (2003). The above two methods, ELECTRE III and ELECTRE Tri, were integrated in Mousseau and Dias (2004) where a modified version of valued outranking relation was considered. To obtain the values of the parameters, authors adopt disaggregation approach which has been rarely used in case of outranking methods. These modifications were then showed to make the computation of inference problems easier.

Authors have also reviewed MCDA approaches to create a sustainable environment by saving the environment, forest, and natural resources (Mendoza & Martins, 2006; Mysiak, 2006). For instance, Mysiak (2006) focused on application of MCDA in environmental and natural resource management. The author reviewed various experiments that were conducted to make comparisons between the results of different MCDA methods. It was highlighted that multimethod MCDA should be given preference in comparison to traditional sensitivity analysis while dealing with unstructured decision problems. A similar review on MCDA methods in natural resource management was conducted by Mendoza and Martins (2006) where the methods were classified based on its characteristics and properties. The point of differentiation from the review of Mysiak (2006) is that Mendoza and Martins (2006) described new MCDA approaches in forest management and pointed out the need to shift from the concept of problem solving to that on problem structuring. Other set of reviews include those by Malczewski (2006) and Farahani et al. (2010), where the former integrated MCDA with GIS and reviewed the relevant papers to identify the trends and developments in this domain, and the latter reviewed articles on the multi-criteria location problems.

4.3.1 Machine learning and sustainability

There are 15 papers (37.5%) in this subset. With the shift towards the digital era, the role of Machine Learning in attaining sustainability is deemed to receive much attention (Breiman, 2001; Ceballos-Fuentealba et al., 2019; Chahidi et al., 2021; Chu et al., 2019; Diaz et al., 2021; Duan et al., 2020; Fallah et al., 2018; Fujimoto et al., 2019; Hegedűs et al., 2021; Lim et al., 2017; Rafique & Jianhua, 2018; Schreiber et al., 2021; Shaharum et al., 2020; Trivedi et al., 2021; Tsai et al., 2011).

To promote sustainable development of non-residential buildings, Ceballos-Fuentealba et al. (2019) proposed a simulation and optimization methodology to predict the energy consumed in any building and the impact various energy conservation measures have on that building. Anther work to monitor energy consumption was done by Tsai et al. (2011) where life cycle assessment is used to analyse the cost of carbon dioxide emission and mathematical programming technique is used to study the distribution of limited resources. Rafique and Jianhua (2018) reviewed the literature on energy management, generation and consumption for microgrids. As greenhouse cultivation has greatly increased, Chahidi et al. (2021) compared different ML models such as, Artificial Neural Networks, Gaussian Process Regression, Support Vector Machine and Boosting trees, to predict the greenhouse energy demand and production. Moreover, Schreiber et al. (2021) utilized ML methods to generate automated data-driven model that can optimize the cooling system of the entire campus. For distribution of oil-palm over a large area, Shaharum et al. (2020) adopted non-linear ML techniques and showed that Support Vector Machine and Random Forest are equally effective, Trivedi et al. (2021) utilized random forest ensemble learning model based on mobile sensing and crowdsensing to predict the ambient temperature in buildings, Diaz et al. (2021) proposed

a random forest model predictive control for paste thickening, a new method in mineral processing, to ensure an environmentally sustainable operation, and Breiman (2001) studied Random Forests to solve regression and classification problems.

ML based approach has also been used to assess the crop quality and consumption of electricity (Fujimoto et al., 2019), to forecast energy load in smart energy management grids (Fallah et al., 2018), to address the sustainable operations of power control by incorporating energy harvesting and internet of things (Chu et al., 2019), to reduce waste and conserve industrial resources and implement process graph framework to deal with resource conservation network issues (Lim et al., 2017), to evaluate the relationship between sustainable operation of rail transit and land use by employing data envelopment analysis (Duan et al., 2020) and to achieve sustainable transportation, explore vehicle automation through closed loop matching where the dataset is generated, trained and evaluated using neural network (Hegedűs et al., 2021).

4.4 Theme 3: Data mining and statistical techniques

With 30 papers, this is the second largest theme. In today's digital world, huge amounts of data is being produced every nano second and to develop patterns and relationships from this data, data mining techniques have come to the forefront. Another set of technique which is being employed to analyze data is statistical techniques. Thus, content analysis is done by dividing and studying this theme according to two subsections: (1) Data mining techniques and Customer Relationship Management (CRM), and (2) Multivariate Statistical Techniques.

4.4.1 Data mining techniques and CRM

There are seven papers (20%) which solely studied the role of data mining techniques in customer relationship management. To be more specific, Moon and Russell (2008) proposed a product recommendation model using joint space mapping and spatial choice modeling to predict product purchase behavior. The model when applied on a customer database of an insurance firm provided good forecasts results. With the idea that number of previous buyers effect the purchase timing of new product, Bass (1969) developed a growth model for consumer durables and forecasted the sales of television sets. Another step in the direction of customer relationship was taken by Neslin et al. (2006) and Holtrop et al. (2017) who studied the effectiveness of customer churn predicted models. Here, Neslin et al. (2006) noted significant differences among various modelling approaches and Holtrop et al. (2017) developed a method to predict churn without sacrificing consumer privacy. Moreover, Moon and Kamakura (2017) emphasized that online product reviews reflect information about the reviewer. The authors translated wine and hotel reviews to a product positioning map by combining ontology learning-based text mining and psychometric techniques. This framework is beneficial to product managers as it offers insights into consumer segmentation strategy. For sustainable operation of social networking sites, Chin et al. (2018) conducted a survey on 1108 users to determine the intention behind self-disclosure as privacy of these websites has recently come under scrutiny. More insight into the application of data mining techniques in CRM was provided by Ngai et al. (2009) who reviewed the literature for a period of 2000–2006. The papers were categorized on four dimensions of CRM (customer identification, attraction, retention and development) and the review revealed that consumer retention has been widely studied by researchers and, data mining functions of classification and association are the two most commonly used techniques in CRM.

