Technological Forecasting & Social Change 170 (2021) 120927

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

A fuzzy based hybrid decision framework to circularity in dairy supply chains through big data solutions

Yigit Kazancoglu [a], Muhittin Sagnak [b], Sachin Kumar Mangla [c,d,*], Muruvvet Deniz Sezer [e], Melisa Ozbiltekin Pala [f]

[a] Yasar University, Department of Logistics Management, Yasar University 35100 İzmir/Turkey
[b] Izmir Kâtip Celebi University, Department of Information and Document Management, Balatcik Kampusu, 35620, Cigli/Izmir/Turkey
[c] Jindal Global Business School, O P Jindal Global University, Haryana, India
[d] Plymouth Business School, University of Plymouth, Plymouth, United Kingdom
[e] Yasar University, Business Administration Department, Yasar University 35100 İzmir/Turkey
[f] Yasar University, Logistics Management Department, Yasar University 35100 İzmir/Turkey

A R T I C L E I N F O

Keywords:
Dairy supply chain
Barriers
Circular economy
Big data solution
Fuzzy ANP - VIKOR
Group decision making system

A B S T R A C T

This study determines the potential barriers to achieving circularity in dairy supply chains; it proposes a framework which covers big data driven solutions to deal with the suggested barriers. The main contribution of the study is to propose a framework by making ideal matching and ranking of big data solutions to barriers to circularity in dairy supply chains. This framework further offers a specific roadmap as a practical contribution while investigating companies with restricted resources. In this study the main barriers are classified as 'economic', 'environmental', 'social and legal', 'technological', 'supply chain management' and 'strategic' with twenty-seven sub-barriers. Various big data solutions such as machine learning, optimization, data mining, cloud computing, artificial neural network, statistical techniques and social network analysis have been suggested. Big data solutions are matched with circularity focused barriers to show which solutions succeed in overcoming barriers. A hybrid decision framework based on the fuzzy ANP and the fuzzy VIKOR is developed to find the weights of the barriers and to rank the big data driven solutions. The results indicate that among the main barriers, 'economic' was of the highest importance, followed by 'technological', 'environmental', 'strategic', 'supply chain management' then 'social and legal barrier' in dairy supply chains. In order to overcome circularity focused barriers, 'optimization' is determined to be the most important big data solution. The other solutions to overcoming proposed challenges are 'data mining', 'machine learning', 'statistical techniques' and 'artificial neural network' respectively. The suggested big data solutions will be useful for policy makers and managers to deal with potential barriers in implementing circularity in the context of dairy supply chains.

1. Introduction

Conserving the earth's resources is becoming a major issue as the traditional linear "take, do and throw" model adopted to date is losing its effect (Ellen MacArthur Foundation, 2013). In this context, the ability to include wastes in the production loop or to be recycled and used again is an important solution in terms of conserving resources (Joensuu et al., 2020). The concept of circular economy (CE), in which recycling, reuse and reduction principles are adopted, is based on higher resource effectiveness and eco-efficiency (Cruz Rios and Grau, 2019).

The circular supply chain is a form of management that enables the use of renewable, recyclable or biodegradable materials (Joensuu et al., 2020). The adoption of CE in supply chains minimizes waste (Kopyto et al., 2020) and reduces environmental impact (Clift and Wright, 2000). Furthermore, CE is extremely important, especially in terms of minimizing the losses in food supply chains (FSCs) (Kumar et al., 2021; Esposito et al., 2020).

Dairy supply chain management has a delicate structure as food

Abbreviations: CE, circular economy; FSC, food supply chain; GSC, green supply chain; ANP, Analytic network process; VIKOR, VlseKriterijumska Optimizacija I Kompromisno Resenje.

* Corresponding author.
E-mail addresses: yigit.kazancoglu@yasar.edu.tr (Y. Kazancoglu), muhittin.sagnak@ikc.edu.tr (M. Sagnak), sachin.kumar@plymouth.ac.uk, sachinmangl@gmail.com, smangla@jgu.edu.in (S.K. Mangla), deniz.sezer@yasar.edu.tr (M.D. Sezer), melisa.ozbiltekin@yasar.edu.tr (M.O. Pala).

https://doi.org/10.1016/j.techfore.2021.120927
Received 30 October 2020; Received in revised form 28 May 2021; Accepted 29 May 2021
Available online 10 June 2021

losses can be experienced at different stages of the chain. Due to the perishability of the products, it is necessary to be effective at each stage of the supply chain (Djekic et al., 2014). In order to prevent wastes from turning into losses, the CE concept can be adopted and the resulting wastes can be recaptured in the chain (Sharma et al., 2019). For example, waste products of dairy products such as whey, can be used as raw materials or biogas in the framework of CE and sustainability (Valenti et al., 2020). Recently, one of the most important solutions to ensure CE (Bag et al., 2020) and sustainability standards in dairy supply chains has been identified as the use of big data (Liu et al., 2020).

Humanity is no longer dependent on physical data storage elements. An innovative system called "big data", in which data is collected increasingly day by day, has been adopted (Sivarajah et al., 2017; Shamim et al., 2020). Moreover, supply chains generate enormous amounts of data (Mardani et al., 2020a). Therefore, almost all decisions taken by industries such as production decisions, deciding on the products themselves, how much and when to produce, investment etc. can be made based on this data. In particular, industries attach great importance to the data in order to reduce risks in their supply chains (Sivarajah et al., 2017). Businesses and their supply chains can also trust this data in optimizing their operations and processes (Quieroz et al., 2020).

Big data applications also provide various benefits to FSCs such as in data storage and processing of real-time knowledge (Ji et al., 2016). Therefore, relevant organizations in the FSC can achieve operational excellence allied with economic value with the help of big data applications (Liu et al., 2018). Especially in dairy supply chains because of perishability of products, big data could be vital to manage the supply chain efficiently (Kamilaris et al., 2017; Singh et al., 2018).

To the best of our knowledge, this is a unique study that considers identifying barriers to circularity in dairy supply chains and overcoming those barriers through big data solutions using a hybrid decision model. The research questions of this study can be specified as;

- **RQ1: What are the barriers to circularity in dairy supply chains?**
- **RQ2: What are the potential big data solutions to overcome barriers to circularity in dairy supply chains?**
- **RQ3: What is the ideal matching and ranking of big data solutions to overcome barriers to circularity in dairy supply chains?**

To find answers to the above questions, six main barriers and twenty-seven sub-barriers are identified based on a literature review. Determining these barriers are the key points to stating that there actually are main barriers to circularity and also sustainability in dairy supply chains. The weights of barriers are needed to find practical solutions based on the importance and impact of each barrier. With these issues in mind, we aim to find answers to our first research question as mentioned above. Furthermore, after considering the literature review, there is an obvious gap around a framework to find big data solutions for dairy supply chains as mentioned in the second research question. Therefore, there is a need to understand how big data solutions overcome such barriers. Subsequently, it is aimed to propose ideal matching and ranking of big data solutions corresponding to the barriers to find the best solutions to overcome those barriers as stated in the third research question. In addition, the case study is conducted in the dairy supply chain to indicate applicability of this study. As a motivation of the study, there is a need of analysing circularity of food, especially in dairy supply chains, and integrating new solutions based on new technologies (Tseng et al., 2019).

The main contribution of the study is to propose a framework by making ideal matching and ranking of big data solutions to barriers to circularity in dairy supply chains. From existing literature, to have circularity in supply chains, it is crucial to know the barriers to locate proper solutions (Tseng et al., 2019). The second major contribution of the study is to determine the importance order by knowing the weights of the barriers, thus providing a specific roadmap for circularity in the dairy sector. Large-scale group decision-making has been adopted to present the multi-stakeholder structure of the dairy supply chain with a holistic view.

The remaining sections of this paper are organised as follows. In Section 2, a literature review is provided. The literature review covers circularity in dairy supply chains, barriers in circular dairy supply chains, the need for big data in dairy supply chains and big data solutions in the dairy supply chain. Section 3 covers research methodology. Section 4 provides a case study. Section 5 presents implications for policymakers and managers. Finally, Section 6 details the conclusion of the study.

2. Literature Review

2.1. Circularity in Dairy Supply Chains

CE is a sustainable and innovation-based production model where different kinds of waste generated in a production system are re-evaluated, while minimizing the raw material cost and keeping resource efficiency and environmental benefit at the maximum level (Chaudhary and Vart, 2020). In a CE, waste is eliminated, materials are reused and recycled to reduce the industry's impact on the environment. CE has also been presented as an important part of sustainability (Stanchev et al., 2020). The CE focuses on resource use reduction, reuse and efficiency, while accelerating economic growth and linking directly to sustainable waste management, material and energy flow and redesign (Blomsma and Brennan, 2017).

Animal husbandry is one of the main types of farming, especially in emerging economies such as Turkey (FAO, 2013). Animal products and by-products are crucial for both human nutrition and the country's economy (Alao et al., 2017). Dairy products play an important role as they are extremely important for human nutrition, accounting for about 14% of total calorie consumption (Stanchev et al., 2020). In other words, dairy products are an essential source of human consumption (Alonso et al., 2019).

Losses or wastes occur when circularity is ignored across the chain from the production of dairy products to the consumption stage (Kayikci et al., 2019). Losses due to technological deficiencies, uncertain operations, the animal feed, the production and distribution of dairy products, waste products and how to use waste water have become very important issues in the dairy sector (Paraskevopoulou and Vlachos, 2020).

Considering the world's rapidly increasing population growth and demand increase, it becomes extremely important to minimize losses and to extract raw materials from waste (Ellen MacArthur Foundation, 2013). At this stage, the adoption of CE in dairy supply chains is the most important solution.

The dairy industry has waste materials with different characteristics depending on the product such as yoghurt, cheese, butter, milk, ice cream etc. (Rocha and Guerra, 2020). By-products contain a variety of valuable nutrients; so, re-use in the production process ensures the efficient use of nutrients in raw milk (Banaszewska et al., 2014). For example, whey is a main by-product of the dairy industry. This is also an important source of environmental pollution due to the large quantities generated, the high organic loads and their impact (Asunis et al., 2020). Whey includes valuable substances containing minerals and lactose such as functional proteins, peptides, lipids and vitamins. However, whey can be used in many ways as it is an ingredient in animal feed, food products, baked goods and beverages (Paraskevopoulou and Vlachos, 2020). It has also been widely used as a biogas infrastructure in animal feed or in unprocessed form (Stamatelatou et al., 2014).

In view of these considerations, there are various barriers to adopting a CE approach in dairy supply chains. These barriers can prevent the adoption of circularity and sustainability orientation in dairy supply chains. In the following section, a literature review about barriers in circular dairy supply chains is discussed.

2.2. Barriers to Circularity in Dairy Supply Chains

In FSCs, the depletion of natural resources, ascending quality standards, short shelf life and increasing food security and safety concerns of consumers have led to environmental degradation. This calls for business organizations to adopt sustainability and CE practices despite there being several barriers linked to this process. However, there are only a limited number of studies addressing the barriers to CE in the dairy industry (Bourlakis et al. 2014; Glover et al. 2014; Ghadge et al 2020).

Ghadge et al. (2020) used survey data to determine barriers and their priorities with the help of a fuzzy analytic hierarchy process to implement sustainability. They identified two main categories, internal and external, to classify these barriers. One of the internal barriers in implementation of CE is the initial cost of investment (Ghadge et al. 2017; Bourlakis et al., 2014). Since the initial implementation costs of sustainability and transformation to a CE are relatively high, investment costs pose an important barrier for companies with limited resources. Schrettle et al. (2014) suggested that it is necessary to effectively manage financial resources and the skillsets of the workforce to carry out successful sustainability and CE activities.

