Production Planning & Control
The Management of Operations

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/tppc20

Enabling explainable artificial intelligence capabilities in supply chain decision support making

Femi Olan, Konstantina Spanaki, Wasim Ahmed & Guoqing Zhao

To cite this article: Femi Olan, Konstantina Spanaki, Wasim Ahmed & Guoqing Zhao (27 Feb 2024): Enabling explainable artificial intelligence capabilities in supply chain decision support making, Production Planning & Control, DOI: 10.1080/09537287.2024.2313514

To link to this article: https://doi.org/10.1080/09537287.2024.2313514

Published online: 27 Feb 2024.

PRODUCTION PLANNING & CONTROL
https://doi.org/10.1080/09537287.2024.2313514

Enabling explainable artificial intelligence capabilities in supply chain decision support making

Femi Olan[a], Konstantina Spanaki[b], Wasim Ahmed[c] and Guoqing Zhao[d]

[a]Essex Business School, University of Essex, Southend-on-Sea, UK; [b]Audencia Business School, Nantes, France; [c]Hull Business School, University of Hull, Hull, UK; [d]School of Management, Swansea University, Swansea, Wales, UK

ABSTRACT

Explainable artificial intelligence (XAI) has been instrumental in enabling the process of making informed decisions. The emergence of various supply chain (SC) platforms in modern times has altered the nature of SC interactions, resulting in a notable degree of uncertainty. This study aims to conduct a thorough analysis of the existing literature on decision support systems (DSSs) and their incorporation of XAI functionalities within the domain of SC. Our analysis has revealed the influence of XAI on the decision-making process in the field of SC. This study utilizes the SHapley Additive exPlanations (SHAP) technique to analysis the online data using Python machine learning (ML) process. Explanatory algorithms are specifically crafted to augment the lucidity of ML models by furnishing rationales for the prognostications they produce. The present study aims to establish measurable standards for identifying the constituents of XAI and DSSs that augment decision-making in the context of SC. This study assessed prior research with regards to their ability to make predictions, utilization of online dataset, number of variables examined, development of learning capability, and validation within the context of decision-making, emphasizes the research domains that necessitate additional exploration concerning intelligent decision-making under conditions of uncertainty.

ARTICLE HISTORY
Received 18 September 2023
Accepted 24 January 2024

KEYWORDS
Explainable artificial intelligence; supply chains; decision support systems; supply chains management; SHAP; innovation

1. Introduction

The need for expeditious and accurate decision-making has necessitated the adoption of novel explainable artificial intelligence (XAI) and methods. The conventional process of decision-making has been swiftly impacted by the progressions made in XAI (Haque, Islam, and Mikalef 2023; Mikalef et al. 2023). In contemporary times, the intricacy of systems has increased because of their interaction with cloud technology, various online platforms, and advanced tools for generating data (Olan, Arakpogun, et al. 2022; Olan, Arakpogun, et al. 2022; Fosso Wamba et al. 2022). Consequently, it is imperative that a decision support system DSS exhibits robustness, as emphasized by Zhai et al. (2020). DSSs aid management in various functions, spanning from strategic planning to operational execution across the entire value chain. The DSS has undergone a transformation in its orientation from a decision-making system that was computer-based to one that can adapt and organize itself in a dynamic and uncertain supply chain environment (Bochtis, Sørensen, and Green 2012). Giusti and Marsili-Libelli (2015) have pointed out that the third industrial revolution was characterized by digitization. In response, various firms across industries such as logistics, financial services, and electronic markets have incorporated artificial intelligence (AI) into their business operations in a proactive manner (Olan, Arakpogun, et al. 2022). SC is a conventional approach utilized for routine business decision-making, which facilitates the establishment of DSSs. The process of digitization has resulted in a significant increase in the volume of data generated by SC firms, which needs to be effectively utilized to enhance decision-making capabilities (Moynihan and Wang 2015; Banerjee and Golhar 2013). This integration aims to enhance the decision-making processes and cognitive approaches of businesses. The ability of AI to generate business scenarios and decisions that closely resemble reality renders it highly suitable for SC as a game-changing technology (Hu et al. 2011). The integration of AI within the context of the fourth industrial revolution is expected to facilitate a significant overhaul of production, operations, logistics, and public governance systems. Hence, the integration of XAI with SC is imperative to facilitate prompt and efficient decision-making processes. Historically, the majority of research in this area has treated DSS and SC as distinct domains, or alternatively, as a fusion of AI and DSS or DSS and SC (Essien, Dzisi, and Addo 2018; Fikar 2018; Gromov, Kuznietzov, and Pigden 2019; Krishnaiyer and Chen 2017). The integration of XAI and SC has not been extensively investigated. The absence of relevant information in the existing literature motivated this research to conduct a comprehensive and methodical review.

The capacity of XAI to offer self-governance and adaptability in a constantly changing setting has been identified as a DSS capability (Dellino et al. 2018). XAI is utilized in

CONTACT Femi Olan femi.olan@essex.ac.uk; femiolan@outlook.com Essex Business School, University of Essex, Southend-on-Sea, SS1 1LW, UK

high-performance computing systems to facilitate cognitive processes such as learning from behaviour, recalling information, acquiring knowledge, making inferences, and interpreting codes within a given context (Linardatos, Papastefanopoulos, and Kotsiantis 2020; Meske et al. 2022). The employment of neural network models is a common practice in the decision-making process of AI (LeCun, Bengio, and Hinton 2015). During the early 2000s, advancements in machine learning, big data, and computing power led to a new direction in AI research (Adadi and Berrada 2018; Polikar 2012).

Various methodologies, including fuzzy logic, genetic algorithms, agent-based systems, data mining, and neural networks, can be employed to construct a DSS (Kingma et al. 2014; Pan, Harrou, and Sun 2023). According to Pan, Harrou, and Sun (2023), the utilization of agent-based systems has proven to be advantageous in various business functions such as demand planning and forecasting, customer relationship management, order fulfilment, and negotiating with suppliers and other value stream partners. The utilization of genetic algorithms has been found to be advantageous in the process of network design. Furthermore, the utilization of expert systems has demonstrated utility in the domains of inventory planning, make-or-buy determinations, and supplier selection-related endeavours, as evidenced by studies conducted by Alkahtani et al. (2019); Amir-Heidari and Raie (2019); Cankaya et al. (2023); Teniwut and Hasyim (2020).

DSS is a crucial requirement for firms in various operational aspects such as product and process design, machine and equipment scheduling for optimal utilisation, quality assurance, maintenance, fault identification, and other constraints in supply chain activities. This has been highlighted in several studies including those conducted by Attadjei, Madhwal, and Panfilov (2018); Azzamouri et al. (2019); Balaman et al. (2018); Olan, Arakpogun, et al. (2022). XAI is a DSS tool that utilizes computer vision to analyze and evaluate data, ultimately facilitating decision-making processes within a business context. According to Belciug et al. (2020), DSSs possess the capability to analyze extensive volumes of data and facilitate crucial decision-making processes. DSSs possess the ability to capture, store, and retrieve data while utilizing a feedback control mechanism. The design of DSS is contingent upon the network strategies implemented and the mechanisms employed in business operations. DSSs exhibit the ability to engage in problem-solving and decision-making activities within the realm of business operations, particularly in the presence of demand-related uncertainties. DSSs are utilized in a diverse range of fields, including both humanitarian operations and real-world business scenarios. The utilization of case-based reasoning in AI systems facilitates decision support.

DSSs that are integrated with AI technology are present in various business domains (Balaman et al. 2018). Contemporary enterprises necessitate the integration of XAI across various stages encompassing the conception and promotion of commodities and amenities. The development of has facilitated the creation of autonomous vehicles that possess the capacity to acquire knowledge and recognize patterns. XAI possesses the capability to measure uncertainty and predict the information requirements of users (Arakpogun et al. 2021). This entity exhibits substantial prognostic capability and logical reasoning with regards to both planning and object manipulation.

Thus, AI techniques to identify the most suitable tools and cutting parameters, resulting in a noteworthy enhancement of milling, and turning operations. Moreover, within the realm of SC, the movement of goods and services can be simulated through the utilization of distributed AI (Biswas and Samanta 2016; Brauner et al. 2019). A comprehensive evaluation of the relevant literature was carried out by examining the following crucial aspects of each examined study:

1. Does the DSS offer any predictive capacity regarding XAI potential future scenarios that could impact its functionality?
2. What is the number of factors taken into account during the development of the DSS?
3. Has any learning capability been developed to tackle decision making in the field of SC?

