A Decision Process for the Applications of Artificial Intelligence in Sustainable Operations and Supply Chain Management

Reza Akbar Muhammad, Benny Tjahjono, Babul Salam KSM Kader Ibrahim, Sri Rachmi Karimah Dewi Ridlo
Coventry University
Coventry, CV1 5FB, UK
rezaakbr@uni.coventry.ac.uk, benny.tjahjono@coventry.ac.uk, ad1465@coventry.ac.uk, ridlos@uni.coventry.ac.uk

Tri Yogi Yuwono
Institut Teknologi Sepuluh Nopember
Surabaya, Indonesia
triyogi@me.its.ac.id

Abstract

Artificial Intelligence (AI) has a growing and wider presence in academic studies and this presence has affected many fields, such as business research, which has picked up on the subject, and AI is now researched from a more holistic perspective, with operations and supply chain management being recognised as one of the areas that is most likely to benefit from AI applications. In addition, many companies have pushed towards using AI in their supply chain processes in order to achieve sustainability. The influence of AI inevitably extends well beyond the production line. It refers to all business units involved in planning, manufacturing, transporting and selling goods. As a result, companies will need engineering business managers who are well-equipped with know-how of the technological changes that may affect their market and workplace in order to effectively navigate them. This paper proposes a framework that can be used as decision making tools, providing steps for practitioners to consider before and after implementing the AI techniques in their engineering businesses. The framework was developed considering the barriers, enablers and challenges of AI implementation.

Keywords
Artificial Intelligence, Operations, Supply Chain Management, Sustainability, Engineering Management

1. Introduction

Operations and supply chain management (OSCM) has played a significant role in the global business world in recent decades. It has become an important part of business and fundamental for customer satisfaction in many sectors such as agriculture, manufacturing, energy, food industry and even the public sector. However, intelligent processes and practices in OSCM pose numerous problems and challenges in terms of sustainability. Bové and Swartz (2016) reported that the supply chain (SC) of a goods and services company affects both social and environment aspects, accounts for 90% of the impact on land, air, water and biodiversity, and more than 80% of greenhouse gas emissions in consumer goods, such as food industry, textile and electronic equipment produced in the SC. Thus, studies have been conducted to mitigate these issues. Furthermore, several methods and tools have been used in order to minimise and reduce the sustainability risk and one of these methods is using the Artificial Intelligence (AI).

AI is a field study in science and engineering that defines machine learning capability that has similarities to humans to adapt under certain situations and circumstances, and the ability to respond to certain orders, actions and behaviours as well as detect and extrapolate patterns (Russell and Norvig 2016). Within the context of the SC, in order to attain sustainability, the term 'artificial intelligence' has been widely used by both industrial practitioners and scholars.

AI is now being studied from a more comprehensive viewpoint, considering SCM as one of the area that most likely to benefit from applications of AI. Moreover, in order to achieve sustainability, many businesses have moved towards using AI in their SC processes. AI undoubtedly reaches far beyond the production line; this refers to all business units involved in the planning, development, processing, transport and sale of goods. As a result, engineering business managers need to consider the risks and possibilities associated with AI's rapid technical advances. In order to successfully handle AI, businesses will need engineering managers who are informed about technological developments that impact their business and workforce. While the interest of practitioners and researchers is thus strong, the contribution of AI to the field of SCM needs to be explored, therefore requiring the need for this study.

This paper aims to propose a decision-making process for the applications of AI in sustainable OSCM for practitioners through a desk-based review. This approach will be use as tools and steps for practitioners to consider before implementing the AI technique. The specific objectives are to produce a descriptive analysis of sustainability in the applications of AI in OSCM, develop a thematic analysis of sustainability in the applications of AI in OSCM, collate AI applications (or cases) for sustainability and elaborate their commercial implications, and finally, develop a decision-making process for the applications of AI in OSCM to attain sustainability. In order to reach and develop a better understanding of the above-mentioned issues, a desk review of relevant studies using a systematic literature review (SLR) is needed.

2. Methodology

This study will use the systematic literature review (SLR) method to collect the factors relevant to the development of the framework. The SLR uses systematic approaches to gather data, then identifies, defines, chooses and objectively appraises the study to respond to a clearly articulated problem or issue, both quantitatively and qualitatively (Dewey et al. 2016). The SLR offers a number of benefits; it provides a clear, comprehensive, transparent search conducted over several journal databases and grey studies that other researchers can replicate and repeat. Moreover, this literature review method may help to identify the research gaps in the current understanding of the subject areas (Peričić and Tanveer 2019).

There are four steps in conducting an SLR: the planning phase, data collection, analysis and synthesis. In the first phase, a review question was developed. The review question was used to produce combinations in the search strings. Then, in the second phase, the journal databases were selected in order to collect the data. The journal screening was conducted afterwards. This included title screening, abstract screening as well as removal of the duplicate articles from different journal databases. Then, the collected journal papers were reviewed both qualitatively and quantitatively. Several methods were used in order to generate the themes, using software such as VOSviewer, Leximancer and NVivo. These software tools are text mining programs which are mainly used for qualitative analysis, and can produce both themes and analyses of unstructured text. Finally, the analysed articles were synthesised, where the findings were discussed, and the critiques provided by the author. On the basis of these, a framework was developed.

