**Drivers of Implementing Big Data Analytics in Food Supply Chains for Transition to a Circular Economy and** **Sustainable Operations Management**

**Abstract**

**Purpose:** The aim of this study is to evaluate Big Data Analytics (BDA) drivers in the context of food supply chains (FSC) for transition to a Circular Economy (CE) and Sustainable Operations Management (SOM).

**Design/methodology/approach:** Ten different BDA drivers in FSC are examined for transition to CE; these are Supply Chains (SC) Visibility, Operations Efficiency, Information Management & Technology, Collaborations between SC partners, Data-driven innovation, Demand management & Production Planning, Talent Management, Organizational Commitment, Management Team Capability and Governmental Incentive. An interpretive structural modelling (ISM) methodology is used to indicate the relationships between identified drivers to stimulate transition to CE and SOM. Drivers and pair-wise interactions between these drivers are developed by semi-structured interviews with a number of experts from industry and academia.

**Findings:** The results show that Information Management & Technology, Governmental Incentive and Management Team Capability drivers are classified as independent factors; Organizational Commitment and Operations Efficiency are categorized as dependent factors. SC Visibility, Data-driven innovation, Demand management & Production Planning, Talent Management and Collaborations between SC partners can be classified as linkage factors. It can be concluded that Governmental Incentive is the most fundamental driver to achieve BDA applications in FSC transition from linearity to CE and SOM. In addition, Operations Efficiency, Collaborations between SC partners and Organizational Commitment are key BDA drivers in FSC for transition to CE and SOM.

**Originality/value:** The main contribution of the study is to analyse BDA drivers in the context of FSC for transition to CE and SOM. This study is unique in examining these BDA drivers based on FSC. We hope to find sustainable solutions to minimize losses or other negative impacts on these SC.

**Research Implications:** The interactions between these drivers will provide benefits to both industry and academia in prioritising and understanding these drivers more thoroughly when implementing BDA based on a range of factors. This study will provide valuable insights. The results from this study will help in drawing up regulations to prevent food fraud, implementing laws concerning government incentives, reducing food loss and waste, increasing tracing and traceability, providing training activities to improve knowledge about BDA and focusing more on data analytics.

***Keywords:*** Food Supply Chains, Circular Economy, Sustainable Operations Management, Big Data Analytics, Drivers, Interpretive Structural Modelling

1. **Introduction**

The disappearance of commercial boundaries between countries and the fact that companies' competitors are now not only at national but also global level makes SC complex and difficult to manage (Kappelman and Sinha, 2021). The ability of companies to survive, develop and become stronger in an intense competitive environment depends on the effective management of SC structures and sustainable SC operations (Ewbank et al., 2020; Ghoushchi and Hushyar, 2020). Management of SC covers not only the production stage but every link of the chain, such as communication between the supplier and the manufacturing company (De Giovanni, 2020). In addition, factors such as the follow-up of new technologies, their adaptation and the ability to collect data become extremely important in the management of SC (Erol et al., 2020; Wong et al., 2020).

FSC are more vulnerable to deterioration and destruction (Kaur et al., 2020; Tirkolaee et al., 2020) in our competitive environment compared to the SC of other products, especially due to the sensitivity of both the product structure and the stages in the SC (Djekic et al., 2014; Liu et al., 2020). This problem becomes more critical in closed loop FSC (CLFSC). Food companies aim for speed, quality, good communication between partners and minimum cost at every stage of their FSC (Béné, 2020). In order to increase the resilience and sustainability of FSC, the control mechanisms at every stage of the SC must be well planned (Heck et al., 2020; Khan et al., 2020).

CE has more uncertainty and more ambiguous situations (Levering and Vos, 2019; Ethirajan et al., 2020) in CLFSC operations. In contrast with a linear economy, traceability is problematic in CLFSC in CE and SOM (Bressanelli et al., 2018; Beckmann et al., 2020). Due to uncertainties in the number of products needed, product type to be used in the evaluation of the products, the traceability of supply chains is more critical in a circular economy (Nadeem et al., 2019) as opposed to a linear economy (Glass et al., 2018). Moreover, because of the uncertain environment, operational efficiency is low in CLFSC in CE (Sharma et al., 2019). For example, not only operational efficiency but also in logistics processes in SC, there is low efficiency in vehicle performance. Furthermore, having more Rs or more stakeholders can make it harder for operations to have sustainable FSC and to adapt to CE in these CLFSC (Mishra et al., 2018). From the production process view, there is again huge uncertainty in the demand side (Yang et al., 2018) of CLFSC. Having many stakeholders, such as collectors, with various opinions makes it sticky for FSC operations (Esposito et al., 2020; Gupta et al., 2018). Therefore, one of the most important issues in CLFSC for transition to CE and SOM, is to have effective collaboration between SC partners (Farooque et al., 2019). In addition to the problems mentioned, in contrast with a linear economy, in CE, a huge data set is generated from FSC operations (Akhtar et al., 2016). The management of this data set can be another problem in CLFSC; in managing this data, circular and sustainable solutions have to be identified in CLFSC operations (Gawankar et al., 2020). A critical problem has now arisen given the lack of data-driven innovations in CLFSC (Akhtar et al., 2016). To cope with all these problems caused by CE (Bag and Pretorius, 2020) in CLFSC, there is a need for new technologies to enhance existing operations (Del Giudice et al., 2020).

BDA, one of the benefits of technological developments (Sharma et al., 2020), enables data collection and recording of processes at every stage of FSC (Ji et al., 2016; Kamilaris et al., 2017; Saleem et al., 2020). BDA, a concept that has been increasingly used in applications (Lamba and Singh, 2017), can be used in various sectors; it needs to be adopted into FSC for transition to CE and SOM because of the perishable product type in the food chains (Liu et al., 2018). BDA provides many benefits to FSC, enabling transition to CE and SOM while creating more effective SC (Singh et al., 2018). Thanks to BDA, firms can store, process and analyse their data concerning FSC (Ji et al., 2016).

The motivation for this study is that given the complex and vulnerable structure of FSCs, using BDA is essential for transition to CE and SOM. However, firstly, it is critical to identify the drivers of implementing BDA in FSC and to evaluate the relationships between these drivers. This is a major research gap in current literature. To the best of our knowledge, this study is unique in determining drivers of implementing BDA in FSC for transition to CE and SOM.

Therefore, the research questions of this study can be specified as;

* **RQ1:** What are the key drivers of adopting BDA in FSC for transition to CE and SOM?
* **RQ2**: What are the relationships between drivers for adopting BDA in FSC for transition to CE and SOM?

To find answers to these questions, different BDA drivers in FSC for transition to CE and SOM are determined. After determining these drivers, ISM methodology is used to indicate the relationships between the identified drivers. Drivers and pair-wise interactions between these drivers are developed by semi-structured interviews with different experts. At the end of the study, it is aimed to analyse the driving and dependence power of each factor of BDA in FSC to make the transition.

In summary, to cope with the problems mentioned above, one of the main contributions of this study is to analyse BDA drivers in the context of FSC for transition to CE and SOM. The second main contribution of the study is proposing new solutions when BDA is integrated into FSCs. The novelty of this study is in the examination of these BDA drivers based on FSC for transition to CE and SOM. We aim to find sustainable solutions to minimize losses or cope with other negative impacts on these SC by using relevant basic concepts and systematic implementation of graph theory, ISM.

The following sections of this paper are organised as follows. In Section 2, a literature review looks at BDA in FSC for transition to CE and SOM; the proposed drivers of BDA in FSC for transition are suggested. Section 3 covers methodology, including ISM. Section 4 consists of implementation and results of the study. In Section 5, discussions and managerial implications are given. Lastly, conclusions of the study are explained.

1. **Literature Review**

The literature review consists of two sections; a) BDA in FSC for transition to CE and SOM and b) proposed drivers of BDA in FSC for transition to CE and SOM. First of all, BDA in FSC for transition to CE and SOM is explained in detail.

* 1. **Big Data Analytics (BDA) in Food Supply Chains (FSC)**

Recently, with increased globalization, a continuing expansion in world population and innovations in technologies (Yadav and Singh, 2020), FSC have become more complex and more vulnerable (Ghadge et al., 2020; Mahroof et al., 2021). The product structure of FSC can deteriorate quickly so that care must be taken from the beginning to the end of the SC process (Saberi et al., 2019). For example, in FSC, both fresh and processed vegetables reach consumers after passing through the SC consisting of manufacturers, importers, wholesalers and retailers (Shankar, et al., 2018). An effective and sustainable management system is needed at every stage of the SC (Nazam et al., 2020) to eliminate risks such as food safety and quality assurance (Mogale et al., 2019).

Especially in a multi-stage FSC, it becomes extremely important to ensure continuity of the processes and keep them under control (Bene, 2020). Besides food safety and eliminating risks about food quality (Luo et al., 2020), in order to survive in a competitive environment, it is necessary to make correct decisions not only at the production stage, but also at every stage of the SC; these decisions must be implemented correctly and at the right time (Kittipanya-Ngam and Tan, 2020). In today’s marketplace, given the developments in digitalization, especially with the help of BDA, businesses that want to improve can record every step in their SC processes (Bansal et al., 2020), collect data from each stage and plan their operations in line with the collected data (Mardani et al., 2020).