The primary outcomes of this study, as demonstrated through the utilization of the SHAP explainable AI technique, offer a comprehension of the XAI-DSSs-SC model. This is accomplished by identifying crucial variables, including tacit knowledge, that play a significant role in enhancing decision-making within the context of supply chain management. The remainder of this article has been organized in the following manner: Section 2 provides an overview of the study's background, specifically in relation to XAI, DSSs and supply chain (SC). The third section of the paper outlines the methodology employed for the study's review process. The fourth section of the paper presents the results obtained from the conducted analysis. The fifth section of the document outlines the discussion. Section 6 presents a discourse on research inquiries, alongside their implications for both theoretical and practical applications, concluded and the scope for future research is established.

2. Theoretical background

XAI approaches lack the ability to offer explanations that effectively pinpoint biased behaviour in some sensitive situations. Providing explanations for DSSs can enhance comprehension and confidence in their functionality (Kämmer et al. 2023; Liberatore and Nydick 2008). However, it is important to note that simplistic explanations may obscure negative aspects of the DSS, thereby leading decision-makers to draw hazardous or baseless conclusions that could be morally wrong (Carnero 2005; Fu, Liu, and Chang 2020). Furthermore, it is crucial to be cognizant of the risks associated with unquestioningly accepting explanations that can conceal complex problems (Jussupow et al. 2021; Twomey, Sammon, and Nagle 2021) or engage in fair-washing, which involves misleadingly presenting a XAI model as adhering to certain ethical principles. This knowledge is necessary in DSSs that employ such predictive capabilities.

The utilization of XAI assumes a pivotal role in the decision-making process within the domain of SC (Haque, Islam, and Mikalef 2023; Meske et al. 2022; Mikalef et al. 2023). The primary objective of SC is to attain optimization, which can be accomplished by leveraging XAI to automate the decision-making process. Historically, conventional DSSs were limited to facilitating decision-making processes solely through the use of data modelling and numerical computations. The integration of XAI into the decision-making process enables the amalgamation of both qualitative and quantitative analyses. XAI facilitates the emulation of intelligence that closely resembles human cognitive abilities within a given system. Research has been carried out to explore diverse implementations of XAI in DSSs. Chou and Benjamin (1992) formulated an AI-DSS model for the purpose of constructing a naval vessel. Subsequently, Beşikçi et al. (2016) created a comparable AI-DSS system to optimize energy consumption on the vessel. DSS for humanitarian supply chains was developed by Guillaume et al. (2014); Sahebjamnia, Torabi, and Mansouri (2018).

The utilization of DSS-based AI, and remote sensing has been implemented to facilitate efficient public decision making (Mikalef et al. 2023; Olan, Arakpogun, et al. 2022; Mohiuddin Babu et al. 2022). The aforementioned studies employed varying AI capabilities that were appropriate for their respective scopes. However, there are lingering inquiries regarding the specific AI capabilities that have been employed thus far to facilitate decision-making across diverse scenarios. Moreover, scholarly sources highlight the utilization of the diagnostic method in decision-making processes, which disregards the presence of ambiguity in the surrounding context (Dong and Srinivasan 2013; Erdem and Göçen 2012). Hence, in a period of ambiguity for numerous enterprises, such as the present, it is more suitable to employ the anticipatory decision-making competencies of artificial intelligence. Various SC applications have been employed in the development of DSSs.

2.1. Explainable artificial intelligence and decision support systems

In practical contexts, various entities such as individuals, groups, organizations, and communities face numerous complexities that necessitate decision-making and subsequent implementation (Dias, Cunha, et al. 2022; Dias, Cunha, et al. 2022; Dong and Srinivasan 2013; Liu et al. 2023; Wen and Liao 2021). In order to exhibit rational behaviour, these groups must gather pertinent information, evaluate said information, and implement suggested courses of action (Alkahtani et al. 2019; Dias, Cunha, et al. 2022; Dias, Cunha, et al. 2022; Dong and Srinivasan 2013; Liu et al. 2023; Teniwut and Hasyim 2020; Wen and Liao 2021).

The level of difficulty increases progressively with each subsequent step, corresponding to the escalating intricacy of the problem (Helo and Hao 2022). In order to tackle these obstacles, it is imperative to develop intelligent and knowledge-based systems that can aid in the process of decision making.

The accuracy of AI systems for SC has significantly increased due to the expansion of structured data and processing capabilities (Bochtis, Sørensen, and Green 2012; Giusti and Marsili-Libelli 2015). In SC scenarios, stakeholders must establish agreements that prioritize security safeguards and privacy measures for regulated data. The aforementioned controlled data is generated through the utilization of sensors that are strategically positioned on machines and equipment that are under computerized supervision and are intended for regular usage (Eydi and Fazli 2019; Fikar 2018). Dubey et al. (2016); Queiroz et al. (2023) have demonstrated that a substantial quantity of data can be leveraged to produce models in significantly less time than conventional methods. Furthermore, the utilization of models aids companies in optimizing their decision-making processes and achieving maximum profitability. The utilization of XAI has been identified as a potential solution for enhancing the efficiency of manufacturing and service firms in their operational activities, as suggested by various studies (Dubey et al. 2021; Papadopoulos et al. 2017). Initially, XAI can be perceived as the discipline concerned with the creation and development of computer-based entities that possess the capability to execute tasks that are typically performed by humans (Haque, Islam, and Mikalef 2023; Meske et al. 2022). The secondary interpretation of XAI pertains to its cognitive characteristics, specifically, 'the study of emulating human beings' (Chou and Benjamin 1992; Polikar 2012). XAI has expanded its range of applications in various domains such as automatic speech, humanoid robots, natural language processing, data mining, and driverless vehicles (Fosso Wamba et al. 2015; Wamba et al. 2017). XAI possesses diagnostic capabilities through various methods such as expert systems, fuzzy logic, rough set theory, and case-based reasoning (Bach et al. 2015; Gunasekaran et al. 2017). Consequently, DSSs that XAI are experiencing a growing utilization in aiding decision makers across various domains such as healthcare, finance, marketing, and cybersecurity. XAI presents a significantly reduced margin of error in decision-making when compared to human decision-making and other systems. Thus, XAI enables swift, meticulous, and precise decision-making processes. AI has the capability to operate in environments that are hazardous to human beings. The XAI tools that provide support to DSSs are commonly known as intelligent decision systems, joint cognitive systems, expert systems, and knowledge-based systems (Charnes et al. 1988). The integration of XAI tools, including artificial neural networks, case-based reasoning, machine learning, cognitive computing, probabilistic reasoning, genetic algorithms, fuzzy theory, and multi-agents, with DSSs can facilitate rapid decision-making processes for the purpose of assessing and identifying optimal alternatives (Lipovetsky and Conklin 2001). Sophisticated DSSs possess the ability to tackle intricate decision-making processes through the utilization of vast and intricate data sets. The concept of XAI can be conceptualized as a tripartite framework consisting of formulation, solution, and investigation (Adadi and Berrada 2018; Ajzen 1991). Initially, the model is formulated to meet the requirements of a solver. Subsequently, the algorithm is formulated and subsequently, a series of solutions are evaluated through the implementation of 'what-if' scenarios.

The process of making decisions in SC operations encompasses a variety of actors and functions. This phenomenon introduces diverse perspectives and limitations into the process of making decisions. XAI is particularly well-suited for addressing intricate situations that involve numerous limitations and criteria. The decision-maker depends on diagnostic tools such as XAI to identify an appropriate problem from a range of alternative options, considering the intricacy involved. Specifically, if there are 10 problems under consideration, with only one of them being accurate, then a maximum of 10 decisions will need to be examined. The emergence of model-driven decision-support systems has been observed in various studies (Dong and Srinivasan 2013; Erdem and Göçen 2012; Eydi and Fazli 2019; Fikar 2018; Gunasekaran et al. 2017; Sahebjamnia, Torabi, and Mansouri 2018; Wamba et al. 2017). The study conducted by Attadjei, Madhwal, and Panfilov (2018) pertains to the utilization of multiple operations research models by a DSS in identifying database features. Over the past twenty years, these models have gained significant strength in their ability to manage substantial quantities of data through contemporary decision-making technologies (Attadjei, Madhwal, and Panfilov 2018; Teniwut and Hasyim 2020).