3. Data Collection

Journal articles were sourced from the Scopus, Proquest and EBSCO database, provided 212, 103 and 111 articles respectively. From the title and abstract screening and deduplication, 336 papers were removed, leaving 90 articles[1] to be reviewed. After the articles were collected, grouping and profiling the journal was conducted before carrying out the analysis stage. The journal articles were classified based on their document type, year published, the research purpose, problem, AI technology, industry sector and its benefit.

After the data were collected, they were analysed into two different analyses: descriptive and thematic. Descriptive analysis is used to describe the distribution of the data and it will enable the identification of associations between variables. In order to carry out descriptive analysis, the journals were classified based on their document type, year published, the research purpose, problem, AI technology, industry sector and its benefits. Thereafter, quantitative information from each journal was extracted. Furthermore, the analysis was conducted from the chart as an interpretation. While the interpretation from the chart is determined as a descriptive analysis, thematic analysis is a qualitative research method to identify, analyse, organise and describe themes found within data. Before undertaking the thematic analysis, themes were proposed, in order to find themes from each article, and identify the excerpts, quotes and passages that are related to or support a certain term. Thereafter, the codes were identified, including artificial technology, barriers, benefits, challenges, enablers and problems.

[1] Due to space limitation, full list of articles will be available upon request.

4. Results

4.1 Descriptive Analysis

The final sample contains 90 journal articles. According to the document type group, most of them were journal articles, accounting for 57 journals, while the others were journal reviews and conference papers, which provided only four and 29 articles respectively. The journal articles to be reviewed were focused on the years between 2010 and 2020 as shown in Figure 1.

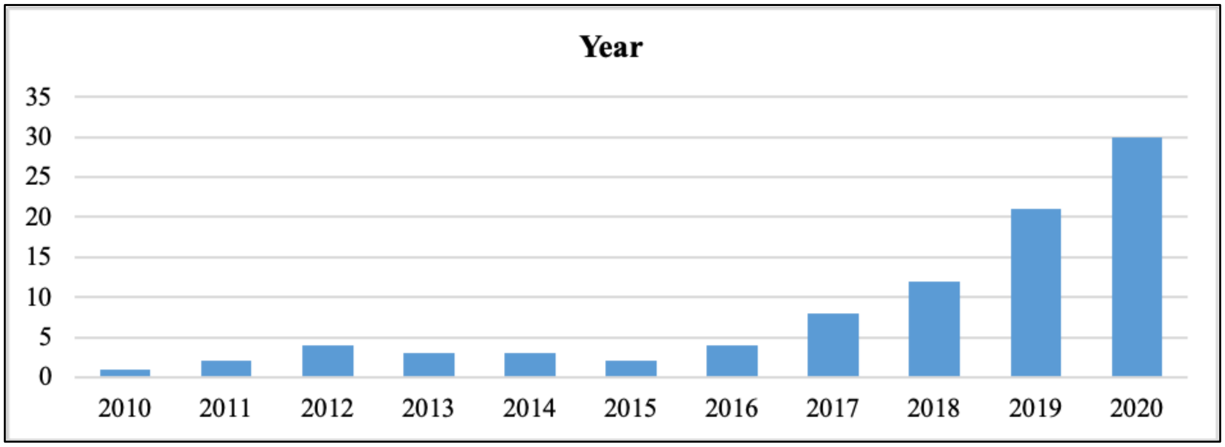

Figure 1. Year of publication

Overall, the number of articles on the proposed topics increased over the period. The studies on the use of AI in operations and management have become popular since 2016, showing significant increase in which, the number of studies reached about 30 articles in 2020. This rise in the number of studies was commensurate with the advancement of the technology.

