Knowledge-Based Systems 235 (2022) 107587

Contents lists available at ScienceDirect

Knowledge-Based Systems

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

Explainability in supply chain operational risk management: A systematic literature review

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ARTICLE INFO

Article history:
Received 5 July 2021
Received in revised form 6 October 2021
Accepted 8 October 2021
Available online 22 October 2021

Keywords:
Artificial Intelligence (AI)
Big data
Explainable AI (XAI)
Supply chain operational risk management (SCORM)

ABSTRACT

It is important to manage operational disruptions to ensure the success of supply chain operations. To achieve this aim, researchers have developed techniques that determine the occurrence of operational risk events which assists supply chain operational risk managers develop plans to manage them by detection/monitoring, mitigation/management, or optimization techniques. Various artificial intelligence (AI) approaches have been used to develop such techniques in the broad activities of operational risk management. However, all of these techniques are black box in their working nature. This means that the chosen technique cannot explain why it has given that output and whether it is correct and free from bias. To address this, researchers argue the need for supply chain management professionals to move towards using explainable AI methods for operational risk management. In this paper, we conduct a systematic literature review on the techniques used to determine operational risks and analyse whether they satisfy the requirement of them being explainable. The findings highlight the shortcomings and inspires directions for future research. From a managerial perspective, the paper encourages risk managers to choose techniques for supply chain operational risk management that can be auditable as this will ensure that the risk managers know why they should take a particular risk management action rather than just what they should do to manage the operational risks.

1. Introduction

Operational disruptions have the potential to significantly impact on a networked supply chain's performance [1]. Such disruptions arise for various reasons, such as (a) frequent changes in demand and supply across the chain [2], (b) the impact of external factors or events on a supply chain partner which then propagates to other partners [3], (c) the lack of transparency in terms of the dependence among the chain's partners [4] etc. To avoid the consequences arising from such disruptions, researchers have emphasized the need for supply chain partners to be proactive rather than reactive in managing operational risks. In the proactive style of supply chain operational risk management (SCORM), each supply chain partner detects beforehand the occurrence of disruption events that may impact on its operations and take appropriate actions to manage them. SCORM is a process that captures disruptions arising from various factors such as internal processes and external events [5], and ascertains the chance of such disruptions occurring before plans are developed to manage them. In the ever-growing digital world, SCORM techniques must deal with large-scale data, process them and predict the chance of disruption risk events occurring [4]. To achieve this aim, researchers have used different artificial intelligence (AI) techniques for SCORM. Advancements in the field of AI have led to the foundation of many advanced methodologies that assist in predicting the chance of disruption events occurring while at the same time, maintaining prediction accuracy [1,6,7]. However, these approaches are "black box" in their working nature. This means that while such methods can show the risk managers what disruption events will occur, they cannot explain why they will occur. Most importantly, these methods ignore the important role of humans in prediction. In other words, they do not consider whether the classifiers or predictors used in determining an output are considered as trustworthy or reliable by the human experts [8]. Due to this drawback, such methods do not have the interpretability or completeness to explain the outputs they give. For AI to assist in such decision-making processes, it should

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https://doi.org/10.1016/j.knosys.2021.107587
0950-7051/

provide information which the risk manager, as the expert, can completely trust and be certain of its fairness.

To address these gaps, e*X*plainable *AI* (XAI) is a new field of research in the literature. In broad terms, XAI is AI in which the results are explained so that humans can understand them in terms of how and why they have been reached. XAI attempts to move from the black box type of solutions in machine learning to more of a "white box" nature. Using this, the experts can judge if the computed output is fair, trustworthy and reliable [9]. Such a requirement for interpretation is motivated by the lack of trust in AI-recommended outcomes, mainly in the enterprise area, where incorrect resolutions can lead to failures of high impact [10]. They are also needed to satisfy the new requirements in corporate governance and regulations that have legal, social, and ethical implications. One such example is the General Data Protection Regulation (GDPR), which requires companies to provide their customers with the proof that led them to make AI-based decisions. These requirements can be met by using XAI methods that will increase transparency in governance and also alleviate concerns related to bias [11,12]. This paper surveys the literature and attempts to answer the question *as to whether the AI techniques used for SCORM satisfy the requirements for their output to be explained to the risk manager?*. For this, we perform a systematic literature review (SLR) that attempts to identify, select and critically analyse papers from the existing literature [13]. As a result of this analysis, we attempt to highlight the gaps and identify the areas which require further research to enable supply chain risk managers to comply with the different regulations governing them. While researchers such as Arrieta et al. [14] attempted to highlight the shortcomings of the existing techniques in meeting XAI requirements, they do not focus on it from the perspective of SCORM in supply chains. This paper attempts to address this gap.

The rest of the paper is organized as follows. Section 2 lists the four key features that an XAI complaint algorithm should possess. These features form the assessment criteria to determine whether the AI techniques used for SCORM satisfy the requirements for their output to be explained to the risk manager. Section 2 also details the inclusion methodology for shortlisting the research papers to be reviewed in the SLR. In Section 3, we perform a survey of the shortlisted papers and identify the techniques they use to identify risks. We also evaluate the capability of the techniques to meet the features of XAI. Section 4 specifies the gaps in the current approaches for risk management using AI in supply chains and provides the future path that supply chain risk management researchers should take to ensure that they build explainability in their models. Section 5 discusses the limitations of this work. Finally, in Section 6, we conclude the paper.

2. Linking the requirements of XAI with AI techniques

This section first discusses the four key features (XR1–XR4) that an XAI system should possess to explain why an output is reached. We then translate these features into three requirements (R1–R3) which we use to determine whether the existing AI approaches for risk management have it in their workings or not. These three requirements form the assessment and comparison criteria that we use to evaluate if the existing AI approaches used in SCORM can assist in determining if the recommended output is transparent, trustworthy, and interpretable. Finally, we conclude this section by discussing the methodology we adopted to select the papers used to perform the SLR.

2.1. Features which an XAI model should meet

The overall aim of XAI is to help experts understand, trust, and efficiently accomplish the results of AI technology. XAI's foremost intention is to provide more explainable models while supporting a high level of learning performance/prediction accuracy [15]. An XAI model should meet the following features:

- *It should be trustworthy (XR1):* To affirm the trustworthiness of the data and methods used, a XAI model should meet the following requirements:
    1. Confirmability: Confirmability establishes that data and interpretations of the findings are data derived, not figments of imagination [16].
    2. Transferability: Transferability is a generalization that provides evidence that the results could apply to other contexts, situations, times, and populations [17].
- *It should be complete (XR2):* Admissibility is the crucial feature of a complete algorithm. An algorithm is admissible if it is guaranteed to pick the best solution when multiple solutions exist and should provide a solution when a single solution exists and terminate after that [18].
- *Its working should be transparent (XR3):* The transparency of an approach should demonstrate how it is using the data to make decisions or predictions. The edible and audible programming features of an algorithm should state and explain why the method, or an assigned part in the structure, provides particular outcomes [19]. In other words, the transparency of an approach should provide a step-by-step explanation of how it has reached the goal [20].
- *Its outputs should be interpretatable (XR4):* Interpretation is the ability to explain the output with mathematical and logical proof [21]. As an extension of interpretation, XAI should aim to design a mental model that can visualize the output according to the user's requirements and demands [22]. Interpretability is also known as comprehensibility in the literature [14].

Fig. 1 represents the key features along with their sub-features that helps to fulfil an XAI model's requirements. Fig. 1 also has features that are not discussed above. These are the secondary features that will ensure the quality of an XAI system.

To check if the existing AI approaches in SCORM meet the required XAI features, we conduct a comprehensive review of AI-based techniques by classifying them into different categories according to their working style. Based on the analysis, we determine whether they can elaborate and explain how the output has been reached. To effectively undertake such an analysis, we determined the following three requirements which an AI model should have as a precondition for them to meet the XAI's requirements.