4.4.2 Statistical techniques

In this subset, a total of 23 papers (77%) are explored. Multivariate statistical techniques, such as Cluster analysis, discriminant analysis, correspondence analysis, have attracted the attention of researchers over decades. For instance, in order to provide an effective measuring scale for input variables, Morrison (1967) modified the cluster analysis procedure so that statistically meaningful results can be obtained. Later, Morey et al. (1983) compared different methods of cluster analysis with respect to derivation, replication, external validation and cross-validation, Tibshirani et al. (2001) proposed a method, The Gap Statistic, for estimating the number of clusters in a dataset, and McNicholas et al. (2010) proposed an algorithm, by modifying the expectation–maximization (EM) algorithm, to implement model-based clustering via Gaussian mixture models and discuss the issue of model selection and convergence criteria. Further, Morrison (1969) provided guidance to interpret the results of linear discriminant analysis, Nenadic and Greenacre (2007) introduced a package for simple, multiple, and joint correspondence analysis in R, Murtagh (2005) studied the mathematics and algorithms behind correspondence analysis, highlighted its significance in artificial intelligence and discussed data coding in Java and R, Mclachlan and Krishnan (2007) focused on the theory and applications of the EM algorithm and its extensions, and Roig-Tierno et al. (2013) used Analytical Hierarchy Process with GIS to determine the retail site location. In many real situations, the random variables representing lifetime of a component, unit or a system are dependent, and hence a separate treatment of this subject is required. In this direction, Nelsen (2003) studied the concept of copulas, which is an efficient way to express multivariate distribution in terms of their marginals. This concept is mainly used to describe the dependence and association between random variables. Further, to model dependency between random variables, Meeuwissen and Bedford (1997) considered bivariate distributions with uniform marginals and a specified rank correlation, and Morales et al. (2008) suggested the use of conditional and unconditional rank correlations. Another work in the multivariate set-up was done by Morales-Nápoles and Worm (2013) who conducted hypothesis testing of multivariate probability distributions.

For forecasting a time series, Newbold and Granger (1974) compared the performance of Box-Jenkins, Holt-Winters and Stepwise Autoregression, and suggested that a combination of these individual forecasts is often profitable. Murphy and Winkler (1970) studied the role of Scoring Rules in probability assessment and evaluation, as well as, in probability forecasts and assessors, Mcnees (1987) studied consensus forecast, Martino (1992) showed how technological forecasting is essential in all domains, engineering, management, and strategic planning, and Myung et al. (1996) employed Shannon's information measure to aggregate opinions of experts on the prediction of outcome of an uncertain event. To assist decision makers, Morris (1974) introduced the concept of involving expert's opinion with their own. This can be done by applying the tools of Bayesian inference. Later, Morris (1977) adopted Bayesian approach to incorporate different probability assessments by experts. In case of single expert, decision maker can multiply expert's probability assessment with his own prior probability assessment and normalize while in case of multi-experts, multiplicative rule is applied. Morris (1983) proposed axioms to combine expert probability assessments and developed a method to merge these probabilities into a single estimate. Nadkarni and Shenoy (2004) constructed Bayesian networks by utilizing the knowledge of experts via casual mapping approach. The authors highlighted how knowledge can be represented as causal maps and their graphical structure can be used to construct Bayes nets. As maintaining the cooling system of data centres is key to sustainable operation, Patnaik et al. (2011) proposed a

data mining solution incorporating motif mining, association analysis and dynamic Bayesian network analysis.

4.5 Theme 4: Sustainable supply chain management

Twenty-six papers make theme 4 the third largest theme. As the theme name itself speaks, researchers mainly seek to develop ways in which supply chains can be made sustainable. We structure this theme as (1) Supply chain management and Sustainability, and (2) Applications of Artificial Intelligence (AI) in Sustainable Supply Chains.

4.5.1 Supply chain management and sustainability

There are 16 papers (61.5%) in this subtheme with a focus on sustainable supply chain management, supplier selection, order allocation and firm performance. With the aim to present guidelines for logistics and supply chain managers to adapt to the circular economy business models, Lopes de Sousa et al. (2019) conducted a systematic literature review and highlighted the changes that are required in the decision making process of operations management so as to support the circular economy business models, Jabbour et al. (2019) integrated big data and circular economy, and Kumar et al. (2021) focused on post-COVID-19 era and analysed barriers in adopting big data analytics for sustainable manufacturing operations. Shaharudin et al. (2019) focussed on the aspect of sustainability by conducting a literature review and social network analysis on low carbon supply chain management. The authors identified six main domains in the area, specifically, sustainability, climate change, green supply chain management, supply chain management, innovation, sustainable development, and environmental management. They also highlighted the benefit of including sustainable management practices and carbon performance indicators in enhancing the integrated performance.

Another important aspect of supply chain is supplier selection and order allocation. In this regard, Scott et al. (2015) proposed a method for supplier selection that integrates stochastic, multi criteria decision analysis and multi stakeholder approaches. It is based on AHP-Quality Process–Quality Function Deployment and optimization algorithm which selects suitable suppliers and then allocates them order optimally. For solving the multi-objective inventory control problem, Moslemi and Zandieh (2011) compared strategies on multi-objective particle swarm optimization and showed that the proposed method significantly reduces computational time and gives optimal solutions. Beyond what has been discussed, researchers also study some mathematical ways to guarantee sustainable operations. For instance, mathematical programming model for addressing the problem faced by service providers in designing an urban electric vehicle sharing system (He et al., 2017), hybrid modelling framework for routing one-commodity pick-up and delivery by bike sharing systems (Lei & Ouyang, 2018), mathematical programming approach to asses process improvement capability index of products (Chen et al., 2015), and mixed integer programming approach to obtain the optimum product mix in a process industry (Galal & Moneim, 2015). Other works on optimization problems include algorithms for simulation based objective functions with large number of parameters (Nedelkova et al., 2018), and three-stage fixed charge multi-objective problem for sustainable transportation (Mehlawat et al., 2019).