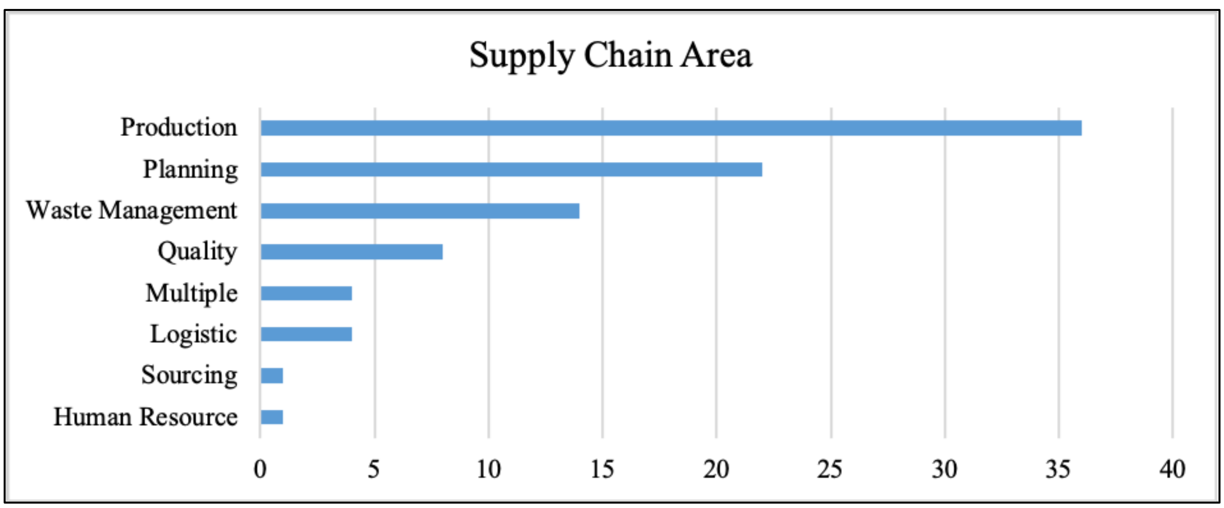

Figure 2. Supply chain areas

Looking at it in more detail, most of studies performed were focused on the production stage, accounting for 36 articles (see Figure 2), followed by the planning and waste management stages, with about 22 and 14 articles respectively. The least research was undertaken on the sourcing and human resource stages which have similar amounts of two articles. Furthermore, the large number of articles in production stage showed that the use of AI could attain sustainability in that stage.

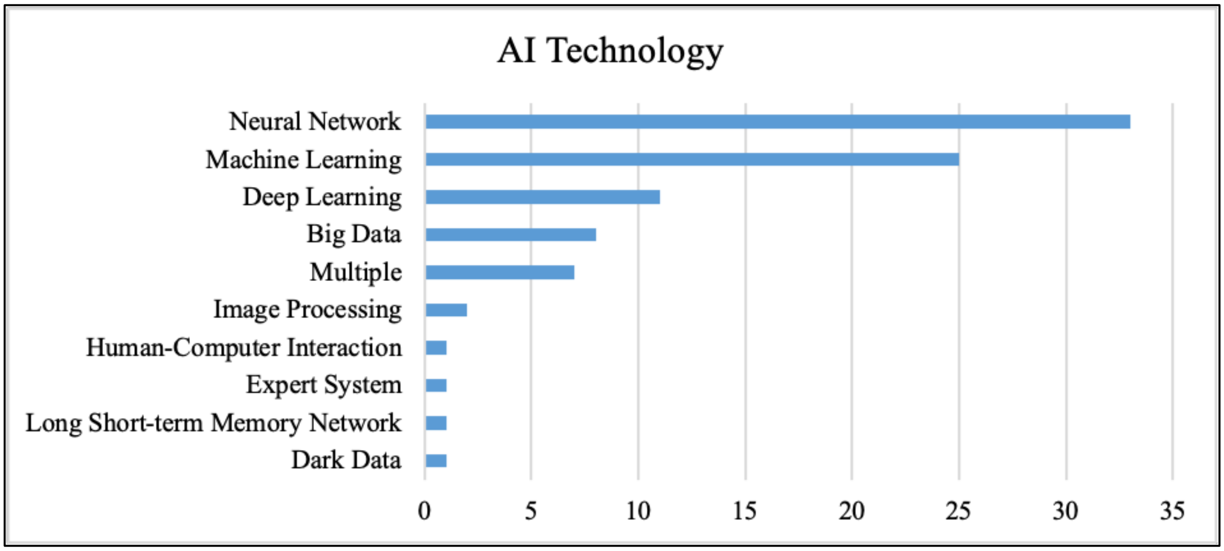

Figure 3. Artificial Intelligence Technologies

The various types of AI are presented in Figure 3. It can be seen that neural network is the most widely used technology in OSCM, accounting for 33 articles, followed by machine learning and deep learning which have about 25 and 11 articles respectively. Only a few studies were found to use dark data, long-short-term memory network, expert systems and image processing with one article each. Interestingly, there are seven articles that used multiple AI technology.

4.2 Thematic Analysis

In this section, the detailed thematic analysis of the 90 selected articles is presented based on the codes in NVivo software, which include AI technologies, problems, barriers, benefits, challenges, and enablers.

4.2.1 Problem

The majority of the studies were conducted because there are number of environmental issues occurring during the SC process. For instance, several studies discussed how the SC process had a lack of proper waste management. Inadequacy of appropriate waste management will lead into the financial issue of companies (Almomani 2020; Farsi and Shirdel 2014; Kavyanifar et al. 2019; Liao and Wang 2019; Naveen Ananda Kumar and Chimmani 2019; Solano Meza et al. 2019; Tarun et al. 2019; Velumani and Saravanan 2014), not to mention that improper waste management has negative impacts on human health and ecology due to hazardous substances. These hazardous substances are generated from manufacturing processes such as cutting fluids (Cica et al. 2020). Secondly, practitioners are concerned about the global climate as it is changing due to rising emissions of greenhouse gases. For example, climate change has a direct impact on agriculture and the forestry industry, such as their productivity, as well as indirect impacts on their ecosystem functioning (Ashraf et al. 2015; Pereira et al. 2019). In a similar manner, climate change could affect rain patterns and may reduce the amount of water which is an essential resource for the agriculture sector (Jimenez et al. 2020; Wahyuni et al. 2017).