- *Requirement 1 (R1): Ability to capture all the features that directly or indirectly trigger the operational activities associated with operational risks:* It has been mentioned in the literature that a lack of information on risk features and not capturing their influence have resulted in a poor risk management system that can lead to complete system failure [23]. So, this requirement determines if the AI technique, at an input level, either captures an ontological representation of features according to the hierarchy present in it [24,25] or mathematically or logically connects the features using conditional probability [26]. Having such an ontological or probabilistic dependency will capture the dependencies among the features. Doing so will ensure that the output risk class will be evaluated by considering all the features

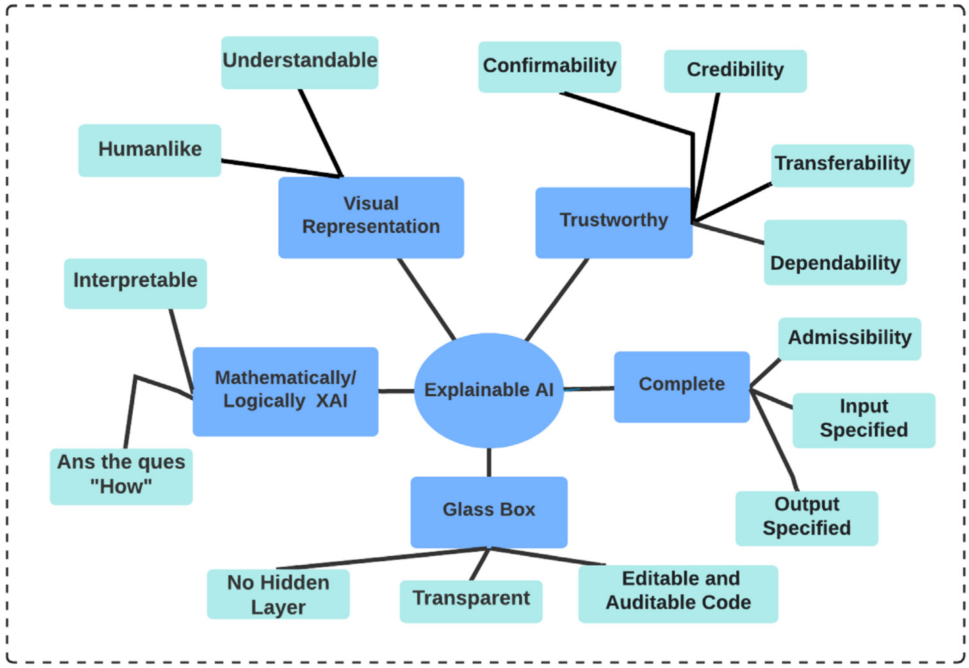

Fig. 1. The scaling features of an Explainable AI methodology.

associated with it and by applying any conditional probability that will help satisfy the trustworthy (XR1) features of an XAI model.

- *Requirement 2 (R2): Ability to assess all the risk-related features using AI approaches that are mathematically proven and logically well-defined:* As algorithms are supposed to be unbiased and impartial when predicting an output, this requirement determines if the applied algorithm can explain how each input feature has been used mathematically or logically. Such a mathematical explanation is a precondition of transparency (XR3 feature of the XAI model), and the level of interpretability depends on the quality of transparency or admissibility (XR2 feature of the XAI model) of the processing system [27].
- *Requirement 3 (R3): The ability to visualize the output with internal and external features associated with operational risks to the users in an explainable way:* Once the risks are recognized, AI systems should visualize the path within the features that led to the high-risk features to assure the model's trustworthiness. This will further assist the risk classification routine to be intelligent enough for automated decision-making [28]. To express such visualizations, at an input level, the antecedent–consequent relationship between the features needs to be captured [29,30]. Another technique that can be used for this is the IF-ELSE relationship. This condition helps to construct a decision tree to show the output/s resulting from inputs [31,32]. So, this requirement determines if the existing algorithm can capture all the features along with their dependencies and use them while visualizing why it has led to the output it is recommending for it to be interpretable (XR4 feature of the XAI model) to the risk manager.

These three requirements form the assessment and comparison criteria we use to evaluate the existing AI approaches used in SCORM in the literature. Fig. 2 shows how the features of XAI relate to the requirements from AI techniques that are looked for in our analysis. Furthermore, the figure also shows what features need to be present at an input level for the AI techniques to meet its requirements. In the following sub-section, we discuss the methodology we adopted to perform the SLR of the articles that adopt AI-based techniques in SCORM.

2.2. Review methodology

To perform the SLR, we adopt the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach, which assists in reporting systematic reviews. Fig. 3 shows the different steps of PRISMA that were used in our selection process to identify the papers that we need to review for our SLR. A brief detail of the selection process is explained next:

Step 1: Query String selection

To formulate the search query, we first need to set the scope of our analysis. As mentioned in Section 1, we analyse if the existing SCORM approaches satisfy the requirements for their output to be explained to the risk manager. So we *only* focus on analysing how AI techniques have been used in:

1. supply chain risk management — this excludes analysing how AI techniques have been used in the broad areas of managing supply chain operations, such as transportation, inventory management etc.
2. operational risks — this excludes analysing how AI techniques have been used in other risk management tasks such as quality risk management, performance risk management etc.

We first developed a basic set of keywords and their derivatives (e.g. operation*, supply chain) to identify articles which apply AI for operational risk management to identify the relevant research articles. We did this by searching for ten articles from highly cited journals related to AI and SCORM. We used their keywords (and derivatives) as our initial list of keywords and used them in subsequent searches to harvest additional articles and expand the keywords used with high frequency in this field. We subsequently refined these keywords, and our final set was as follows:

*(Automatic*OR Automation OR Computational OR Machine Learning OR Neural Network OR Hybrid OR Fuzzy OR Evaluation OR*

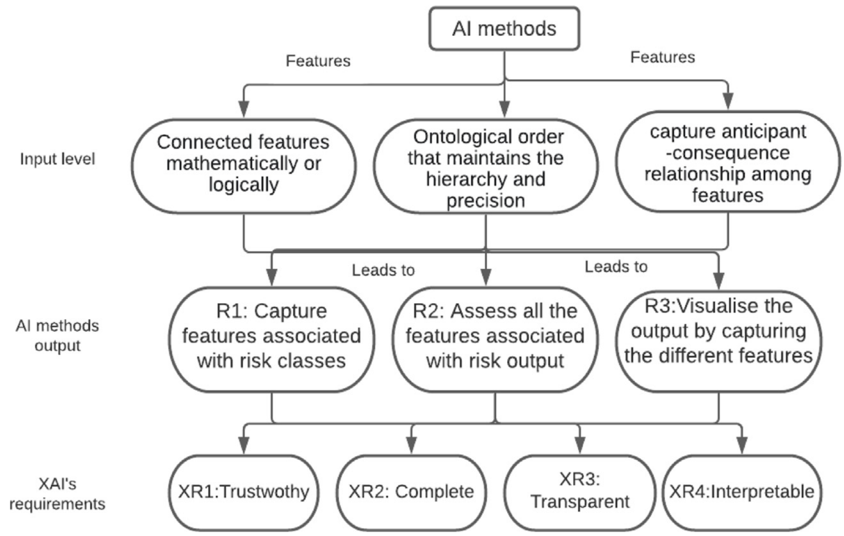

Fig. 2. Linkage between XAI and AI requirements.