Enhancing firm performance is of prime concern to firm managers. In this direction, Akter et al. (2016) and Wamba et al. (2017) proposed models that examine how companies can develop Big data analytics capability to enhance firm performance. Here, Akter et al. (2016) based the model on Resource Based Theory and the entanglement view of sociomaterialism

and highlighted the moderating role of business strategy in this relationship, while Wamba et al. (2017) examined direct effect, as well as, mediating effect of process oriented dynamic capabilities, and provided insights to enhance firm performance. Moreover, it should be noted that "big data" is not only about the size, rather it is a combination of 5Vs, i.e., volume, variety, velocity, veracity, valence, value. Chen et al. (2012). A broader definition of big data was provided by Gandomi and Haider (2015) and methods were developed for analysing unstructured data which accounts for 95% of big data, and at the same time, emphasis was given on the necessity to develop new tools for structured big data.

4.5.2 Applications of AI in sustainable supply chains

There are 10 papers (38.5%) in this subtheme. AI is greatly known to improve the decision-making process of human beings in the areas of supply chain management, supply chain risk management, banks and medicine. Similarly, its sub-field, Deep Learning plays a significant role in speech recognition, object recognition and detection (Lecun et al., 2015). Lee (2021) reviewed the literature and linked sustainability and OM by highlighting the benefits of adopting AI in product design, and that social sustainability is the basis for economic and environmental sustainability. To understand its application in supply chain management, Min (2010) reviewed previous papers on the successful application on AI and identified the core areas of SCM where it can be applied. In the context of textile and apparel supply chains, Ngai et al. (2014) reviewed the literature on applications of decision support and AI systems in these industries. The articles were categorized based on different sectors of production, manufacture and distribution, and research gaps were identified. To further explore the benefits of AI in supply chain risk management (SCRM), Baryannis et al. (2019) reviewed the literature, categorized the papers based on the methodology (i.e., mathematical programming, Machine Learning, Big Data Analytics) and different SCRM tasks they handle, and proposed future research directions.

Fethi and Pasiouras (2010) studied the role of AI and OR techniques for assessing the efficiency and performance of banks. For this purpose, the authors reviewed the relevant literature and pointed the applications of techniques such as data envelopment analysis, neural networks, support vector machines, and MCDA. Srebro et al. (2021) applied different Z-score models to calculate the risk of bankruptcy in agricultural companies. To ensure sustainable operations, it is important these companies report correct financial figures and also provide detailed information on environmental protection. Nazemi et al. (2017) compared the predictions of support vector regression, regression trees and OLS regression, and showed that fuzzy logic approach enhance prediction accuracy of loss-given-default of corporate bonds. To see the role of AI technologies in medical decision making, proposed case-based reasoning as an approach to design a modular architecture. Further, applications of AI in medicine were reviewed by Hamet and Tremblay (2017), and these applications range from robotics to medical diagnosis and statistics to biology branches of omics. A knowledge warehouse architecture was proposed by Nemati et al. (2002) to not only capture, store and code knowledge but also to retrieve and share it across the organization. This model is an architectural integration of knowledge management, decision support, AI and data warehousing.

4.6 Theme 5: Disaster management

With 22 papers, this theme focusses on disaster management, which is a broad area of research in operations management. Due to the frequent occurrences of natural and man-made disasters, it is important to minimize their impact and deliver relief material at the right time to the right people (Mishra et al., 2019). This whole process is divided into four phases: mitigation, preparedness, response and recovery (Araya-Córdova & Vásquez, 2018). Likewise, we categorize the papers based on these four phases as follows: (1) mitigation and preparedness, and (2) response and recovery.

4.6.1 Mitigation and preparedness

There are four papers (18.2%) in this subtheme, two each in mitigation and preparedness phases. Mitigation refers to the measures which are adopted to either delay the onset of disaster or reduce its impact once it occurs whereas, preparedness basically aims to prepare the community to respond if any such event occurs (Altay & Green, 2006).

With respect to the mitigation phase, Das et al. (2008) presented a large-scale simulation model to develop mitigation strategies for communicable disease like influenza. The results of the experiment can be utilized during decision making by healthcare professionals. Moreover, Nigmatulina and Larson (2009) used mathematical models to study the impact of travel restrictions, social distancing and improved hygiene during influenza outbreak. It was suggested that if these precautions are strictly performed by the society then the spread of the disease can be significantly mitigated. To prepare for natural disasters, Rawls and Turnquist (2010) proposed a two-stage stochastic mixed integer program so that the location and quantity of relief supplies can be determined. Matopoulos et al. (2014) emphasized that during humanitarian operations, it is important to identify what resources are needed and how to procure them. In this regard, authors conducted an empirical study on housing reconstruction projects and showed that procurement of local resources has positive influence on supply chain performance.

4.6.2 Response and recovery

With 18 papers (81.8%), this is the largest subtheme in this theme. In the response phase, majority of the papers focus on either the ways to evacuate the threatened populations (6 papers) or investigate the channels through which relief material can be delivered in a sustainable way (9 papers). However, only 1 paper has appeared in the recovery phase with regard to the fund allocation post disaster. In addition, two review papers have also appeared.