4.2.2 Artificial Intelligence Technology

1. Big Data and Predictive Analytics (BDPA)

Big data analytics is an area consisting of big data, analytical instruments and techniques to extract actionable insights from big data to deliver sustainable value, enhance business efficiency as well as present competitive advantage (Jeble et al. 2018). They could also be used to enhance the ability to help with sustainability of sourcing decisions (Rodriguez 2018). In addition, big data can be used to identify and address the key issues in carrying out sustainable manufacturing, such as design layout, product decision-making, and planning and scheduling logistics effectively (Bag and Pretorius 2020; Peters et al. 2020; Tayal et al. 2020). Delgado et al. (2019) discussed how the use of big data could contribute to the development of site-specific conservation and management functions which increase profits and the global sustainability of agricultural systems. Furthermore, the development of key performance indicator-based big data could be used for smart energy grids (Serban and Lytras 2020). Moreover, big data can be used for a sustainable oil and gas industry (Sivakumar et al. 2016).

2. Deep Learning

Deep learning is widely used in the agriculture sector as this industry has high accuracy measurements which can enhance overall production, such as forecasting banana harvest yields, essential for extensive planning for sustainable production (Rebortera and Fajardo 2019), supporting sustainable agriculture for accurate prediction of weather as it has good appearance in complex sensor data (Jin et al. 2020; Pereira et al. 2019), plant disease identification (Guo et al. 2020) and monitoring the environmental pollution space in harvesting fields in order to cut down the cost of obtaining agricultural information as well as advancing the production efficiency (Li et al. 2019). Furthermore, deep learning could be used for sustainable cities such as monitoring anomalous influent conditions for resilient wastewater operations (Dairi et al. 2019), predicting the air quality for smart cities using numerical studies, such as simulating air quality compared to a baseline case under conditions of decreased precursor emission levels (Xing et al. 2020) as well as urban sustainability management for sustainable smart cities (Madu et al. 2017).

3. Expert System

The expert system is used for basic strategic planning. Wang et al. (2013) developed the expert system to derive the latent causes of pollution and describe the difference in parameters of water quality. Likewise, it can be used for the rehabilitation of a geological ecosystem contaminated by petroleum products in Russia (Khaustov et al. 2015).

4. Image Processing

Yudong et al. (2010) pointed out that image processing could be used for automatic reading of a pointer-type meter that has significantly higher performance, lower energy consumption and lower costs of production. This technology could also be implemented to withdraw the texture features in order to predict air permeability and porosity (Gültekin et al. 2020). Liao and Wang (2019) proposed an intelligent reverse logistics using image processing to identify industrial waste then recycle the waste.

5. Machine Learning

Machine learning has an important role in evaluating complex numerical models and providing insight into decision making, which provides efficient, computationally feasible and cheaper to run models. Moreover, it provides high accuracy of model simulation (Arshad et al. 2020; Tayal et al. 2020). Furthermore, it can be used to analyse both qualitative and quantitative data (Bertoni et al. 2018). There is also a study conducted stating that machine learning is useful to predict air quality (Šimić et al. 2020). Serban and Lytras (2020) discussed how this technology can be applied in the renewable energy sector. Furthermore, this technology is used in the production area such as in the labelling process (Peters et al. 2020) and food industry (Fauvel et al. 2019). It is also used in sustainable manufacturing in the cutting process (Du Preez and Oosthuizen 2019), which can reduce the time, cost, and resources as well as increase safety. Machine learning is also used in groundwater to estimate the water quality and predict water pollution (Fan et al. 2013; Knoll et al. 2020; Lal and Datta 2018). Frost et al. (2019) discussed how it could be used to classify the image which can improve waste sorting accuracy.

6. Neural Network

Neural network is a huge parallel simulation model for processing and representing data (Tufaner et al. 2017). Artificial neural networks are frequently used to model complex and non-linear interactions. It is concluded that in terms of prediction precision, neural network-based techniques are far more precise than regression analysis (Almomani 2020; Kavyanifar et al. 2019; Song et al. 2017; Tota-Maharaj and Scholz 2012). This has made neural networks the most used AI technology in OSCM in order to attain sustainability. Several studies have highlighted the usage of neural networks for monitoring air quality and air pollution prediction (Alimissis et al. 2018; Gültekin et al. 2020; Mingjian et al. 2011; Relvas and Miranda 2018; Stamenković et al. 2016; Xing et al. 2020; Xiong et al. 2019; Yi et al. 2018). Neural networks have also been highlighted for simulating water quality parameters accurately as well as predicting pollutant concentration (Fan et al. 2013; Tota-Maharaj and Scholz 2012; Vasilescu et al. 2011; Zhao et al. 2014).

4.2.3 Barriers

Most of studies conducted were about the lack of an integrated framework as the technology was less developed (Kavyanifar et al. 2019; Sajedi-Hosseini et al. 2018; Sharma et al. 2020). Furthermore, in order to implement AI technology, high investment is needed, and returns on the investment may take a long time (AlZu'bi et al. 2019; Du

Preez and Oosthuizen 2019). Also, several studies posed policy issues due to its implementation (Serban and Lytras 2020). In addition, most AI applications need a computational model. Hence, a reliable simulation is required (Stamenković et al. 2016; Tota-Maharaj and Scholz 2012; Vicentini et al. 2012). Another consideration is that a major limitation of using machine learning is that mathematical and regression models cannot be directly applied (Arshad et al. 2020; Solano Meza et al. 2019; Tayal et al. 2020). Also, the major studies of neural network application suffer from subjective preference of the experts (Zhao et al. 2014).