In all types of SC, structures are becoming more complex every day (Vivaldini, 2020). The introduction of BDA, where data is collected incrementally and easily, eliminates physical storage processes (Mangla et al., 2020; Papadopoulos et al., 2020). BDA can be used in many areas such as tourism, food, education and production (Wang et al., 2020).

With a vulnerable and complex structure in its SC operations, the food sector is one of the most important sectors where big data technologies need to adapt to CLFSC (Jin et al., 2020; Liu et al., 2020). In CLFSC, BDA provides many advantages such as SC visibility, ease in control of whole SC, increase in food safety and minimization in losses (Govindan et al., 2018; Kappelman and Sinha, 2020). BDA provides accurate and real time data to minimize losses and provide maximize efficiency in CLFSC operations through the use of sensors, RFID and cameras (Irani et al., 2018).

CLFSC are more complex with more uncertain situations arising in their operations from a circular and sustainable perspective (Mangla et al., 2018; Zhang et al., 2020). Based on visibility, demand planning, operational efficiency, design and data-driven innovations (Nisar et al., 2020; Seyedan and Mafakheri, 2020), there is a need for new technologies such as BDA that can provide sustainable solutions to achieve effective CLFSC (Xiang and Xu, 2019).

To sum up, there is a need to specify drivers of BDA, especially in FSC for transition to CE and SOM. Problems prevalent in FSC operations must be overcome to have more effective and sustainable CLFSC. It is essential to know the drivers of BDA in FSC for transition to CE and SOM and take decisions based on these drivers. The proposed drivers of BDA in FSC for transition to CE and SOM are determined as explained in the following section.

* 1. **Proposed Drivers of Big Data Analytics (BDA) in Food Supply Chains (FSC) for transition to Circular Economy (CE) and** **Sustainable Operations Management (SOM)**

Initially, 15 drivers are determined from the literature review with these drivers being evaluated by experts in the field of FSC. As a result of validations, a final list of ten drivers of BDA in FSC for transition to CE and SOM is drawn up. These drivers are validated with industrial experts and academicians who are professionals in information technology, FSC and food engineering; all have a background in CE and sustainable supply chain management.

These drivers are specified as SC visibility, operations efficiency, information management and technology, collaboration between SC partners, data-driven innovation, demand management and production planning, employee knowledge, organizational commitment, management team capability and governmental incentives. These are shown in Table I.

**Table I.** Drivers of BDA in FSC for transition to CE and SOM

|  |  |
| --- | --- |
| **Drivers**  | **Support references**  |
| SC Visibility | Ding et al., 2019; Kamble et al., 2020; Yu et al., 2020 |
| Operations Efficiency | Kache and Seuring, 2015; Lamba and Singh, 2017; Sivananda Devi et al., 2020 |
| Information Management and Technology | Kache and Seuring, 2015; Lamba and Singh, 2017; Wamba et al., 2020 |
| Collaboration Between SC Partners | Dubey et al., 2018; Giannakis and Louis, 2016; Siddique et al., 2020 |
| Data-Driven Innovation | Li and Wang, 2017; Zong et al., 2017; Siddique et al., 2020 |
| Demand Management and Production Planning | Kache and Seuring, 2015; Nguyen et al., 2018; Raut et al., 2019 |
| Employee Knowledge | Kache and Seuring, 2015; Sivananda Devi et al., 2020 |
| Organizational Commitment  | Busse et al., 2011; Ferenhof et al. 2019; Siddique et al., 2020 |
| Management Team Capability | Gunasekaran et al., 2017; Raut et al., 2019; Kumar et al., 2020; Siddique et al., 2020; Sivananda Devi et al., 2020 |
| Governmental Incentives | Dunleavy, 2016; Milakovich, 2016 |

BDA drivers in FSC for transition to CE and SOM are defined as follows;

*SC Visibility:* Visibility becomes extremely important in complex and globalized SC (Ding et al., 2019). High SC visibility ensures that the firm's SC operations run near perfect (Kamble et al., 2020; Yu et al., 2020). Although, a linear economy has more stable SC, in CE there is a need for greater traceability in SC because of ambiguity and uncertainty about product quantity and quality (Bressanelli et al., 2018). Therefore, it is critical to have sustainable and circular FSC. With BDA, the visibility of the FSC for transition to CE and SOM can be increased and real-time control can be achieved (Kamble et al., 2020).

*Operations Efficiency:* Operations efficiency includes the operations and processes in the company SC structure (Kache and Seuring, 2015; Lamba and Singh, 2017). In CE, FSC produce an environment that needs close monitoring - product type, quantity or evaluation of products (Saroha et al., 2018). Moreover, therefore, operations efficiency remains lower in FSC for transition to CE than in a linear economy (Kache and Seuring, 2015). With the adoption of BDA, more accurate decisions are made in SC operations, while continuous productivity improvements and leaner processes are achieved (Sivananda Devi et al., 2020).

*Information Management and Technology:* The use of efficient information management and technologies in SC help companies in a number of areas; better stock and material control, faster distribution, better forecasting, promotion, marketing changes and sustainable operations (Zeng and Lu, 2020; Wamba et al., 2020). In contrast with a linear economy, since there is lots of R in CE, new technologies are needed for effectiveness in information management and technology (Mangla et al., 2018; Yu et al., 2020). However, big data adaptation is required for efficient information management and technology (Kache and Seuring, 2015) in FSC for transition to CE. The help of BDA provides a highly competitive advantage in the management of complex and large sustainable SC (Colin et al., 2015; Bamel and Bamel, 2020).

*Collaboration between SC Partners:* In developed or developing SC, collaboration between partners is one of the most important stages in sustainable SC management (Giannakis and Louis, 2016). Moreover, in closed loop SC, there are a range of stakeholders in the domain of CE. In order to ensure the continuity of operations in a sustainable SC, collaboration between partners should be kept dynamic and lively in terms of sharing knowledge with the help of BDA (Dubey et al., 2018; Siddique et al., 2020).

*Data-Driven Innovation:* In contrast with a linear economy, there is a huge amount of data available in SC operations in CE (Mangla et al., 2018). To manage data, there is a need for data-driven innovations such as network design. Moreover, when moving from linear economy, managers in CE need know-how in FSC operations (Siddique et al., 2020). The readiness of the SC infrastructure for data use, its openness to data-oriented innovations and its applicability will increase the use of BDA in SC (Li and Wang, 2017; Siddique et al., 2020). Web-based computing infrastructures and data-based initiatives can be created thanks to the adoption of BDA in FSC for transition to CE and SOM (Zong et al., 2017).

*Demand Management and Production Planning:* Production planning is made in line with demand management (Kache and Seuring, 2015). In companies with high levels of demand, demand planning is done on a shorter and optimized planning cycle with the help of big data (Raut et al., 2019). However, in contrast with linear economy, there is a huge uncertainty about demand and production planning because of more complex operations in CE (Raut et al., 2019). The use of BDA in demand and production management contributes to the improvement of the company's SC structure to embrace CE adaptations and SOM (Nguyen et al., 2018; Raut et al., 2019).

*Employee Knowledge:* Employee knowledge is a critical issue for SOM and circularity in FSC. In-depth knowledge about SOM and CE in FSC affects all operations in SC (Mangla et al., 2018). A company can optimise the use of BDA if it has employees who are knowledgeable in the SC structure, who volunteer for training and who are open to learning (Sivananda Devi et al., 2020). When this happens, there are improvements in both the knowledge level of the employees and SC performance (Kache and Seuring, 2015).

*Organizational Commitment:* Organizations need to constantly update their knowledge level and show willingness to learn if they are to make meaningful progress. With a high level of commitment and the ability to develop new processes, innovations in terms of CE can be introduced into SC (Contador et al., 2020). The level of knowledge and willingness of organization are among the most important factors in the efficiency and sustainability of the SC in CE (Ferenhof et al. 2019). This willingness and knowledge ensures that innovations are followed through and that new technologies are adopted. Big data needs to be used in FSC for transition to CE and SOM. However, big data adaptation needs investment (Busse et al., 2011; Siddique et al., 2020). If a more professional, fast and efficient SC emerges as a result, organizations will support the operations for big data adaptation (Ferenhof et al., 2019). Therefore, organizational commitment is a crucial issue for big data adaptation in SC.

*Management Team Capability:* Management team capability is an important aspect in the global SC (Kumar et al., 2020; Siddique et al., 2020). A management team should have expertise about CE and SOM in their closed loop SC operations (Saroha et al., 2018). The necessity of applying BDA tools is now emerging in modern production (Gunasekaran et al., 2017; Sivananda Devi et al., 2020). However, this adaptation can be achieved with a management team that includes information and data scientists and has mastery knowledge about the subject (Ferenhof et al., 2019; Siddique et al., 2020).