In order to respond to the disaster, Chiu et al. (2007) formulated a no-notice mass evacuation model using a dynamic traffic flow optimization technique. As the model has a single-destination linear structure, it is computationally efficient than the other models available in the literature. Yi and Ozdamar (2007) undertook a different approach for evacuation at the time of disaster. They emphasized that logistics coordination is an important issue as medicines and medical personnel have to be allocated in an optimal way in disasters. A mixed integer multi-commodity network flow model is proposed to coordinate evacuation and support and operations. Other works on evacuation planning include discrete event simulation for emergency evacuation in case of offshore oil industry (Mould, 2001), multi-objective evolutionary algorithms and GIS to propose a three-step approach for evacuation planning (Saadatseresht et al., 2009), a framework for reliable evacuation planning by taking

into account the fluctuation in number of evacuees and the road capacities (Ng & Waller, 2010), and an agent based simulation model to see the behavior of neighborhoods when the warning message to evacuate is circulated (Nagarajan et al., 2012).

To design a relief delivery system, Tzeng et al. (2007) adopted multi-objective programming approach to ensure efficient distribution of relief materials to all the demand centers. In addition, Lee et al. (2006) developed a simulation and decision support system to distribute medicines at the time infectious disease outbreaks and biological threats, Naji-Azimi et al. (2012) suggested a covering tour approach to locate the satellite distribution centers so that medical aid can be provided in a split delivery fashion. As transportation routes and distribution of relief material play a critical role during relief operations, Huang et al. (2012) measured their performance in terms of efficiency, efficacy and equity, Najafi et al. (2013) proposed a multi-objective model and Najafi et al. (2014) proposed a dynamic model to plan logistic activities at the time of earthquake. Another framework for transportation planning was proposed by Barbarosoğlu and Arda (2004) wherein a two-stage programming model was introduced to disperse medical aid at the time of disaster. To improve decision making during large scale disasters, Moskowitz et al. (2011) employed machine learning tool of multistage linear support vector machine to quickly assess the response strategy, and Mendonça (2007) developed a decision support system which can be improvised based on the response to natural disasters.

With regards to the Recovery phase, Natarajan and Swaminathan (2014) viewed humanitarian operations through the lens of funding as these operations are heavily affected by the amount, timings and regularity of the funding provided by various organizations. The authors present an optimal procurement policy with the emphasis that funding delays should be avoided, and donors should not be forced to pay the entire amount upfront.

In addition, two review papers have also appeared. Altay and Green (2006) reviewed the literature and explored the possible future avenues of research in OR/MS. Later, Galindo and Batta (2013) also reviewed the literature on OR/MS in disaster operations management and revealed that no drastic development has been made in this area since the previous review of Altay and Green (2006). However, they evaluated various assumptions of the literature and provided future research directions.

Now, we try to highlight the major relationships among the above five themes (see Fig. 5). To provide more clarity, we have used different colors and numberings for each of these themes; red for theme 1, green for theme 2, purple for theme 3, orange for theme 4 and blue for theme 5. It is evident that different types of connection exist between each of these themes, and it is represented by the thickness of the arrows reflecting the amount of work published between the themes. For instance, scholars have published a good number of optimization studies for disaster management, and it is highlighted by the thick purple arrow. However, lesser work has been shown using thinner blue arrows such as, the area of data mining and its role in disaster management, sustainable supply chain management and sustainable operations management have been comparatively explored less.

It is important to emphasize that these research gaps are highlighted in Table 3 along with the detailed research objectives for scholars to explore in future.

5 Conceptual framework and propositions

From Fig. 5, it can be seen that there is a scope of future research linking Theme 2 and 4 (reflected by a thin arrow between these themes). We make an attempt to address one

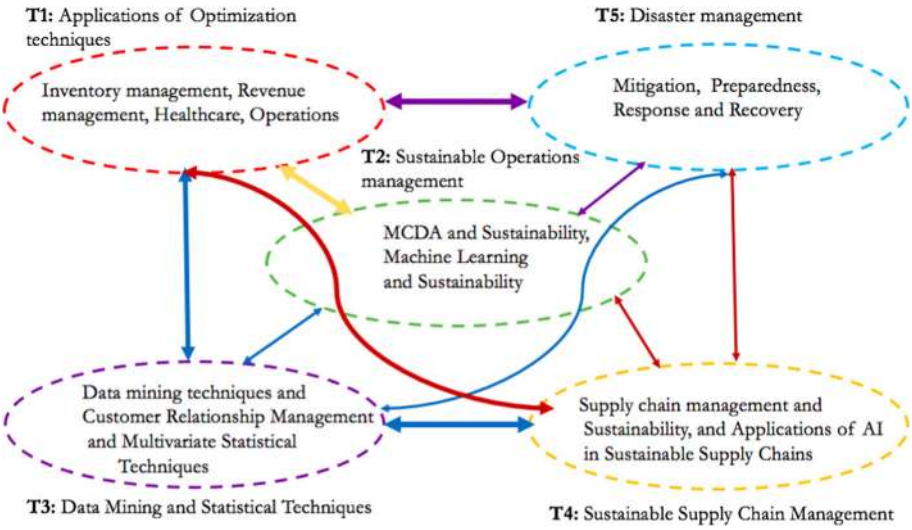

Fig. 5 Relationships between five themes

such research direction by proposing a conceptual framework and propositions highlighting the connection between sustainable practices, prescriptive analytics and sustainable supply chain resilience and performance. The idea to propose a conceptual framework with clearly defined constructs is also backed by researchers working in the area of operations and supply chain management as it helps in bridging the gap between the theory and practice (Babbar & Prasad, 1998; Chen & Paulraj, 2004; Chen & Small, 1996; Meredith, 1993; New et al., 2000).