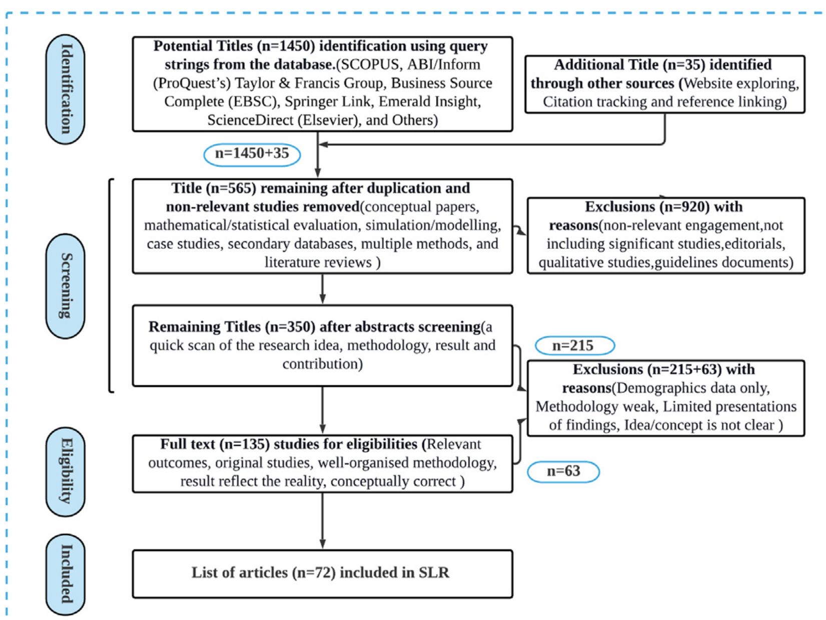

Fig. 3. PRISMA flow diagram to show the screening and selection process of articles.

Probabilistic OR Bayesian OR Markov) AND (Supply Chain OR Industry OR Enterprise OR Entrepreneur OR Business) AND (Operational Risk OR Interruption Risk OR IT Failure OR Fraud risk OR Uncertainty OR Vulnerability OR Threat OR Disruption OR Disturbance OR Crisis OR Disaster OR Catastrophe OR Hazard OR Emergency OR Opportunity OR Security OR Safety OR Flexibility) NOT (Legal Risk OR Financial Risk OR Environmental Risk OR Socio-political Risk OR Organization Risk OR Human Behaviour Risk OR Performance Risk OR Quality Risk) AND (Mitigation OR Optimization OR Handle OR Capture OR Reduce*) NOT (Inventory Management OR Warehouse Management OR Transportation OR Logistic Management OR Supplier Management)*

Step 2: Database selection

Using the defined search criteria and search strings, we collected research articles and their related citation data from the following databases: ScienceDirect, (Elsevier) SCOPUS, Taylor & Francis Group, Business Source Complete (EBSC), Springer Link, Emerald Insight, ABI/Inform (ProQuest's), and IEEE.

Step 3: Article selection

An inclusion criterion for the article to be considered was that it should be from a top-tier peer-reviewed journal or conference. We scanned the selected electronic databases using our defined search strings with no time restriction which returned 1485 articles initially. From this result, 920 of these were either duplicates or non-relevant studies, which were removed. We screened the remaining 565 references on their title and abstract and further removed 278 articles as they did not meet the pre-determined inclusion criteria. 72 articles remained which had a clear focus on SCORM and met the following requirements:

- Each article is peer-reviewed and written in English.
- Each article had at least one practice, technique or methodology that closely assessed the method to analyse the risk-related issues in supply chains.

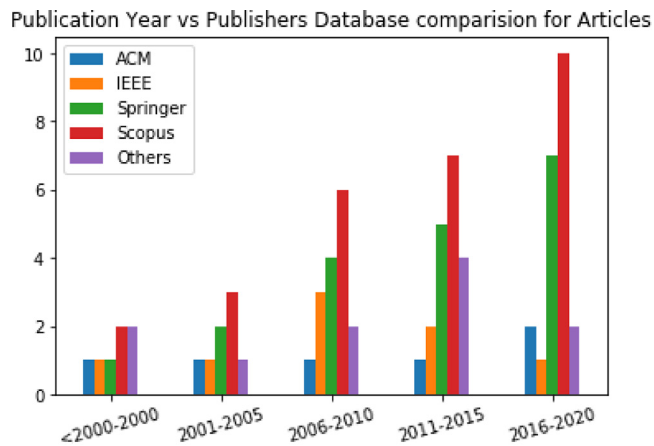

Fig. 4. Publication year Vs Publisher of the included articles.

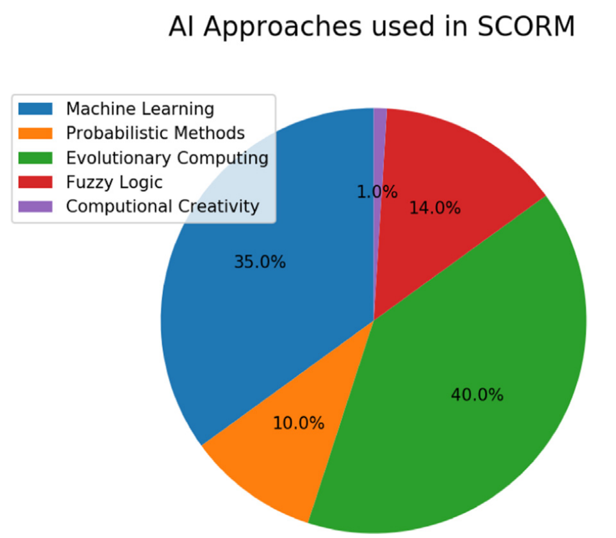

Fig. 5. Classification of AI techniques used in SCORM.

- The technique used in the paper is under the umbrella of artificial intelligence.

Step 4: Analysis of Shortlisted articles
In this section, we visualize the shortlisted articles according to their publication year (Fig. 4), the AI techniques they used (Fig. 5 which are discussed further in the next section) and the risk management step which the shortlisted articles addressed (Fig. 6). The risk management steps are divided into three categories. The first is *detection or monitoring*, in which the approaches either detect or monitor the supply chain risks. The second is *mitigation or management*, in which the methods attempt to reduce the determined levels of risks. The third is *optimization*, in which the risks are reduced based on the best option possible. The next section discusses these articles in detail.

3. Analysis of the articles

To study the workings of each approach, we divide them in five categories based on their input acceptance capabilities, data processing method, and output generating procedures, as follows:

1. Evolutionary Computation (EC),
2. Fuzzy Logic (FL) and similar uncertainty handling algorithms,

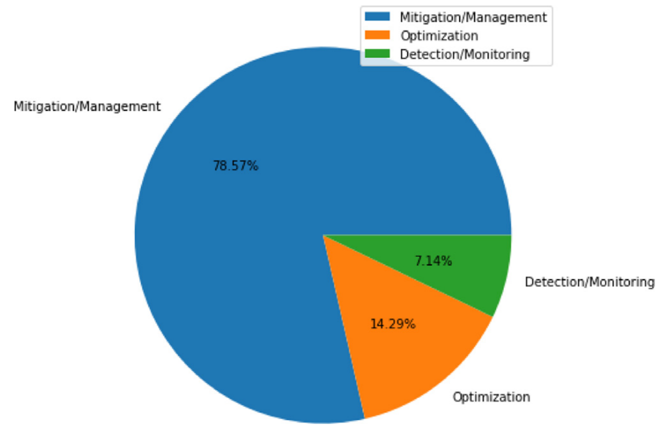

Fig. 6. Pie chart showing the risk management step addressed by the articles.

3. Computational Creativity (CC),
4. Machine Learning (ML) and similar data mining algorithms, and
5. Probabilistic Methods (PMs).

As shown in Fig. 7, these approaches focus on the processing phase of the risk management processes as they form the basis on which the output is generated. In the next sub-sections, the working of the techniques in each category is discussed, which is followed by an evaluation against the requirements R1–R3 and how they link with the XAI requirements XR1–XR4 defined in the previous sub-section.