*Governmental Incentives:* Government incentives are crucial for the sustainability and circularity of FSC changes. Being more sustainable in SOM in the context of CE is a fundamental objective for any organization (Aggarwal et al., 2019; Ghode et al., 2020). The use of big data in FSC for transition to CE and SOM is also related to the support provided by the government (Dunleavy, 2016). If government supports are at a level to encourage the use of big data, the use of BDA in SC can be expanded and will become more attractive to a greater number of companies (Milakovich, 2016).

To sum up, by considering literature review and expert opinions, ten drivers are determined in FSC for transition to CE and SOM. Based on mentioned drivers, it is aimed to analyse the relationships among BDA drivers in FSC, especially based on for transition to CE and SOM. Therefore, in the following section, research methodology is explained in detail.

1. **Research Methodology**

In order to investigate the relationships among BDA drivers in FSC for transition to CE and SOM, ISM is proposed in this study. Firstly, ten different BDA drivers in FSC for transition to CE and SOM are identified; these are SC Visibility, Operations Efficiency, Information Management & Technology, and Collaborations between SC partners, Data-driven innovation, Demand management & Production Planning, Talent Management, Organizational Commitment, Management Team Capability and Governmental Incentives. To investigate the relationships between these drivers, an ISM approach is used. FSCs are a multi-stakeholder structure and various factors and decisions need to be tackled to achieve CE and SOM in the supply chain. To deal with the uncertain environment of FSCs, there needs to be effective demand management, increased visibility, integration among technologies, enhanced relationships among stakeholders and a systematic approach throughout. With the use of ISM, various participants can present their ideas related to a range of issues under consideration and make recommendations on the importance of the variables involved. Hence, better management is made possible to handle the complex and multi-stakeholder nature of FSCs.

 In the following section, ISM methodology is introduced.

**3.1 Interpretive Structural Modelling**

Using the basic concepts and systematic implementation of graph theory, ISM was first developed by Warfield (Warfield, 1974); these basic methods were improved by the U.S. Vanderbilt Columbus Laboratory to show the relations between factors (Kim et al., 2018). ISM is a well-known method to determine interactions between factors (Hughes et al., 2016; Guan et al., 2020; Ma et al., 2020). The method is based on an interactive learning process (Xu & Zou, 2020). The method is also useful to indicate relationships among different elements (Rana et al., 2019a). This modelling approach provides insight into the understanding of different directly and indirectly related factors and relationships (Al-Muftah et al., 2021). Therefore, this method is used to describe complex relations between different variables (Rana et al., 2020). Certain relationships and the system structure are expressed with a digraph (Attri et al., 2013). It is a significant aid to revealing the relationships between direct and indirect factors rather than the individual effects of the factors (Mishra et al., 2018). Firstly, the factors are determined, after a structural self-interaction matrix (SSIM) is constituted considering pairwise comparison of factors based on obtained opinions. In the third stage in this modelling approach, SSIM is converted into a reachability matrix (RM) as a transitivity controlling process is carried out. Finally, a matrix model is created and classifications of the factors and development of a structural model are performed.

ISM has many advantages over other methods. It encourages participants to develop a deeper understanding of the topic under consideration and to reveal the importance of a particular list of elements and explore the relationships between these elements. It creates inter-personal communication related to the problems. It also provides a systematic approach since it considers all possible pair-wise comparisons; it is an efficient process, decreasing relations using a transitive method (Attri et al., 2013). However, this approach also has some disadvantages. It does not deal with a large number of variables. As the number of variables increases, the complexity of ISM also increases. Hence, it is unable to deal with all of the variables that affect the system, with some variables that are involved being ignored (Ma et al., 2020).

The flowchart of the methodology is indicated in Figure I.

Deleting transitivity from

the diagraph

Identifying big data drivers

Literature review related issues

Obtaining expert opinions

Constitution of relationship between Xij

between variables (i, j)

Creating a RM

Partitioning the RM into different

levels

Creating digraph

Establishing a SSIM

Substituting variables nodes with

relationship statements

Represent the ISM model

Is there any consistency?

YES

NO

**Figure I.** Flowchart of the Methodology

Steps of this modelling technique are discussed below.

**Step 1. Structural Self-Interaction Matrix (SSIM):** ISM is developed using expert opinions to establish relations between the factors (Devi et al., 2020). Therefore, through the collection of various experts’ opinions, relationships among the factors are established using the symbols below.

V-The factor i develops to succeed driver j

A-The factor j develops to succeed driver i

X- The factors i and j develop to succeed each other

O- The factors i and j are unrelated.

**Step 2. Reachability Matrix:** This step includes developing an initial and final reachability matrix.Transforming the initial reachability matrix from SSIM can be achieved by replacing different symbols of SSIM using binary metrics in this matrix.

The following rules are used to develop RM.

* If the (i, j) cell is V then replace as 1 and (j, i) cell as 0 in the initial reachability matrix.
* If the (i, j) cell is A then replace as 0 and (j, i) cell as 1 in the initial reachability matrix.
* If the (i, j) cell is X then replace as 1 and (j, i) cell as 1 in the initial reachability matrix.
* If the (i, j) cell is O then replace as 0 and (j, i) cell as 0 in the initial reachability matrix.

After obtaining the Initial Reachability Matrix, the next step is to develop a final reachability matrix.

By using equation 1, the initial reachability matrix is developed from the final reachability matrix.

∀i,j,k, if ∃ k such that k≠i and k≠j

(M [i, k] = 1) ∧ (M [k, j] = 1) ∧ (M [i, j] = 0) then M [i, j] = 1∗ [1]

* M shows initial reachability matrix.
* While i indicate rows and j show columns.
* k indicates the (i, j) entry of the transitivity process
* ∀ cover all conditions of i, j, k.
* ∃ indicates matching with column and row instance ‘1’ and ‘1’ respectively at location k (Hughes et al., 2020).

**Step 3. Level partitions:** After developing RM, the reachability set and antecedent sets generate the factors. An intersection set is created for all factors to determine the level of factors. Factors where accessibility and intersection sets are identical to each other are shown at the top of the ISM diagraph. After determining this, the factor is deleted from the matrix. The same steps are applied to find all the levels of factors. The graph and the ISM model are created through these levels.

**Step 4. Conical matrix:** A conical matrix is created by classifying factors based on depending and dependency power using the final reachability matrix. The driving power of a factor and the dependency power are determined by summing the number of ones in the lines and the number of ones in the columns respectively.

**Step 5. Digraph:** The graphic is created from the reachability matrix using nodes and borders. In order to show relations between factors, a digraph visual representation is used.

**Step 6. ISM Model:** To represent the ISM model, a digraph is developed.

1. **Implementation of the Study**

An ISM approach is used to investigate the relationship of factors and structure the inter-relationships between driving power and dependence factors. The ten BDA drivers in FSC for transition to CE and SOM are used as factors in this study. Table II show these drivers.

**Table II.** BDA driversin FSC for transition to CE and SOM

|  |  |
| --- | --- |
|  | ***Factors/Drivers*** |
| D1 | Supply Chain Visibility |
| D2 | Operations Efficiency |
| D3 | Information Management & Technology |
| D4 | Collaborations between supply chain partners |
| D5 | Data-driven innovation |
| D6 | Demand management & Production Planning |
| D7 | Talent Management |
| D8 | Organizational Commitment |
| D9 | Management Team Capability |
| D10 | Governmental Incentive |

Experts from industry are SC managers in food companies, food engineers and information technology managers; all have more than 5 years’ experience in their area of expertise. The expertise of academicians is in SC management, digital technologies, FSC and BDA. They are professors in their departments and have conducted studies on CE and SOM. Details are shown in Table III.

**Table III.** Expert Classification from Industry and Academics

|  |  |  |  |
| --- | --- | --- | --- |
| ***Experts*** | ***Position*** | ***Work Experiences (Year)*** |  |
| 1 | Supply Chain Manager in Food Company | 10 | *Industry* |
| 2 | Food Engineer | 15 |
| 3 | Information Technology Manager | 8 |
| 4 | Sustainability Environmental Engineer | 7 |
| 5 | Sustainability Analysist | 9 |
| 6 | Food Supply Chain | 6 | *Academics* |
| 7 | Supply Chain Management | 7 |
| 8 | Digital Technologies | 10 |
| 9 | Sustainability Engineering | 8 |
| 10 | Big Data Analytics | 4 |

Experts from industry and academia identified all the bilateral relationships between factors, determining whether one factor affects another and also how these factors affect each other. Considering the relationships obtained by experts, SSIM is established. SSIM is shown in Table 4. Symbols V, A, X, O were used to show the relationships among BDA drivers in FSC for transition to CE and SOM. The (j, i) in the matrix in Table IV is ignored because it indicates duplicate references.