The proposed framework will help practitioners in deciding upon the type of resources that the company should focus in terms of adopting prescriptive analytical capability and achieve competitive advantage, Sustainable Supply Chain Resilience and Sustainable Supply Chain Performance. The conceptual framework has nine constructs: Environmental Practices (EP), Social Practices (SP), Circular Economic Practices (CEP), Prescriptive Analytical Capabilities (PAC), Sustainable Supply Chain Resilience (SSCR), Competitive Advantage (CA), Sustainable Supply Chain Performance (SSCP), Flexible Orientation (FO) and Control Orientation (CO). Here, FO and CO act as mediator variables. By considering all these constructs together, we intend to offer a thorough insight on the impact of sustainable practices on PAC and then the final effect on SSCR, CA and SSCP. We also try to understand the role of organizational orientation (FO, CO) in terms of implementation or adoption of Prescriptive analytical techniques. Subsequently, we unify the defined propositions in a conceptual framework as depicted in Fig. 6. The following subsections discuss the theoretical background of the framework and the proposed research propositions.

5.1 Underpinning theory

The proposed framework can be understood from the perspective of resource based view (RBV). It focuses on firms' external and internal resources and capabilities for gaining competitive advantage (Hitt et al., 2016; Taylor & Taylor, 2009). These resources can be defined as the assets, capabilities, processes and information controlled by a firm in order to enhance

Table 3 Research gaps and potential research objectives

Theme label	Sub-themes	Current research focus	Future Research challenges/research questions?
Applications of Optimization Techniques	Optimization in Inventory Management Optimization in Revenue Management Optimization in Healthcare Operations Management and Operations Research	Algorithm to compute the best assortment of the products Bayesian approach an intelligent inventory management tool Stochastic demand distribution in a time-dynamic context Decision support tool to enhance the service efficiency of an emergency unit in a hospital	What type of theories and frameworks can help in better understanding the impact of deep learning tools on sustainability and operations research? How technologies like; blockchain can be used in the hospitals without violating patients privacy? What are the important tools, technologies and the challenges in the context of smart healthcare (using sensors, blockchain, Machine Learning, etc.)?
Sustainable Operations Management	MCDA and Sustainability Machine Learning and Sustainability	Machine learning based approach to assess the crop quality and consumption of electricity Use of Internet of things (IoT) in sustainable operations Simulation and optimization methodology to predict the energy consumed ELECTRE III for ranking the alternatives in a vendor selection process MCDA technique in evaluating water resource management strategies and selecting the best one	How to use Machine learning and AI for sustainable operations? What is the optimal simulation method for carbon emission and carbon footprint? More quantitative and empirical studies to study the impact on carbon emission and sustainability What are the main factors for managing operations using digital twin? What is the right analytical tools for managing operations by firms having different business strategy?

Table 3 (continued)

Theme label	Sub-themes	Current research focus	Future Research challenges/research questions?
Data Mining and Statistical Techniques	Data mining techniques and CRM Statistical techniques	Analytical Hierarchy Process with GIS to determine the retail site location Data mining solution incorporating motif mining, association analysis and dynamic Bayesian network analysis	Safety and Privacy issues related to data should be examined How Data quality issues help in making better decisions? What are the main drivers for identifying the role of Deep Learning in understanding customer relationships?
Sustainable Supply Chain Management	Supply Chain Management and Sustainability Applications of AI in Sustainable Supply chains	Mathematical programming approach to asses process improvement capability index of products AHP model for supplier selection Three-stage fixed charge multi-objective problem for sustainable transportation Conceptual study for assessing the benefits of AI in risk management	How advanced techniques like, AI, Machine learning and virtual reality can help in achieving sustainability in supply chain? How to develop an optimal model for emission evaluation and social welfare associated with sustainability? How advanced analytical tools is useful in reverse logistics and closed-loop supply chain?
Disaster management	Mitigation and Preparedness Response and Recovery	Large-scale simulation model to develop mitigation strategies for communicable disease Mathematical models to study the impact of travel restrictions Two-stage stochastic mixed integer program for determining the location and quantity of relief supplies	How can data help in better preparing for disasters? Limited paper acknowledge the role of data analytics in locating injured people after the disaster Identify the optimal model for locating injured people after any types of disasters By using text mining and customer footprints what factors associate with evacuation, and risk assessment? How to use virtual reality for improving disaster response/rescue? What are appropriate tools and techniques for the recovery phase of the disaster, specifically post disaster housing?