Diagnostic methods in decision-making involve the identification of the accurate problem from a range of problems based on a set of indicators that signal the presence of a problem (Carnero 2005; Fu, Liu, and Chang 2020; Jussupow et al. 2021). Common experiences with this procedure involve identification of supply difficulties such as supply chain financing, supply networks or emerging suppliers, and forecasting reason (defect) of an inadequate running supply chain transaction. Regardless of the situation, diagnostic tools provide information about the indicators of the issue to the decision-maker, who then identifies the most probable reason that effectively accounts for these symptoms (Kämmer et al. 2023; Liberatore and Nydick 2008; Twomey, Sammon, and Nagle 2021). However, in the more common scenario when several problems (namely, concerns with suppliers) may occur simultaneously, the difficulty of finding a comprehensible solution utilising AI-based DSSs grows exponentially as the number of problems increases (Olan et al. 2023; Carnero 2005). For instance, by considering the 10 aforementioned difficulties, the scenario shifts to a situation where any of the 1024 potential combinations of problems might potentially provide the correct conclusion. Through the comparison of various automated diagnostic methods for decision-making on multiple simultaneous problems, it is evident that diagnostic tools, such as XAI, vary in their approach. Some tools employ an exhaustive method, testing every possible combination and selecting the most likely diagnosis. Others use a heuristic approach, testing only a small percentage of the total combinations but still achieving a satisfactory diagnosis. The drawbacks of each technique restrict the comprehensibility, and their respective execution times and dependability are compared.

2.2. Explainable artificial intelligence and supply chain

The utilization of XAI methodologies and instruments in the domains of reasoning and forecasting has the potential to enhance human dependence on SC (Alkahtani et al. 2019; Cankaya et al. 2023). The field of AI encompasses a diverse range of information demonstration techniques that can be applied to address a variety of real-world issues. The aforementioned instances encompass the portrayal of restricted programming, rational deduction, functional and declarative programming dialects in contrast to rule-based formalism, prolog and lisp, and Bayesian models (Adadi and Berrada 2018; Bach et al. 2015; Beşikçi et al. 2016; Chou and Benjamin 1992). Nevertheless, the aforementioned comprehensive representations give rise to rigid issues, rendering them less appropriate for practical applications. However, the field of SC places greater emphasis on manageable representations, such as linear programming constructions (LeCun, Bengio, and Hinton 2015). The SC discipline possesses the capacity to recognize and offer the most effective resolutions within a clearly defined realm of issues. Hence, the difficulty lies in presenting visual representations that possess ample capacity for conveying meaning in practical situations and can ensure prompt and accurate resolutions (Meske et al. 2022).

XAI and SC have the potential to be implemented in various operational domains, including but not limited to: (1) scheduling, (2) quality assurance, maintenance, and fault detection, (3) process prediction and regulation, and (4) process and job development (Adadi and Berrada 2018; Beşikçi et al. 2016; Chou and Benjamin 1992; Polikar 2012). The aforementioned domains can be reinforced through the utilization of XAI methodologies such as case-based reasoning, fuzzy logic, knowledge-based systems, genetic algorithms, and hybrid techniques (Olan, Arakpogun, et al. 2022; Zhao et al. 2022).

Currently, SC finds application in various industries, including but not limited to transportation, shipping, production, education, telecommunications, and healthcare (Dias and Rocha 2023; Fu, Huang, and Singh 2021; Liu et al. 2023; Hernández et al. 2014). Presently, it has become exceedingly challenging to operate a business entity without employing AI techniques to enhance the efficiency of operations and allocation of resources (Dias and Rocha 2023; Fosso Wamba et al 2015; Fu, Huang, and Singh 2021; Liu et al. 2023). The utilization of XAI is evident in routine decision-making procedures that involve the prediction and arrangement of airline schedules, factory operations, and hospital operating room management. The use of XAI aids executives in making decisions related to capacity planning and facility planning, spanning across various industries from manufacturing to service sectors (Adadi and Berrada 2018; Beşikçi et al. 2016; Mikalef et al. 2023). The utilization of AI can aid in the planning and development of a company's business by determining the necessary capacity and competency for the upcoming fiscal year. Therefore, XAI facilitates the provision of optimal offers to customers by finance firms based on their specific needs and preferences (Modgil, Gupta, and Bhushan 2020). The implementation of sales promotions can contribute to the enhancement of customer value and lifetime value. These promotions can be effectively executed through the utilization of AI applications. The utilization of analysis, logic, and qualitative factors is facilitated by AI to assist professionals in the identification of problems (Zhao et al. 2022). The implementation of XAI has been observed to be efficacious in facilitating cost-efficient modes of transportation, the substitution of outdated equipment, job sequencing, and production scheduling. The utilization of DSS models and techniques has been found to enhance the process of decision making and mitigate the likelihood of erroneous decisions (Azzamouri et al. 2019; Balaman et al. 2018). The planning models offered by SC facilitate the coordination among various divisions within a company, thereby enhancing the efficiency of the supply chain operations. In a SC context, data can assist decision makers in achieving profit maximisation and minimising losses (Gunasekaran et al. 2017; Wamba et al. 2017).

3. Classification method

3.1. Method architecture

The SHAP value was postulated by Lundberg and Lee (2017) as an important tool for building any XAI model. The SHAP value is the average of the small inputs from all the possible combinations. This is a new way to explain the results of any machine learning method, like SHAP outputs. Most tests that measure the value of variables, like Pearson correlation, only look at the link between variables across the whole population, not at the level of each individual case (Lundberg, Erion, and Lee 2018). This problem could be fixed by SHAP by allowing local interpretation, which compares and figures out the effects of the factors. A preliminary assessment was conducted on the online data gathered from https://www.crunchbase.com apparatus, and the utilization of SHAP techniques for SC explanations aids in comprehending the specific features within the input instance that are contributing to the final decision of the model. Additionally, these methods provide insight into how the model's decision can be altered by adjusting the values of certain features by a particular finding. For ML explainability and interpretability, this study adopts models from Gall (2018); Joseph (2020); Misheva et al. (2021) to provides global understanding of model's behaviour.

The crunchbase dataset comprises 42 distinct features, encompassing 3 categorical features, 6 binary features, 23 discrete features, and 10 continuous features. All features remain unchanged, with the exception of the categorical features. One hot encoding is a technique utilized to transform categorical features into binary features. When dealing with categorical data, it is preferable to use one hot encoding instead of ordinal/integer encoding. This is because integer encoding can create a natural order relationship between categorical variables, which is not necessarily accurate. The model may acquire the knowledge that certain ordering of elements may lead to suboptimal performance. The quantity of features has increased from 42 to 122. The data was normalized using the min-max normalization method prior to model fitting.

3.2. Generating explanations with validation

The concept of XAI has garnered significant attention within the data science community in recent years (Adadi and Berrada 2018; Joseph 2020). This is currently a popular area of research, with numerous tools and libraries being developed to increase transparency of black box models. Nonetheless, a dearth of universally accepted performance measurement metrics exists for the purpose of comparing the efficacy of said methods. There is no singular approach to explainability that can be deemed superior to alternative methods. Various methods exist for producing explanations for machine learning models, including model-specific versus model-agnostic approaches, local versus global explanations, and intrinsic versus post-hoc explanations. Consequently, this study has employed multiple explainability techniques to explicate the deep learning model (Moscatelli et al. 2020).

The SHAP package will be utilized to showcase its functionality, employing a crushbase online dataset consisting of 315 observations. The dataset will be utilized for the purpose of explainability of the relationship of XAI-DSSs-SC. SHAP technique serves the purpose of producing explanations that are specific to a given instance. This is achieved through the application of a local linear approximation to the behaviour of the model. When examining the decision function of a model, it may exhibit a high degree of complexity on a global scale. However, when focusing on a specific instance, it can be approximated with ease through the perturbation of samples. A linear model has the capability to be fitted in the vicinity of perturbed samples, thereby providing localised insights into the model.

The SHAP methodology employs a game-theoretic framework to produce both global and local explanations. Game theory is comprised of two fundamental components: the game itself and the players involved. In this context, the game refers to the process of replicating the outcome of a given model, while the players represent the features utilized to train said model. It is assumed that a machine learning model has already been trained for this purpose. The SHAP metric quantifies the degree to which individual features contribute to the model's prediction. In order to ascertain feature importance, the outcome of each conceivable combination of features is taken into account. If a dataset comprises 'n' features, the SHAP technique trains '2n' unique predictive models. The dataset employed remains constant across all models, with the sole variation being the number of features taken into account. The disparity among prognostications generated by these models can aid in determining the overall significance of the characteristic.

Python is an open-source toolkit that facilitates the interpretability and explainability of machine learning models and data. The system provides support for a total of eight distinct algorithms that enable explainability. Three algorithms have been employed to elucidate the functioning of deep neural networks, based on their respective applications in different stages of the AI modelling pipeline.