3.1. Evolutionary computing

The evolutionary computation (EC) approaches are stochastic algorithms. Computational intelligence (CI) and evolutionary algorithms (EA) are subsets of evolutionary computation [33]. An EC uses mechanisms inspired by natural evolution, such as reproduction, recombination, and selection. Evolutionary algorithms often perform well-approximating solutions to all types of problems because they ideally evaluate the participating parameters and do not assume the underlying problem specifications [34]. Various types of evolutionary mechanisms are applied to measure, shape, and optimize risks in different fields such as supply chain, image processing etc. Commonly used optimization approaches include meta-heuristic optimization algorithms applying the fitness function, fitness approximation, differential evolution, and numerical optimization, different evolution strategies, and different learning classifier systems [35]. Standard and popular EC algorithms are ant colony optimization, cuckoo search, bees algorithm, particle swarm optimization, eclecticism optimization and other optimization algorithms [36]. Most of these are used for combinatorial optimization, graph problems, numerical optimization, and to solve connective, constrained and behaviour model problems [37]. EC algorithm-based articles can be classified into three categories, as follows:

3.1.1. Survey or simulation-based articles
A simulation is the imitation of the operation of a real-world process or system over time. The authors applied survey data or simulation techniques to shed light on the underlying mechanisms that control the behaviour of a system and to predict the future behaviour of a system and determine its influence [38–40]. The main drawback of simulations is that they are not real, and outcomes can vary in different environments and situations. This drawback impacts the trustworthiness of an AI system. For

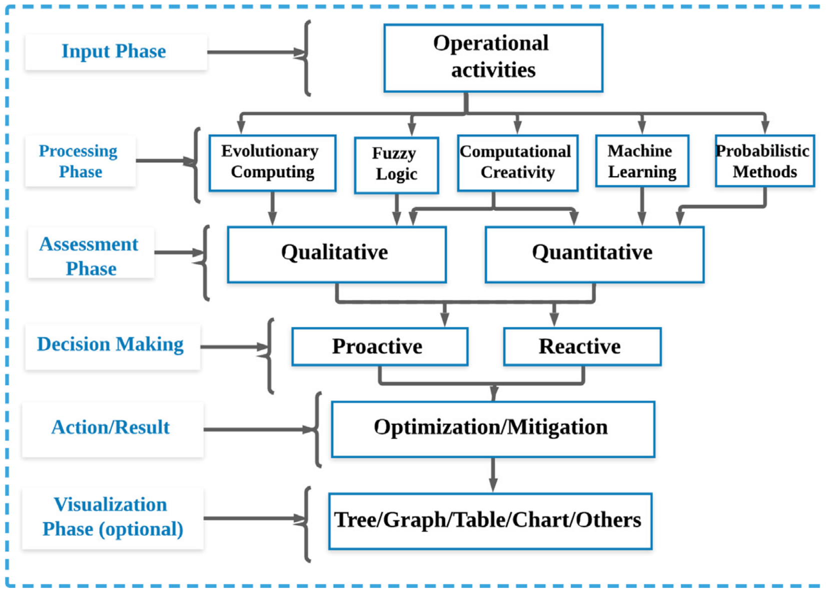

Fig. 7. An overall structure of AI methodologies to encapsulate supply chain operational risks.

example, Daohai et al. [38] developed a simulation model that consists of multi-agents (MA) and which integrates various entities related to operational threats. This results in a reactive estimation of risks from probabilistic models that can develop a response to risks. While the system is mathematically well-defined but uses a simulation approach, the transferability of the model is not guaranteed. This violates the trustworthiness requirement needed from an XAI model. Chen et al. [39] performed a survey-based study to verify the relationship between supply chains and integrated operational activities to reduce the risk. The authors followed the knowledge-based view that supports "Theory of Swift" and implemented several statistical methods such as structural equation modelling (SEM) to test the hypotheses. Confirmatory factor analysis (CFA) was also used to examine convergent and discriminant validity. Scale reliability was assessed through a construct reliability (CR) value, and the linear structural relations tool (LISREL) where the likelihood estimation method was used to validate the system. The research mainly focused on operational risk and adopted a variance-based view of risk. Still, it does not consider the other risk aspects that represent risk by evaluating cross-sectional data. Furthermore, SEM and CR involve using a hypothesis. Therefore, the system may give different results based on a different set of hypotheses that question the system's trustworthiness. However, the SEM and CR methods are statistically well-defined, satisfying the transparency and trustworthy requirement.

Tazelaar et al. [40] used the process-performance paradox in estimating operational risks by professionals in the domain of operations and supply chain management (OSCM), based on survey data. The authors cross-validated the sample data and designed a behaviour experiment scheme. The limitations of the research are as follows: (1) the system expects that OSCM-professionals will ensure that they are adequate to predict their daily business risks; and (2) valuations do not improve with augmenting expertise. The process performance paradox model considers only selected characteristics as risk factors. The system is not able to capture all aspects involved in risk. Therefore, the system is suitable for a small section of the system where the parameters are fixed and permanent and not the entire risk management system. Thus, it violates the trustworthiness requirement of the XAI model. Van et al. [41] presented a survey-based study on the performance of horizontal control features and an administration analysis on improving supply chain functionalities. A horizontal alliance is the integration between companies that are opponents in a similar sector. Contenders team up to mutually increase their position in the business. The study shows how a horizontal and cross-functional management control strategy configure innovative supply chain setups and contribute additional insights into how precisely horizontal control policies are formed and which approaches are used. Based on the experimental validation of associations among constructs, it was observed that a focus of third parties on the integration of the supply chain and a comprehensive performance measurement system contributes to the connection of supplementary services. Moreover, the expansion of computation operations contributes significantly to the extension of third-party logistics alliances in the supply chain and explains how third-party logistics service providers are extending their grip on supply chains and focusing on practice areas through re-configuring the supply chain setup. The proposed system is a survey-based study based on experimental validation. In general, a static model using experimental data cannot evaluate all supply chain functions, and third-party logistics vary with the structure and objectives of the company. As a result, the system is not trustworthy and may produce misguided output. Table 1 presents and compares different survey- or simulation-based articles using EC techniques to determine whether they meet the requirements to satisfy the features of an XAI system.

3.1.2. Statistical or mathematical algorithm-based articles

Statistical or mathematical algorithms have well-defined explanations of the steps used to process the input data and produce the output. An explanation of each step is the fundamental requirement of any XAI approach that also builds on the transparency of the system and validates the output. For example, Lajimi et al. [42] proposed a Failure Mode, Effects and Criticality Analysis method (FMECA) to determine and characterize short-time operational fluctuations and vulnerabilities. The algorithm calculates the risk priority number (RPN) scores used to quantify risks for users, designs, and processes. Finally, a behaviour model is developed using petri nets to categorize the threats according to the degree of risk level. The technique uses both qualitative and quantitative data to make a proactive decision. FMECA is a well-known statistical approach for capturing risk and risk-related activities. The system is complete and the applied

Table 1
Comparison of Survey or Simulation-based articles using EC algorithms in committing to AI and XAI requirements.

Ref.	AI methods	Step of risk management	AI requirements			XAI requirements			
			R1	R2	R3	XR1	XR2	XR3	XR4
[38]	MA	Mitigation/Management	×	✓	x	×	✓	✓	x
[39]	SEM, CFA, CR, LISREL	Mitigation	×	✓	x	×	✓	✓	x
[40]	Process-Performance Paradox	Assessment/Management	×	✓	x	x	✓	✓	×
[41]	Horizontal Alliance	Mitigation/Management	×	✓	x	×	✓	×	×

methods are transparent. Lin et al. [43] introduced an extended balanced scorecard (BSC) with the idea of risk-adjusted returns and insolvency risk. The authors assessed qualitative data and the results executed from the forecasting model that incorporates a hybrid filter-wrapper (HFW), random vector functional link network (RVFLN), and ant colony optimization (ACO). HFW decreases the storage requirement and overcomes the dimensionality problem. RVFLN has a high-speed learning capacity used to construct the forecasting model. ACO is used to handle the opaque nature of RVFLN and extract the decision rules from RVFLN. The outcome is a proactive definition of business policies, including operation strategies and capital structure, to survive in a turbulent environment. From the XAI's point of view, while the system is complete, it is not interpretable and trustworthy.