4.2.4 Enablers

It is concluded that it is important to understand the interplay between policy pressures, tangible resources and human skills for AI technology (Bag and Pretorius 2020). Carrying out machine learning techniques requires a high-level scenario language which can be obtained from simulation results (Cordier et al. 2020; Lal and Datta 2018), whereas artificial neural networks require data acquisition, neural network training, optimum model structure as well as model validation (Ashraf et al. 2015). In a similar manner, conducting a deep learning technique requires training as well (Jin et al. 2020; Rebortera and Fajardo 2019). In order to use the air quality monitors, a health impact assessment will also be needed (Li et al. 2019).

4.2.5 Challenges

The major challenge to using AI for OSCM is that most technologies are not yet fully developed (Bertoni et al. 2018; Cordier et al. 2020; Lal and Datta 2018; Weng and Chen 2020). Similarly, practitioners face uncertain data that will affect the results (Ashraf et al. 2015; Knoll et al. 2020; Sajedi-Hosseini et al. 2018). Furthermore, Ghoreishi and Happonen (2020) discussed how implementing AI should be balanced with the benefits that can be gained in returns because it has high initial set-up costs and high costs involved in using this practice. Other challenges include the SC complexity, such as inadequate information on the design of products and the manufacturing process (Bag and Pretorius 2020).

4.2.6 Benefits

In this section, the benefits from each study are presented. Most of the studies conducted have the potential capability to reduce the cost of SC practice (Kuik et al. 2012; Naveen Ananda Kumar and Chimmani 2019; Olukan et al. 2020; Papagiannis et al. 2020; Yudong et al. 2010), whereas several other studies achieved waste reduction using AI implementation (Farsi and Shirdel 2014; Ghoreishi and Happonen 2020; Kavyanifar et al. 2019; Liao and Wang 2019; Velumani and Saravanan 2014). In a similar manner, time savings could be obtained from AI implementation (Singh et al. 2020). Kang et al. (2019) discussed how the use of AI could improve sustainability as it will help to reduce energy used. Moreover, it will help to develop the quality of the product (Du Preez and Oosthuizen 2019; Zhao et al. 2014). In the agriculture sector, the use of AI could be implemented in order to predict and reduce uncertainties in growth forecasting as regularly affected by climate change scenarios, thus it could enhance agricultural productivity and sustainability (Almomani 2020; Ashraf et al. 2015)

5. Discussion

5.1 The potentials of AI

The review findings indicate that AI has vast potential to attain sustainability in OSCM. The use of AI in SCM has been increasing significantly in recent years. AI can be applied in almost all the SC processes, but most of the studies have been undertaken on the production stage as it has brought many benefits. For instance, it could enhance productivity (Almomani 2020; Ashraf et al. 2015; Delgado et al. 2019; Jimenez et al. 2020; Jin et al. 2020; Li et al. 2019; Rebortera and Fajardo 2019; Sharma et al. 2020), provide better monitoring systems for waste management treatment (Farsi and Shirdel 2014; Ghoreishi and Happonen 2020; Kavyanifar et al. 2019; Liao and Wang 2019; Velumani and Saravanan 2014), and also minimise energy consumption that leads to cost reduction (Kang et al. 2019). Although many AI approaches can be used to solve sustainability problems in SCM, the study findings indicate that some are used more than others. It can be seen that the most influential and prevalent is the neural network. Because of its ability to learn nonlinear relations, the use of artificial neural networks in solving complex problems is becoming widespread in disciplines such as environmental engineering (Almomani 2020; Kavyanifar et al. 2019; Song et al. 2017; Tota-Maharaj and Scholz 2012). By using its architecture and nonlinearity, the neural network captures the embedded spatial and unstable behaviour of the permeable pavement system. Moreover, in terms of prediction accuracy, it is better than regression analysis. Therefore, the neural network is regularly used to predict and monitor the environment quality such as water, air and soil (Alimissis et al. 2018; Gültekin et al. 2020; Mingjian et al. 2011; Relvas and Miranda 2018; Stamenković et al. 2016; Xing et al. 2020; Xiong et al. 2019; Yi et al. 2018). Furthermore,

the results also show that one of the most potential AI tools in SCM is machine learning. Machine learning algorithms have efficient models that can be used as a valid approximation of the complex numerical model and are computationally feasible and cheaper to operate (Arshad et al. 2020; Tayal et al. 2020).
Despite the fact that AI could bring plenty of benefits, there are crucial factors such as barriers, enablers and challenges that need to be considered. For instance, the high investment cost of AI technology should be balanced with the benefits to be gained in returns because it has high initial set-up costs and other high costs involved in using this practice (Ghoreishi and Happonen 2020). Also, most of the AI technology is still under-developed (Kavyanifar et al. 2019; Sajedi-Hosseini et al. 2018; Sharma et al. 2020). Moreover, some of practitioners have faced policy issues during AI implementation (Serban and Lytras 2020).