The Python algorithm utilizes training data to generate exemplar-based explanations for the purpose of summarizing a given dataset. Additionally, it provides explanations for the predictions generated by the model. Python utilizes a supervised learning algorithm to train an interpretable model for binary classification. The system acquires knowledge of Boolean rules through the analysis of data that consists of a combination of either simple OR of ANDs rules or AND of ORs rules. The Contextual Explanation Method (CEM) is employed to produce localized explanations pertaining to a specific instance within a given dataset, based on a trained model. The process identifies the minimum sufficiency (PP - Pertinent Positive) and necessary absence (PN - Pertinent Negative) required to preserve the initial classification.

4. SHAP results

The SHAP summary plot is a comprehensive explanation of a model that integrates feature importance and feature effect on a global scale. A point on a summary plot represents the Shapely value for a feature and a specific sample. The Y-axis represents the features, while the X-axis represents the shapely values. Colours are utilized to symbolize values that are either low or high. The arrangement of features is based on their respective levels of importance. In the summary plot, the feature located at the top is considered the most significant, while the one at the bottom is deemed the least significant.

The SHAP global explanations are derived by taking into account either the complete or partial dataset. The SHAP method provides local explanations by focusing on individual instances and generating explanations that indicate which feature values are contributing positively or negatively towards the decision-making process. The local interpretation of the model output is presented in Figure 1, indicating a probability of 1.00 for the occurrence of an attack. The corresponding features and their respective values are displayed, including 'Food_supply_chain', 'Explainable_artificial_intelligence', 'Decision_making', among others. The characteristics that increase the likelihood of a prediction are depicted in red, while those that decrease the likelihood of a prediction are represented in blue. It should be noted that the aforementioned explanation undergoes alterations in accordance with variations in the input instance.

The SHAP force charts for a group of points from the test dataset is depicted in Figure 2. Fifty points were aggregated from each category, including normal and three types of attacks. As force charts ware generated based on this data, which is presented below. The methodology involves generating multiple force plots for a single instance, as depicted in Figure 3, and subsequently rotating them by 90 degrees before stacking them together. A distinct categorization of attack types is evident from the provided explanations. This demonstrates the variability of the influencing feature across the set of data points.

It is imperative that ML models exhibit transparency for their end users. It is imperative that individuals receive responses to all their inquiries, including but not limited to the rationale behind a model's decision-making process, the contributing factors that influenced said decision, and the potential modifications that could be implemented to alter the model's decision. The utilization of the SHAP algorithm facilitates the provision of responses to various inquiries posed by end users.

In this study, a specific scenario was examined in which a prediction was deemed to be 'normal'. Through the use of SHAP, it was demonstrated that even slight modifications to the feature values can result in a change in the decision outcome.

The SHAP approach has the capability to identify a minimal set of features and their corresponding values that are necessary to uphold the model's prediction. By examining the statistical data of explanations provided by the SHAP algorithm across a group of applicants, one can gain valuable insight into the essential features that play a significant role. It is feasible to obtain the values of said features for each category of assault.

5. Discussion

SC firms utilize data mining and ML methodologies to automate decision-making processes. In highly fluid and dynamic business environments, various computational techniques such as machine learning, multi-agent systems, evolutionary algorithms, and artificial neural networks can be effectively utilized. According to Adadi and Berrada (2018); Bach et al. (2015); Beşikçi et al. (2016), the application of particle swarm optimization can effectively optimize the network design problem in complex systems such as transportation. Further investigation is necessary in relation to the subsequent aspects: (1) What strategies can be employed to foster trust among decision makers in the context of AI-mediated decision making? (2) What strategies can be employed to reduce the reliance on machine processing power in making business decisions? What is the potential impact of integrating convolutional neural networks with AI on enhancing DSSs? Furthermore, the inquiry pertains to the incorporation of social and ethical considerations within decision-making processes facilitated by AI. According to Meske et al. (2022), the utilization of hybrid techniques in AI presents a promising avenue for advancement. Misheva et al. (2021) emphasized the investigation of the correlation between minimum description length and the bullwhip effect as a means of minimizing and enhancing the efficiency of SC operations. Sufficient data is available for the purpose of conducting a study on the modelling of categorical and binary issues in the prediction of negotiation counteroffers (Polikar 2012). In addition, the implementation of multilingual tacit knowledge has the potential to address the challenge of cross-lingual interoperability through the utilization of sophisticated AI methodologies.

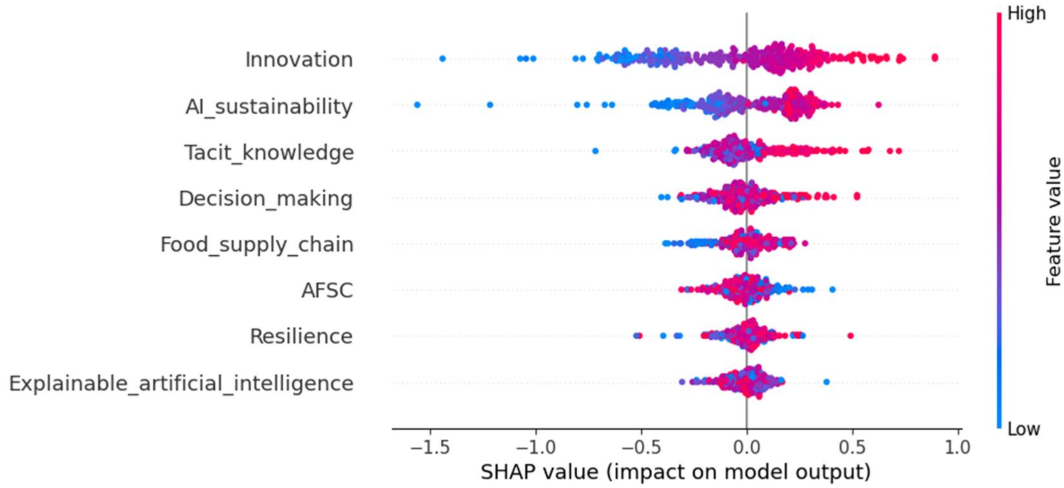


Figure 1. SHAP summary plot XAI-DSSs-SC.

Figure 2. SHAP force plot used for local explanations to explain a particular instance where output result of 'decision_making' is 6.2 and shows features contributing in decision.

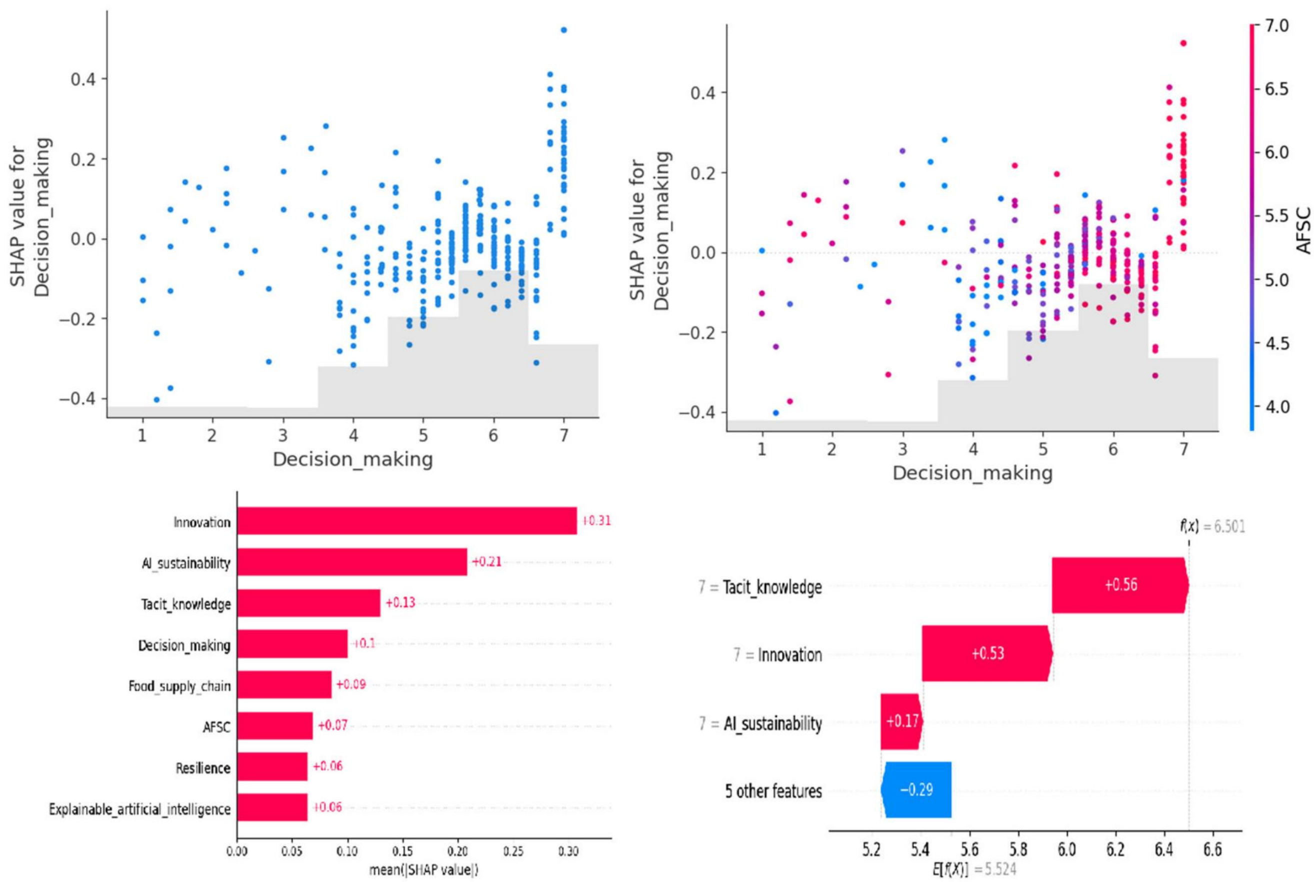


Figure 3. SHAP force charts for 4 types of data points.