As one of the important actors of the global supply chain network, suppliers are considered as an important factor in the integration of sustainability practices and cooperation with supply chain partners (Grimm et al. 2014). The problem of supplier's commitments to supporting environmentally friendly initiatives for sustainability management can be caused by lack of information sharing in an FSC context (Mudgal et al., 2010; Schrettle et al. 2014; Ghadge et al. 2020). As a result of this, collaboration of all actors in the dairy supply chain is necessary to develop a sustainable environment (Govindan et al., 2014). Farooque et al. (2019) determined and investigated the causality relations of barriers to circular FSCs. Their study identified eight different barriers in FSC; these are "lack of financial resources", "limited expertise, technology, and information", "organizational culture and management", "uncertainty about benefits", "lack of economies of scale", "weak environmental regulations and enforcement", "lack of market preference/pressure" and "lack of collaboration/support from supply chain actors".

Organizations can adopt CE as a strong conceptual idea for planning and creating closed loop systems; they can further implement this concept to enhance food security and decrease food waste and spoilage (Pheifer, 2017; Kirchherr et al., 2017). These losses arise from the perishable and dynamic nature of food products and how they are managed (Tseng et al., 2018). Besides, the short shelf life of dairy products also creates issues in storage and the transportation stage of supply chains (Ghadge et al. 2020; Simms et al, 2020). Tseng et al. (2019) stated that technology and industry 4.0 tools can be used to tackle such challenges in dairy supply chains.

The food industry has a negative effect on environmental factors because of the lack of effective food processing and packaging systems (Zeng et al., 2021); huge amounts of food are also wasted. Simms et al. (2020) suggested that eco-innovation and technological improvements have several benefits to reduce these negative environmental effects. Besides, through an efficient technological process in dairy supply chains, various advantages such as waste hindering and reduction, reuse, energy recovery, recycling and disposal are provided. However, lack of integration between technological processes (Powell et al. 2017; Gianni et al. 2017) and eco-efficiency can cause important challenges in minimizing food waste, unnecessary material usage and inefficient resource usage (Simms et al. 2020). IMSA (2013) and Mont et al. (2017) highlighted that innovative circular business models can decrease waste and promote more efficient resources to achieve sustainable competitive advantages. Prior studies have considered eco-innovation adaptation as a barrier due to the lack of awareness and knowledge on sustainable and technological improvements (Long et al., 2016; Song et al., 2019; Shao et al., 2020). Moreover, eco-innovation processes and applications of CE activities require financial investment (Ghadge et al. 2017; Mont et al., 2017; Urbinati et al. 2018). Prendeville and Bocken (2017) suggested that the transition to CE needs research and development costs; these include the creation of new complementary network structures, product remarketing, remanufacturers and establishing reversing logistics companies. Therefore, increased research and development costs and lack of economic incentives in implementing CE can be considered as barriers to the dairy supply chain (Markianidou, 2015; Spaini, 2017; Mazzanti et al., 2016; Ghisellini and Ulgiati, 2020). In addition, IMSA (2013) stated that technical infrastructure deficiency is also a problematic issue for adopting CE. At the same time, businesses also need to improve their ability in using digital technologies (Hadar et al., 2015).

The lack of cooperation between supply chain actors has emerged with inadequate knowledge transfer between different partners (Despoudi, 2020; Schrettle et al., 2014; Eastwood et al., 2012). All actors through the dairy supply chain should integrate to create value. As a result, there is a need for collaboration and coordination among stakeholders to improve dairy production systems by sharing knowledge and resources (Bonamigo, 2016; do Canto et al., 2020). Khalafi et al. (2020) stated that green supply chain (GSC) incentives can improve the overall performance.

The ability to access data about where and how a product is made is a key issue in a food value chain. Lack of transparency and information sharing can hinder innovations in the dairy supply chain (Dolinska and d'Aquino, 2016; Bonamigo, 2016) leading to inadequate interaction between actors.

In addition, Yakovleva (2007) and Ghadge et al. (2020) stated that efficient use of natural resources, the development of sustainable food processes and the creation of safe, healthy and nutritious food for consumers are significant challenges; addressing these is difficult due to the complex and dynamic structure of a food value chain.

The safety and quality of dairy products affects the welfare of the consumer and has a direct impact in achieving higher competitive advantage in the dairy supply chain. According to Pant et al. (2015) public awareness of the need for increased food security, improved safety and better value of dairy products can only be achieved through supply chain traceability, transparency, data security and integrity (Roth et al. 2008; Ding et al. 2019). Agenbag and Lues (2009), Bailey and Garforth (2014) and Simms et al. (2020) concluded that a lack of quality control and assurance, the inadequacy of legal systems to build a circular system (Simms et al. 2020; Ghadge et al. 2020), lack of enterprise policies and missions in CE adoption plus inadequacies in environmental standards in the adoption of CE are considered as the major challenges to achieving sustainable competitive advantage (Pant et al. 2015; Ding et al. 2019; Simms et al., 2020).

With senior management support and commitment, the need to regulate dairy activity restrictions, increase productivity and improve technology can be improved (Somda et al. 2005; Ferenhof et al. 2019; Markard, 2020). Lamprinopoulou et al. (2014) highlighted the importance of innovation in creating shared value, suggesting that lack of management support can be a significant barrier to enhancing high technology adoption levels in the dairy supply chain. Failure to procure the support of top management and lack of coordination among all stakeholders in the supply chain emerged as important barriers in achieving CE in the dairy supply chain (Ferenhof et al. 2019).

Current literature shows that it is important to determine barriers to circularity in the dairy supply chain. It is necessary to tackle the challenges faced in economic, social and legal, environmental and technological facets of supply chain management in order to gain competitive advantages. Therefore, this study needs to address the barriers suggested in Table 1 to create more sustainable and circular dairy supply chains. 27 barriers have been identified with six main dimensions developed to determine the challenges when implementing CE in the dairy sector.

When considering by-products derived from dairy products, it is important to take a holistic and integrated approach to CE (Fassio and Tecco, 2019). However, to manage dairy supply chains in the CE context, some innovative big data solutions can be considered

Table 1
Barriers to Circularity in Dairy Supply Chains

Main Dimensions	Barriers	Author(s)
ECONOMIC DIMENSIONS	Lack of economic incentives by implementing CE	Mazzanti et al., 2016; Ghisellini and Ulgiati, 2020
	High cost of implementation of various 'R' initiatives	Bourlais et al, 2014; Ghadge et al., 2020
	Increased research and development cost	Markianidou 2015; Spaini 2017; Urbinati et al., 2018; Micoli 2018; Ghisellini and Ulgiati, 2020
	High investment cost for circular system transformation	Ghadge et al., 2017; Mont et al., 2017; Ghadge et al., 2020
SOCIAL AND LEGAL DIMENSIONS	Inadequacy of legal systems to build a circular system	Pheifer, 2017; Simms et al., 2020; Ghadge et al., 2020
	Inadequate knowledge transfer between different partners	Eastwood et al., 2012; Schrettle et al., 2014; Ferenhof et al., 2019; Despoudi, 2020
	Lack of skilled workforce to implement CE	Schrettle et al., 2014; Farooque et al., 2019
	Lack of supplier's commitment in building a circular system	Mudgal et al., 2010; Gualandris and Kalchschmidt, 2014; Schrettle et al., 2014; Ghadge et al., 2020
ENVIRONMENTAL DIMENSIONS	Inefficient environmental standards for CE adoption	Agenbag and Lues 2009; Bailey and Garforth, 2014; Farooque et al., 2019
	Problems related to carbon emissions while closing the loop of supply chain	Jouzdani and Govindan, 2020
	Lack of efficient use of resources	Simms et al.. 2020; Powell et al., 2017; Gianni et al., 2017
	Lack of incentives for GSC	Khalafi et al. 2020
TECHNOLOGICAL DIMENSIONS	Issues related to data security, integration and privacy	Roth et al., 2008; Pant et al., 2015; Ding et al., 2019
	Technical infrastructure deficiency in CE adoption	IMSA, 2013
	Lack of integration between technological processes and eco-efficiency	Urbinati et al., 2018; Micoli, 2018; Farooque et al., 2019; Simms et al., 2020
	Lack of implementation of emerging technologies	Farooque et al., 2019; Tseng et al.,2019
SUPPLY CHAIN MANAGEMENT DIMENSIONS	Difficulties in establishing the balance between supply and demand	Tseng et al., 2018; Tseng et al., 2019
	Little understanding and knowledge about CE in dairy supply chain	Eastwood et al., 2012; Bonamigo et al., 2016; Long et al., 2016
	Inefficient information sharing system across the value chain	Dolinska and d'Aquino, 2016; Bonamigo, 2016
	Lack of transparency across the value chain	Roth et al., 2008; Pant et al., 2015; Ding et al., 2019
	Inability to cope with the dynamic nature and complexity of the dairy supply chain	Yakovleva 2007; Ghadge et al. 2020
	Shorter product life style	Ghadge et al., 2020; Simms et al., 2020
STRATEGIC DIMENSIONS	Lack of enterprise policies and missions in CE adoption	Pant et al., 2015; Ding et al., 2019; Simms et al., 2020
	Inefficient top management commitment and support	Somda et al., 2005; Lamprinopoulou et al., 2014; Ferenhof et al., 2019
	Lack of collaboration, coordination and cooperation among stakeholders	Bonamigo et al., 2016; Mont et al., 2017; Ferenhof et al., 2019; Farooque et al., 2019; Simms et al., 2020; Ghadge et al., 2020; do Canto et al., 2020
	Lack of effective business models and frameworks in implementing CE	IMSA 2013; Mont et al., 2017
	Issues related to cultural change during CE adoption	Kirchherr et al., 2018; Pheifer 2017; Farooque et al., 2019

(Kamilaris et al., 2017; Mani et al., 2017; Liu et al., 2020). The need for big data solutions to achieve circularity in dairy supply chains is explained in detail below.

2.3. Big Data in the context of Dairy Supply Chains

Recently, supply chains have been transformed into a complex structure in the increasingly competitive business environment (Rajesh, 2017; Quieroz et al., 2020). In order to survive in this competitive environment, businesses act according to the data they collect; this includes making general production decisions, deciding which products will be produced for how much and when (Rialti et al., 2020). However, such data is vital not only for production but is needed at every stage of the supply chain (Roßmann et al., 2018; Maheshwari et al., 2021).

Big data applications have now been extended to different areas such as health (Liao et al., 2018), finance, intelligence, tourism, education, food and marketing technologies (Papadopoulos et al., 2021; Wang et al., 2020). The food sector, one of the most comprehensive and topical areas, is also influenced by the power of big data and advanced analytical technologies; this change manifests itself at every stage from food production to the consumer, starting from agricultural processes (Kamble et al., 2020; Kazancoglu et al., 2021).

It has become important to obtain real-time and accurate data in order to reduce food losses in dairy supply chains, ensure sustainability and survive in the competitive environment; this is especially relevant due to perishability and the short shelf life of dairy products (Gholizadeh et al., 2020). The dairy supply chain consists of production of feed for animal, dairy production, dairy product transportation, processing, packaging, distribution, retail and consumer (Glover, 2020).

Losses in dairy products are experienced at different stages of the supply chain, from procurement and production to the time it reaches the customer (Stanchev et al., 2020). There are many reasons for these losses such as animal diseases, deficiencies in slaughtering, technology deficiencies or unregistered production. As an important food source, dairy products need control at each stage of the supply chain (Cannas et al., 2020). For example, milk, one of the main dairy products, produced after milking should be cooled at 4C within a certain period of time (SNV, 2017). Having a temperature control inside the tank to be used for cooling the milk and connecting the system to the internet with the correct data formation will produce the necessary information during the cooling stage of the milk (Balaman, 2019). In order to be successful in reaching the consumers of perishable dairy products, accurate and real-time data flow is required (Yu et al., 2020). Sensors to collect data with radio frequency identification systems or cameras etc., they undertake functions in scales (He et al., 2020).