5.2 Research Gap

The use of AI in SCM has increased significantly in recent years, and many businesses have implemented or developed their processes using critical technology, as illustrated in the previous sections. There are, therefore, several research journals that have focused mainly on the application of technology in industry, analysing the advantages of technology implementation and its related disadvantages. However, almost all the studies reviewed did not emphasise on the business perspective, although the influence of AI inevitably extends well beyond the production line, which refers to all business units involved in the planning, development, processing, transport and sale of goods. Thus, engineering business managers need to consider the risks and possibilities associated with AI's rapid technical advances. In order to successfully handle AI, companies will need people who are competent and well-informed about technological developments that impact both their business and workforce (Greenough and Tjahjono 2007). In addition, it is necessary for companies to quantify the benefits from AI technologies that will affect their business rather than just its number of features.

5.3 Decision-Making Process

Based on the entire process of carrying out this study, through a process of desk-based review, it was found that there are many factors in AI application to be acknowledged, such as barriers, challenges and AI technologies as well as the problems that could be solved by using AI technology. In this section, the decision-making process of AI application in OSCM to attain sustainability will be proposed. The decision process can be used by practitioners, such as engineering business manager, as tools and steps to consider before implementing AI techniques. The decision-making process is shown as a flow chart in Figure 4.

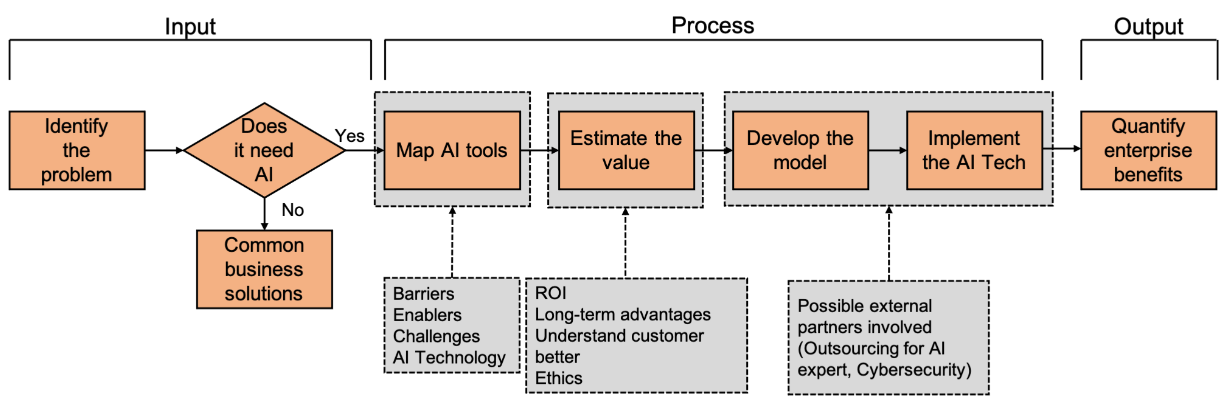

Figure 4. Decision-making process

The following section discusses the decision-making process.

1. Identify the problem

It is crucial for engineering business managers to analyse the factors that causes sustainability issues. The sustainability issues in OSCM may occur within its process, such as logistics, distribution, production process and waste treatment. One example is climate change that has affected forest growth and yield, as well as forest ecosystems (Ashraf et al. 2015). However, the problems are regularly complex. It is important to dig beneath the surface in order to understand the system that underlies the problem. Furthermore, identifying the issue of only one (or a small group) of those concerned normally leads to other stakeholder resistance. Instead, an integrated strategy should be planned that takes into account the positions and objectives of all the main individuals involved in the complex problems. This can done with help from staff in reporting a potential problem that has occurred in their division; a robust problem identification might then be achieved.

2. Analyse needs

It is important to compare the AI technique with the common business method such as existing SC models (SCOR model, forecasting), optimisation or multi-criteria decision making. Calculate the value that can be obtained using both approaches, then select the one with the higher value. Return on investment (ROI) is important, but pace is also crucial. When selecting the method for a business problem to be solved, one common mistake that many companies make is choosing the one that will produce the greatest ROI; however, it is not actually producing the biggest or best outcome for the company as a whole. There are also much simpler ways that can more easily produce greater value. For example, using inventory management to reduce the cost of production is more beneficial in terms of speed and customer satisfaction than using AI tools. Therefore, the use of AI technology in that SC process is not needed.