The utilization of XAI in conjunction with extensive data sets for the purpose of semantic reasoning is a prevalent practice in DSSs. The accuracy of a DSS is contingent upon its architecture and the way it interfaces with the underlying principles of the system. Moreover, the output of a DSS is contingent upon the input it receives, which is determined by the technological and economic factors it encompasses. Bochtis, Sørensen, and Green (2012) suggests that the integration of DSSs with cloud technology could enable event-based decision-making in business. DSSs have the capability to provide diverse scenarios, trends, and rankings within a specified timeframe. However, integrated DSSs with AL driven SC have the capability to handle decisions that are structured, semi-structured, and unstructured. In their study, Hu et al. (2011) identified potential avenues for further investigation into the configuration of SC, particularly with regard to the fluctuating and unpredictable nature of product demand. Humanitarian logistics is a multifaceted concern within the SC, particularly in the context of disaster management (Gunasekaran et al. 2017). The establishment of a rescue program poses a challenge in terms of optimization and network development, as well as determining the appropriate scale based on the extent of performance.

The domain of on-road transportation in logistics poses a formidable challenge owing to the issue of traffic congestion. The present investigation has not examined the potential interdependence among traffic control measures implemented at different sites, nor has it taken into account the network's topology. In a business setting, decisions are made through the integration of diverse expert opinions, often lacking in structure. The integration of agent-based models within particle swarm intelligence has the potential to effectively tackle this issue. In addition, it is possible to incorporate multi-agent-based knowledge integration mechanisms into agent-based models to enhance the process of decision-making.

6. Implications and conclusion

6.1. Implications for research

The utilization of SHAP for XAI and SC in decision-making has limited research in supply chain management. Our review presents three significant attributes that make a valuable contribution to the literature on SC. In the current age of extensive data and digitalization, it is imperative to automate decision-making processes and prioritize the collaboration between humans and machines. The amalgamation and interplay of humans and machines necessitates the consideration of ethical and social trends.

It is imperative to acknowledge that the ability to predict and learn should be regarded as dynamic capabilities and resources that aid in managing SC uncertainty. Our findings demonstrate that the implementation of XAI can have significant implications for an SC's immediate and future objectives, as each decision pertaining to a shared goal can be influenced by this technology. Previous research has primarily concentrated on the establishment of experimental models (Chou and Benjamin 1992; Gall 2018; Haque, Islam, and Mikalef 2023; LeCun, Bengio, and Hinton 2015). However, these theories can be applied to incorporate the interconnection between XAI, DSSs, and SC. Our research has found that the utilization of dynamic capabilities, statistical learning, and XAI capabilities' can enhance the development of intelligent DSSs in SC. This contribution adds to the existing literature on the subject. The authors have constructed a systems framework that has the potential to facilitate the creation of an intelligent DSSs by means of the amalgamation of XAI and SC.

The integration of XAI has been observed to mitigate several constraints associated with SC, thereby fostering a synergistic and resilient system. The present study espouses a comprehensive perspective on the amalgamation of XAI and DSSs, which is corroborated by prior research conducted by Beşikçi et al. (2016); Gunasekaran et al. (2017); Misheva et al. (2021). Nevertheless, the aforementioned studies fail to include the crucial element of SC that we have examined in this literature review. The framework advocated in this study advocates for the utilization of cutting-edge technologies to tackle issues pertaining to security, speed, and precision, as posited by Mikalef et al. (2023). The present investigation has not examined the interdependence among SC measures implemented at different operations management or taken into account the network's topology. In the context of business operations, decisions are made through the integration of diverse expert perspectives, which are frequently unstructured in nature. The integration of SHAP models in particle swarm intelligence can potentially offer a solution to this issue. In addition, the incorporation of multi-agent-based knowledge integration mechanisms can be likened to the utilization of agent-based models to enhance the process of making informed decisions.

6.2. Implications for practice

The results from the analysis suggest that scholars in the field of DSSs exhibit a greater propensity towards investigating and constructing AI-assisted DSSs through scientific programming, as opposed to exploring the prospective amalgamation of AI-DSSs and SC (Pullan, Bhasi, and Madhu 2013; Spanaki et al. 2022; Wang, Skeete, and Owusu 2022; Yildiz and Ahi 2022). The possible explanation for this phenomenon could be attributed to the limited familiarity with big data, SC-based reasoning, and ML within the research domain of DSSs. Additionally, scholars possess limited knowledge regarding methodologies such as support vector machines, swarm intelligence, and stochastic programming.

The lack of awareness regarding the potential of AI-DSS-SC-based intelligent systems in the domains of uncertainty and risk management has an adverse effect on business decision makers. The integration of XAI with operations research principles presents a promising avenue for enhancing the conventional DSSs.

This solution is designed to assist executives in effectively addressing complex decision-making scenarios involving extensive data sets and multiple constraints. DSSs that are developed in such a manner have the potential to enhance decision-making accuracy, while also exhibiting superior learning and predictive capabilities. It is imperative for professionals who encounter uncertainty in decision-making to acknowledge and utilize relevant techniques and technologies. Collaborating with researchers can further enhance the decision-making process. It should be noted that while XAI is capable of providing decision-making support, it does not possess autonomous decision-making capabilities. Rather, XAI can be regarded as a valuable instrument to aid decision makers in making optimal decisions. Meske et al. (2022) deliberated on the expansion of human decision-making to XAI. The utilization of extensive data by XAI can enhance decision-making processes that are better suited for contemporary businesses. This is due to the fact that modern businesses generate substantial quantities of data through their operational procedures. Thus, it is imperative for managers and other stakeholders to prioritize the assurance of data security and precision. Managers have the potential to assist researchers in the identification and creation of appropriate frameworks for their decision-making procedures by providing access to relevant data. XAI leverages data, learning algorithms, and patterns to make decisions on behalf of organizations, and can be customized to align with the specific context of the business.

7. Conclusions

This study undertook a comprehensive examination of XAI, DSSs, and SC and their respective attributes that facilitate their utility in the context of commercial enterprises. Using a SHAP approach, which was deemed relevant for the purposes of this review. Our methodology involved a SHAP modelling process consisting of initial planning, execution, and subsequent reporting of the data. The findings serve to delineate the characteristics and effects of XAI, DSSs, and SC. Individual research inquiries were addressed in order to enhance clarity.

One of the limitations of our study is that despite our thorough efforts, it is conceivable that we may have omitted certain keywords pertaining to the topics under investigation.

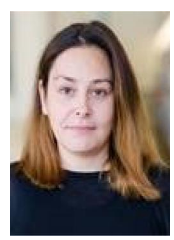
The studies that were reviewed have formulated several decision-making models. Contemporary algorithms are required to possess the ability to adapt to changing circumstances and evolve over time to optimize their performance. The integration of diverse data types for immediate decision-making is a prospective area of investigation for XAI and SC to develop an advanced DSS. This is commonly referred to as inter-operability. By integrating data from both fields and leveraging XAI and SC tools, it is possible to develop a robust and sustainable decision support system. The potential of SC can be further optimized through the integration of quantum computing to facilitate deep learning, which can then be amalgamated with XAI to create highly efficient decision support systems. The integration of XAI with the parameters of stakeholders in a supply chain, including their respective limitations in capacity, demand, and profit projections, can facilitate the determination of the requisite contributions from each stakeholder towards the attainment of the desired outcome.

Disclosure statement

No potential conflict of interest was reported by the author(s).