Big data can be used as a solution to overcome CE barriers in dairy supply chains. Big data analytics is a powerful technology-based industry 4.0 tool to cope with the development of the transformation of GSC networks by increasing information sharing among stakeholders by providing real-time information flow and sharing facilities (Shamim et al., 2020).

The present work focuses on seven types of big data techniques; optimization, data mining, machine learning, cloud computing, statistical techniques, artificial neural network and social network analysis can overcome the barriers encountered in adopting the CE in the dairy supply chain. The challenges confronted in economic, environmental, technological and supply chain dimensions can be tackled with one of the big data solutions, machine learning. Machine learning operates by learning behaviours through simulations, by constantly exploring existing knowledge structures, thus creating new information to support decision making (Huo and Chaudhry, 2020; Liu et al., 2020). Machine learning increases the cost effectiveness of reproduction processes by dealing with uncertainties in prices, customer behaviours, markets and competitors (Carbonneau et al., 2008; Seyedan and Mafakheri, 2020; McKinsey and Company, 2020). Information sharing problems where stakeholders need to be related with the system can be overcome by managing uncertainties (Raut et al. 2019). The high cost of implementation of various 'R' initiatives allied with higher research and development costs can be decreased through machine learning as well (Seyedan and Mafakheri, 2020; McKinsey and Company, 2020; Chalmeta and deLeón, 2020). Machine learning encourages businesses to evaluate their environmental performance focused data such as CO_2 emissions and build insights to improve their green performance (Wu et al., 2016; Shabanpour et al., 2017; Mardani et al., 2020b; Liu et al., 2020). Developing efficient environmental standards for CE adoption becomes possible (Wu et al. 2016; Dubey et al. 2015).

The optimization models include genetic algorithms, simulated annealing, tabu search and evolutionary algorithms (Hedar and Fukushima, 2006). Searches are made to find optimal solutions under the constraints. The above-mentioned models could also be effective in dealing with environmental risks by modelling the environmental impacts of the value chain operations, such as the effective use of resources (Dekker et al. 2012; Liu et al., 2020). Meneghetti and Monti (2015) and Seyedan and Mafakheri (2020) suggested that optimization tools can be used to deal with high investment and implementation costs for circular system transformation in unforeseen demand forecasts. Optimization models provide a data driven decision-making environment for supply chain managers to increase a firm's performance (Martínez-Caro et al., 2020). Using this model, managers can deal with barriers such as lack of effective business models and frameworks in implementing CE (Zhao et al., 2017; Niu and Zou 2017). The nature of supplier relationships and supplier commitment to the processes in CE is an important indicator for effective supply chain design. Therefore, optimization models ensure the best supplier options by dealing with multiple uncertainty factors (Singh et al. 2018; Raut et al., 2019; Liu et al., 2020; Del Giudice et al., 2020).

When it comes to data mining, this is carried out through different algorithms that have been developed. This means that new knowledge can be discovered to investigate large volumes of data. Therefore, this information gives an opportunity to collaborate, coordinate and cooperate (Dubey et al. 2018; Arunachalam et al., 2018). Exploring and investigating this data with the help of data mining leads to improved transparency and security in the supply chain (Eugene et al. 2017; Pappas et al. 2018) and to increasing understanding and knowledge about CE in the dairy supply chain (Choi et al. 2018; Geissdoerfer et al., 2018; Liu et al., 2020). Data mining techniques also aim to offer approaches to improve forecasts by dealing with the challenge of short-term forecasting for food products with high demand uncertainty and short shelf-life (Maaß et al, 2014). In addition, with an accurate forecast, the issues in establishing the balance between supply and demand can also be managed (Pappas et al. 2018; Blackburn et al., 2015; Arunachalam et al. 2018). Data mining also helps businesses to make strong predictions for future decisions by analysing their historical data and making analyses based on these predictions (Gregor et al. 2006; Richey et al., 2016; Jeble et al. 2018). Using data mining, organizations are also motivated to improve their organizational and technical capabilities to extract value from data. Therefore, companies can also improve their technical infrastructure based on digital technologies (Dubey et al. 2015; Pappas et al. 2018). Legal standards also demand data integrity for creating useful data sources and to provide security (Basukie et al., 2020). By creating clear legal standards for government data mining, issues related to inadequacy of legal systems to build a circular system can be addressed (Seele 2017; Zhang et al. 2018; Wu and Huang 2018).

With the adoption of cloud technology, all stakeholders in the supply chain can be accessed and further information sharing can be facilitated to deal with inadequate knowledge transfer among different partners (Neaga et al. 2015; Arunachalam et al. 2018; Ergun et al., 2020). This helps in promoting a positive circular supply chain culture by providing knowledge and education to increase the skills of the workforce who are tasked to implement CE (Singh et al., 2018).

Statistical techniques is a fundamental aspect of big data solutions. They provide collection and analysis of big data including correlation, regression, forecasting, clustering and classification (Choi et al., 2018; Iqbal et al., 2020). These techniques can help a business in providing insight into potential patterns of green practices (Zhang et al. 2018) based on historical data to deal with environmental challenges such as carbon emissions (Song et al., 2020) and determining green suppliers (Tseng et al., 2019; El-Kassar and Singh 2019; Liu et al., 2020). Forecasting enhances accuracy of demand in the supply chain by predictive analysis. In addition, it enables companies to make better decisions by making effective production planning and inventory management based on real-time forecast demands (Lee and Klassen, 2008; El-Kassar and Singh, 2019).

Artificial neural network is a useful tool to monitor and control the complex nature of supply chains. By investigating the complex relationships between supply chain components and actors via artificial neural network, it can cope with the dynamic nature and complexity of the dairy supply chain (Chen and Zhang, 2015). Big data tools can be used to better understand how supply chain processes should be designed, how operations and networks will be coordinated and how the supply will be provided in cooperation with CE concepts (Gupta et al, 2019).

Social network analysis is useful in managing different business operations whose structure changes during the adoption of CE (Lea et al, 2006) and further improving their performance by optimizing the CE activities in their supply chains (Müller et al., 2018). It is an important solution tool to help supply chain managers to develop policies (Khedra et al., 2019) that are suitable for changing conditions as a result of adapting CE while making strategic and operational decisions (Tseng et al., 2018; Polyakova and Thalassinos, 2019).

In order to deal with CE focused barriers, a framework that matches big data solutions corresponding to each barrier within the dairy supply chain is presented in Fig. 1.

The barrier list includes six main barriers, 27 sub-barriers and seven big data solutions. The main barriers cover economic, social and legal, environmental, technological, supply chain management and strategic barriers. Big data solutions include machine learning, optimization, data mining, cloud computing, artificial neural network, statistical techniques and social network analysis. Each big data solution was matched with CE barriers in order to show which solution is useful for each particular barrier. The proposed framework is generic and applicable to similar studies where CE barriers in other industrial sectors are studied; however, the results are unique and are not generalized for different sectors.

3. Methodology

Figure 2 shows the overall flow of the present work. Based on an extensive literature review, the barriers to circularity and corresponding big data solutions were derived. The proposed barriers and big data solutions are further validated by three academics, four industry and two governmental experts. The academic experts consist of professors in

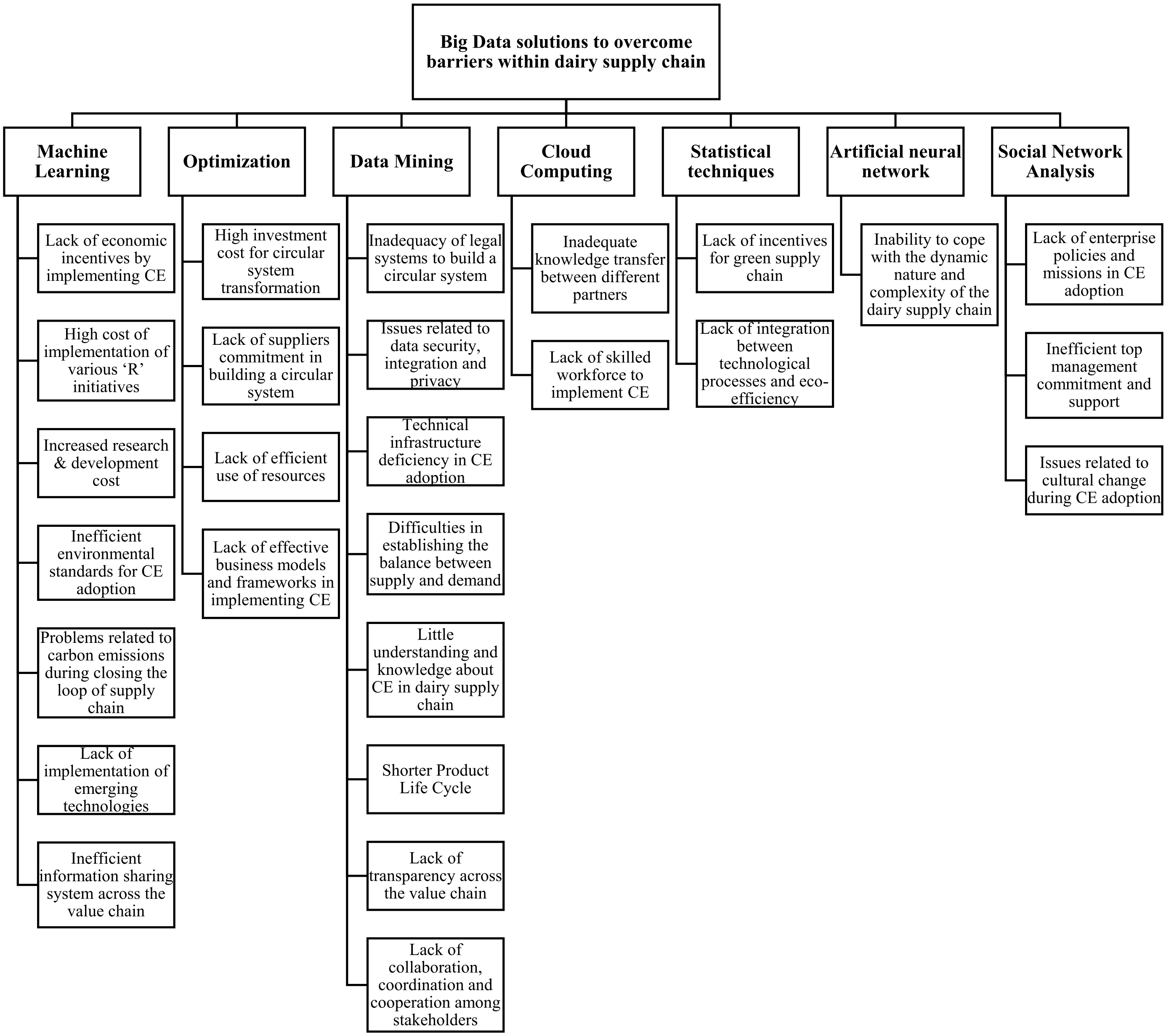

Fig. 1. A framework to match big data solutions to the barriers

universities from food engineering, information technology and supply chain management. The industrial experts include four supply chain experts in the dairy sector. Supply chain managers of a well-known company in the dairy sector are selected. These experts have experience in the sector of more than 20 years. The two governmental experts are selected from the Republic of Turkey Ministry of Agriculture and Forestry and Turkey Milk Producers' Central Union. The barriers and proposed big data solutions are discussed with these experts through interviews. After the validation stage, the barriers were matched with each big data solution. The Fuzzy ANP technique is then implemented to find the respective weights of the barriers, whereas the fuzzy VIKOR method is implemented to rank the big data solutions. The reason for using fuzzy logic is its capability to deal with uncertainties and vagueness inherent in the decision-making process (Zadeh, 1965). The reason for selecting fuzzy ANP is that it is one of the most common and effective multi-criteria decision-making (MCDM) techniques to calculate weights of different criteria. Also, fuzzy ANP helps decision-makers to deal with every type of feedback and dependence (Yadav and Singh, 2020). Fuzzy VIKOR also has the ability to rank a set of alternatives with respect to conflicting criteria.