Shou et al. [44] optimized operational performance dimensions based on the interactions between external supply chain integration and internal production systems. The authors apply the proposed model to different production models such as one-of-a-kind, batch and mass systems. The authors considered both qualitative and quantitative data to proactively optimize operational performance. But the authors only focus on internal production systems and they do not consider the external contingency factors that impact them. Thus, while the system is complete, it is not trustworthy and interpretable. Singh et al. [45] developed a multi-stage global network (MsGN) model that incorporates a set of risk factors to make optimal decisions regarding the facility locations, and inter-rank quantity flows. As with other mathematical models, while the results proposed by the model have a mathematical explanation, they lack interpretability in terms of how they are computed. Ali et al. [46] developed a knowledge sharing framework to manage operational risks in food supply chains. The authors used several evolutionary methods such as confirmatory factor analysis (CFA), common method bias (CMB), and average variance extracted (AVE). While the techniques used are explainable in mathematical terms, the output represented by them is not interpretable. Soliman et al. [47] studied the link between industry efficiency standards and the dimensions of coordination, e-supply-chain operators and knowledge supervision. An analytic network process was used to study the different dimensions that give an output based on a firm's characteristics and objective. So, while the system consistently processes the underlying dataset, its results are not interpretable and transferable. Table 2 compares the different statistical or mathematical model-based articles using EC techniques to determine whether they meet the requirements to satisfy the features of an XAI system.

3.1.3. Algorithms that use hypotheses in their workings

A hypothesis is an educated guess that can be tested through study and experimentation. Any system using a hypothesis is making a guess initially, after which the hypothesis is either proven or disproven. Although these algorithms include vague and complex processing with fewer explanations, they are very effective for complex and extensive data processing and used analysis has been applied in many supply chain-based risk management applications. For example, Munir et al. [48] explored supply chain risk management as a mediator among internal, supplier and customer integration and operational activities to improve operational performance. Structural equation modelling (SEM) was used for experimental examination and confirmatory factor analysis (CFA) was used to observe a shared variance between the hypothesized variables and a marker variable. Principal component analysis (PCA) was applied to reduce the dimensions of the dataset and Common Method Bias (CMB) based on chi-square statistical significance was used to check for statistical difference between the original model and a measurement model, including hypothesized variables and the theoretically irrelevant marker variable. While different mathematical models were used in the analysis, a key drawback in terms of explainability is that it defines latent variables using observed variables and uses a structural model that assigns relationships between latent variables to produce a causal model that conveys assumptions. This violates the features of trustworthiness required from an XAI model. Swierczek et al. [49] proposed an approach to manage operational risks in supply chain through demand planning. The authors use a partial least squares (PLS) path model to model the constructs and their hypothesized relationships with latent (unobserved) and manifest (observed) items. Principal component analysis (PCA) and average variance extracted (AVE) were used to calculate the unidimensionality, reliability and validity of the model. The proposed approach used parameters related to demand planning, however there are other parameters which they did not consider which affect operational risk. Furthermore, while PLS, PCA and AVE are well-known statistical approaches with an appropriate mathematical explanation, they may give different results with a shift in the order of predictors. These characteristics impact the trustworthiness of the system.

Bruque et al. [50] utilized hypotheses to analyse the effects of community cloud computing on integrated supply chain operations based on information and physical flows. The authors applied factorial analyses and SEM to test their hypotheses. Techniques such as resource-based view (RBV), knowledge management (KM) and social capital theory (SCT) were used to build the theoretical framework. However, with a hypothesis-based model, the model considers causal assumptions which violates the trustworthiness of a system in terms of XAI requirements. Anggraeni et al. [51] developed a Failure Mode and Effect Analysis-House of Risk (FMEA-HOR) approach to model supply chain operational risk identification and develop proactive actions for mitigation. The proposed approach works through two stages of modelling, namely HOR 1&2. In HOR1, the risk events and risk agents are identified, and in HOR2, strategies to mitigate and handle the potential risk types are developed. While FMEA is a popular statistical approach for capturing risk and risk-related events, HOR1 and HOR2 assume that all the risk factors are known. If these are not captured, then the result violates the trustworthiness of the system in terms of XAI requirements. Voldrich et al. [52] created a quantitative multi-objective approach in a global supply chain model to integrate processing time and cost (PT & C) with operational risk for designing and optimizing a monitoring system. Failure Mode and Effects Analysis (FMEA) was used to enable, identify, and rank critical hazards and risks. A Pareto-efficient monitoring model was implemented to quantify and resolve the seeming contradictions among these measures.

Table 2
Comparison of the Statistical or Mathematical model-based articles using EC algorithms in committing to AI and XAI requirements.

Ref.	AI methods	Step of risk management	AI requirements			XAI requirements			
			R1	R2	R3	XR1	XR2	XR3	XR4
[42]	FMECA	Detection/Monitoring	×	✓	×	×	✓	✓	×
[43]	HFW, RVFLN, and ACO	Management	x	✓	x	×	✓	×	×
[44]	OKP, BP, and MP	Mitigation/Management	x	✓	x	×	✓	×	×
[45]	MsGN	Optimization	×	✓	x	×	✓	✓	x
[46]	CFA, CMB, AVE	Management	×	✓	x	×	✓	✓	x
[47]	KC, KS, KT, KA	Mitigation/Management	×	✓	x	×	✓	×	×

However, the Pareto operation partially assesses a collection of "actions" with multi-dimensional outputs. This assumes a weak "desirability" partial arrangement which considers that only one process is better for all the outcomes. For this reason, it is challenging to construct an accurate, trustworthy and multi-action-based system. Arashpour et al. [53] proposed optimization techniques to boost supply network execution. However, the authors' model is based on hypotheses, which has drawbacks in terms of ensuring the trustworthiness of the model. Hacioglu et al. [54] evaluated how new technical knowledge and cyber-security concerns of automatic transport assists in developing new supply chain supervision policies. The authors applied techniques such as artificial neural networks, image processing, multi-purpose decision-making, blurred linguistic variables, and electronic operations to enhance the production of the supply chain system. While these algorithms are popular AI approaches, they are black box in nature and do not include humans in the loop. Table 3 compares different hypothesis-based approaches using EC to determine whether they meet the requirements to satisfy the features of an XAI system.

3.2. Fuzzy logic and other uncertainty handling algorithms

Fuzzy logic has been widely applied in many fields to handle uncertainty, remove noise and optimize solutions [55]. In an uncertain domain, an entity is a form of multi-valued logic in which the truth values of the entities are a real number between 0 and 1, both inclusive. Fuzzy logic uses this phenomenon to handle the concept of partial truth and determine the output [56]. This enables them to represent vagueness and ambiguous information that changes the membership values [57]. Fuzzy logic, belief rule based (BRB), evidential reasoning (ER), rule-based inference methodology using the evidential reasoning (RIMER), Dempster Shafer (DS) theory, fuzzy neural networks (FNNs) and other qualitative assessment algorithms widely use fuzzy (opaque/uncertain) data handling [58]. These models can recognize, represent, manipulate, interpret, and utilize data and information that are vague and lack certainty. For example, Fattahi et al. [59] developed a data-driven decision-making approach using multi-stage stochastic programs (MSSP) and conic quadratic mixed-integer programming (CQMIP). The proposed method obtains risk-averse decisions by employing the conditional value at risk (CVaR) as the objective function on both the qualitative and quantitative data. The system includes humans in the loop to initially assign the "degree of influence" which indicates how strongly a feature supports the output. However, the result varies in different scenarios, thus its trustworthiness can be questioned. Rokou et al. [60] introduced a proactive risk breakdown structure (RBS) that identifies all the risk categories related to each step of supply chain operational activity. The proposed approach ranks the risks in a hierarchical order, demonstrates the solution strategies, and follows up on the risks that arise from demand variability and other supply chain activities. Kazancoglu et al. [61] proposed a fuzzy analytic network process (ANP) to score an organization's overall operational performance. Both qualitative and quantitative factors were used to determine the weights of the criteria before using a scoring method to calculate the weighted total score.