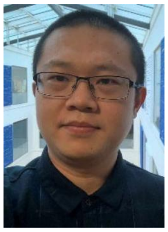
Notes on contributors

Femi Olan, PhD, is a Senior Lecturer ® (Associate Professor) in Innovation at Essex Business School, UK. He obtained his PhD degree from Plymouth University, UK. He has research, teaching, and industry experience in the field of information systems, particularly in the areas of information systems, business process automation, knowledge management, KM systems, digitisation (digital innovation & productivity), business intelligence, data analytics and business process re-engineering. He has published research in various renowned conferences, books and journals. He has involved in several research projects internally and externally. He is a reviewer for several journals and international conferences. He has editorial experience in various journals. He is a member of several scientific/technical/programme committees.



Konstantina Spanaki, PhD, is an Associate Professor of IS and Supply Chain Management at Audencia Business School. Prior to this role Konstantina has been working at Loughborough University and Imperial College London in areas around Technology Management. Konstantina's main research areas lie within the intersection of Information Systems (IS) and Operations Management (OM). Recently, she is actively involved in projects related to Digital Supply Chain, Data and Technology Management, Data Sharing and Disruptive Technologies. Konstantina's research has been published in Information Technology and People, Information Systems Frontiers, Computers in Industry, the International Journal of Production Research, Production Planning and Control and other IS/OM outlets. She has served as Guest Editor for several Special Issues. Konstantina also is an AIS and EurOMA member and has served the AIS community as track chair, AE and a reviewer multiple times in the past.

Wasim Ahmed, PhD, is a Senior Lecturer in Marketing at Hull University Business School with research interests in marketing analytics, data science, and the use of social media in health and sport. He has previously held positions at Newcastle University, the University of Stirling, and Northumbria University. He has also completed an internship at Manchester United FC producing an in-depth research report. Dr Ahmed has published a range of impactful research in international peer-reviewed journals. Additionally, Dr. Ahmed has delivered over 100+ invited talks across industry, government and academia, and his research often features across print and broadcast media. He completed his PhD at the at the University of Sheffield's Information School and holds an MSc in Information Systems and BA (Hons) Degree in Philosophy also completed at the University of Sheffield.



Guoqing Zhao, PhD, is a lecturer in operations management at the School of Management, Swansea University. He got his Ph.D in supply chain management from the University of Plymouth. He has published research in a variety of prestigious journals including the Journal of Business Logistics, Journal of Business Research, International Journal of Production Research, Production Planning & Control, and among others. Moreover, his research was funded by several funding agencies, such as European Commission Horizon 2020 programme, European Regional Development Fund, The UK Royal Society, and The Government of Oman. He also received several awards, such as high citation award, Chinese Government Award, MCAA small research grant, and best conference paper award. He currently acts as regional coordinator of UK Academy for Information Systems.

ORCID

Femi Olan http://orcid.org/0000-0002-7377-9882
Konstantina Spanaki http://orcid.org/0000-0001-6332-1731
Wasim Ahmed http://orcid.org/0000-0001-8923-1865
Guoqing Zhao http://orcid.org/0000-0003-4553-2417

References

Adadi, A., and M. Berrada. 2018. "Peeking Inside the Black-Box: A Survey on Explainable Artificial Intelligence (XAI)." *IEEE Access*. 6: 52138–52160. https://doi.org/10.1109/ACCESS.2018.2870052

Ajzen, I. 1991. "The Theory of Planned Behavior." *Organizational Behavior and Human Decision Processes* 50 (2): 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Alkahtani, M., A. Choudhary, A. De, and J. A. Harding. 2019. "A Decision Support System Based on Ontology and Data Mining to Improve Design Using Warranty Data." *Computers & Industrial Engineering* 128: 1027–1039. https://doi.org/10.1016/j.cie.2018.04.033

Amir-Heidari, P., and M. Raie. 2019. "Response Planning for Accidental Oil Spills in Persian Gulf: A Decision Support System (DSS) Based on Consequence Modeling." *Marine Pollution Bulletin* 140: 116–128. https://doi.org/10.1016/j.marpolbul.2018.12.053

Arakpogun, E. O., Z. Elsahn, F. Olan, and F. Elsahn. 2021. "Artificial Intelligence in Africa: Challenges and Opportunities." *The Fourth Industrial Revolution: Implementation of Artificial Intelligence for Growing Business Success* 935: 375–388.

Attadjei, D. D., Y. Madhwal, and P. B. Panfilov. 2018. "A Decision Phases of a Supply Chain Management: A Proposed Decision Support System to Boost Organizational Decision Making." *International Journal of Engineering & Technology* 7 (2.28): 157–159. https://doi.org/10.14419/ijet.v7i2.28.12901

Azzamouri, A., I. Essaadi, S. Elfirdoussi, and V. Giard. 2019. "Interactive Scheduling Decision Support System a Case Study for Fertilizer Production on Supply Chain." *ICT for a Better Life and a Better World: The Impact of Information and Communication Technologies on Organizations and Society* 30: 131–146.

Bach, S., A. Binder, G. Montavon, F. Klauschen, K.-R. Müller, and W. Samek. 2015. "On Pixel-Wise Explanations for Non-Linear Classifier Decisions by Layer-Wise Relevance Propagation." *PLOS One* 10 (7): e0130140. https://doi.org/10.1371/journal.pone.0130140

Balaman, Ş Y., A. Matopoulos, D. G. Wright, and J. Scott. 2018. "Integrated Optimization of Sustainable Supply Chains and Transportation Networks for Multi Technology Bio-Based Production: A Decision Support System Based on Fuzzy ε-Constraint Method." *Journal of Cleaner Production* 172: 2594–2617. https://doi.org/10.1016/j.jclepro.2017.11.150

Banerjee, S., and D. Y. Golhar. 2013. "A Decision Support System for a Third-Party Coordinator Managing Supply Chain with Demand Uncertainty." *Production Planning & Control* 24 (6): 521–531. https://doi.org/10.1080/09537287.2011.639586

Belciug, S., F. Gorunescu, S. Belciug, and F. Gorunescu. 2020. "How Can Intelligent Decision Support Systems Help the Medical Research?" *Intelligent Decision Support Systems—A Journey to Smarter Healthcare* 157: 71–102.

Beşikçi, E. B., O. Arslan, O. Turan, and A. I. Ölçer. 2016. "An Artificial Neural Network Based Decision Support System for Energy Efficient Ship Operations." *Computers & Operations Research* 66: 393–401. https://doi.org/10.1016/j.cor.2015.04.004

Biswas, T., and S. Samanta. 2016. "A Strategic Decision Support System for Logistics and Supply Chain Network Design." *Sādhanā* 41 (6): 583–588. https://doi.org/10.1007/s12046-016-0496-5

Bochtis, D. D., C. G. Sørensen, and O. Green. 2012. "A DSS for Planning of Soil-Sensitive Field Operations." *Decision Support Systems* 53 (1): 66–75. https://doi.org/10.1016/j.dss.2011.12.005

Brauner, P., R. Philipsen, A. Calero Valdez, and M. Ziefle. 2019. "What Happens When Decision Support Systems Fail?—the Importance of Usability on Performance in Erroneous Systems." *Behaviour & Information Technology* 38 (12): 1225–1242. https://doi.org/10.1080/0144929X.2019.1581258

Cankaya, B., K. Topuz, D. Delen, and A. Glassman. 2023. "Evidence-Based Managerial Decision-Making with Machine Learning: The Case of Bayesian Inference in Aviation Incidents." *Omega* 120: 102906. https://doi.org/10.1016/j.omega.2023.102906

Carnero, M. Carmen. 2005. "Selection of Diagnostic Techniques and Instrumentation in a Predictive Maintenance Program. A Case Study." *Decision Support Systems* 38 (4): 539–555. https://doi.org/10.1016/j.dss.2003.09.003

Charnes, A., B. Golany, M. Keane, and J. Rousseau. 1988. "Extremal Principle Solutions of Games in Characteristic Function Form: Core, Chebychev and Shapley Value Generalizations." *Econometrics of Planning and Efficiency* 11: 123–133.