Next, fuzzy set theory, fuzzy ANP and fuzzy VIKOR techniques are introduced.

3.1. *Fuzzy Set Theory*

Any decision-making process includes uncertainties owing to the vagueness inherent in the process itself. In attempting to deal with uncertainty, fuzzy set theory was introduced by Zadeh (1965). This theory helps decision-makers to minimize any human subjectivity and vagueness. A fuzzy set is called an objects group with a continuum of grades. In this paper, triangular fuzzy numbers indicated as l_{ij}, m_{ij}, r_{ij} were used (Ayouni et al., 2021).

3.2. *Fuzzy Analytical Network Process (FANP)*

Saaty (1996) introduced the Analytic Network Process (ANP) technique. It is one of the most common MCDM techniques. Its main advantage is its capability to cope with qualitative and quantitative

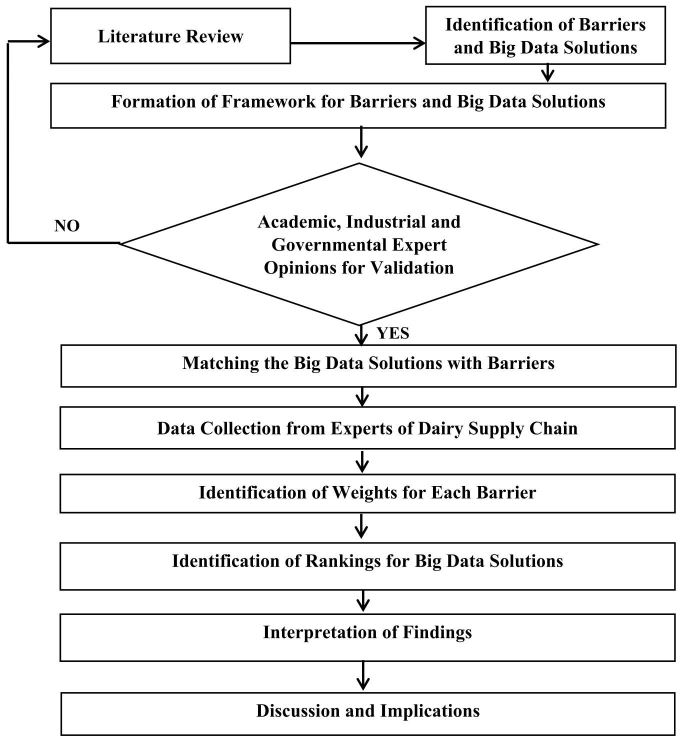

Fig. 2. The overall flow of present research work

variables (Sagnak and Kazancoglu, 2019). However, its applicability is limited due to the uncertainties and vagueness inherent in the decision-making process (Kazancoglu et al., 2020). Therefore, in this study, ANP was integrated with fuzzy set theory.

Fuzzy ANP is different to Saaty's (1996) approach (Kazancoglu et al., 2020). Pairwise comparisons were carried out using triangular fuzzy numbers. Saaty's (1980) scale has advantages in terms of simplicity; however, using fuzzy numbers instead of crisp values to translate human judgments into numerical values is always a better option with regards to flexibility and eliminating vagueness in the decision-making process. Linguistic terms (equally important (E), moderately more important (M), strongly more important (S), very strongly more important (VS) and extremely more important (EM)) were used to establish the preferences of the decision-makers.

The steps of Fuzzy ANP are as follows (Sagnak and Kazancoglu, 2019; Yadav and Singh, 2020):

Step 1: Establishment of pairwise comparisons: pairwise comparisons were established to identify the relations among criteria.
Step 2: Formation of initial super matrix: the initial super matrix is formed to present the relative importance of cluster k to cluster 1.
Step 3: Weighted super matrix formation: the weighted super matrix is formed by multiplying the first element of the respective eigenvector by all entries in the first block of that column, second element by second block and so on.
Step 4: Formation of limit super matrix: the limit super matrix is calculated by taking the power of the weighted super matrix until all values for the same row are the same.
Step 5: Normalization: the final weights are found by the normalization process for each block of the limit super matrix.

3.3. Fuzzy VIKOR

The VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) method has been used by Opricovic (1998) and Opricovic and Tzeng (2002) (Salimi et al., 2020). The objective of the VIKOR method is defined as the selection of the best solution among other alternatives (Alsolame and Alshehri, 2020).

Usually, the VIKOR method is implemented with fuzzy logic due to the vagueness and subjectivity inherent in the decision-making process (Salimi et al., 2020; Akram et al., 2021).

Opricovic (2011) and Liu et al. (2012) summarized the application stages of Fuzzy VIKOR as follows:

Stage 1: Finding the fuzzy best and the fuzzy worst values: The fuzzy best value $\widetilde{f}_j^* = (l_j^*, m_j^*, r_j^*)$ and fuzzy worst value $\widetilde{f}_j^- = (l_j^-, m_j^-, r_j^{-*})$ are found using the following formulas, respectively.

$$\widetilde{f}_j^* = \underset{i}{max} \widetilde{x}_{ij}$$

$$\widetilde{f}_j^- = \underset{i}{min} \widetilde{x}_{ij}$$

Stage 2: Finding the fuzzy difference: the fuzzy difference $\widetilde{d}_{ij}$ is found by:

$$\widetilde{d}_{ij} = \left(\widetilde{f}_j^* - \widetilde{x}_{ij}\right) \Big/ \left(r_j^* - l_j^-\right)$$

Stage 3: Calculating the Si and Ri values: the separation values, $\widetilde{S}_i$, and $\widetilde{R}_i$ of i^{th} alternative are found by:

$$\widetilde{S}_i = \sum_{j=1}^{m} \widetilde{w}_j \times \widetilde{d}_{ij}$$

$$\widetilde{R}_i = \underset{j}{max} \widetilde{w}_j \times \widetilde{d}_{ij}$$

where $\widetilde{S}_i = (S_i^l,\ S_i^m,\ S_i^r)$ is a weighted sum with regards to the separation value of i^{th} option from f_j^*. Likewise, $\widetilde{R}_i = (R_i^l,\ R_i^m,\ R_i^r)$ identifies the separation value of i^{th} alternative from f_j^-; w_i is the weight of respective criterion, C_j.

Stage 4: Finding the Qi value: the value of $\widetilde{Q}_i = (l_i, m, r_i)$ is found by

$$\widetilde{Q}_i = v\left[\left(\widetilde{S}_i - \widetilde{S}^*\right) \Big/ \left(S^{-r} - S^{*l}\right)\right] + (1-v)\left[\frac{\widetilde{R}_i - \widetilde{R}^*}{R^{-r} - R^{*l}}\right]$$

where $\widetilde{S}^* = min_i \widetilde{S}_i$, $\widetilde{S}^{-r} = max_i \widetilde{S}_i^r$, $\widetilde{R}^* = min_i \widetilde{R}_i$, $\widetilde{R}^{-r} = min_i \widetilde{R}_i$. v is used as weight for the maximum group utility, whereas $(1 - v)$ is used as weight for individual regret. The best values of S and R are represented as $\widetilde{S}^*$ and $\widetilde{R}^*$, respectively. Then, in order to find the crisp numbers, $\widetilde{S}_i$, $\widetilde{R}_i$, and $\widetilde{Q}_i$ values are defuzzified. After the defuzzification process, the values of S_i, R_i and Q_i are organized in ascending order. The best solution is provided by the minimum Q_i value when the following two circumstances are fulfilled:

1 $Q(A^{(2)}) - Q(A^{(1)}) \geq DQ$, where $A^{(1)}$, and $A^{(2)}$ is the first- and second-best alternatives, respectively.
2 $A^{(1)}$ must also be found as best alternative regarding S_i, and R_i values (Sanayei et al., 2010).

4. Case Study

This paper shows the real-world applicability of the proposed framework. A study is conducted in a food company including dairy, meat and soft drink sectors located in Izmir, Turkey. This dairy products company has one of the largest production facilities in Turkey and has well-established trademarks. The reason to select a food company is the critical importance of CE within a dairy supply chain. The company aims to protect the environment and reduce waste by using resources efficiently. Thanks to the TS EN ISO 14001 Environmental Management System, the company is focused on minimizing their negative impacts on the environment. The CE focuses on sustainable waste management, efficient resource use and material flow, thus accelerating economic growth (Blomsma and Brennan, 2017). The company, which has a multi-stakeholder supply chain structure, aims to ensure food safety and improve food quality. The company is also committed to making decisions quickly and accurately using digital technologies to ensure flow throughout the supply chain. It is important for the case company to overcome the obstacles in implementing a sustainable and CE culture in the supply chain to achieve these goals.

Within this framework, the case dairy company hopes to improve the traceability of their chain activities. The company aims to obtain accurate and simultaneous data in order to ensure circularity and sustainability in dairy supply chains and to survive in a competitive environment in spite of the perishability and shorter shelf life of their dairy products. The dairy supply chain faces several problems due to its multi-stakeholder, dynamic and complex structure to create safe, healthy and secure food for consumers. Therefore, for the company, it is important to identify and deal with barriers in adopting sustainable and CE processes. In order to deal with these barriers, big data solutions can be adopted into the food supply chain. Big data solutions provide opportunities to companies and help to overcome barriers by enhancing supply chain capacity and ensuring waste minimization by effective logistics and production scheduling in the food supply chain (Zhong et al., 2016).

In the data collection process, data was gathered through pairwise comparisons. These comparisons are conducted with the permission and approval of the Board of Directors. Large-scale group decision-making has been adopted in order to present the multi-stakeholder structure of the dairy supply chain with a holistic perspective. Thirty authorities - Supply Chain Manager, Supply Chain Vice Manager, Sustainability Manager, Information Technology Manager, Information Technology Vice Manager, Total Quality Manager, Total Quality Vice Manager, Operations Manager, Operations Vice Manager, three raw milk suppliers, two other suppliers, Information Technology Expert, Sustainability Expert, Circularity Expert, three customers, Company Consultant, Ministry of Agriculture and Forestry Personnel, Ministry of Industry and Technology Personnel - carried out pairwise comparisons. Table 2 presents information about the participants in detail.

The weights of the main barriers and sub-barriers are shown in Tables 4 and 5, respectively. These weights were found by applying the step-by-step formation of Fuzzy ANP. Firstly, pairwise comparisons were established to identify the relations among criteria. As an example, Table 3 shows the pairwise comparison matrix of one of the experts for the main barriers.

Then, the initial super matrix is formed to present the relative importance clusters. Weighted super matrix is then calculated. Lastly, the limit super matrix is obtained by taking the power of weighted super matrix until all values for the same row are the same. After all values are normalized, the weights were finalized as seen in Tables 4 and 5.

According to Table 4, the most important barrier for CE was seen to be economic barriers with a weight of 0.241, followed by technological and environmental barriers with weights of 0.198 and 0.169, respectively. Analysis of the results demonstrated that economic, technological and environmental barriers have a total of 60% importance weight. The remaining 40% comes from social and legal, supply chain and strategic barriers.