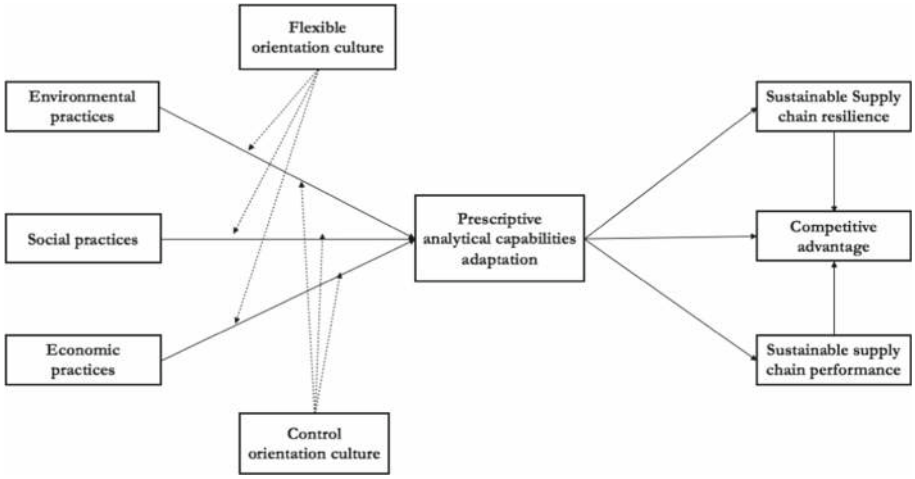

Fig. 6 Conceptual framework

its efficiency and effectiveness (Sarkis et al., 2011). In the last few years, RBV has gained significant attention among the scholars working in the area of operations and supply chain management (Bowen et al., 2001; Rungtusanatham et al., 2003; Taylor & Taylor, 2009; Hunt & Davis, 2012; Gligor & Holcomb, 2014; Brandon-Jones et al., 2014). Through RBV, firms can better explain the importance of focusing on the internal strength and weaknesses (Foss & Eriksen, 1995; Grant, 1996) which can be easily controlled rather than focusing on the external opportunities and threats (Grant, 1996). There is no harm in saying that RBV provides the best way to achieve competitive advantage by focusing on the resources. The main reason behind is that the competitive advantage can be sustained by utilizing the resources that are unique, important and irreplaceable by any competitors (Barney, 1991). Based on RBV, we suggest that firms can achieve the prescriptive analytic capability by utilizing their resources which are; environmental, economic and social practices and consequently, gain competitive advantage. The development of resources and capabilities may be exemplified through improvements in various organizational performance metrics. As an example, for attaining sustainable supply chain, firms need to focus on the three dimensions; environmental, economic and social practices, and these three resources are valuable, unique and irreplaceable for any firms that supports the aspect of RBV (Sarkis et al., 2011). Studies have found and argued that the above mentioned resources can help a firm in implementing technological capabilities, such as, big data analytics, blockchain technology, green information systems and later, prescriptive analytics capability can help a firm in achieving competitive advantage as per RBV concept.

5.2 Research propositions

In line with Edwin Cheng et al. (2021), we consider three types of sustainability practices in the supply chain—environment, social and economic. Environment friendly practices are embodied in water management, waste management, reduction in energy usage, eco design and pollution prevention. Adopting socially sustainable practices ensure that the human rights of workers are intact, their health and safety are promoted, and ethical norms are practiced

providing them a safe working environment (Sodhi, 2015). Lastly, economic practices focus on creating a balance between firm's assets and liabilities and thus improving sales and market share and efficiently maintaining the resources (Ageron et al., 2012). As Elkington and Fennell (1998) and Seuring and Müller (2008) articulated, all three practices have to be considered together in order to have a sustainable supply chain. These practices reflect essential aspects of business (Raut et al., 2019) as responding to social, environmental and financial demands has become a primary challenge for firms (Dubey et al., 2019; Gunasekaran & Irani, 2014; Park-Poaps & Rees, 2010). Khan et al. (2021) argued that sustainable supply chain practices have a significant positive association with blockchain technology and green information systems, and hence, have a significant impact on organizational performance. In addition, literature suggests that sustainability can be improved with the application of big data predictive analytics (Liu & Zhang, 2017; Song et al., 2017a, 2017b; Zhang et al., 2017). Benzidia et al. (2021) also insisted that making big data analytics and AI enabled decisions would enhance the environmental performance, and hence, firms should adopt practices that respect the environment (Singh & El-Kassar, 2019). Nonetheless, there is a noticeable paucity of empirical research investigating the association between big data predictive analytical capability and social and environmental sustainability practices (Song et al., 2017a, b). When firms value these practices as an instrument to gain competitive advantage, they can move towards sustainable growth and development (Carvalho et al., 2018) and those who are yet to adopt, witness difficulties (Mittal et al., 2018). Since our actions and decisions generate data which in turn can drive business practices (Pappas et al., 2018), it is important for firms to follow sustainable practices as it would influence the adoption of prescriptive analytics capabilities. As Petrini and Pozzebon (2009) articulated, sustainability practices and business intelligence and analytics have to be integrated to attain firm's strategic goals. Thus, sustainable practices and prescriptive analytics capabilities can prove rewarding for the firms. In light of the above arguments, the first set of propositions are:

P1: Environmental practices positively influence the adaptation of prescriptive analytical capabilities.
P2: Social practices positively influence the adaptation of prescriptive analytical capabilities.
P3: Economic practices positively influence the adaptation of prescriptive analytical capabilities.

Next, organizational culture allows the firms to ensure their rules, regulation, perspectives and procedures are properly implemented (Dowty & Wallace, 2010; Prasanna & Haavisto, 2018) and, is unique due to firms individual unique history, mission, structure and leadership (Wentz, 2006). It can also be viewed as a combination of assumption, values and beliefs which is clearly depicted in the practices and goals of a firm (Schein, 2010; Shao, 2019; White et al., 2003). Various frameworks have been proposed by scholars to empirically measure organizational culture and among them, Competing Values Model, proposed by Quinn and Rohrbaugh (1983), emerges as one of the most widely used, validated and accepted frameworks (Dubey et al., 2019; Shao, 2019). The most important feature of their framework is it focusses on the two dimensions of organizational culture rather than having a single point (Khazanchi et al., 2007; Stock et al., 2007) as; flexible focus and internal activities or external environments focus (Quinn & Spreitzer, 1991). These focuses are termed as flexible oriented (FO) culture and control oriented (CO) culture. Firms having FO culture are more risk takers and oriented toward creativity (Khazanchi et al., 2007) whereas firms with CO culture give

more preference to hierarchy, productivity and efficiency (Khazanchi et al., 2007; Liu et al., 2010).

In a similar vein, Prasanna and Haavisto (2018) highlighted the difference between FO and CO culture based on firm's interpretations of external events, and the way they respond to environmental needs (Deshpandé et al., 1993; Khazanchi et al., 2007). For instance, military organizations are more particular on following traditions and hierarchy whereas the relief providing organizations have a flat structure and follow an informal approach to traditions with lesser authoritarian attitude (Tatham & Rietjens, 2016; Wentz, 2006). The literature has proved that firms should align organizational culture and supply chain practices in order to gain supply chain performance (Braunscheidel et al., 2010; Schwartz & Davis, 1981). As the FO firms focuses more on creativity and innovation, it is suitable for visionary leaders having strategic focus and high expectations to the members of the organization. On the other side, CO firms are more suitable for leaders who are more process oriented and have problem solving skills as it is necessary for these firms to increase efficiency and productivity (Shao, 2019). CO firms are not very keen in terms of implementing any new or risky technique (cloud computing, machine learning) as it can impact their productivity and processes as well while, firms having FO culture are more inclined towards these tools for developing new products and services (Albanese & Manning, 2015).