Chou, Y. C., and C. O. Benjamin. 1992. "An AI-Based Decision Support System for Naval Ship Design." *Naval Engineers Journal* 104 (3): 156–165. https://doi.org/10.1111/j.1559-3584.1992.tb02235.x

Dellino, G., T. Laudadio, R. Mari, N. Mastronardi, and C. Meloni. 2018. "A Reliable Decision Support System for Fresh Food Supply Chain Management." *International Journal of Production Research* 56 (4): 1458–1485. https://doi.org/10.1080/00207543.2017.1367106

Dias, L. C., M. C. Cunha, E. Watkins, and G. Triantaphyllidis. 2022. "A Multi-Criteria Assessment of Policies to Achieve the Objectives of the EU Marine Litter Strategy." *Marine Pollution Bulletin* 180: 113803. https://doi.org/10.1016/j.marpolbul.2022.113803

Dias, L. C., J. Dias, T. Ventura, H. Rocha, B. Ferreira, L. Khouri, and M. do Carmo Lopes. 2022. "Learning Target-Based Preferences through Additive Models: An Application in Radiotherapy Treatment Planning." *European Journal of Operational Research* 302 (1): 270–279. https://doi.org/10.1016/j.ejor.2021.12.011

Dias, L. C., and H. Rocha. 2023. "A Stochastic Method for Exploiting Outranking Relations in Multicriteria Choice Problems." *Annals of Operations Research* 321 (1–2): 165–189. https://doi.org/10.1007/s10479-022-04903-0

Dong, C.-S J., and A. Srinivasan. 2013. "Agent-Enabled Service-Oriented Decision Support Systems." *Decision Support Systems* 55 (1): 364–373. https://doi.org/10.1016/j.dss.2012.05.047

Dubey, R., A. Gunasekaran, S. J. Childe, S. Fosso Wamba, D. Roubaud, and C. Foropon. 2021. "Empirical Investigation of Data Analytics Capability and Organizational Flexibility as Complements to Supply Chain Resilience." *International Journal of Production Research* 59 (1): 110–128. https://doi.org/10.1080/00207543.2019.1582820

Dubey, R., A. Gunasekaran, S. J. Childe, S. F. Wamba, and T. Papadopoulos. 2016. "The Impact of Big Data on World-Class Sustainable Manufacturing." *The International Journal of Advanced Manufacturing Technology* 84 (1–4): 631–645. https://doi.org/10.1007/s00170-015-7674-1

Erdem, A. S., and E. Göçen. 2012. "Development of a Decision Support System for Supplier Evaluation and Order Allocation." *Expert Systems with Applications* 39 (5): 4927–4937. https://doi.org/10.1016/j.eswa.2011.10.024

Essien, E., K. Dzisi, and A. Addo. 2018. "Decision Support System for Designing Sustainable Multi-Stakeholder Networks of Grain

Storage Facilities in Developing Countries." *Computers and Electronics in Agriculture* 147: 126–130. https://doi.org/10.1016/j.compag.2018.02.019

Eydi, A., and L. Fazli. 2019. "A Decision Support System for Single-Period Single Sourcing Problem in Supply Chain Management." *Soft Computing* 23 (24): 13215–13233. https://doi.org/10.1007/s00500-019-03864-0

Fikar, C. 2018. "A Decision Support System to Investigate Food Losses in e-Grocery Deliveries." *Computers & Industrial Engineering* 117: 282–290. https://doi.org/10.1016/j.cie.2018.02.014

Fosso Wamba, S., M. M. Queiroz, C. Guthrie, and A. Braganza. 2022. "Industry Experiences of Artificial Intelligence (AI): Benefits and Challenges in Operations and Supply Chain Management." *Production Planning & Control* 33 (16): 1493–1497. https://doi.org/10.1080/09537287.2021.1882695

Fosso Wamba, S., S. Akter, A. Edwards, G. Chopin, and D. Gnanzou. 2015. "How 'Big Data' Can Make Big Impact: Findings from a Systematic Review and a Longitudinal Case Study." *International Journal of Production Economics* 165: 234–246. https://doi.org/10.1016/j.ijpe.2014.12.031

Fu, Chao, Weiyong Liu, and Wenjun Chang. 2020. "Data-Driven Multiple Criteria Decision Making for Diagnosis of Thyroid Cancer." *Annals of Operations Research* 293 (2): 833–862. https://doi.org/10.1007/s10479-018-3093-7

Fu, R., Y. Huang, and P. V. Singh. 2021. "Crowds, Lending, Machine, and Bias." *Information Systems Research* 32 (1): 72–92. https://doi.org/10.1287/isre.2020.0990

Gall, R. 2018. "Machine Learning Explainability Vs Interpretability: Two Concepts That Could Help Restore Trust In AI-Kdnuggets." *Kdnuggets*. https://www. kdnuggets. com/2018/12/machine-learning-explainability-interpretability-ai. html.

Giusti, E., and S. Marsili-Libelli. 2015. "A Fuzzy Decision Support System for Irrigation and Water Conservation in Agriculture." *Environmental Modelling & Software* 63: 73–86. https://doi.org/10.1016/j.envsoft.2014.09.020

Gromov, V. A., K. A. Kuznietzov, and T. Pigden. 2019. "Decision Support System for Light Petroleum Products Supply Chain." *Operational Research* 19 (1): 219–236. https://doi.org/10.1007/s12351-016-0290-5

Guillaume, Y. R. F., J. F. Dawson, V. Priola, C. A. Sacramento, S. A. Woods, H. E. Higson, P. S. Budhwar, and M. A. West. 2014. "Managing Diversity in Organizations: An Integrative Model and Agenda for Future Research." *European Journal of Work and Organizational Psychology* 23 (5): 783–802. https://doi.org/10.1080/1359432X.2013.805485

Gunasekaran, A., T. Papadopoulos, R. Dubey, S. F. Wamba, S. J. Childe, B. Hazen, and S. Akter. 2017. "Big Data and Predictive Analytics for Supply Chain and Organizational Performance." *Journal of Business Research* 70: 308–317. https://doi.org/10.1016/j.jbusres.2016.08.004

Haque, A. K. M. B., A. K. M. N. Islam, and P. Mikalef. 2023. "Explainable Artificial Intelligence (XAI) from a User Perspective: A Synthesis of Prior Literature and Problematizing Avenues for Future Research." *Technological Forecasting and Social Change* 186: 122120. https://doi.org/10.1016/j.techfore.2022.122120

Helo, P., and Y. Hao. 2022. "Artificial Intelligence in Operations Management and Supply Chain Management: An Exploratory Case Study." *Production Planning & Control* 33 (16): 1573–1590. https://doi.org/10.1080/09537287.2021.1882690

Hernández, J. E., A. C. Lyons, P. Zarate, and F. Dargam. 2014. "Collaborative Decision-Making and Decision Support Systems for Enhancing Operations Management in Industrial Environments." *Production Planning & Control* 25: 636–638.

Hu, J., W. Chen, J. Yuan, and J. Zhang. 2011. "AgriRiskIDSS: development of an Intelligent Decision Support System for Price Risk Management of Agricultural Product Supply Chain." Journal of Food *Agriculture & Environment*, 9 (1): 299–303.

Joseph, M. 2020. "Interpretability Part 3: Opening the Black Box with LIME and SHAP." *Section: 2019 Dec Tutorials, Overviews*. Accessed February 7, 2024. https://www.kdnuggets.com/2019/12/interpretability-part-3-lime-shap.html.

Jussupow, Ekaterina, Kai Spohrer, Armin Heinzl, and Joshua Gawlitza. 2021. "Augmenting Medical Diagnosis Decisions? An Investigation into Physicians' Decision-Making Process with Artificial Intelligence." *Information Systems Research* 32 (3): 713–735. https://doi.org/10.1287/isre.2020.0980

Kämmer, J. E., K. Ernst, K. Grab, S. K. Schauber, S. C. Hautz, D, Penders, and W, E. Hautz. 2023. "Collaboration during the Diagnostic Decision-Making Process: When Does It Help?" *Journal of Behavioral Decision Making* 37 (1): e2357. https://doi.org/10.1002/bdm.2357. https://doi.org/10.1002/bdm.2357

Kingma, D., P. S. Mohamed, D. Rezende, and M. Welling. 2014. "Semi-Supervised Learning with Deep Generative Models." *Advances in neural information processing systems* 27.

Krishnaiyer, K., and F. F. Chen. 2017. "A Cloud-Based Kanban Decision Support System for Resource Scheduling & Management." *Procedia Manufacturing* 11: 1489–1494. https://doi.org/10.1016/j.promfg.2017.07.280

LeCun, Y., Y. Bengio, and G. Hinton. 2015. "Deep Learning." *Nature* 521 (7553): 436–444. https://doi.org/10.1038/nature14539

Liberatore, M. J., and R. L. Nydick. 2008. "The Analytic Hierarchy Process in Medical and Health Care Decision Making: A Literature Review." *European Journal of Operational Research* 189 (1): 194–207. https://doi.org/10.1016/j.ejor.2007.05.001

Linardatos, P., V. Papastefanopoulos, and S. Kotsiantis. 2020. "Explainable AI: A Review of Machine Learning Interpretability Methods." *Entropy* 23 (1): 18. https://www.mdpi.com/1099-4300/23/1/18. https://doi.org/10.3390/e23010018

Lipovetsky, S., and M. Conklin. 2001. "Analysis of Regression in Game Theory Approach." *Applied Stochastic Models in Business and Industry* 17 (4): 319–330. https://doi.org/10.1002/asmb.446

Liu, Z., H. Liao, M. Li, Q. Yang, and F. Meng. 2023. "A Deep Learning-Based Sentiment Analysis Approach for Online Product Ranking with Probabilistic Linguistic Term Sets." *IEEE Transactions on Engineering Management* 1–18. https://doi.org/10.1109/TEM.2023.3271597

Lundberg, S. M., G. G. Erion, and S.-I. Lee. 2018. "Consistent Individualized Feature Attribution for Tree Ensembles." *arXiv preprint arXiv:1802.03888*.