According to Table 5, the most important barrier for CE was high investment cost for circular system transformation with a weight of 0.076, followed by high cost of implementation of various 'R' initiatives, increased research and development cost, inefficient environmental standards for CE adoption, and problems related to carbon emissions while closing the loop of supply chain; weights are 0.070, 0.064, 0.061 and 0.051, respectively. Analysis of the results demonstrated that among 27 sub-barriers, high investment cost for circular system transformation, high cost of implementation of various 'R' initiatives, increased research and development cost, inefficient environmental standards for CE adoption and problems related to carbon emissions while closing the loop of supply chain have 32% importance weight.

Table 6 shows the rankings of the big data solutions in order to overcome the barriers associated with a CE. The rankings for the barriers are obtained through the fuzzy VIKOR method.

According to Table 6, optimization is the most important big data solution for overcoming CE barriers. The other important solutions are data mining, machine learning, statistical techniques and artificial neural network.

5. Discussions and Research Implications

CE is very important in terms of recycling wastes and obtaining new products (Esposito et al., 2020). The CE approach, especially in dairy supply chains with short shelf lives, ensures the continuity of operations and the utilization of waste (Sharma et al., 2019). This study makes a practical contribution to the industry by proposing a framework to make ideal matching and ranking of big data solutions to barriers to circularity in dairy supply chains. The importance order offers a specific roadmap for companies who need to invest but have restricted resources at their disposal. In contrast with other studies (Ahearn et al., 2016; Annosi et al., 2021; Astill et al., 2019; Duong et al., 2020), this study is focused

Table 2
Information about Participants

Experts	Position	Total Work Experience in Years	Experts	Position	Work Experience (Years)
1	Supply Chain Manager	12	16	Information Technology Expert	6
2	Supply Chain Vice Manager	8	17	Information Technology Expert	8
3	Sustainability Manager	6	18	Information Technology Expert	6
4	Sustainability Vice Manager	4	19	Information Technology Expert	5
5	Information Technology Manager	11	20	Sustainability Expert	4
6	Information Technology Vice Manager	8	21	Sustainability Expert	5
7	Total Quality Manager	10	22	Sustainability Expert	4
8	Total Quality Vice Manager	7	23	Circularity Expert	3
9	Operations Manager	9	24	Circularity Expert	3
10	Operations Vice Manager	4	25	Customer 1	8
11	Raw Milk Supplier 1	3	26	Customer 2	9
12	Raw Milk Supplier 2	4	27	Customer 3	10
13	Raw Milk Supplier 3	6	28	Company Consultant	5
14	Other Suppliers	4	29	Ministry of Agriculture and Forestry Personnel	7
15	Other Suppliers	4	30	Ministry of Industry and Technology Personnel	8

Table 3
Pairwise comparison matrix of one expert for main barriers

Main Barriers	Economic	Social and Legal	Environmental	Technological	SCM	Strategic
Economic	1	M	M	M	M	E
Social and Legal		1	1/M	E	E	1/M
Environmental			1	E	M	E
Technological				1	M	M
SCM					1	E
Strategic						1

Table 4
Weights of Barriers

Barriers	Weights
Economic Barriers	0.241
Social and Legal Barriers	0.103
Environmental Barriers	0.169
Technological Barriers	0.198
Supply Chain Barriers	0.135
Strategic Barriers	0.154

Table 6
Rankings of Big Data Solutions

Rankings	Solutions	Q_j
1	Optimization	0.076
2	Data Mining	0.082
3	Machine Learning	0.368
4	Statistical Techniques	0.640
5	Artificial Neural Network	0.687
6	Social Network Analysis	0.920
7	Cloud Computing	1.000

Table 5
Sub-Barrier Weights

BARRIER	SUB-BARRIERS	WEIGHTS
Economic	Lack of economic incentives by implementing CE	0.046
	High cost of implementation of various ‘R’ initiatives	0.070
	Increased research and development cost	0.048
	High investment cost for circular system transformation	0.076
Social and Legal	Inadequacy of legal systems to build a circular system	0.036
	Inadequate knowledge transfer between different partners	0.018
	Lack of skilled workforce to implement CE	0.027
	Lack of supplier’s commitment in building a circular system	0.021
Environmental	Inefficient environmental standards for CE adoption	0.061
	Problems related to carbon emissions while closing the loop of supply chain	0.051
	Lack of efficient use of resources	0.028
	Lack of incentives for GSC	0.029
Technological	Issues related to data security, integration and privacy	0.049
	Technical infrastructure deficiency in CE adoption	0.064
	Lack of integration between technological processes and eco-efficiency	0.045
	Lack of implementation of emerging technologies	0.040
Supply Chain Management	Difficulties in establishing the balance between supply and demand	0.019
	Little understanding and knowledge about CE in dairy supply chain	0.033
	Inefficient information sharing system across the value chain	0.019
	Lack of transparency across the value chain	0.024
	Inability to cope with the dynamic nature and complexity of the dairy supply chain	0.018
	Shorter product life cycle	0.023
Strategic	Lack of enterprise policies and missions in CE adoption	0.044
	Inefficient top management commitment and support	0.038
	Lack of collaboration, coordination and cooperation among stakeholders	0.024
	Lack of effective business models and frameworks in implementing CE	0.025
	Issues related to cultural change during CE adoption	0.022

solely on dairy supply chains.

According to Bourlakis et al. (2014) and Ghadge et al. (2020), the most important barrier for dairy and FSCs based on CE and sustainability is determined as “cost of investment”; this equates to ‘economic barriers’ in this study. Similarly, in this paper, “economic barriers” are selected as the most important barriers followed by “social and legal”, “environmental”, “technological”, “supply chain management” and “strategic” barriers. Under “economic” barriers, “high investment cost for circular system transformation” is determined as the most important barrier ahead of “lack of economic incentives by implementing CE”, “high cost of implementation of various ‘R’ initiatives” and “increased research and development cost”.

The second important barrier is determined as “technological”. Having solutions for “technological” barriers provides benefits to CE in FSCs (Simms et al., 2020). Under “technological” main barriers, “technical infrastructure deficiency in CE adoption”, “issues related to data security, integration and privacy”, “lack of integration between technological processes and eco-efficiency” and “lack of implementation of emerging technologies” are prioritized according to their importance rates, respectively.

Farooque et al. (2019) stated that lack of market preference and environmental regulations are key barriers in circular FSCs. However, in this study, the “environmental” barrier is selected as the third most important barrier among “economic”, “social and legal”, “technological”, “supply chain management” and “strategic” barriers in contrast with Farooque et al. (2019). Under “environmental” barriers, “inefficient environmental standards for CE adoption” is determined as the most important barrier ahead of “problems related to carbon emissions while closing the loop of supply chain”, “lack of incentives for GSC” and “lack of efficient use of resources”, respectively

“Strategic” barriers are selected as the fourth important barrier within the main barriers. According to Ding et al. (2019), barriers about strategies prevent sustainability and CE practices in FSCs. Under “strategic” barriers, “lack of enterprise policies and missions in CE adoption” is selected as the most important barrier followed by “inefficient top management commitment and support”, “lack of effective business frameworks and models in implementing CE”, “lack of collaboration, coordination and cooperation among stakeholders”, “issues related to cultural change during CE adoption” and “lack of enterprise policies and missions in CE adoption”, respectively.

“Social and legal” barriers are determined as the least important barrier among the others. However, “inadequacy of legal systems to build a circular system” is determined as the most important barrier in this category, similar to the findings of Schrettle et al. (2014). Other barriers under "social and legal" are "lack of skilled workforce to implement CE", "lack of suppliers commitment in building a circular system" and "inadequate knowledge transfer between different partners", respectively.

From a managerial perspective, these results show that barriers to circularity and sustainability in food chains, especially in the dairy sector, can be improved with "big data" solutions. According to the ranking of big data techniques, it can be seen that optimization provides benefits for almost every type of problem. However, when there are NP-hard problems, optimization might not be an effective solution. Therefore, machine learning and data mining can be used as solution measures for barriers to CE and sustainability in dairy FSCs. Optimization techniques prevent not only economic problems but also evaluate other issues such as environmental, social and supply chain management factors by modelling the impacts of the operations of the companies in the dairy sector (Liu et al., 2018). In this study, "high investment cost for circular system transformation", "lack of suppliers' commitment in building a circular system", "lack of efficient use of resources", "lack of effective business models and frameworks in implementing CE" problems can be tackled by integrating optimization techniques with existing dairy supply chain operations to improve circularity and sustainability in these supply chains.

In the food industry, data mining is an extremely useful method for dealing with food products with high demand uncertainty and short shelf life; dairy products are a prime example (Maaß et al, 2014). In this study, for "inadequacy of legal systems to build a circular system", "issues related to data security, integration and privacy", "technical infrastructure deficiency in CE adoption", "difficulties in establishing the balance between supply and demand", "little understanding and knowledge about CE in dairy supply chain", "lack of transparency across the value chain", "shorter product life cycle" and "lack of collaboration, coordination and cooperation among stakeholders" problems, data mining can be a solution to prevent losses caused by the lack of circular and sustainable processes. By analysing historical data with the help of data mining, companies can make predictive analyses and obtain better information to make more informed decisions. This will enable them to find circular and sustainable solutions to the barriers identified in their dairy supply chains.

Machine learning is another important technique of big data in dairy supply chains. Machine learning enables companies to make the right decisions in operational follow-up by learning behaviours through simulations and constantly discovering existing information structures (Liu et al., 2020). For economic, environmental, technological and supply chain management problems, such as "lack of economic incentives by implementing CE", "high cost of implementation of various 'R' initiatives", "increased research and development cost", "inefficient environmental standards for CE adoption", "problems related to carbon emissions during closing the loop of supply chain", "lack of implementation of emerging technologies" and "inefficient information sharing system across the value chain", machine learning can be a suitable tool for decision making by managers.

Optimization, data mining and machine learning can be beneficial for almost every problem in dairy supply chains. However, there are some specific techniques related to big data. For example, statistical techniques allow for the collection and analysis of big data, often addressing environmental challenges such as carbon emissions and identifying green suppliers. Similarly, for "lack of incentives for GSC" and "lack of integration between technological processes and eco-efficiency" barriers, statistical techniques can be beneficial solutions in dairy supply chains.

Besides these solutions already mentioned, another technique of big data is artificial neural network. Artificial neural network, used to monitor and control the complex structure of the supply chain, is beneficial for circularity and sustainability of dairy supply chain operations. It is an important solution to the complex structure of the dairy supply chain.

In order to use the big data techniques mentioned above, a specialised workforce is needed. Competencies of human resources or other departments should be improved in understanding and implementing big data solutions. Briefly, there should be human expertise in data analytics within the companies.

Furthermore, in the light of information obtained from this study, necessary investment should be made for data collection, processing and management operations. Any investment made will help to improve supply chains in terms of circularity and sustainability by supporting the collection of data, the creation of large data sets, data processing and management. In addition, information transparency should be adopted in order to manage operations effectively in dairy supply chains and to ensure data flows between supply chain stages.

For policy makers, it is essential to follow the United Nations agenda on dairy supply chains. Therefore, integrating big data into dairy supply chains will provide increasing agricultural productivity and investment and ensure sustainable food production under the "zero hunger" concept. In this way, improvements can be made not only in companies, but also at a macro level.

Using big data and integrating its different techniques into dairy supply chains can improve sustainable consumption and production trends. Based on important decisions taken for dairy supply chains, environmental concerns, such as energy consumption and waste generation, can be addressed; economic concerns directly linked with environmental impacts can also be considered.

Besides managerial and policy maker implications, big data and integration of its tools are crucial to develop circular and sustainable practices in dairy supply chains. This issue has recently gained increased attention from an academic perspective. It is hoped that the current research would motivate scholars and practitioners to focus on big data technologies in improving circularity in the food supply chain. It is not only the dairy sector that has to deal with such issues; it is expected that there will be further research on how to integrate circularity into different sectors in the food industry with the help of big data.