Moreover, firms with FO culture give more importance to information systems strategy as compared to CO culture firms (Shao, 2019). In this direction, Leidner and Kayworth (2006) highlighted the role of organizational culture in adopting Information technology and diffusion. For instance, firms with FO culture are more interested in adopting any new advanced manufacturing technology as compared to firms with CO culture (Kitchell, 1995). Thus, the adoption of internet is more successful in firms with innovation and flexible culture (Ruppel & Harrington, 2001). Based on the arguments mentioned above, we support the idea that FO culture and sustainable practices have a positive effect on prescriptive analytical capabilities adoption, while CO culture has a negative effect. On this line of reasoning, we propose our next set of propositions as:

P4: Flexible orientated culture positively moderates the relationship between environmental, social and economic practices and prescriptive analytical capabilities adoption.
P5: Control orientated culture negatively moderates the relationship between environmental, social and economic practices and prescriptive analytical capabilities adoption.

From the perspective of Resource Based Theory, capabilities are developed in order to gain competitive advantage (Barney, 2001; Benzidia et al., 2021; Wernerfelt, 1984). Large and Thomsen (2011) also insisted on the need to develop capabilities in order to have a sustainable supply chain.

As articulated by De Oliveira et al. (2012) and Lepenioti et al. (2020), business analytics, in general, is known to create capabilities and empower supply chains by leveraging its sustainable performance. Further, it has been shown that big data analytics capability have a significant positive relation with supply chain agility, supply chain risk resilience, competitive advantage and firm performance (Dubey et al., 2019; Gu et al., 2021; Singh & Singh, 2019). Following the same rationale, with the adaption of PAC, it becomes easier for firms to achieve their goals of cost reduction, customer satisfaction, maximization of profit and enhanced efficiency (Kuttapa, 2020). Since prescriptive analytics identifies the optimal course of action, it takes the business decision making to another level, and thus, leads to superior performance (den Gartner, 2017; Hertog & Postek, 2016). Moreover, it is known that superior performance is one of the indicators to adjudge competitive advantage (Schilke, 2014). As the label itself suggests, competitive advantage is the manner in which a firm implements business strategies

in order to gain leverage over the competitors (Porter, 1985). It can be derived by identifying appropriate resources and/or capabilities, which can be then exploited to achieve superior performance and hence, competitive advantage (Barney, 1991; Reed & DeFillippi, 1990; Schilke, 2014).

To excel in this competitive environment, firms need to distinguish themselves from others by making their supply chains sustainable. Sustainable supply chains can effectively reduce their operational cost, build image and improve efficiency and effectiveness by making data driven decisions (Jose et al., 2020; Tsai et al., 2021). With the application of prescriptive analytics, supply chain activities can be monitored, and corrective actions can be taken to manage issues of resilience and risk management, thus attain the sustainability agenda (Mageto, 2021). Supply chain resilience, which is known as the ability of a supply chain to regain its original state and meet the needs of customers (Ambulkar et al., 2015; Christopher & Peck, 2004; Holling, 1973), has recently gained attention because in the current uncertain environment, supply chains have become vulnerable to disruptions, thereby creating financial loses (Adobor & McMullen, 2018; Ivanov & Dolgui, 2021). Therefore, it is important for a supply chain to quickly respond and survive in a turbulent environment. It is not only a tool to minimize risk and vulnerability but also a source of competitive advantage (Klibi et al., 2010). As supply chain resilience can be built by making sustainable use of resources (Edgeman & Wu, 2016), firm's performance can be enhanced by incorporating sustainability in supply chains (Negri et al., 2021; Pinto, 2020). Sustainable supply chain provides an opportunity to achieve competitive advantage by enhancing performance and earning the loyalty of its customers (D'Agostini et al., 2017; Markley & Davis, 2007). Hence, it is vital to measure and understand sustainable supply chain performance (Kumar & Goswami, 2019). Following Kumar and Goswami (2019) and Schilke (2014), we argue that sustainable supply chain resilience and sustainable supply chain performance are two important building blocks of competitive advantage. Based on this discussion, we have the following set of propositions:

P6: Adoption of prescriptive analytical capabilities positively influence sustainable supply chain resilience, performance and competitive advantage.
P7: Sustainable supply chain resilience and sustainable supply chain performance positively influence competitive advantage.

6 Future research directions

This section highlights some interesting research opportunities for scholars working in the area of prescriptive analytics and sustainable operations research. In order to answer RQ3, the suggestions for future directions are developed as follows:

- From the content analysis, it is clear that research in applications of optimization technique in sustainable operations management is an emerging topic. In order to accelerate this adoption and maximise the full potential, it is critical to conduct theory-based research as it will provide a firm foundation to explore future avenues of research. This will also assist in developing theoretical frameworks for understanding the impact of employing deep learning tools in sustainability and operations research. Another aspect which is evident from the content analysis of theme 1 is the lack of studies on applications of blockchain in improving the healthcare by maintain the privacy of the patients and also in order to build smart healthcare.