Caiado et al. [62] developed a fuzzy rule-based maturity model (MM) with a probabilistic approach, namely a Monte Carlo simulation, to evaluate companies on their supply chain management criteria. A fuzzy rule-based model imposes a degree of belief to assess the weight of any feature associated with any rule. Azar et al. [63] proposed a method combining fuzzy cognitive maps (FCM) and Bayesian belief networks (BBN) to improve BBN capability in modelling operational risks. FCM was used as a problem structuring method to construct the migration from FCM to BBN. FCM is a hybrid methodology that combines fuzzy logic (FL) and artificial neural networks (ANNs). As such, it inherits the ambiguity and vague characteristics of FL and ANN. However, researchers have strengthened FCM using the activation Hebbian algorithm (AHL), which address transparency in the decision model. Sun et al. [64] presented a risk-hedging policy for shipment assignment to diversify the shipment selection when enough reliable shipments are available. The authors used a stochastic optimization model to calculate the weighted value-at-risk using the Pareto frontier. The Pareto operation partially assesses a collection of "actions" with multi-dimensional outputs assuming a weak "desirability" partial arrangement. It considers that only one process is better for all outcomes. So, the resultant system is not trustworthy for all scenarios. From the above discussion, it can be summarized that fuzzy and other uncertainty handling algorithms can handle a large amount of data and assist in making complex decisions by capturing uncertain and irregular patterns of data. But the main limitations of this group of algorithms, as shown in Table 4, is that they use an opaque or unexplainable way to process the data, and thus their processing is a black-box model.

3.3. Computational creativity

Computational creativity (CC) or artificial creativity involves applying computer technologies to emulate, study, stimulate and enhance human creativity [65]. CC involves experimentation to find innovative ideas and thought processes in different fields. The approach often applies artificial intelligence (AI) to create humanly features such as bio-metrics analysis and implementation (fingerprint, retina identification, DNA blueprint, etc.). While computers apply mathematical precision and logic, creativity is closely related to the conscious exclusive domain [66]. CC algorithms use inductive or deductive reasoning, such as Deep Blue or Watson, respectively. Other systems using CC algorithms may use a knowledge-based procedure, case-based reasoning (CBR) or a novelty algorithm. Creativity is one of the requisite components of artificial general intelligence, which implies a system that can find unfamiliar problems [67]. Wichmann et al. [68] generated automated supply chain maps using supply chain mining for operational supply chain risk management. The process uses natural language processing (NLP) technology from openly available text sources that could automatically generate, verify, and

Table 3
Comparison of hypothesis-based articles using EC algorithms in committing to AI and XAI requirements.

Ref.	AI methods	Steps of risk management	AI requirements			XAI requirements			
			R1	R2	R3	XR1	XR2	XR3	XR4
[48]	CFA, PCA, CMB	Mitigation/Management	×	✓	×	×	✓	×	×
[49]	PLS, PCA, AVE	Mitigation/Management	×	✓	x	×	✓	✓	x
[50]	RBV, KM, SCT	Mitigation/Management	×	✓	x	×	✓	×	×
[51]	FMEA-HOR	Mitigation	×	✓	x	×	✓	×	×
[52]	Pareto Model, FMEA	Optimization	×	✓	x	×	✓	×	×
[53]	Supply Chain Optimization	Optimization	x	✓	×	×	✓	✓	x
[54]	ANN, Image processing etc.	Mitigation/Management	×	×	×	×	×	×	×

Table 4
Comparison of fuzzy logic and other uncertainty handling algorithms in committing to AI and XAI requirements.

Ref.	AI methods	Steps of risk management	AI requirements			XAI requirements			
			R1	R2	R3	XR1	XR2	XR3	XR4
[59]	MSSP, CQMIP, CVaR	Management/Mitigation	×	✓	×	×	✓	×	×
[60]	RBS	Management/Mitigation	×	✓	×	×	✓	×	×
[61]	Fuzzy ANP	Management/Mitigation	×	✓	×	×	✓	×	×
[62]	Fuzzy rule-based Maturity Model	Management/Mitigation	×	✓	×	×	✓	×	×
[63]	FCM, BBN	Optimization	×	✓	×	×	✓	✓	×
[64]	Risk-hedging policy with Pareto frontier	Management/Mitigation	×	✓	×	×	✓	×	×

enlarge existing maps with supplementary supplier information. The authors chose the Toyota supply chain as a case study, where supply chain mappings were based on short-sighted 1-to −1 relationships and could not be automatically derived. Moreover, the result was strongly dependent on the amount and quality of the available input data. In this case, the data was provided by search engines whose performance could not be controlled. As shown in Table 5, this particularity does not comply with the transitivity feature and breaks the trustworthiness of the system.

3.4. Machine learning

Machine learning (ML) is a subgroup of artificial intelligence that implements computer algorithms to update automatically through experience. ML algorithms form a model based on sample data, also known as "training data". This data is then used to make predictions or decisions in various fields [69]. Specific to supply chains, ML has been extensively applied for operational optimization, cost optimization, demand and supply synchronization, and E-commerce data management activities [70]. ML approaches can conventionally be split into three broad classes, based on the nature of the "signal" or "feedback", namely supervised learning, unsupervised learning and reinforcement learning [71]. These algorithms include various forms of ANNs, deep learning (DL), and other classification and clustering algorithms to determine and give their output. For example, Lejarza et al. [72] developed an approach to optimize the operational risk of handling perishable products. The authors used multi-integer linear programming (MILP) in their model. However, the issues with MILP is that it can either give an infinite solution, no solution or an unbounded solution as an output. Several features, such as partitioning, slack, surplus, and artificial variables, are included in the algorithm to avoid these unexpected outputs. These additions, however, make the processing of MILP complex and opaque. Wong et al. [73] addressed the issue of demoralization in supply chains by establishing trust among the nodes. The authors provided an overview of potential consideration factors via the TOE (technology, organization and environment) framework among Malaysian small-medium enterprises. The framework adopted the blockchain technology that incorporates an ANN and partial least squares structural equation modelling (PLS-SEM) approach. Using the proposed method, the authors eliminated inter-executive entrepreneurs and established trust via the networked nodes. Helo et al. [74] implemented a blockchain-based logistics monitoring system (BLMS) within the operational and supply chain context to create transparency, automation and trust in supply chains. The proposed model used blockchains and digital twins to secure assets and encode legal documents for digital identity. However, several cryptographic protocols are used in the application of blockchain in supply chain management to establish public–private key and digital twins. This makes the system imprecise and elusive in terms of its transparency. Dolgui et at. [75] developed a blockchain-oriented dynamic model for smart contract design with multiple logistics service providers using a control methodology. The authors modelled virtual operations of physical transactions to model the cyber information service. Virtual functions technically can reduce continuous state variables to determine the start and completion of information services. However, the proposed approach is complex and involves opaque processing steps.

To summarize, ML algorithms are mathematically well-defined, process a large amount of data and make complex decisions. However, as shown in Table 6, these approaches depend on the data on which they are trained. This does not guarantee that they will work as they should on a different set of data. Furthermore, their outputs cannot be interpreted, which violates one of the main requirements of an XAI model.