6. Conclusion

This research aimed to achieve two main contributions. First of all, with ideal matching and ranking of big data solutions to barriers to circularity in dairy supply chains, a framework is proposed. Secondly, a specific road map is offered to companies with limited resources in their supply chains by drawing up an order of importance of the barriers. In this study, in order to understand the multi-stakeholder structure of the dairy supply chain from a holistic perspective, large-scale group decision-making is considered.

There are barriers that affect the circularity of dairy supply chains. In this study, these barriers are listed based on a literature review with the aim of finding solutions to manage them with the help of big data technology. In total, six main barriers and twenty-seven sub-barriers are identified. The main barriers are listed as economic, environmental, social and legal, technological, supply chain management and strategic barriers.

From our findings, economic barriers are determined as the most important among the main barriers. While technological, environmental, strategic, supply chain management and social and legal barriers are ranked next according to their importance. In addition, from these findings, big data is shown as an effective solution methodology for each barrier to overcome circularity related issues in dairy supply chains. Notably, optimization, machine learning and data mining as big data driven solutions are more beneficial and applicable in most barriers; statistical techniques and artificial neural network can manage only a few barriers.

Among limitations acknowledged, the identified barriers and solutions to manage such barriers could be modified as per developments in technology and the passage of time. This research has been conducted considering data from a dairy company in Turkey. Further possible research may focus on the implementation of the proposed framework in other emerging economies. Notably, the transition to digitalization in the dairy industry is a bit slow in emerging economies. So, it might be interesting to compare the results of this study with findings from a developed country. In this research, we have used a fuzzy based approach to handle inherent uncertainty. Additional studies may also use grey set theory and different variants of fuzzy based membership functions to further evaluate the findings. The identified barriers and their corresponding solutions may also be verified empirically in the future. Further research may also be needed to determine the cause and effect relationships between barriers to circularity and big data solutions. In addition, the impact of Industry 4.0 and blockchain in a successful adoption of CE in a dairy supply chain is an area for further study.

Credit Author Statement

- **There is no conflict of interests among author (s).**
- **All author (s) have contributed equally and significantly throughout the manuscript. Though, a specific contribution for each author is mentioned as below -**

Yigit Kazancoglu: Investigation, Project administration, Writing - Original draft preparation

Muhittin Sagnak: Writing - Original draft preparation, Formal analysis, Methodology Validation

Sachin Kumar Mangla: Writing - Original draft preparation, Writing: Review and editing; Conceptualization, Formal analysis, Methodology, Supervision

Muruvvet Deniz Sezer: Writing - Original draft preparation, Data curation, Software, Methodology

Melisa Ozbiltekin Pala: Writing - original draft preparation, Data curation, Software, Methodology

References

Agenbag, M.H.A., Lues, J.F.R, 2009. Resource management and environmental health service delivery regarding milk hygiene. Br. Food J. 111 (6), 539–553.

Ahearn, M.C., Armbruster, W., Young, R., 2016. Big data's potential to improve food supply chain environmental sustainability and food safety. Int. Food and Agribus. Manag. Rev. 19 (A), 155–171.

Akram, M., Kahraman, C., Zahid, K., 2021. Group decision-making based on complex spherical fuzzy VIKOR approach. Knowledge-Based Syst. 216, 106793.

Alao, B., Falowo, A., Chulayo, A.Y., Muchenje, V., 2017. The Potential of Animal By-Products in Food Systems: Production, Prospects and Challenges. Sustainability 9, 1089–1107.

Alonso, S., Dominguez-Salas, P., Grace, D., 2019. The role of livestock products for nutrition in the first 1,000 days of life. Anim. Front. 9 (4), 24–31.

Alsolame, B., Alshehri, N.O., 2020. Extension of VIKOR Method for MCDM Under Bipolar Fuzzy Set. Int. J. Anal. Appl. 18 (6), 989–997.

Annosi, M.C., Brunetta, F., Bimbo, F., Kostoula, M., 2021. Digitalization within food supply chains to prevent food waste. Drivers, barriers and collaboration practices. Industrial Market. Manag. 93, 208–220.

Arunachalam, D., Kumar, N., Kawalek, J.P., 2018. Understanding big data analytics capabilities in supply chain management: Unravelling the issues, challenges and implications for practice. Transport. Res. Part E: Logistics and Transport. Rev. 114, 416–436.

Astill, J., Dara, R.A., Campbell, M., Farber, J.M., Fraser, E.D., Sharif, S., Yada, R.Y., 2019. Transparency in food supply chains: A review of enabling technology solutions. Trends Food Sci. Technol. 91, 240–247.

Asunis, F., Gioannis, G., Dessi, P., Isipato, M., Lens, P.N.L., Muntoni, A., Polettini, A., Pomi, R., Rossi, A., Spiga, D, 2020. The dairy biorefinery: Integrating treatment processes for cheese whey valorisation. J. Environ. Manage. 276, 111240.

Ayouni, S., Menzli, L.J., Hajjej, F., Madeh, M., Al-Otaibi, S., 2021. Fuzzy VIKOR Application for Learning Management Systems Evaluation in Higher Education. *Int. J. Inform. Commun. Technol. Education (IJICTE)* 17 (2), 17–35.

Bag, S., Pretorius, J.H.C., Gupta, S., Dwivedi, Y.K, 2020. Role of institutional pressures and resources in the adoption of big data analytics powered artificial intelligence, sustainable manufacturing practices and circular economy capabilities. Technol. Forecasting and Soc. Change, 120420.

Bailey, A.P., Garforth, C., 2014. An industry viewpoint on the role of farm assurance in delivering food safety to the consumer: The case of the dairy sector of England and Wales. Food Policy 45, 14–24.

Balaman, S.Y., 2019. *Sustainability Issues in Biomass-Based Production Chains*. Decision-Making for Biomass-Based Production Chains, 1st Edition. Academic Press, pp. 77–112.

Banaszewska, A., Cruijssen, F., Claassen, G.D.H., Van der Vorst, J, 2014. Effect and key factors of by-products valorization: The case of dairy industry. J. Dairy Sci. 97 (4), 1893–1908.

Basukie, J., Wang, Y., Li, S., 2020. Big data governance and algorithmic management in sharing economy platforms: A case of ridesharing in emerging markets. Technol. Forecasting and Soc. Change 161, 120310.

Blomsma, F., Brennan, G., 2017. The emergence of CE: a new framing around prolonging resource productivity. J. Ind. Ecol. 21 (3), 603–614.

Bonamigo, A., Ferenhof, H.A., Forcellini, F.A., 2016. Dairy production diagnosis in Santa Catarina, Brazil, from the perspective of business ecosystem. Br. Food J. 118 (9), 2086–2096.

Bourlakis, M., Maglaras, G., Gallear, D., Fotopoulos, C., 2014. Examining Sustainability Performance in the Supply Chain: The Case of the Greek Dairy Sector. Industrial Market. Manag. 43 (1), 56–66.

Cannas, V.G., Ciccullo, F., Pero, M., Cigolini, R., 2020. Sustainable innovation in the dairy supply chain: enabling factors for intermodal transportation. Int. J. Prod. Res. 58 (24), 7314–7333.

Carbonneau, R., Laframboise, K., Vahidov, R., 2008. Application of machine learning techniques for supply chain demand forecasting. Eur. J. Operat. Res. 184 (3), 1140–1154.

Chalmeta, R., Santos-deLeón, N.J., 2020. Sustainable Supply Chain in the Era of Industry 4.0 and Big Data: A Systematic Analysis of Literature and Research. Sustainability 12 (10), 4108–4132.

Chaudhary, K., Vrat, P., 2020. Circular economy model of gold recovery from cell phones using system dynamics approach: a case study of India. *Environ., Develop.*Sustain. 22 (1), 173–200.

Choi, T.M., Wallace, S.W., Wang, Y., 2018. Big data analytics in operations management. Product. Operat. Manag. 27 (10), 1868–1883.

Clift, R., Wright, L., 2000. Relationships between environmental impacts and added value along the supply chain. Technol. Forecast. Soc. Change 65 (3), 281–295.

Cruz Rios, F., Grau, D, 2019. Circular Economy in the Built Environment: Designing, Deconstructing, and Leasing Reusable Products. Reference Module in Materials Science and Materials Engineering. Elsevier Inc.

Dekker, R., Bloemhof, J., Mallidis, I., 2012. Operations Research for green logistics–An overview of aspects, issues, contributions and challenges. Eur. J. Operat.l Res. 219 (3), 671–679.

Del Giudice, M., Chierici, R., Mazzucchelli, A., Fiano, F., 2020. Supply chain management in the era of circular economy: the moderating effect of big data. The Int. J. Logistics Manag. 32 (2), 337–356.

Despoudi, S., 2020. Challenges in reducing food losses at producers' level: the case of Greek agricultural supply chain producers. Industrial Market. Manag. 93, 520–532.

Ding, H., Fu, Y., Zheng, L., Yan, Z., 2019. Determinants of the competitive advantage of dairy supply chains: Evidence from the Chinese dairy industry. Int. J. Prod. Econ. 209, 360–373.

Djekic, I., Miocinovic, J., Tomasevic, I., Smigic, N., Tomic, N., 2014. Environmental life-cycle assessment of various dairy products. J. Cleaner Prod. 68, 64–72.

do Canto, N.R., Bossle, M.B., Marques, L., Dutra, M., 2020. Supply chain collaboration for sustainability: a qualitative investigation of food supply chains in Brazil. Manag. Environ. Qual.: An Int. J. https://doi.org/10.1108/MEQ-12-2019-0275. Vol. ahead-of-print No. ahead-of-print.

Dolinska, A., d'Aquino, P., 2016. Farmers as agents in innovation systems. Empowering farmers for innovation through communities of practice. Agric. Syst. 142, 122–130.

Dubey, R., Gunasekaran, A., Childe, S.J., Luo, Z., Wamba, S.F., Roubaud, D., Foropon, C., 2018. Examining the role of big data and predictive analytics on collaborative performance in context to sustainable consumption and production behaviour. J. Cleaner Prod. 196, 1508–1521.

Dubey, R., Gunasekaran, A., Papadopoulos, T., Childe, S.J., 2015. Green supply chain management enablers: Mixed methods research. Sustain. Product. Consumpt. 4, 72–88.

Duong, L.N., Al-Fadhli, M., Jagtap, S., Bader, F., Martindale, W., Swainson, M., Paoli, A., 2020. A review of robotics and autonomous systems in the food industry: From the supply chains perspective. Trends Food Sci. Technol. 106, 355–364.

Eastwood, C.R., Chapman, D.F., Paine, M.S., 2012. Networks of practice for co-construction of agricultural decision support systems: case studies of precision dairy farms in Australia. Agric. Syst. 108, 10–18.

El-Kassar, A.N., Singh, S.K., 2019. Green innovation and organizational performance: the influence of big data and the moderating role of management commitment and HR practices. Technol. Forecast. Soc. Change 144, 483–498.

Ellen MacArthur Foundation, 2013. Towards the CE. Retrieved from. https://www.ellenmacarthurfoundation.org/assets/downloads/publications/Ellen-MacArthur-Foundation-Towards-the-Circular-Economy-vol.1.pdf.

Ergun, S., Kirlar, B.B., Alparslan Gök, S.Z., Weber, G.W, 2020. An Application of Crypto Cloud Computing in Social Networks by Cooperative Game Theory. J. Industrial and Manag. Optim. 16, 1927–1941.

FAO, 2013. Food Losses and Waste in Turkey. Retrieved from: http://www.fao.org/3/a-au824e.pdf.

Farooque, M., Zhang, A., Liu, Y., 2019. Barriers to circular FSCs in China. Supply Chain Manag.: An Int. J. 24 (5), 677–696.