- The content analysis of theme 2 exposes potential gaps in the area of sustainable operations management. Develop case studies with more emphasis on the application of prescriptive analytics tools like AI, machine learning and digital twin, in sustainable operation research area. Although there have been few studies on natural resource management, research should investigate specific problems of applications of prescriptive analytics on carbon emission, closed-loop supply chains and green supply chain management. Quantitative and case studies in this direction can be a valuable and fruitful area for future scholars. In addition, a thorough comparative study on different ranking tools would create transparency and add more values to decision makers. Another interesting research gap is the selection and usage of appropriate technique to identify the right analytical tool for firms with different strategical orientation.
- Although data mining techniques have been there for quite some time, safety and privacy issues associated with data are still largely understudied. This aspect when explored together with data quality issues would lead to an efficient decision-making process. Researchers should also identify the role of Deep Learning in understanding customer relationships management. In addition, application of latest statistical tools for data analysis would add more value to the services and products and enhance customer experience.
- In-depth content analysis has exposed research gap in sustainable supply chain management. It is witnessed that although research in this area has been evolving in these years, more empirical research is needed to see the role of AI in achieving sustainability in supply chain. In addition, research should further investigate and develop models for emission evaluation and social welfare associated with sustainability. With the concept of integrating analytical tools and supply chain, it would be interesting to further look into other supply chain aspects such as reverse logistics and closed-loop supply chain.
- From the content analysis, it is clear that research in disaster management has potential gaps. It is evident that usage of data analytics tools would be highly beneficial in all four phases of disaster management. For instance, more studies should be done to investigate the role of data in predicting disasters in advance for better preparedness and in locating injured people post-disaster. More specifically, virtual reality is tested so that better preparation can be fixed before any actual disasters. These studies can be also extended to different types of disasters like hurricanes, floods, and terrorist attacks. It is also evident that analytics and data mining techniques for risk mitigation and risk recovery is scant. Better modelling techniques for the recovery phase of the disaster, specifically post disaster housing, and comparison of different models and techniques would assist decision makers in better managing the situation.

7 Conclusions

We began this article with a brief overview of prescriptive analytics and its applications in sustainable operations research and highlighted the uniqueness of the current work. A content analysis was performed on 147 articles and from the five major themes, we identified the current research area and the scope for future research directions. Our study makes the following contributions that can help sustainable operations researchers position their research against this mapping.

- From the five main themes and the sub-themes developed in Sect. 3, it is evident that prescriptive analytics has substantially diffused in sustainable operations research (RQ1). The

applications of prescriptive analytics can be seen in the various areas of healthcare, inventory management, revenue management, supply chain management, wate management, water management, energy conservation, disaster management and many more.

- Five main themes (RQ2) and their sub-themes connecting prescriptive analytics and sustainable operations have been identified using content analysis. These are applications of optimization techniques, sustainable operations management, data mining and statistical techniques, sustainable supply chain management, and disaster management. By utilizing these themes, researchers can avoid saturated research ideas while working on their own research work.
- Having studied the past works on prescriptive analytics and sustainable operations in RQ2, the present and future (RQ3) of this research area can be found in Sect. 4. Five actionable future research directions are developed based on the content analysis for the scholars working in this area of research.
- A conceptual framework (RQ4) and a couple of propositions have been established in order to enhance our understanding about prescriptive analytics and its role in sustainable operations management. The framework is grounded in DCV and utilizes the three pillars of sustainable supply chain practices: environmental, social, and economic practices. We believe that this framework would bridge the gap between the theory and practice.

As rightly pointed out by Terwiesch (2019), Fisher et al. (2020) and Dubey et al. (2020), the primary objective of any theory-based study is to identify its relevance in the practical-world and explore the differences in theory and practice. Thus, we make an attempt to offer some practical implications of our study. First, by collating the recent published articles on prescriptive analytics and its applications in sustainable operations research, we intend to provide an overview to professionals and scholars trying to implement digital transformation strategy in their respective firms with the intent to achieve sustainable supply chain practices. Second, from the proposed conceptual framework, managers can understand the role of investing in supply chain practices: "environmental", "economic" and "social"; as these practices can accelerate the adoption of prescriptive analytical capabilities in a firm. Third, managers would realise how a firm's orientation can help them in implementing prescriptive analytical capabilities and gaining competitive advantage. It would be helpful for top managers to take decision of investing in these three supply chain practices.

Further, from the bibliometric analysis, it is quite evident that the pattern of publications is increasing over time which indicates that the applications of prescriptive analytics in sustainable operations research are growing significantly and prescriptive analytics has become an important tool for achieving sustainable supply chain performance, sustainable supply chain resilience and competitive advantage. Also, it is noticeable that the maximum number of articles that are published is from computer science followed by mathematics, engineering and business management area. Last, every country is working towards the area of prescriptive analytics, majorly countries like USA, UK, China and Canada are the most contributing ones. The study not only guides senior managers to focus on sustainable supply chain practices; environmental, economic and social, for the successful adaptation of prescriptive analytical capabilities, but also, helps in understanding the importance of firms orientation which acts as a mediating factor for implementing prescriptive analytics. From our descriptive statistics, practitioners can see which countries have made significant achievements in the area of prescriptive analytics and its application in sustainable operations. Also, the top subject areas will provide better understanding of the applications of prescriptive analytics in various fields and that would provide various future opportunities.

We believe that our study gives an accurate information of the recent development in the area of prescriptive analytics literature. We sincerely hope that our results and suggestions will contribute towards the improvement of the area and also inspire other scholars to develop work in order to fill the gaps identified. This study provides interesting research avenues for scholars or practitioners who want to explore the area of prescriptive analytics and sustainable operations research.

This study has its own limitations, some of which can stimulate future research. First, the data is collected using Scopus, so there could be a possibility of not including relevant research articles not registered in this database. Second, this study only focuses on peer-reviewed articles published in English which might not be enough for managers to understand this area and the challenges completely. In future, scholars could extend this work by including non-academic literature i.e., government and public sectors reports, white papers, newspaper articles, conference papers, editorials and books, and also the ones published in other languages for understanding problems from global perspective.

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