**Table IV**. Structured Self Interaction Matrix

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **i , j** | **D10** | **D9** | **D8** | **D7** | **D6** | **D5** | **D4** | **D3** | **D2** |
| D1 | O | O | O | O | V | O | A | A | V |
| D2 | O | O | A | A | A | A | V | A | 1 |
| D3 | A | O | V | O | O | X | V | 1 |   |
| D4 | O | V | V | A | O | O | 1 |   |   |
| D5 | A | O | O | A | X | 1 |   |   |   |
| D6 | O | O | O | X | 1 |   |   |   |   |
| D7 | A | A | O | 1 |   |   |   |   |   |
| D8 | O | A | 1 |   |   |   |   |   |   |
| D9 | O | 1 |   |   |   |   |   |   |   |
| D10 | 1 |   |   |   |   |   |   |   |   |

The next step in ISM is the constitution of the initial reachability matrix and final reachability matrix. The structured self-interaction matrix is transformed to a binary format based on rules as discussed in the methodology section.

In Table V, the initial reachability matrix is developed by converting it into binary form using the data in SSIM.

**Table V.** Initial Reachability Matrix

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **i, j** | **D1** | **D2** | **D3** | **D4** | **D5** | **D6** | **D7** | **D8** | **D9** | **D10** |
| **D1** | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| **D2** | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| **D3** | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 0 |
| **D4** | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 0 |
| **D5** | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 |
| **D6** | 0 | 1 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 |
| **D7** | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 0 | 0 | 0 |
| **D8** | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| **D9** | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 0 |
| **D10** | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 1 |

The final reachability matrix is constructed, as shown in Table VI, by using the transitivity processes discussed in the methodology section. Transitivity is indicated by the notation 1\*.

**Table VI.** Final Reachability Matrix

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **i, j** | **D1** | **D2** | **D3** | **D4** | **D5** | **D6** | **D7** | **D8** | **D9** | **D10** | ***Driving Power*** |
| **D1** | 1 | 1 | 0 | 1\* | 1\* | 1 | 1\* | 0 | 0 | 0 | 6 |
| **D2** | 1\* | 1 | 0 | 1 | 0 | 0 | 0 | 1\* | 1\* | 0 | 5 |
| **D3** | 1 | 1 | 1 | 1 | 1 | 1\* | 0 | 1 | 1\* | 0 | 8 |
| **D4** | 1 | 1\* | 0 | 1 | 0 | 1\* | 1\* | 1 | 1 | 0 | 7 |
| **D5** | 1\* | 1 | 1 | 1\* | 1 | 1 | 1\* | 1\* | 0 | 0 | 8 |
| **D6** | 0 | 1 | 1\* | 1\* | 1 | 1 | 1 | 0 | 0 | 0 | 6 |
| **D7** | 1\* | 1 | 1\* | 1 | 1 | 1 | 1 | 1\* | 1\* | 0 | 9 |
| **D8** | 0 | 1 | 0 | 1\* | 0 | 0 | 0 | 1 | 0 | 0 | 3 |
| **D9** | 0 | 1\* | 0 | 1\* | 1\* | 1\* | 1 | 1 | 1 | 0 | 7 |
| **D10** | 1\* | 1\* | 1 | 1\* | 1 | 1\* | 1 | 1\* | 0 | 1 | 9 |
| ***Dependence*** | 7 | 10 | 5 | 10 | 7 | 8 | 7 | 8 | 5 | 1 | 68 |

The final reachability matrixis evaluated considering the reachability and antecedent sets for each factor to determine the levels of factors (Warfield 1974; Hughes et al., 2020). Ten drivers are placed in six levels after six iterations. Table VII illustrates the iteration process.

**Table VII.** Level Partition of iterations process

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **i, j** | **Reachability Set** | **Antecedent Set** | **Intersection Set**  | **Iteration Level** |
| D1 | 1,2,4,5,6,7 | 1,2,3,4,5,7,10 | 1,2,4,5,7 |   |
| D2 | 1,2,4,8,9 | 1,2,3,4,5,6,7,8,9,10 | 1,2,4,8,9 | I |
| D3 | 1,2,3,4,5,6,8,9 | 3,5,6,7,10 | 3,5,6 |   |
| D4 | 1,2,4,6,7,8,9 | 1,2,3,4,5,6,7,8,9,10 | 1,2,4,6,7,8,9 | I |
| D5 | 1,2,3,4,5,6,7,8 | 1,3,5,6,7,9,10 | 1,3,5,6,7 |   |
| D6 | 2,3,4,5,6,7 | 1,3,4,5,6,7,9,10 | 3,4,5,6,7 |   |
| D7 | 1,2,3,4,5,6,7,8,9 | 1,4,5,6,7,9,10 | 1,4,5,6,7,9 |   |
| D8 | 2,4,8 | 2,3,4,5,7,8,9,10 | 2,4,8 | I |
| D9 | 2,4,5,6,7,8,9 | 2,3,4,7,9 | 2,4,7,9 |   |
| D10 | 1,2,3,4,5,6,7,8,10 | 10 | 10 |   |
| **i, j** | **Reachability Set** | **Antecedent Set** | **Intersection Set**  | **Iteration Level** |
| D1 | 1,5,6,7 | 1,3,5,7,10 | 1,5,7 |   |
| D3 | 1,3,5,6,9 | 3,5,6,7,10 | 3,5,6 |   |
| D5 | 1,3,5,6,7 | 1,3,5,6,7,9,10 | 1,3,5,6,7 | II |
| D6 | 3,5,6,7 | 1,3,5,6,7,9,10 | 3,5,6,7 | II |
| D7 | 1,3,5,6,7,9 | 1,5,6,7,9,10 | 1,5,6,7,9 |   |
| D9 | 5,6,7,9 | 3,7,9 | 7,9 |   |
| D10 | 1,3,5,6,7,10 | 10 | 10 |   |
| **i, j** | **Reachability Set** | **Antecedent Set** | **Intersection Set**  | **Iteration Level** |
| D1 | 1,7 | 1,3,7,10 | 1,7 | III |
| D3 | 1,3,9 | 3,7,10 | 3 |   |
| D7 | 1,3,7,9 | 1,7,9,10 | 1,7,9 |   |
| D9 | 7,9 | 3,7,9 | 7,9 | III |
| D10 | 1,3,7,10 | 10 | 10 |   |
| **i, j** | **Reachability Set** | **Antecedent Set** | **Intersection Set**  | **Iteration Level** |
| D3 | 3 | 3,7,10 | 3 | IV |
| D7 | 3,7 | 7,10 | 7 |   |
| D10 | 3,7,10 | 10 | 10 |   |
| **i, j** | **Reachability Set** | **Antecedent Set** | **Intersection Set**  | **Iteration Level** |
| D7 | 7 | 7,10 | 7 | V |
| D10 | 7,10 | 10 | 10 |   |
| **i, j** | **Reachability Set** | **Antecedent Set** | **Intersection Set**  | **Iteration Level** |
| D10 | 10 | 10 | 10 | VI |

Iteration I of the level partition matrix, as shown in Table VII, indicates intersection sets by matching with the reachability and intersection sets. In the first iteration, the matching drivers are D2- Operations Efficiency, D4- Collaborations between SC partners, D8- Organizational Commitment; these are located at the top level of the ISM diagram. The matching drivers are in iteration 2, D5- Data-driven innovation, D6- Demand management & Production Planning. These drivers are shown at the second level of the ISM diagram. Matching drivers are in iteration 3, D1- SC Visibility, D9- Management Team Capability. In iteration 4, the matching driver is D3- Information Management & Technology. This driver is shown at level four in the ISM diagram. Factor D7- Talent Management is found in iteration 5. Therefore, this driver is shown at level five in the ISM diagram. In the last iteration of the process, the matching driver is D10- Governmental Incentive. This driver is shown at level six in the ISM diagram. The effect of this driver on other drivers in the model is located at the lowest level as it exhibits high levels.

Table VIII shows the canonical form of the matrix that is structured via the final reachability matrix where the drivers are classified by the level.

**Table VIII.** Canonical form of Final Reachability Matrix

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Drivers** | **D2** | **D4** | **D8** | **D5** | **D6** | **D1** | **D9** | **D3** | **D7** | **D10** | **Level** | **Reachability Set** |
| **D2** | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | I | 1,2,4,8,9 |
| **D4** | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 0 | I | 1,2,4,6,7,8,9 |
| **D8** | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | I | 2,4,8 |
| **D5** | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | II | 1,2,3,4,5,6,7,8 |
| **D6** | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | II | 2,3,4,5,6,7 |
| **D1** | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 1 | 0 | III | 1,2,4,5,6,7 |
| **D9** | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 0 | 1 | 0 | III | 2,4,5,6,7,8,9 |
| **D3** | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | IV | 1,2,3,4,5,6,8,9 |
| **D7** | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | V | 1,2,3,4,5,6,7,8,9 |
| **D10** | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | VI | 1,2,3,4,5,6,7,8,10 |

Table IX indicates the driving power and dependence power of the model.