Lundberg, Scott M., and Su-In Lee. 2017. "A Unified Approach to Interpreting Model Predictions." *Advances in Neural Information Processing Systems* 30. https://proceedings.neurips.cc/paper/2017/file/8a20a8621978632d76c43dfd28b67767-Paper.pdf.

Meske, C., E. Bunde, J. Schneider, and M. Gersch. 2022. "Explainable Artificial Intelligence: Objectives, Stakeholders, and Future Research Opportunities." *Information Systems Management* 39 (1): 53–63. https://doi.org/10.1080/10580530.2020.1849465

Mikalef, P., K. Lemmer, C. Schaefer, M. Ylinen, S. O. Fjørtoft, H. Y. Torvatn, M. Gupta, and B. Niehaves. 2023. "Examining How AI Capabilities Can Foster Organizational Performance in Public Organizations." *Government Information Quarterly* 40 (2): 101797. https://doi.org/10.1016/j.giq.2022.101797

Misheva, B. H., J. Osterrieder, A. Hirsa, O. Kulkarni, and S. F. Lin. 2021. "Explainable AI in Credit Risk Management." *arXiv preprint arXiv:2103.00949*.

Modgil, S., S. Gupta, and B. Bhushan. 2020. "Building a Living Economy through Modern Information Decision Support Systems and UN Sustainable Development Goals." *Production Planning & Control* 31 (11–12): 967–987. https://doi.org/10.1080/09537287.2019.1695916

Mohiuddin Babu, M., S. Akter, M. Rahman, M. M. Billah, and D. Hack-Polay. 2022. "The Role of Artificial Intelligence in Shaping the Future of Agile Fashion Industry." *Production Planning & Control* 1–15. https://doi.org/10.1080/09537287.2022.2060858

Moscatelli, M., F. Parlapiano, S. Narizzano, and G. Viggiano. 2020. "Corporate Default Forecasting with Machine Learning." *Expert Systems with Applications* 161: 113567. https://doi.org/10.1016/j.eswa.2020.113567

Moynihan, G. P., and S. Wang. 2015. "Web-Based Decision Support System for Integrated Supply Chain Management." *International Journal of Logistics Systems and Management* 21 (3): 269–283. https://doi.org/10.1504/IJLSM.2015.069727

Olan, F., E. O. Arakpogun, J. Suklan, F. Nakpodia, N. Damij, and U. Jayawickrama. 2022. "Artificial Intelligence and Knowledge Sharing: Contributing Factors to Organizational Performance." *Journal of Business Research* 145: 605–615. https://doi.org/10.1016/j.jbusres.2022.03.008

Olan, F., S. Liu, J. Suklan, U. Jayawickrama, and E. O. Arakpogun. 2022. "The Role of Artificial Intelligence Networks in Sustainable Supply Chain Finance for Food and Drink Industry." *International Journal of Production Research* 60 (14): 4418–4433. https://doi.org/10.1080/00207543.2021.1915510

Olan, F., R. B. Nyuur, E. Ogiemwonyi Arakpogun, and Z. Elsahn. 2023. "AI: A Knowledge Sharing Tool for Improving Employees' Performance." *Journal of Decision Systems* 1–21. https://doi.org/10.1080/12460125.2023.2263687

Olan, F., J. Suklan, E. O. Arakpogun, and A. Robson. 2022. "Advancing Consumer Behavior: The Role of Artificial Intelligence Technologies and Knowledge Sharing." *IEEE Transactions on Engineering Management* 1–13. https://doi.org/10.1109/TEM.2021.3083536

Pan, Q., F. Harrou, and Y. Sun. 2023. "A Comparison of Machine Learning Methods for Ozone Pollution Prediction." *Journal of Big Data* 10 (1): 63. https://doi.org/10.1186/s40537-023-00748-x

Papadopoulos, T., A. Gunasekaran, R. Dubey, N. Altay, S. J. Childe, and S. Fosso-Wamba. 2017. "The Role of Big Data in Explaining Disaster Resilience in Supply Chains for Sustainability." *Journal of Cleaner Production* 142: 1108–1118. https://doi.org/10.1016/j.jclepro.2016.03.059

Polikar, R. 2012. "Ensemble Learning." In *Ensemble Machine Learning*, edited by C. Zhang and Y. Ma, 1–34. New York, NY: Springer. https://doi.org/10.1007/978-1-4419-9326-7_1

Pullan, T. T., M. Bhasi, and G. Madhu. 2013. "Decision Support Tool for Lean Product and Process Development." *Production Planning & Control* 24 (6): 449–464. https://doi.org/10.1080/09537287.2011.633374

Queiroz, M. M., S. Fosso Wamba, S. C. F. Pereira, and C. J. Chiappetta Jabbour. 2023. "The Metaverse as a Breakthrough for Operations and Supply Chain Management: Implications and Call for Action." *International Journal of Operations & Production Management* 43 (10): 1539–1553. https://doi.org/10.1108/IJOPM-01-2023-0006

Sahebjamnia, N., S. A. Torabi, and S. A. Mansouri. 2018. "Building Organizational Resilience in the Face of Multiple Disruptions." *International Journal of Production Economics* 197: 63–83. https://doi.org/10.1016/j.ijpe.2017.12.009

Spanaki, K., E. Karafili, U. Sivarajah, S. Despoudi, and Z. Irani. 2022. "Artificial Intelligence and Food Security: swarm Intelligence of AgriTech Drones for Smart AgriFood Operations." *Production Planning & Control* 33 (16): 1498–1516. https://doi.org/10.1080/09537287.2021.1882688

Teniwut, W., and C. Hasyim. 2020. "Decision Support System in Supply Chain: A Systematic Literature Review." *Uncertain Supply Chain Management* 8 (1): 131–148. https://doi.org/10.5267/j.uscm.2019.7.009

Twomey, M., D. Sammon, and T. Nagle. 2021. "The Role of Information Retrieval in the Diagnostic/Decision Making Process within the Medical Appointment: A Review of the Literature." *Journal of Decision Systems* 30 (4): 378–409. https://doi.org/10.1080/12460125.2021.1901334

Wang, Y., J.-P. Skeete, and G. Owusu. 2022. "Understanding the Implications of Artificial Intelligence on Field Service Operations: A Case Study of BT." *Production Planning & Control* 33 (16): 1591–1607. https://doi.org/10.1080/09537287.2021.1882694

Wamba, S. F., A. Gunasekaran, S. Akter, S. J-f Ren, R. Dubey, and S. J. Childe. 2017. "Big Data Analytics and Firm Performance: Effects of Dynamic Capabilities." *Journal of Business Research* 70: 356–365. https://doi.org/10.1016/j.jbusres.2016.08.009

Wen, Z., and H. Liao. 2021. "Capturing Attitudinal Characteristics of Decision-Makers in Group Decision Making: application to Select Policy Recommendations to Enhance Supply Chain Resilience under COVID-19 Outbreak." *Operations Management Research* 15 (1–2): 179–194. https://doi.org/10.1007/s12063-020-00170-z

Yildiz, K., and M. T. Ahi. 2022. "Innovative Decision Support Model for Construction Supply Chain Performance Management." *Production Planning & Control* 33 (9–10): 894–906. https://doi.org/10.1080/09537287.2020.1837936

Zhai, Z., J. F. Martínez, V. Beltran, and N. L. Martínez. 2020. "Decision Support Systems for Agriculture 4.0: Survey and Challenges." *Computers and Electronics in Agriculture* 170: 105256. https://doi.org/10.1016/j.compag.2020.105256

Zhao, G., F. Olan, S. Liu, J. H. Hormazabal, C. Lopez, N. Zubairu, J. Zhang, and X. Chen. 2022. "Links between Risk Source Identification and Resilience Capability Building in Agri-Food Supply Chains: A Comprehensive Analysis." *IEEE Transactions on Engineering Management* 1–18. https://doi.org/10.1109/TEM.2022.3221361