3. Map AI tools

There is plenty of existing AI technology that has been widely used to successfully resolve sustainability issues. There are number of journals that can be adapted to choose the right AI technology. For example, using deep learning to monitor air quality (Xing et al. 2020), the use of deep learning in the agriculture sector as they have high accuracy measurements which can enhance the overall production (Rebortera and Fajardo 2019), monitoring the environmental pollution space in harvesting fields (Li et al. 2019) and using a fuzzy logic approach to assess product returns and recovery operations (Kuik et al. 2012).
Furthermore, it is crucial to put the barriers, challenges and enablers from the adopted AI technique to the key consider. For example, the major barriers to AI implementation are high initial set-up costs and the high costs involved in the actual operation (Ghoreishi and Happonen 2020). Many AI technologies are also still under-developed (Kavyanifar et al. 2019; Sajedi-Hosseini et al. 2018; Sharma et al. 2020). In addition, during implementation, some practitioners have faced policy problems (Serban and Lytras 2020). Thus, businesses and technology managers should work quickly to develop all those keys, otherwise they risk losing the present and potential of AI. With daily technical changes, it is difficult to determine the best time for new technologies to be introduced. It is important to ensure that the latest technology actually adds value both in the short and long term. It also takes time to integrate emerging innovations into existing organisations, so the long-term competitive advantage of its technology should be taken into account.

4. Estimate the value

It is important to estimate the value that can be obtained from AI usage. For an engineering business manager, there are several values that should be identified and analysed from using AI technology. Firstly, the most important value is that the AI tools should be able to facilitate the company to better project itself with the goal of sustainability, for instance, the capability to reduce the cost of SC practice (Yudong et al. 2010) and the ability to reduce waste (Kavyanifar et al. 2019). Likewise, the tools should be able to predict demand forecasting, research and development optimisation and sourcing improvement. In addition, AI should be able to understand the customer better, such as enabling the AI to have deep, personal and easy user experiences, also it should have the ability to deliver products and services at lower costs and higher quality. Furthermore, ROI is a crucial factor to consider. Adopting modern technologies is an arduous task that requires the development team to spend significant time on it, and often demands the availability of a task-oriented support system (Tjahjono 2009). This is because, in certain cases, the techniques today may be mature and the data available, but given the value that could be created, the cost and complexity of deploying AI may simply not be worthwhile. Understanding the cost advantages provided by the technology and how it affects the bottom line of the business not only justifies the effort made, but also more significantly, offers precise figures to assess the ROI. However, applying AI technology may have detrimental effects if misused. In order to combat this, organisations need to eliminate prejudices from their processes and ensure that anything in their strategy is at the forefront of data privacy and security. To ensure that AI programmes are in accordance with legal standards, organisations should have specific ethical and governance structures in place.

5. Develop the model

Developing the AI model requires highly skilled practitioners. The solution here is to create a plan for skills and data literacy that serves as a roadmap for acquiring and building the necessary individuals and teams. Upgrading current staff, growing data and technology awareness across the board, and finding the right partners are the key to making this step successful. If needed, the business could use outsourcing or an external partner to develop their AI in order to have the best possible expertise. A partner with expertise in the industry and implementation will bring to the company both technical and change management points of view. As well as keeping the project consistent with the business case, such an expert can close the gap between perceived and real demands. More significantly, the success of the business case would be assisted by partners that are outcome-focused, rather than technology-focused.

6. Implement the AI technology

After the model has been developed, the AI may be ready to apply to the SC process. It is important for the engineering business manager to take a note of the results of using the new technology. These results will be analysed in the next section as accomplishing results from analysis requires not only the distribution of these capacities within the organisation, but also a real awareness and dedication on the part of leaders to drive big-scale change, as well as placing emphasis on the management of change rather than on the innovation itself. Furthermore, it is also important to control standards, as 100% automation or 100% accuracy can never be assured by AI. Therefore, understanding the tolerable margin of error is necessary for the company and how the company aims to fix mistakes or exceptions when they occur is particularly relevant. This understanding clarifies when, how and to what degree AI may assist the organisation and where a contingency plan will be needed for engineering business managers. In addition, while AI is used in many organisations in different sectors, security is a significant problem that companies need to take into account when implementing AI in their system to support new business functions and customers. Businesses need to consider the effect of possible security threats that can emerge and take effective steps to avoid attacks on their system. When it comes to data protection, many industries have their own rules and requirements, so organisations need to ensure that their device upgrades are consistent with those regulations. Thus, the IT department will need to be involved to assist with the installation to get it up and running. Therefore, it is necessary to identify the party responsible for setting up the product as needed and to obtain an estimate of the set-up time required.

7. Quantify enterprise benefits

Finally, quantify all the enterprise benefits that are generated from AI adoption, for instance the actual ROI, how far the new technology resolves the problem and also identify how AI implementation supports the business cases that have been presented in previous steps. One of the key ideas for implementing AI technology is to adequately consider the requirements and desires of customers as this helps to understand any strengths and weaknesses in the application of the process (Rashid et al. 2018). This is mainly because many businesses that build AI, or provide AI to others, have great strength in the technology itself and the data scientists necessary to make it work, but they may lack a comprehensive understanding of the end markets. Understanding the value potential across industries and functions will help shape these AI technology portfolios. Companies should not necessarily prioritise only the areas with the greatest potential benefit. Instead of forming their investment portfolios, they should combine the data with complementary assessments of the competitor environment, their own current strengths, sector or feature expertise, and customer relationships. In addition, they should communicate the results with the involved stakeholders in order to receive feedback. Moreover, while in the lead up to going live, a review must be undertaken of the processes that feed into and out of the teams using the technology. A focus on best practice should be adopted, and planned reviews of what is best practice should be undertaken until fully incorporated in the months following implementation. These processes can be helped with input from suppliers, but most need to be handled internally by the top-level management with oversight. Lastly, after the problem has been resolved, make predictions for how the problem could develop in the future based on past and current trends and patterns. Therefore, conducting this step will help to introduce the right technology for the right result.