**Table IX.** Driving and dependence power of ISM

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Factors** | **D2** | **D4** | **D8** | **D5** | **D6** | **D1** | **D9** | **D3** | **D7** | **D10** | **Driving Power** | **Reachability Set** |
| **D2** | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 5 | 1,2,4,8,9 |
| **D4** | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 0 | 7 | 1,2,4,6,7,8,9 |
| **D8** | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 2,4,8 |
| **D5** | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 8 | 1,2,3,4,5,6,7,8 |
| **D6** | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 6 | 2,3,4,5,6,7 |
| **D1** | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 6 | 1,2,4,5,6,7 |
| **D9** | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 7 | 2,4,5,6,7,8,9 |
| **D3** | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 8 | 1,2,3,4,5,6,8,9 |
| **D7** | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 9 | 1,2,3,4,5,6,7,8,9 |
| **D10** | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 9 | 1,2,3,4,5,6,7,8,10 |
| **Dependence Power** | 10 | 10 | 8 | 7 | 8 | 7 | 5 | 5 | 7 | 1 | 68 |  |

MICMAC analysis is beneficial to show driving and dependency power visually (Mishra et al., 2017). The MICMAC diagram indicates the factors which are independent, dependent, with autonomous and linkage clusters (Bond et al., 2020). The MICMAC figure of this study is shown in Figure 2. From the chart it can be seen that the dependent measures are Operations Efficiency and Organizational Commitment. Linkage measures are SC Visibility, Collaborations between SC partners, Demand management & Production Planning, Data-driven innovation and Talent Management. Independent measures are Information Management & Technology, Management Team Capability and Governmental Incentive as shown in Figure II.



**Figure II.** MICMAC Analysis

The independent drivers - Information Management & Technology, Management Team Capability and Governmental Incentive - are necessary to understand the system. Most other drivers depend on them. This group, which has high driving power but low dependency, provides an analysis of the system without being influenced by other drivers in the system. These drivers have the power to greatly influence other drivers in the system. Improvements in these drivers will enable other drivers to be improved. Dependent drivers have a high dependency and low driving power. Dependent drivers, Operations Efficiency and Organizational Commitment, are heavily affected by other drivers. Those in the linkage cluster have both strong driving power and dependency. Therefore, any change in the factor affects other drivers. SC Visibility, Collaborations between SC partners, Demand management & Production Planning, Data-driven innovation and Talent Management drivers affect all other drivers.

Governmental Incentive (D10)

Supply Chain Visibility (D1)

Operations Efficiency (D2)

Collaborations between supply chain partners (D4)

Organizational Commitment (D8)

Data-driven innovation (D5)

Demand management & Production Planning (D6)

Management Team Capability (D9)

Information Management & Technology (D3)

Talent Management (D7)

*Level I*

*Level II*

*Level III*

*Level IV*

*Level V*

*Level VI*

**Figure III.** ISM Diagraph for BDA drivers in FSC

As shown in Figure III., drivers with high driving power in the diagraph are at the lower level; drivers with high dependency power are at the higher level. Therefore, Governmental Incentive is the most basic driver to achieve BDA applications in FSC for transition to CE and SOM. Talent Management is located in level 5. Governmental Incentives enable businesses to act to implement Talent Management strategies. Programmes can be set up to provide employees with education and training as governmental regulations are introduced. With effective Talent Management, technology development and effective information management become available within the company. An increase in Information Management & Technology will act as a driver for SC Visibility and Management Team Capability. Developing strategies on SC Visibility will make Demand management & Production Planning more effective; a strong Management Team Capability is a driving force in Data-driven innovation development. Finally, Operations Efficiency, Collaborations between SC partners and Organizational Commitment, located in Level 1, are key drivers for the application of BDA in FSC for transition to CE and SOM.

1. **Discussions and Implications**

FSC are more vulnerable to the effects of disruptions (Djekic et al., 2014). Therefore, features such as visibility, transparency (Kumar and Ganguly, 2020) and data integrity are extremely important and useful in FSC for transition to CE and SOM (Rejeb et al., 2020). To provide these features in FSC to enable transition, it is necessary to implement BDA (Tasnim, 2020). BDA provides efficient data collection and recording to ensure sustainable SC operations (Kamilaris et al., 2017). A deep understanding of the drivers of BDA in SC is essential for successful implementation of BDA in SC operations (Darvazeh et al., 2020). There is a critical research gap of analysing drivers of BDA in FSC for transition to CE and SOM; this gap needs to be filled.

In accordance with Devi et al. (2020), operations efficiency is determined to be in the category of dependent factors. Although, Yang and Lin (2020) do not analyse BDA, they do analyse the SC drivers, stating that information and knowledge sharing with SC partners and technological capabilities are dependent factors. In contrast with Yang and Lin (2020), in this study, collaboration between SC partners is seen as one of the linkage factors with information management and technology also accepted as a linkage factor in their findings. According to Ganbold et al. (2020), information technology has several benefits for supply chains. Furthermore, although the paper of Xu and Zhou (2020) does not examine the role of BDA, for the energy sector, collaboration and communication is determined as a linkage factor, similar to the findings of this paper. However, in contrast with this study, Rana et al. (2019b) conclude that ‘governance’ is the most important barrier for smart cities.

Based on the results of the study, driving, linkage and dependent factors have been determined. According to these factors, several implications are drawn up for using BDA in FSC for transition to CE and SOM. These are shown in Figure IV.

**DRIVING FACTORS**

**LINKAGE FACTORS**

**DEPENDENT FACTORS**

Governmental Incentives (D10)

Information Management and Technology (D3)

Management Team Capability (D9)

**Reliability Strategy**

**Increasing Resilience**

**Packaging Design**

**Integrating ERP Systems**

Collaborations between supply chain partners (D4)

Supply Chain Visibility (D1)

Talent Management (D7)

Data-driven innovation (D5)

Demand management & Production Planning (D6)

Operations Efficiency (D2)

Organizational Commitment (D8)

**Preventing food fraud**

**Reducing Food Loss and Waste**

**Increasing Tracing and Traceability**

**Training Activities**

**Figure IV.** Implications based on drivers of BDA in FSC

As shown in Figure IV, there are various implications for driving, linkage and dependent factors of BDA in FSC. Governmental incentives have been identified as the most important dependent factor for the use of BDA in FSC transition. Incentives introduced by government should be regulated to prevent food fraud and laws should be created accordingly. The most important way to prevent food fraud is through strict government guidelines that should be rigorously enforced. Governments should implement a variety of regulations to cover a range of possible scenarios in uncertain environments to achieve environmental, economic and social sustainability in FSC. The aim must be to prevent food waste and ensure more efficient use of resources throughout the distribution chain.

Reducing food loss and waste is another implication. Food loss and waste is a critical problem in FSC. New ways should be explored to reduce food losses through regulating government policies to prevent food fraud, increase operational efficiency and facilitate collaboration between SC partners with the help of BDA. Besides, when considering reverse activities in the reverse food supply chain from a CE perspective, both the type and variety of data are seen to increase. New SC partners can therefore be added to the FSC processes. However, the transition to circularity means that an increasing number of reverse activities in FSC are generated. Therefore, to manage the complex structure of FSC, understanding the inter-relations of BDA drivers is a really significant issue to enable transition from linearity to CE.

Increasing tracing and traceability is essential for using BDA in FSC transition to CE and SOM. Therefore, governmental incentives should be planned based on tracing and traceability activities in FSC enabled by know-how or new technologies. Furthermore, because of applicable SC visibility and collaboration between SC partners, tracing and traceability in FSC can be increased. Making innovative decisions and managing effectively in SC, which are inherently complex activities and full of uncertainties, are only possible with more sustainable management of resources. Thus, for a company to achieve lasting success, BDA drivers are required to make the transition from linear to CE and to achieve SOM.

Management team capability and talent management depend must include knowledge about BDA in FSC transition to CE and SOM. All companies need qualified management teams and skilled workers experienced in data science to use BDA in their operations. This is a prerequisite to ensuring more effective operations in their SC management. Therefore, training activities should be planned based on data science or MIS. Since big data develops new and innovative ways for managers to handle an excessive amount of data, business managers should focus on data analytics; it is not possible to implement data analytics without well-trained human resources. Businesses should set up ongoing training programmes to improve the know-how of employees in terms of CE and SOM and to ensure that staff have up to date knowledge as new technologies emerge.

To encourage organizational commitment and collaborations between SC partners, there is a need for a holistic view. This view should embrace all of the stakeholders in FSC. Implementing BDA to make the transition to CE and SOM can help to provide this holistic view, based on provision of a reliability strategy as a competitive advantage in SC. Based on CE perspectives and considering the reverse and closed loop activities, the increasing number of stakeholders and the presence of trust among stakeholders have become even more important issues. Creating and developing a more reliable supply chain can ultimately be achieved by ensuring traceability of information between multi-stakeholders.

BDA provides increased resilience in a crisis situation as it has the capacity to accelerate decision-making processes in reinstatement. This has been demonstrated during the COVID-19 pandemic. Therefore, BDA is essential for demand management and production planning to ensure operational efficiency. The increasing production processes and greater number of supply chain stakeholders involved in the transition to CE can be managed more effectively by adapting BDA to the process.