Fassio, F., Tecco, N., 2019. Circular Economy for Food: A Systemic Interpretation of 40 Case Histories in the Food System in Their Relationships with SDGs. Systems 7, 43.

Ferenhof, H.A., Bonamigo, A., Da Cunha, A., Tezza, R., Forcellini, F.A., 2019. Relationship between barriers and key factors of dairy production in Santa Catarina, Brazil. Br. Food J. 121 (2), 304–319.

Geissdoerfer, M., Morioka, S.N., de Carvalho, M.M., Evans, S., 2018. Business models and supply chains for the circular economy. J. Cleaner Prod. 190, 712–721.

Ghadge, A., Er Kara, M., Mogale, D.G., Choudhary, S., Dani, S, 2020. Sustainability implementation challenges in FSCs: A case of UK artisan cheese producers. Production Planning & Control. https://doi.org/10.1080/09537287.2020.1796140 ahead of print.

Ghadge, A., Kaklamanou, M., Choudhary, S., Bourlakis, B., 2017. Implementing Environmental Practices within the Greek Dairy Supply Chain: Drivers and Barriers for SMEs. Industrial Manag. Data Syst. 117 (9), 1995–2014.

Ghisellini, P., Ulgiati, S., 2020. CE transition in Italy. Achievements, perspectives and constraints. J. Cleaner Prod. 243, 118360.

Gholizadeh, H., Fazlollahtabar, H., Khalilzadeh, M., 2020. A robust fuzzy stochastic programming for sustainable procurement and logistics under hybrid uncertainty using Big Data. J. Cleaner Prod. 258, 120640.

Gianni, M., Gotzamani, K., Vouzas, F., 2017. Food integrated management systems: dairy industry insights. Int. J. Qual. Reliability Manage. 34 (2), 194–215.

Glover, J., 2020. The dark side of sustainable dairy supply chains. Int. J. Operat. Product. Manag. https://doi.org/10.1108/IJOPM-05-2019-0394 ahead of print.

Glover, J.L., Champion, D., Daniels, K.J., Dainty, A.J.D, 2014. An Institutional Theory Perspective on Sustainable Practices across the Dairy Supply Chain. Int. J. Prod. Econ. 152, 102–111.

Govindan, K., Kaliyan, M., Kannan, D., Haq, A.N., 2014. Barriers Analysis for Green Supply Chain Management Implementation in Indian Industries Using Analytic Hierarchy Process. Int. J. Prod. Econ. 147, 555–568.

Gualandris, J., Kalchschmidt, M., 2014. Customer pressure and innovativeness: Their role in sustainable supply chain management. J. Purchasing and Supply Manage. 20 (2), 92–103.

Gupta, S., Qian, X., Bhushan, B., Luo, Z., 2019. Role of cloud ERP and big data on firm performance: a dynamic capability view theory perspective. Management Decision 57 (8), 1857–1882.

Hadar, R., Bilberg, A., Bogers, M., 2015. Business models for additive manufacturing: exploring digital technologies, consumer roles, and supply chains. Technol. Forecast. Soc. Change 18291, 59.

He, S., Li, S., Nag, A., Feng, S., Han, T., Mukhopadhyay, S.C., Powell, W., 2020. A comprehensive review of the use of sensors for food intake detection. Sensors and Actuators: A Phys. 315, 112318.

Hedar, A.R., Fukushima, M., 2006. Tabu search directed by direct search methods for nonlinear global optimization. Eur. J. Operat. Res. 170 (2), 329–349.

Huo, D., Chaudhry, H.R., 2020. Using machine learning for evaluating global expansion location decisions: An analysis of Chinese manufacturing sector. Technol. Forecast. Soc. Change, 120436.

IMSA, 2013. Unleashing the Power of the CE. Retrieved from: http://mvonederland.nl/system/files/media/unleashing_the_power_of_the_circular_economycircle_economy.pdf.

Iqbal, R., Doctor, F., More, B., Mahmud, S., Yousuf, U., 2020. Big data analytics: Computational intelligence techniques and application areas. Technol. Forecast. Soc. Change 153, 119253.

Ji, G., Hu, L., Tan, K., 2016. A study on decision-making of food supply chain based on Big Data. J. Syst. Sci. Syst. Eng. 26, 183–198.

Joensuu, T., Edelman, H., Saari, A., 2020. CE practices in the built environment. J. Cleaner Prod. 276, 124215.

Jouzdani, J., Govindan, K., 2020. On the sustainable perishable food supply chain network design: A dairy products case to achieve sustainable development goals. J. Cleaner Prod. https://doi.org/10.1016/j.jclepro.2020.123060 ahead of print.

Kamble, S.S., Gunasekaran, A., Gawankar, S.A., 2020. Achieving sustainable performance in a data-driven agriculture supply chain: A review for research and applications. Int. J. Prod. Econ. 219, 179–194.

Kamilaris, A., Kartakoullis, A., Prenafeta-Boldu, F., 2017. A review on the practice of Big Data analysis in agriculture. Comput. Electron. Agric. 143, 23–37.

Kayikci, Y., Ozbiltekin, M., Kazancoglu, Y., 2019. Minimizing Losses at Red Meat Supply Chain with Circular and Central Slaughterhouse Model. J. Enterprise Inform. Manag. 33 (4), 791–816.

Kazancoglu, Y., Ekinci, E., Mangla, S.K., Sezer, D.M., Kayikci, Y., 2021. Performance evaluation of reverse logistics in FSCs in a CE using system dynamics. Bus. Strategy Environ. 30 (1), 71–91.

Kazancoglu, Y., Sagnak, M., Kayikci, Y., Mangla, S.K., 2020. Operational Excellence in a Green Supply Chain for Environmental Management – a Case Study. Bus. Strategy Environ. 29 (3), 1532–1547.

Khalafi, S., Hafezalkotob, A., Mohammaditabar, D., Sayadi, M.K., 2020. Multi objective Fuzzy programming of remanufactured green perishable products using supply contracts. Int. J. Manage. Sci. Eng. Manag. 15 (4), 274–287.

Khedra, M.A., Abd EL-Aziz, A.A., Hefny, H.A, 2019. Social Network Analysis through Big Data Platform Review. In: 2019 International Conference on Computer and Information Sciences (ICCIS). IEEE, pp. 1–5.

Kirchherr, J., Piscicelli, L., Bour, R., Kostense-Smit, E., Muller, J., Huibrechtse-Truijens, A., Hekkert, M., 2018. Barriers to the CE: evidence from the European Union (EU). Ecol. Econ. 150, 264–272.

Kopyto, M., Lechler, S., Heiko, A., Hartmann, E., 2020. Potentials of blockchain technology in supply chain management: Long-term judgments of an international expert panel. Technol. Forecast. Soc. Change 161, 120330.

Kumar, A., Mangla, S.K., Kumar, P., Song, M., 2021. Mitigate risks in perishable food supply chains: Learning from COVID-19. Technol. Forecast. Soc. Change 166, 120643.

Lamprinopoulou, C., Renwick, A., Klerkx, L., Hermans, F., Roep, D., 2014. Application of an integrated systemic framework for analysing agricultural innovation systems and informing innovation policies: Comparing the Dutch and Scottish agri-food sectors. Agric. Syst. 129, 40–54.

Lea, B.R., Yu, W.B., Maguluru, N., Nichols, M., 2006. Enhancing business networks using social network based virtual communities. Industrial Management & Data Systems 106 (1), 121–138.

Lee, S.Y., Klassen, R.D., 2008. Drivers and enablers that foster environmental management capabilities in small-and medium-sized suppliers in supply chains. Product. Operat. Manage. 17 (6), 573–586.

Liao, H., Tang, M., Luo, L., Li, C., Chiclana, F., Zeng, X.-J., 2018. A Bibliometric Analysis and Visualization of Medical Big Data Research. Sustainability 10, 166.

Liu, G., Li, G., Yang, R., Guo, L., 2018. Improving Food safety in Supply Chain based on Big Data. In: 3rd International Conference on Advances in Energy and Environment Research (ICAEER 2018), E3S Web of Conferences, 53, p. 03084.

Liu, H.C., Liu, L., Liu, N., Maod, L.X., 2012. Risk evaluation in failure mode and effects analysis with extended VIKOR method under fuzzy environment. Expert Syst. Appl. 39 (17), 12926–12934.

Long, T.B., Blok, V., Coninx, I., 2016. Barriers to the adoption and diffusion of technological innovations for climate-smart agriculture in Europe: evidence from the Netherlands, France, Switzerland and Italy. J. Cleaner Prod. 112 (1), 9–21.

Maaß, D., Spruit, M., de Waal, P., 2014. Improving short-term demand forecasting for short-lifecycle consumer products with data mining techniques. Decision Anal. 1 (1), 1–17.

Maheshwari, S., Gautam, P., Jaggi, C., 2021. Role of Big Data Analytics in supply chain management: current trends and future perspectives. Int. J. Prod. Res. 59 (6), 1875–1900.

Mani, V., Delgado, C., Hazen, B.T., Patel, P., 2017. Mitigating Supply Chain Risk via Sustainability Using Big Data Analytics: Evidence from the Manufacturing Supply Chain. Sustainability 9, 608.

Mardani, A., Kannan, D., Hooker, R.E., Ozkul, S., Alrasheedi, M., Tirkolaee, E.B., 2020a. Evaluation of green and sustainable supply chain management using structural equation modelling: A systematic review of the state-of-the-art literature and recommendations for future research. J. Cleaner Prod. 249, 119383.

Mardani, A., Liao, H., Nilashi, M., Alrasheedi, M., Cavallaro, F., 2020b. A multi-stage method to predict carbon dioxide emissions using dimensionality reduction, clustering, and machine learning techniques. J. Cleaner Prod. 275, 122942.

Markard, J., 2020. The life cycle of technological innovation systems. Technol. Forecast. Soc. Change 153, 119407.

Markianidou, P., 2015. Eco-Innovations Observatory. Country Profile 2014, Italy.

Martínez-Caro, E., Cegarra-Navarro, J.G., Alfonso-Ruiz, F.J., 2020. Digital technologies and firm performance: The role of digital organisational culture. Technological Forecasting and Social Change 154 (C), 119962.

Mazzanti, M., Ghisetti, G., Gilli, M. (2016). Eco-Innovation Observatory, Country Profile 2015. Italy.

McKinsey & Company, 2020. How industrial companies can cut their indirect costs—fast. By Philipp Espel, Michael Herbener, Frederic Rupprecht, Christian Schröpfer, and Andreas Venus. Retrieved from: https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/how-industrial-companies-can-cut-their-indirect-costs-fast.

Micoli, S., 2018. L'Economia Circolare che cambia le Imprese: Principi, Modelli e Casi Aziendali. Master Degree Dissertation, Universita degli studi di Padova, Dipartimento di Scienze Economiche e Aziendali "M. Fanno". Available at: http://tesi.cab.unipd.it/57021/1/MICOLI_STEFANIA.pdf.

Mont, O., Plepys, A., Whalen, K., Nußholz, J.L.K, 2017. Business model innovation for a CE: Drivers and barriers for the Swedish industry – the voice of REES companies. Mistra REES. Available at: http://lup.lub.lu.se/search/ws/files/33914256/MISTRA_REES_Drivers_and_Barriers_Lund.

Mudgal, R.K., Shankar, R., Talib, P., Raj, T., 2010. Modelling the barriers of green supply chain practices: an Indian perspective. Int. J. Logistics Syst. Manage. 7 (1), 81–107.

Müller, J.M., Kiel, D., Voigt, K.I., 2018. What drives the implementation of Industry 4.0? The role of opportunities and challenges in the context of sustainability. Sustainability 10 (1), 247.