5.4 Contributions to Knowledge

Based on the discussions in this study, the following broad areas needing further investigation from researchers are presented. The following points were identified as key improvement suggestions for researchers:

1. More academic study related to the use of AI by OSCM in order to solve sustainability problems needs to be carried out as publishing journal articles brings plenty of benefits. More studies conducted on this field would provide more insight and scope for improvement to other researchers and practitioners
2. Studies on identifying the relationships between the different barriers to the implementation of AI in OSCM are needed. The recognition of the barriers to driving and dependency would enhance the implementation of AI.
3. Future research should provide a cost estimation for the AI application to the SC process.
4. Future research should strive to develop oriented consumer frameworks to capture insights into the purchasing behaviour of consumers.
5. Future research may focus on comparing sustainability solutions, both the use of the AI technique and the traditional technique of SCM, therefore, an effective and efficient result will be achieved.

5.5 Contributions to Policymakers

There are many local government demands regarding sustainability. Given the high cost of digital technology investments and the growth of AI capacity, policymakers are expected to subsidise digital technology investments and make them more affordable so that they can be widely used. There is a significant difference in emerging markets between the available sources of capital and education. Many employees may not have access to new software and data interpretation preparation. Advisors must be established to help employees understand the data and to suggest effective mechanisms for improving efficiency. Therefore, it is suggested that policymakers should prepare to link employees and collaborate with governments and technology firms to reduce data collection equipment and software costs. There is also the need to provide thorough and comprehensive preparation, which revolves around using these implementation measures globally

6. Conclusion

This study has explored how AI might support smart and intelligent operations in multiple industrial sectors, with an ultimate goal to improve and attain sustainability. The study has reviewed 90 articles collected from journal databases. The journals have been classified based on their document type, year published, the research purpose, problem, AI technology, industry sector and its benefits, in order to carry out a descriptive analysis. It has also developed a thematic analysis of sustainability in the applications of AI in OSCM. Themes were proposed before undertaking the thematic analysis. The findings from the review indicated that some techniques have been used more widely than others among the many distinct AI techniques available. The results indicated that Artificial Neural Networks are the most prevalent AI tool, which are typically used to find complex patterns that cannot be identified by humans. The barriers, enablers and challenges that could be posed from implementing the AI were also presented. Most of the studies conducted presented similar challenges, that using AI in OSCM is difficult because most of the technologies were not fully developed and lacked an integrated framework. The review findings indicated that AI has vast potential to attain sustainability in OSCM, for instance, it could enhance productivity, provide better monitoring systems for waste management treatment, and could also minimise energy consumption thus leading to cost reduction. The decision-making process for an engineering business manager has been proposed in this study, which was based on the findings from the literature review. There are several steps and key factors to be considered by the engineering business manager before implementing the AI technique, as AI technology implementation is not only about the technology itself. It is important for success to consider the business case and apply the technology to it, rather than the other way round.

Acknowledgment

The project described in this paper was under the auspices of the bilateral research collaboration between Coventry University and Institut Teknologi Sepuluh Nopember (ITS), Indonesia. The authors are grateful with the support given by the two institutions.

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Biographies

Reza Akbar Muhammad obtained his MSc in Engineering Business Management from Coventry University. His research interests are in Sustainability and Supply Chain Management. He was involved in the Electric Vehicle Research Team on his undergraduate campus, funded by the Ministry of Research, Technology and Higher Education in order to develop Indonesian electric vehicles.

Prof Benny Tjahjono is Professor of Sustainability and Supply Chain Management at Coventry University, UK. His overarching research area includes Sustainable Operations and Supply Chain Management, in particular, the exploration of Circular Economy principles in manufacturing and supply chains. He has a vested interest in ensuring the achievement of the triple sustainability objectives, 'doing good for people, planet and profit'. His research track record has been demonstrated by winning and successfully delivering several research grants from EPSRC, ESRC, InnovateUK, European Union, overseas funding agencies and directly from the UK industry. He has published over 100 papers in refereed academic journals, conference proceedings, books, practitioners' journals and newspapers.

Dr Babul Salam KSM Kader Ibrahim is an Assistant Professor at the School of Mechanical, Aerospace and Automotive Engineering, Coventry University.

Sri Rachmi Karimah Dewi Ridlo obtained her MSc in International Business Management from Coventry Business School University. Her research interests are Supply Chain Management and Inventory Management.

Prof Tri Yogi Yuwono is Professor of Mechanical Engineering at Institut Teknologi Sepuluh Nopember (ITS), Indonesia. He is a Head of the Laboratory of Fluid Mechanics and Fluid machinery Machines, Department of Mechanical Engineering FTI-ITS. His research interests are in Fluid Mechanics, Wind Turbines and Energy.