Another implication concerns the data-driven innovation factor. Packaging design should be given greater importance rather than product design. In order to increase BDA, packaging that can collect data, such as QR Codes, will provide more data and will not be lost over time. This should be the preferred design. Besides, the increasing number of stakeholders and higher complexity and uncertainty in closed loop supply chains highlight the importance of data security. From linearity to CE transition, data-driven technologies play a fundamental role. Data availability and security are important for both internal and external stakeholders.

ERP (enterprise resource planning) systems should be integrated with other tools and technologies using BDA. This will benefit information management and technology, demand management and production planning plus collaboration among SC partners. BDA should also be used in analysing and developing new processes. With the use of BDA, new possibilities should be investigated and new processes based on the transition to CE should be developed.

Besides managerial and policy maker implications, BDA and its impact on innovation in FCS is an essential, new and trending issue for the world. It is an increasingly important topic of study for academics. It is hoped that this paper will motivate academics to further research BDA technologies and help propose new and different types of technologies not only for FSC, but for SC from every sector in the long term.

1. **Conclusions**

With the rapidly increasing population around the world and the globalization of markets, it is becoming more difficult to manage and track goods and resources. The management of SC that are particularly sensitive, such as FSC, is becoming more complex. Collecting, storing and analysing data becomes extremely important as the SC structure becomes more complex with advancing technology. Especially in CLFSC, the process is becoming more critical in contrast with a linear economy. Because of this, it is extremely important to determine the criteria that affect the use of BDA in FSC transition to CE and SOM and to identify the relationships between them.

Initially, experts and academicians with many years of experience on the subject were consulted to determine the drivers of BDA in FSC transition to CE and SOM. After deciding on the drivers, ISM was used to find the interactions between these drivers.

Results show that the main drivers are Information Management & Technology, Governmental Incentives and Management Team Capability. The most basic driver to achieve BDA applications in FSC for transition to CE and SOM is found to be Governmental Incentives. The independent factors are categorized as Organizational Commitment and Operations Efficiency. SC Visibility, Data-driven innovation, Demand management & Production Planning, Talent Management and Collaborations between SC partners can all be classified as linkage factors. In addition, improving strategies in SC visibility provide effective Demand management & Production Planning. Management Team Capability is an essential driving force in Data-driven innovation development. Lastly, Operations Efficiency, Collaborations between SC partners and Organizational Commitment are determined as key BDA drivers in FSC for transition to CE and SOM.

This study shows that the interactions between these drivers will benefit industry and academia to prioritize and actively research the effects of BDA applications in FSC. The transition to CE and SOM for many sectors of industry needs further examination. Areas that have been highlighted are regulations to prevent food fraud, laws concerning government incentives, reducing food loss and waste, increasing tracing and traceability and training activities to improve knowledge about BDA. Focusing on data analytics and adopting these implications with the help of BDA is essential for SOM in CE.

There are some limitations to this study. It is difficult to cover many variables related to a particular topic. Any increase in the number of variables increases the complexity of the model. This model can only be created with a limited number of variables. Relationships can be developed by obtaining more expert opinions for the problem under consideration. The developed model is a static model; it cannot address the dynamic relationships between factors. This analysis considers binary type of relationships and therefore the strength of interactions among elements is not considered. Moreover, the evaluations used in the study consist of subjective judgments. For this reason, it becomes difficult to generalize. Lastly, in the study, since big data is a newly spreading issue, there have been delays in the search for an expert in this field.

As a future course of study, relationships between variables can be increased. Besides, proposed factors in this study can be enhanced and different drivers may affect for implementing Big Data Analytics in food supply chains for transition to a circular economy and sustainable operations management and these drivers need to be adapt applications in the future. In order to validate the model, Structural Equation Modelling can be used. This work can be carried out in other sectors other than the food sector to obtain more widespread findings. Besides other sectors, it can be analysed on a stage-by-stage basis in FSCs. The drivers of different industry 4.0 tools and Blockchain technologies can be determined using this model.

**List of Abbreviations:**

BDA – big data analytics;

CE - circular economy;

CLFSC – closed loop food supply chain;

ERP - enterprise resource planning;

FSC - food supply chain;

ISM - interpretive structural modelling;

RM - reachability matrix;

SC - supply chain

SOM – sustainable operations management;

SSIM - structural self-interaction matrix;

MICMAC – Matrice d'Impacts Croises Multiplication Appliques a un Classement, or Impact Matrix Cross-Reference Multiplication Applied to a Classification

**REFERENCES**

Aggarwal, A., Gupta, S., Ojha, M.K. (2019). Evaluation of key challenges to industry 4.0 in Indian context: a Dematel approach. *Advances in Industrial and Production Engineering.* Springer, Singapore, 387–396.

Akhtar, P., Tse, Y. K., Khan, Z., & Rao-Nicholson, R. (2016). Data-driven and adaptive leadership contributing to sustainability: Global agri-food supply chains connected with emerging markets. *International Journal of Production Economics*, 181, 392-401.

Al-Muftah, H., Weerakkody, V., Rana, N.P., Sivarajah, U., and Irani, Z. (2018). E-diplomacy Implementation: Exploring Causal Relationships Using Interpretive Structural Modelling. *Government Information Quarterly*, 35(3), 502-514.

Attri, R., Dev, N., & Sharma, V. (2013). Interpretive structural modelling (ISM) approach: an overview. *Research Journal of Management Sciences*, *2319*, 1171.

Bag, S., & Pretorius, J. H. C. (2020). Relationships between industry 4.0, sustainable manufacturing and circular economy: proposal of a research framework. *International Journal of Organizational Analysis,* https://doi.org/10.1108/IJOA-04-2020-2120.

Bamel, N., & Bamel, U. (2020). Big data analytics based enablers of supply chain capabilities and firm competitiveness: a fuzzy-TISM approach. *Journal of Enterprise Information Management.*

Bansal, P., Gualandris, J., & Kim, N. (2020). Theorizing supply chains with qualitative Big Data and Topic Modeling. *Journal of Supply Chain Management*, 56(2), 7-18.

Beckmann, A., Sivarajah, U., & Irani, Z. (2020). Circular economy versus planetary limits: a Slovak forestry sector case study. *Journal of Enterprise Information Management*, https://doi.org/10.1108/JEIM-03-2020-0110.

Béné, C. (2020). Resilience of local food systems and links to food security – A review of some important concepts in the context of COVID-19 and other shocks. Food Sec. 12, 805–822 (2020). <https://doi.org/10.1007/s12571-020-01076-1>

Bond, P. L., Green Jr, K. W., & Inman, R. A. (2020). Relationships among JIT practices: an interpretive modeling approach. *Production Planning & Control*, *31*(5), 400-411.

Bressanelli, G., Perona, M., Saccani, N. (2018). Challenges in supply chain redesign for the circular economy: a literature review and a multiple case study*. Int. J. Prod. Res*. 1–28.

Busse, J. A., Green, T. C., & Baks, K. (2011). Fund Managers Who Take Big Bets: Skilled or Overconfident. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.891727>

Colin, M., Galindo, R., & Hernández, O. (2015). *Information and communication technology as a key strategy for efficient supply chain management in manufacturing SMEs.* Paper presented at the Procedia Computer Science.https://doi.org/10.1016/j.procs.2015.07.152

Contador, J. C., Cardoso, W., Contador, J. L., & de Mesquita Spinola, M. (2020). Taxonomy of organizational alignment: implications for data-driven sustainable performance of firms and supply chains. *Journal of Enterprise Information Management*, 34(1), 343-364.

Darvazeh, S. S., Vanani, I. R., & Musolu, F. M. (2020). Big Data Analytics and Its Applications in Supply Chain Management. In New Trends in the Use of Artificial Intelligence for the Industry 4.0. IntechOpen.

De Giovanni, P. (2020). Smart Supply Chains with Vendor Managed Inventory, Coordination, and Environmental Performance. *European Journal of Operational Research.*

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 International Journal of Logistics Management*, 1-20.

Devi K, S., Paranitharan, K. P., & Agniveesh A, I. (2020). Interpretive framework by analysing the enablers for implementation of Industry 4.0: an ISM approach. *Total Quality Management & Business Excellence*, 1-21.

Diabat, A., & Govindan, K. (2011). An analysis of the drivers affecting the implementation of green supply chain management. *Resources, conservation and recycling*, *55*(6), 659-667.

Ding, H., Fu, Y., Zheng, L., & Yan, Z. (2019). Determinants of the competitive advantage of dairy supply chains: Evidence from the Chinese dairy industry. *International Journal of Production Economics,* 209, 360-373.

Djekic, I., Miocinovic, J., Tomasevic, I., Smigic, N., & Tomic, N. (2014). Environmental life-cycle assessment of various dairy products. *Journal of Cleaner Production*, 68, 64-72.

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. *Journal of Cleaner Production*, 196, 1508-1521.

Dunleavy, P. (2016). Big Data and policy learning. Evidence-based policy making in the social sciences: methods that matter, 143.