3.5. Probabilistic models

Probabilistic methods are nonconstructive and primitively used in combinatorics to provide a specific kind of mathematical entity [76]. Probabilistic approaches calculate the probability of an object being randomly chosen from a precise class. The chance of an arbitrary entity from a particular event is strictly greater than zero and smaller than one [77]. Another way to use probabilistic approaches is by determining the expected value of a random variable. If the current probability of any random event is known, then it is possible to calculate that specific event's future likelihood [78]. This particular feature of probabilistic methods is specially used in supply chains to set future goals, avoid risks and optimize decision making. For example, Guertler et al. [79] introduced a system dynamics simulation (SDS) approach to detect the changes in risk magnitude as continuous evaluations. The authors used mathematical equations to simulate results that assist them in determining their system's reaction to operational risk. While the proposed approach uses clear mathematical and logical explanations that demonstrate its completeness, it does

Table 5
Comparison of the CC algorithm in committing to AI and XAI requirements.

Ref.	AI methods	Steps of risk management	AI requirements			XAI requirements			
			R1	R2	R3	XR1	XR2	XR3	XR4
[68]	NLP	Management	×	✓	×	×	✓	×	×

Table 6
Comparison of the ML algorithm-based studies in committing to AI and XAI requirements.

Ref.	AI methods	Steps of risk management	AI requirements			XAI requirements			
			R1	R2	R3	XR1	XR2	XR3	XR4
[72]	MILP	Optimization	×	✓	×	×	✓	×	×
[73]	Blockchain, ANN, PLS-SEM	Mitigation/Management	×	✓	×	×	✓	×	×
[74]	BLMS	Management	×	✓	×	×	✓	×	×
[75]	Blockchain-oriented dynamic model	Mitigation/Management	×	✓	×	×	✓	×	×

not consider the finer details, such as individual features or events that produce a general representation of the system. This impacts the trustworthiness of the model. Stefanovic et al. [7] developed a proactive supply chain performance management approach that incorporates data mining predictive analytics. The system merges process modelling, performance monitoring, data mining and web portal techniques into a single model that models a supply chain configuration. This assists in a specialized collaborative analytical web portal that offers performance monitoring and decision making. While the approach uses probabilistic models with a mathematical explanation, it is based on previous history and activities which are not appropriate for new and challenging decision making. To summarize, as shown in Table 7, Probability-based models include mathematical or statisticalapproaches that have a precise mathematical and logical explanation of each step, making them complete and transparent. But in terms of their interpretability and trustworthiness, they need improvement.

4. Discussion and directions for future work

In this section, we summarize the existing AI methods used for SCORM and identify the gaps in meeting the XAI features. We then discuss some of the widely used XAI methods and highlight the gaps that need to be addressed.

4.1. Summary of the gaps in the existing AI approaches in meeting the features of XAI

Most AI algorithms work at an acceptable level when there is enough data and domain knowledge. While some of them, such as decision trees and regression models, are transparent in their working nature, others are not to the extent that even the designer cannot fully understand how they work. This is specifically true for deep learning models. However, like other sectors, AI has been used in the SCM domain due to its proven power in big enterprises such as Google and Facebook. As its current stands, AI is safe to use in low stake context but digitalized SCM, which is evolving fast, is a high stake context in which the impact of wrong decisions based on algorithms can be very costly. The current literature of AI applications in SCRM, such as [80,81] does not consider this impact. Specific to the application of AI in SCORM, from the discussion in the above section, it can be seen that they possess a unique set of capabilities and have a varying degree of applicability. While such techniques assist in the various tasks of risk management, as shown in Fig. 8, not all of them do this while meeting the features of XAI, as follows:

- Researchers have applied EC algorithms to detect, reduce and optimize operational risks. Generally, EC algorithms take a group of operation-related features as input and after evaluating the features either identify, reduce or optimize the corresponding risks based on supervised learning methods. Such algorithms can process multiple risk-related parameters and can detect multiple risks simultaneously [42–54]. While these approaches can produce highly optimized solutions and are capable of a large amount of data handling, dimensional variants and extensions which are used for better management planning in industrial organizations [82], the disadvantage is that they use a hypothesis or case-based reasoning which makes the system unreliable and elusive [83].

- Fuzzy logic and other uncertainty capturing algorithms are logic-based concepts that can assess the membership of a specific set expressed in ''degrees of truth'' or "degree of belief" values ranging from 0 to 1 [84]. Techniques in this category combine the inputs based on the composition rules, and computes the output based on interpolation and the distance concept. The imprecise information handling feature of this category of techniques is used to explain and handle uncertainty [85]. Thus, while techniques in this category combine the inputs based on the composition rules, and compute the output based on interpolation, the imprecise nature to handle uncertainty [85] makes the processing of these techniques ambiguous, vague and black box in nature, thus they are unsuitable in terms of explainability [86].

- CC techniques combine the study and simulation of natural and artificial behaviour, which would, if observed in humans, be deemed creative by computational means [87]. Generally, these approaches collect hybrid models that provide a qualitative assessment of human imagination and creativity in an artificial way by applying complex methods and sophisticated techniques to extract features and variations in the output that emerges from the same input dataset [88]. However, most of the CC algorithms apply vague and complex processing and need expert knowledge to handle and implement the system [89].

- ML and similar data mining algorithms are a subgroup of artificial intelligence that increase the performance of a machine through experience [23]. Machine learning algorithms, also referred to as predictive analytics, build a model in order to make predictions or decisions based on training data. An extent of machine learning is closely related to computational statistics, which focuses on making predictions using statistical learning [1]. This category of approaches commonly focuses on mathematical optimization, data mining, and exploratory data analysis through unsupervised learning [90]. This subclass of algorithms is the core of an artificial intelligence system and covers a wide range of applications from decision making to risk management, from small-scale

Table 7
Comparison of the existing probabilistic model-based studies in committing to AI and XAI requirements.

Ref.	AI methods	Steps of risk management	AI requirements			XAI requirements			
			R1	R2	R3	XR1	XR2	XR3	XR4
[79]	SDS	Management/Mitigation	×	✓	✓	×	✓	✓	×
[7]	BI, KPI	Management/Mitigation	×	✓	✓	×	✓	✓	✓

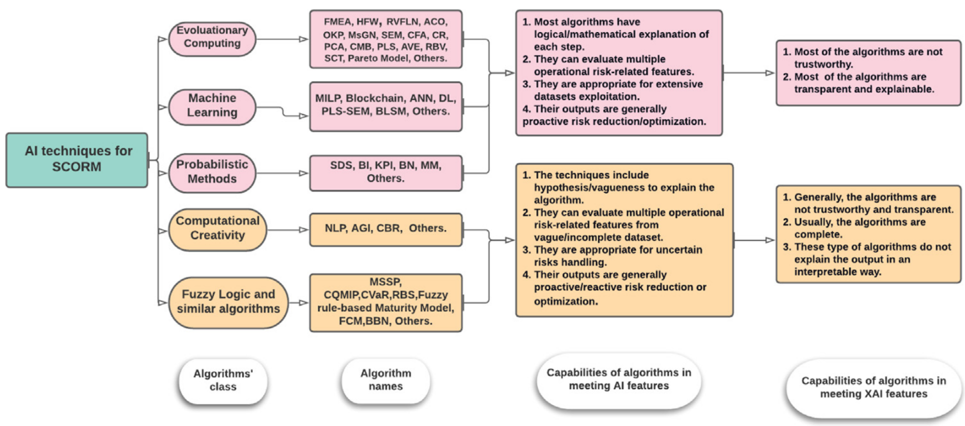

Fig. 8. Gaps in the existing AI approaches used in SCORM in meeting the features of XAI.

conquer to large data manipulation [91]. Conventional machine learning algorithms need long offline training and have a very poor ability in relation to transferable learning, reusing systems and integration, in addition to being opaque which makes them very hard to debug [92].

- PMs are based on probability theory and predict future events based on current events or previous history. PMs calculate a group of risk-related features from previous history as input after evaluating the features; and identify, reduce or optimize the corresponding risks. However, the limitations of PM approaches are that they cannot detect the change of dimensions or features of the dataset and thus are not appropriate for dynamic system design [93]. As a result, PM approaches cannot detect risks from a chain that is dynamic and change according to the occurrence of different events.