Neaga, I., Liu, S., Xu, L., Chen, H., Hao, Y., 2015, May. Cloud enabled big data business platform for logistics services: A research and development agenda. In: International Conference on Decision Support System Technology. Springer, Cham, pp. 22–33.

Niu, B., Zou, Z., 2017. Better demand signal, better decisions? Evaluation of big data in a licensed remanufacturing supply chain with environmental risk considerations. Risk Anal. 37 (8), 1550–1565.

Opricovic, S., 1998. Multi-criteria optimization of civil engineering systems. Faculty of Civil Engineering, Belgrade.

Opricovic, S., 2011. Fuzzy VIKOR with an application to water resources planning. Expert Syst. Appl. 38 (10), 12983–12990.

Opricovic, S., Tzeng, G.H., 2002. Multicriteria planning of post-earthquake sustainable reconstruction. Comput. Aided Civ. Infrastruct. Eng. 17 (3), 211–220.

Pant, R.R., Prakash, G., Farooquie, J.A., 2015. A framework for traceability and transparency in the dairy supply chain networks. Procedia-Social and Behavioural Sciences 189, 385–394.

Papadopoulos, T., Singh, S.P., Spanaki, K., Gunasekaran, A., Dubey, R., 2021. Towards next generation of Manufacturing: Implications of Big Data and Digitalization in the context of Industry 4.0. Production Planning and Control. https://doi.org/10.1080/09537287.2020.1810767.

Pappas, I.O., Mikalef, P., Giannakos, M.N., Krogstie, J., Lekakos, G., 2018. Big data and business analytics ecosystems: paving the way towards digital transformation and sustainable societies. Inform. Syst. e-Bus. Manag. 16, 479–491.

Paraskevopoulou, C., & Vlachos, D. (2020). *A CE Perspective for Dairy Supply Chains.* In: Handbook of Research on Interdisciplinary Approaches to Decision Making for Sustainable Supply Chains.

Pheifer, A.G., 2017. Barriers and Enablers to Circular Business Models. Available at: https://www.circulairondernemen.nl/uploads/4f4995c266e00bee8fdb8fb34fbc5c15.pdf.
Powell, D., Lundeby, S., Chabada, L., Dreyer, H., 2017. Lean Six Sigma and environmental sustainability: the case of a Norwegian dairy producer. Int. J. Lean Six Sigma 8 (1), 53–64.
Queiroz, M., Fosso Wamba, S., Bourmont, M., Telles, R., 2020. Blockchain adoption in operations and supply chain management: empirical evidence from an emerging economy. Int. J. Prod. Res. https://doi.org/10.1080/00207543.2020.1803511 ahead of print.
Rajesh, R., 2017. Technological capabilities and supply chain resilience of firms: A relational analysis using Total Interpretive Structural Modeling (TISM). Technol. Forecast. Soc. Change 118, 161–169.
Raut, R.D., Mangla, S.K., Narwane, V.S., Gardas, B.B., Priyadarshinee, P., Narkhede, B.E., 2019. Linking big data analytics and operational sustainability practices for sustainable business management. J. Cleaner Prod. 224, 10–24.
Rialti, R., Marzi, G., Caputo, A., Mayah, K.A., 2020. Achieving strategic flexibility in the era of Big Data: The importance of knowledge management and ambidexterity. Manage. Dec. 58 (8), 1585–1600.
Rocha, J.M., Guerra, A., 2020. On the valorisation of lactose and its derivatives from cheese whey as a dairy industry by-product: an overview. Eur. Food Res. Technol. 246, 2161–2174.
Roßmann, B., Canzaniello, A., von der Gracht, H., Hartmann, E., 2018. The future and social impact of Big Data Analytics in Supply Chain Management: Results from a Delphi study. Technol. Forecast. Soc. Change 130, 135–149.
Roth, A.V., Tsay, A.A., Pullman, M.E., Gray, J.V., 2008. Unraveling the food supply chain: strategic insights from China and the 2007 recalls. J. Supply Chain Manage. 44 (1), 22–39.
Saaty, T., 1980. The Analytic Hierarchy Process, 1st ed. RWS Publications McGraw-Hill, Pittsburgh, PA.
Saaty, T., 1996. Decision Making with Dependence and Feedback. RWS Publications, Pittsburgh, PA.
Sagnak, M., Kazancoglu, Y., 2019. Integrated Fuzzy Analytic Network Process and 0-1 Goal Programming Technique for Enterprise Resource Planning (ERP) Software Selection. Ege Acad. Rev. 19 (1), 75–88.
Salimi, A.H., Noori, A., Bonakdari, H., Masoompour Samakosh, J., Sharifi, E., Hassanvand, M., Agharazi, M., 2020. Exploring the role of advertising types on improving the water consumption behavior: An application of integrated fuzzy AHP and fuzzy VIKOR method. Sustainability 12 (3), 1232.
Sanayei, A., Mousavi, S.F., Yazdankhah, A., 2010. Group decision making process for supplier selection with VIKOR under fuzzy environment. Expert Syst. Appl. 37, 24–30.
Schrettle, S., Hinz, A., Scherrer-Rathje, M., Friedli, T., 2014. Turning Sustainability into Action: Explaining Firms' Sustainability Efforts and Their Impact on Firm Performance. Int. J. Prod. Econ. 147, 73–84.
Seele, P., 2017. Predictive Sustainability Control: A review assessing the potential to transfer big data driven 'predictive policing' to corporate sustainability management. J. Cleaner Prod. 153, 673–686.
Seyedan, M., Mafakheri, F., 2020. Predictive Big Data analytics for supply chain demand forecasting: methods, applications, and research opportunities. J. Big Data 7 (1), 1–22.
Shabanpour, H., Yousefi, S., Saen, R.F., 2017. Forecasting efficiency of green suppliers by dynamic data envelopment analysis and artificial neural networks. J. Cleaner Prod. 142, 1098–1107.
Shamim, S., Zeng, J., Zia, N., 2020. Big Data analytics capability and decision-making performance in emerging market firms: The role of contractual and relational governance mechanisms. Technol. Forecast. Soc. Change 161, 120315.
Shao, X.F., Liu, W., Li, Y., Chaudhry, H.R., Yue, X.G., 2020. Multistage implementation framework for smart supply chain management under industry 4.0. Technol. Forecast. Soc. Change 162, 120354.
Sharma, Y., Mangla, S.K., Patil, P., Liu, S., 2019. When challenges impede the process: For CE-driven sustainability practices in food supply chain. Manage. Dec. 57 (4), 995–1017.
Simms, C., Trott, P., van den Hende, E., Hultink, E.J., 2020. Barriers to the adoption of waste-reducing eco-innovations in the packaged food sector: A study in the UK and the Netherlands. J. Cleaner Prod. 244, 1–14.
Singh, A., Kumari, S., Malekpoor, H., Mishra, N., 2018. Big data cloud computing framework for low carbon supplier selection in the beef supply chain. J. Cleaner Prod. 202, 139–149.
Singh, A., Subramanian, N., Pawar, K., Bai, R., 2018. Cold chain configuration design: Location-allocation decision-making using coordination, value deterioration, and Big Data approximation. Annals Operat. Res. 270, 433–457.
Sivarajah, U., Kamal, M., Irani, Z., Weerakkody, V., 2017. Critical analysis of Big Data challenges and analytical methods. J. Bus. Res. 70, 263–286.
SNV, 2017. Hygienic and Quality Milk Production, Training Package for Dairy Extension workers. Retrieved from: https://snv.org/cms/sites/default/files/explore/download/hygienic_and_quality_milk_production_training_manual_and_guideline.pdf.
Somda, J., Kamuanga, M., Tollens, E., 2005. Characteristics and economic viability of milk production in the smallholder farming systems in The Gambia. Agric. Syst. 85 (1), 42–58.
Song, M., Fisher, R., Kwoh, Y., 2019. Technological challenges of green innovation and sustainable resource management with large scale data. Technol. Forecast. Soc. Change 144, 361–368.
Song, M., Zhu, S., Wang, J., Zhao, J., 2020. Share green growth: Regional evaluation of green output performance in China. Int. J. Prod. Econ. 219, 152–163.
Spaini, C., 2017. EU Eco-Innovation Observatory. (2016-2017). Available at: https://ec.europa.eu/environment/ecoap/sites/ecoap_stayconnected/files/field/field-country-files/italy_eio_country_profile_2016-2017.pdf.
Stamatelatou, K., Giantsiou, N., Diamantis, V., Alexandridis, C., Alexandridis, A., Aivasidis, A., 2014. Biogas production from cheese whey wastewater: Laboratory- and full-scale studies. Water Sci. Technol. 69 (6), 1320–1325.
Stanchev, P., Vasilaki, V., Egas, D., Colon, J., Ponsá, S., Katsou, E., 2020. Multilevel environmental assessment of the anaerobic treatment of dairy processing effluents in the context of circular economy. J. Cleaner Prod. 261, 121139.
Tseng, M.L., Chiu, A.S., Chien, C.F., Tan, R.R., 2019. Pathways and barriers to circularity in food systems. Resour. Conserv. Recycl. 143, 236–237.
Tseng, M.L., Tan, R.R., Chiu, A.S., Chien, C.F., Kuo, T.C., 2018. Circular economy meets industry 4.0: Can big data drive industrial symbiosis? Resour. Conserv. Recycl. 131, 146–147.
Urbinati, A., Latilla, V.M., Chiaroni, D., 2018. The Role of Product Design in CE Business Model. In: ISPIM Innovation Conference e Innovation, the Name of the Game. Stockholm, Sweden, pp. 17–20.
Valenti, F., Liaob, W., Porto, S.M.C, 2020. Life cycle assessment of agro-industrial by-product reuse: a comparison between anaerobic digestion and conventional disposal treatments. Green Chem. 22, 7119–7139.
Wang, H., Yao, Y., Salhi, S., 2020. Tension in Big Data using machine learning: Analysis and applications. Technological Forecasting and Social Change 158, 120175.
Wu, J., Guo, S., Li, J., Zeng, D., 2016. Big data meet green challenges: Big data toward green applications. IEEE Syst. J. 10 (3), 888–900.
Wu, P.J., Huang, P.C., 2018. Business analytics for systematically investigating sustainable food supply chains. J. Cleaner Prod. 203, 968–976.
Yadav, S., Singh, S.P., 2020. An integrated fuzzy-ANP and fuzzy-ISM approach using blockchain for sustainable supply chain. Journal of Enterprise Information Management 34 (1), 54–78.
Yakovleva, N., 2007. Measuring the Sustainability of the Food Supply Chain: A Case Study of the UK. J. Environ. Plann. Policy Manage. 9 (1), 75–100.
Yu, Z., Jung, D., Park, S., Hu, Y., Huang, K., Rasco, B.A., Wang, S., Ronholm, J., Lu, X., Chen, J., 2020. Smart traceability for food safety. Critical Reviews in Food Science and Nutrition. https://doi.org/10.1080/10408398.2020.1830262 ahead of print.
Zadeh, L.A., 1965. Fuzzy Sets. Information Control 8, 338–353.
Zeng, T., Durif, F., Robinot, E., 2021. Can eco-design packaging reduce consumer food waste? an experimental study. Technological Forecasting and Social Change 162, 120342.
Zhao, R., Liu, Y., Zhang, N., Huang, T., 2017. An optimization model for green supply chain management by using a big data analytic approach. J. Cleaner Prod. 142, 1085–1097.
Zhong, R.Y., Lan, S., Xu, C., Dai, Q., Huang, G.Q., 2016. Visualization of RFID-enabled shopfloor logistics Big Data in Cloud Manufacturing. The Int. J. Adv. Manufact. Technol. 84 (1-4), 5–16.