Erol, I., Ar, I. M., Ozdemir, A. I., Peker, I., Asgary, A., Medeni, I. T., & Medeni, T. (2020). Assessing the feasibility of blockchain technology in industries: evidence from Turkey. *Journal of Enterprise Information Management.* Vol. ahead-of-print No. ahead-of-print. https://doi.org/10.1108/JEIM-09-2019-0309

Esposito, B., Sessa, M. R., Sica, D., & Malandrino, O. (2020). Towards Circular Economy in the Agri-Food Sector. A Systematic Literature Review. *Sustainability,* 12(18), 7401.

Ethirajan, M., Arasu M, T., Kandasamy, J., K.E.K, Vimal, Nadeem, S.P., Kumar, A., (2020). Analysing the risks of adopting circular economy initiatives in manufacturing supply chains. *Business Strategy and the Environment*, In Press <https://doi.org/10.1002/bse.2617>

Ewbank, H., Roveda, J. A. F., Roveda, S. R. M. M., ĺrio Ribeiro, A., Bressane, A., Hadi-Vencheh, A., & Wanke, P. (2020). Sustainable resource management in a supply chain: a methodological proposal combining zero-inflated fuzzy time series and clustering techniques. *Journal of Enterprise Information Management*, 33(5), 1059-1076.

Farooque, M., Zhang, A., & Liu, Y. (2019). Barriers to circular food supply chains in China. *Supply Chain Management: An International Journal.*

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. *British Food Journal,* 121(2), 304-319.

Ganbold, O., Matsui, Y., & Rotaru, K. (2020). Effect of information technology-enabled supply chain integration on firm's operational performance. *Journal of Enterprise Information Management.* DOI: 10.1108/JEIM-10-2019-0332

Gawankar, S. A., Gunasekaran, A., & Kamble, S. (2020). A study on investments in the big data-driven supply chain, performance measures and organisational performance in Indian retail 4.0 context. *International Journal of Production Research*, 58(5), 1574-1593.

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

Ghode, D., Yadav, V., Jain, R., & Soni, G. (2020). Adoption of blockchain in supply chain: an analysis of influencing factors. *Journal of Enterprise Information Management.* 33(3), 437-456.

Ghoushchi, S. J., & Hushyar, I. (2020). Designing A Closed-Loop Supply Chain Network and Providing A Multi-Objective Mathematical Model to Select A Third-Party Logistics Company and Supplier Simultaneously. *International Journal of Industrial Engineering*, 27(2).

Giannakis, M. & Louis, M. (2016). A multi-agent based system with Big Data processing for enhanced supply chain agility. *Journal of Enterprise Information Management*, 29(5), 706-727.

Glass, R., Meissner, A., Gebauer, C., Stürmer, S., Metternich, J. (2018). Identifying the barriers to Industrie 4.0. *Procedia CIRP* 72, 985–988.

Govindan, K., Cheng, T.C.E., Mishra, N., Shukla, N. (2018). Big Data analytics and application for logistics and supply chain management. *Transportation Research Part E: Logistics and Transportation Review,* 114, 343-349.

Guan, L., Abbasi, A., & Ryan, M. J. (2020). Analyzing green building project risk interdependencies using Interpretive Structural Modelling. *Journal of Cleaner Production*, *256*, 120372.

Gunasekaran, A., Papadopoulos, T., Dubey, R., & Wamba, S. F., Childe, S. J., Hazen, B. & Akter, S. (2017). Big Data and predictive analytics for supply chain and organizational performance. *Journal of Business Research, Elsevier,* 70(C), 308-317.

Gupta, S., Chen, H., Hazen, B. T., Kaur, S., & Gonzalez, E. D. S. (2019). Circular economy and big data analytics: A stakeholder perspective. *Technological Forecasting and Social Change,* 144, 466-474.

Heck, S., Campos, H., Barker, I., Okello, J. J., Baral, A., Boy, E., ... & Birol, E. (2020). Resilient agri-food systems for nutrition amidst COVID-19: evidence and lessons from food-based approaches to overcome micronutrient deficiency and rebuild livelihoods after crises*. Food Security,* 12(4), 823-830.

Hughes, D. L., Rana, N. P., & Dwivedi, Y. K. (2020). Elucidation of IS project success factors: an interpretive structural modelling approach. *Annals of Operations Research*, *285*(1), 35-66.

Hughes, D.L., Dwivedi, Y.K., Rana, N.P., and Simintiras, A.C. (2016). Information Systems Project Failure – Analysis of Causal Links using Interpretive Structural Modelling. *Production Planning & Control,* 27(16), 1313-1333.

Irani, Z., Sharif, A. M., Lee, H., Aktas, E., Topaloğlu, Z., Van't Wout, T. and Huda, S. (2018). Managing food security through food waste and loss: Small data to Big Data. *Computers & Operations Research*, *98*, 367-383.

Ji, G., Hu, L. & Tan, K. (2016). A study on decision-making of food supply chain based on Big Data. *Journal of Systems Science and Systems Engineering*, 26, 183-198.

Jin, C., Bouzembrak, Y., Zhou, J., Liang, Q., van den Bulk, L. M., Gavai, A., ... & Marvin, H. J. (2020). Big Data in food safety-A review. Current Opinion in Food Science.

Kamble, S., Gunasekaran, A. & Gawankar, S. (2019). Achieving Sustainable Performance in a Data-driven Agriculture Supply Chain: A Review for Research and Applications. *International Journal of Production Economics,* 219, 179-194.

Kamilaris, A., Kartakoullis, A., & Prenafeta-Boldu, F. (2017). A review on the practice of Big Data analysis in agriculture. *Computers and Electronics in Agriculture*, 143, 23-37.

Kappelman, A. C., & Sinha, A. K. (2021). Optimal control in dynamic food supply chains using Big Data. Computers & Operations Research, 126, 105117.

Kaur, P., Dhir, A., Ray, A., Bala, P. K., & Khalil, A. (2020). Innovation resistance theory perspective on the use of food delivery applications. *Journal of Enterprise Information Management.* DOI: 10.1108/JEIM-03-2020-0091

Khan, S. A. R., Yu, Z., Golpîra, H., Sharif, A., & Mardani, A. (2020). A state-of-the-art review and meta-analysis on sustainable supply chain management: Future research directions. *Journal of Cleaner Production,* 123357.

Kim, D., Kim, Y., & Lee, N. (2018). A study on the interrelations of decision-making factors of information system (IS) upgrades for sustainable business using interpretive structural modelling and MICMAC analysis. *Sustainability*, *10*(3), 872.

Kittipanya-Ngam, P., & Tan, K. H. (2020). A framework for food supply chain digitalization: lessons from Thailand. *Production Planning & Control*, 31(2-3), 158-172.

Kumar, A., Moktadir, M. A., Khan, S. A. R., Garza-Reyes, J. A., Tyagi, M., & Kazançoğlu, Y. (2020). Behavioral factors on the adoption of sustainable supply chain practices. *Resources, Conservation and Recycling,* 158, 104818.

Kumar, N., & Ganguly, K. K. (2020). External diffusion of B2B e-procurement and firm financial performance: role of information transparency and supply chain coordination. *Journal of Enterprise Information Management*. DOI: 10.1108/JEIM-02-2020-0060.

Lamba, K., & Singh, S. P. (2017). Big Data in operations and supply chain management: current trends and future perspectives. *Production Planning & Control*, 28(11-12), 877-890.

Levering, R., Vos, B. (2019). Organizational drivers and barriers to circular supply chain operations. *Operations Management and Sustainability*. Palgrave Macmillan, Cham, 43–66.

Li, D., & Wang, X. (2017). Dynamic supply chain decisions based on networked sensor data: an application in the chilled food retail chain. *International Journal of Production Research*, 55(17), 5127-5141.

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

Liu, P., Long, Y., Song, H. C., & He, Y. D. (2020). Investment decision and coordination of green agri-food supply chain considering information service based on blockchain and Big Data. *Journal of Cleaner Production*, 277, 123646.

Liu, P., Long, Y., Song, H. C., & He, Y. D. (2020). Investment decision and coordination of green agri-food supply chain considering information service based on blockchain and big data. *Journal of Cleaner Production*, 277, 123646.

Luo, X., Han, Y., Chen, X., Tang, W., Yue, T., & Li, Z. (2020). Carbon dots derived fluorescent nanosensors as versatile tools for food quality and safety assessment: A review. *Trends in Food Science & Technology,* 95, 149-161.

Ma, H. L., Wang, Z. X., & Chan, F. T. (2020). How important are supply chain collaborative factors in supply chain finance? A view of financial service providers in China. *International Journal of Production Economics*, *219*, 341-346.

Maheshwari, S., Gautam, P. & Jaggi, C.K. (2020) Role of Big Data Analytics in supply chain management: current trends and future perspectives, *International Journal of Production Research*, DOI: 10.1080/00207543.2020.1793011

Mahroof, K.A., Omar, A., Rana, N.P., Sivarajah, S., and Weerakkody, V. (2021). Drone as a Service (DaaS) in promoting Cleaner Agricultural Production and Circular Economy for Ethical Sustainable Supply Chain Development. *Journal of Cleaner Production*, 287, 125522.

Mangla, S. K., Raut, R., Narwane, V. S., & Zhang, Z. J. (2020). Mediating effect of big data analytics on project performance of small and medium enterprises. *Journal of Enterprise Information Management.* DOI: 10.1108/JEIM-12-2019-0394

Mangla, S.K., Luthra, S., Mishra, N., Singh, A., Rana, N.P., Dora, M., Dwivedi, Y. (2018). Barriers to effective circular supply chain management in a developing country context. *Prod. Plan. Control* 29 (6), 551–569.

Mardani, A., Kannan, D., Hooker, R. E., Ozkul, S., Alrasheedi, M., & Tirkolaee, E. B. (2020). 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. *Journal of Cleaner Production*, 249, 119383.

Milakovich, M. E. (2012). Anticipatory government: Integrating Big Data for smaller government. *Internet, politics, policy 2012: Big Data, big challenges*.

Mishra, J. L., Hopkinson, P. G., & Tidridge, G. (2018). Value creation from circular economy-led closed loop supply chains: a case study of fast-moving consumer goods. *Production Planning & Control,* 29(6), 509-521.

Mishra, N., Singh, A., Rana, N.P., and Dwivedi, Y.K.  (2017). Interpretive Structural Modelling and Fuzzy MICMAC Approaches for Customer Centric Beef Supply Chain: Application of a Big Data Technique. *Production Planning & Control*, 28(11-12), 945-963.

Mogale, D., Cheikhrouhou, N. & Tiwari, M. (2020). Modelling of sustainable food grain supply chain distribution system: a bi-objective approach. *International Journal of Production Research,* 58, 5521-5544.

Nadeem, S.P., Garza-Reyes, J.A., Anosike, T., Kumar, V. (2019). Coalescing the Lean and Circular Economy. Proceedings of the 9th Annual International Conference on Industrial Engineering and Operations Management (IEOM), Bangkok, Thailand, Mar. 5-7 (<http://www.ieomsociety.org/ieom2019/papers/279.pdf>)

Nazam, M., Hashim, M., Baig, S. A., Abrar, M., & Shabbir, R. (2020). Modeling the key barriers of knowledge management adoption in sustainable supply chain. *Journal of Enterprise Information Management,* 33(5), 1077-1109.

Nguyen, T., Li, Z.H.O.U., Spiegler, V., Ieromonachou, P. & Lin, Y. (2018). Big Data analytics in supply chain management: a state-of-the-art literature review. *Comput. Oper. Res*. 98, 254e264.

Nisar, Q. A., Nasir, N., Jamshed, S., Naz, S., Ali, M., & Ali, S. (2020). Big data management and environmental performance: role of big data decision-making capabilities and decision-making quality. *Journal of Enterprise Information Management.* https://doi.org/10.1108/JEIM-04-2020-0137.

Papadopoulos, T., Singh, S. P., Spanaki, K., Gunasekaran, A., & Dubey, R. (2020). Towards next generation of Manufacturing: Implications of Big Data and Digitalization in the context of Industry 4.0. *Production Planning and Control*.

Rana, N.P., Barnard, D., Baabdullah, A., Rees, D. and Roderisk, S. (2019a). Exploring Barriers of M-Commerce Adoption in SMEs in the UK: Developing a Framework using ISM. *International Journal of Information Management*, 44, 141-153.

Rana, N.P., Luthra, S., and Rao, H.R. (2020). Key challenges to digital financial services in emerging economies: The Indian context. *Information Technology & People*, 33(1), 198-229

Rana, N.P., Luthra, S., Mangla, S., Islam, R., Roderick, S. and Dwivedi, Y.K. (2019b). Barriers to the Development of Smart Cities in Indian Context. *Information Systems Frontiers*, 21(3), 503-525.

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. *Journal of Cleaner Production,* 224, 10-24.

Rejeb, A., Keogh, J. G., Zailani, S., Treiblmaier, H., & Rejeb, K. (2020). Blockchain Technology in the Food Industry: A Review of Potentials, Challenges and Future Research Directions. *Logistics,* 4(4), 27.

Saberi, S., Kouhizadeh, M., Sarkis, J. and Shen, L. (2019). Blockchain technology and its relationships to sustainable supply chain management. *International Journal of Production Research*, *57*(7), 2117-2135.

Saleem, H., Li, Y., Ali, Z., Ayyoub, M., Wang, Y., & Mehreen, A. (2020). Big data use and its outcomes in supply chain context: the roles of information sharing and technological innovation. *Journal of Enterprise Information Management.* <https://doi.org/10.1108/JEIM-03-2020-0119>.

Saroha, M., Dixit Garg, D., Luthra, S. (2018). Key issues and challenges in circular supply chain management implementation-a systematic review. *Int. J. Appl. Eng. Res*. 13 (9), 91–104.

Seyedan, M., & Mafakheri, F. (2020). Predictive big data analytics for supply chain demand forecasting: methods, applications, and research opportunities*. Journal of Big Data*, 7(1), 1-22.

Shankar, R., Gupta, R. and Pathak, D. K. (2018). Modeling critical success factors of traceability for food logistics system. *Transportation Research Part E: Logistics and Transportation Review*, *119*, 205-222.

Sharma, R., Jabbour, C. J. C., & de Sousa Jabbour, A. B. L. (2020). Sustainable manufacturing and industry 4.0: what we know and what we don't. *Journal of Enterprise Information Management,* 34(1), 230-266.

Sharma, V.K., Chandna, P. & Bhardwaj, A. (2017). Green supply chain management related performance indicators in agro industry: a review. *Journal of Cleaner Production*, 141, 1194e1208.

Singh, A., Kumari, S., Malekpoor, H., & Mishra, N. (2018). Big Data cloud computing framework for low carbon supplier selection in the beef supply chain*. Journal of Cleaner Production,*202, 139-149*.*

Tasnim, Z. (2020).Disruption in global food supply chain (FSC) due to Covid-19 pandemic and impact of digitization through block chain technology in FSC management. *European Journal of Business and Management*, 12(17),73-84.

Tirkolaee, E. B., Mahdavi, I., Esfahani, M. M. S., & Weber, G. W. (2020). A robust green location-allocation-inventory problem to design an urban waste management system under uncertainty. *Waste Management*, 102, 340-350.

Vivaldini, M. (2020). Blockchain platforms in supply chains. *Journal of Enterprise Information Management.* https://doi.org/10.1108/JEIM-12-2019-0416.

Wamba, S. F., Dubey, R., Gunasekaran, A., & Akter, S. (2020). The performance effects of Big Data analytics and supply chain ambidexterity: The moderating effect of environmental dynamism. *International Journal of Production Economics*, *222*, 107498.

Wang, H., Yao, Y. & Salhi, S. (2020). Tension in Big Data using machine learning: Analysis and applications. *Technological Forecasting and Social Change*, 158, 120175.

Warfield, J. N. (1974). Developing interconnection matrices in structural modelling. *IEEE Transactions on Systems, Man, and Cybernetics*, (1), 81-87.

Wong, C. W., Lirn, T. C., Yang, C. C., & Shang, K. C. (2020). Supply chain and external conditions under which supply chain resilience pays: An organizational information processing theorization. *International Journal of Production Economics*, 226, 107610.

Xiang, Z., & Xu, M. (2019). Dynamic cooperation strategies of the closed-loop supply chain involving the internet service platform. *Journal of Cleaner Production,* 220, 1180-1193.

Xu, X., & Zou, P. X. (2020). Analysis of factors and their hierarchical relationships influencing building energy performance using interpretive structural modelling (ISM) approach. *Journal of Cleaner Production*, *272*, 122650.

Xu, X., & Zou, P. X. (2020). Analysis of factors and their hierarchical relationships influencing building energy performance using interpretive structural modelling (ISM) approach. *Journal of Cleaner Production,* 272, 122650.

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.

Yang, S., MR, A., Kaminski, J., Pepin, H. (2018). Opportunities for industry 4.0 to support remanufacturing. *Appl. Sci.* 8 (7), 1177.

Yang, Z., & Lin, Y. (2020). The effects of supply chain collaboration on green innovation performance: An interpretive structural modeling analysis. *Sustainable Production and Consumption*, 1-10.

Yu, Y., Huo, B., & Zhang, Z. J. (2020). Impact of information technology on supply chain integration and company performance: evidence from cross-border e-commerce companies in China. *Journal of Enterprise Information Management*. DOI: 10.1108/JEIM-03-2020-0101.

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*, ahead of print. <https://doi.org/10.1080/10408398.2020.1830262>

Zeng, M., & Lu, J. (2020). The impact of information technology capabilities on agri-food supply chain performance: the mediating effects of interorganizational relationships. *Journal of Enterprise Information Management.* https://doi.org/10.1108/JEIM-08-2019-0237.

Zhang, Y., Che, A., & Chu, F. (2020). Improved model and efficient method for bi-objective closed-loop food supply chain problem with returnable transport items. *International Journal of Production Research*, 1-18.

Zhong, R. Y., Tan, K., & Bhaskaran, G. (2017). Data-driven food supply chain management and systems. *Industrial Management & Data Systems.*