To overcome these gaps, supply chain risk managers should use techniques that assist them to understand their reasoning while reaching an output. Such improvement is a natural evolution of AI-based techniques, thus SCORM researchers should address the challenges that will assist them to achieve these aims. This will have wide implications in corporate governance and decision making, and therefore is a subject that will have many legal, social, and ethical implications. As explained in Section 1, in many industries, explainability is considered to be a regulatory requirement [94] and SCORM researchers should incorporate it in their techniques. In the next subsection, we explain the working of some of the XAI approaches in the literature that have been applied in different domains.

4.2. XAI approaches in the literature

Researchers have started to propose approaches that interpret the output of a model and meet XAI features. Broadly speaking, such approaches can be grouped into two primary models, namely explainable models and interpretable models. Explainable models are those which apply functions/methods/ steps that are glass-box and the operational steps of the methods can be explained such as decision tree, linear regression and logistic regression [95]. On the other hand, interpretable methods introduce model-agnostic approaches or derive information from a black-box decision support system where the output is interpretable by extracting knowledge about the underlying applications of the system [96]. Some of the most commonly used interpretable methods in the literature are local interpretable model-agnostic explanations (LIME) [97], SHapley Additive exPlanations (SHAP) [98], contrastive explanation method (CEM) [99], and anchors [100]. Their working is explained in the next subsections.

4.2.1. LIME

LIME [97] describes the outcomes of any classifier by approximating it with a trustworthy local interpretable approach. Consequently, LIME produces local interpretations by confounding an individual portion around the input vector within a local boundary [101]. Each feature is incorporated with a weight that is estimated by applying a similarity function that includes the gaps between the initial instance prediction and the predicted sample points in the local decision boundary. Linear regression is applied to estimate the local influence of each feature on the final decision. LIME has been widely used to design an interpretable system. For instance, Stiffer et al. [102] applied LIME to produce saliency maps of a specific region. Tan et al. [103] used LIME to increase the performance of black-box representation, decrease the utility of the specifications and detect the diverse sources in it. Their work explains the behaviour of three sources of uncertainty: randomness in the sampling scheme, variety with sampling concurrence, and contrast in the explained pattern across diverse input points. An anchor [104] is an expansion of LIME that addresses some of the drawbacks by maximizing the likelihood of how a specific characteristic might participate in a decision. An anchor applies IF-THEN rules as explanations as well as the knowledge of coverage, which allows users to understand the boundaries in which the produced explanations are valid. Li et al. [105] investigated the fidelity and interpretability properties of local model-agnostic explainers LIME. They introduced the Tree-LIME, a modified method based on LIME that can effectively approximate the original model locally. They represented the final output as a tree representation that explains the service supply chain forecast in a time series.

4.2.2. SHAP

SHAP is an interpretable approach that applies Shapley values [106] from a coalition game design to moderately allocate the earnings among players, where the participation of players is uneven [98]. Shapely values are a theory in economics and game theory. One can outline the theoretical concepts of this game directly to an XAI approach where each step is the prediction assignment for a unique occurrence and the players are the feature preferences of the occurrence that cooperate to receive the gain. Strumbelj and Kononenko [107] showed that in a coalition game, it is generally considered that n players create a grand coalition associated with a specific value. By default, it is known how much each smaller (subset) coalition would have been worth, and the goal is to assign the value of the grand coalition among players equally (that is, each player will receive a fair share, taking into account all sub-coalitions). Lundberg and Lee [98] proposed an explanation using SHAP values and the differences between them to evaluate the gains of each feature. In order to fairly allocate the payoff among players in a collaborative game, SHAP applies two fairness criteria, namely *additivity*, where the sum of the values must total the final game outcome, and *consistency*, where a player will not receive a reward which is lower than the contribution he/she makes in the game. In terms of similar applications, Miller Janny Ariza-Garzon and Segovia-Vargas [108] utilized SHAP values and used the logistic regression method and specific machine learning algorithms to calculate the score using a credit scoring model in peer-to-peer (P2P) lending. Parsa et al. [109] noted that SHAP could offer an insightful interpretation to explain the prediction results. For example, one of the procedures in the model, XGBoost, is not only able to estimate the global influence of features on the outcome, it can also obtain the complex and non-linear mutual influences of local features.

4.2.3. Anchors

Anchors describes individual predictions of any black-box classification model by observing a decision rule that adequately "anchors" the prediction [100]. A rule anchors a prediction if changes in other feature values do not affect the prediction. Anchors uses reinforcement learning techniques combined with a graph search algorithm to minimize the number of model calls while overcoming local optima [110]. The anchor approach uses a perturbation-based strategy to generate local explanations for predictions of black-box machine learning models [111]. The resulting explanations are expressed as easily understandable IF-THEN rules, called anchors. For this purpose, neighbours or perturbations are generated and evaluated for each instance to be explained. In this way, the approach can disregard the structure of the black box and its internal parameters, allowing them to remain both unobserved and unchanged [112]. Thus, the algorithm is model-agnostic, i.e. it can be applied to any class of models. La et al. [113] proposed a model-agnostic technique for XAI called cluster-aided space transformation for local explanation (CASTLE). The proposed model provides rule-based explanations based on the work of both the local and the global model, i.e., its detailed "knowledge" in the neighbourhood of the target instance and its general knowledge about the training dataset, respectively. The framework was evaluated on six datasets in terms of temporal efficiency, cluster quality and model significance. The measures of the central tendency of the results show that the explanation improves the understanding of the model, and that CASTLE slightly outperforms anchors in both metrics and achieves an improvement in precision.

4.2.4. CEM

Contrastive Explanation Method (CEM) is one of the XAI methods that can provide local explanations for a black-box model [99]. CEM defines explanations for classification models by providing information about preferred and undesired features using pertinent positives (PP) and pertinent negatives (PN) [114]. PP finds the features necessary for the model to predict the same output class as the predicted class. PP works similarly to anchors. PN finds the features that should be minimally and sufficiently absent in an instance while maintaining the original output class [115]. PN works similarly to counterfactuals [116]. It is the first method to declare what should be minimally present in the instance being declared and what should be missing to preserve the original prediction class. The method detects the characteristics that should be sufficiently present to predict the same class as in the original instance and identifies a minimal set of features sufficient to distinguish it from the other classes [117,118]. Feature-wise perturbation must be performed in a meaningful way to create interpretable PPs and PNs. Using CEM, it is possible to improve the accuracy of the machine learning model by considering instances of misclassified instances and then processing them using the explanations provided by CEM [119]. Luss et al. [120] took a new approach by using latent features to produce contrastive explanations. Predictions are described not only by highlighting sufficient aspects to justify the classification but also by adding new aspects that, when added, change the classification. The key contribution is the process of adding features to rich data in a formal yet humanly interpretable way. The process produces meaningful results generating local contrastive explanations that create intuitive explanations.

The contrastive explanations method applies monotonic attribute functions (CEM-MAF) to generate contrastive explanations for images. PPs composed of two superpixels are able to identify examples where the classifier requires little relevant information and therefore may not produce meaningful results. The study supports this concept for visual explanations with only a few superpixels. The authors noted that PNs might be the preferred form of explanation when it is not clear why a particular object is the way it is, but can be explained more clearly when contrasted with another very similar object. Amit et al. [121] proposed a method that provides contrastive explanations that justify the classification of an input by a black-box classifier called a deep neural network based on object pixels and certain background pixels in an image. The authors validate the approach on three datasets drawn from different domains: a handwritten digit dataset (MNIST), a procurement fraud dataset, and a brain activity strength dataset. The explanation method called CEM finds what should be minimally present in the input to justify classification by black-box classifiers and finds contrastive perturbation additions that should be missing to justify classification. For the MNIST dataset of handwritten digits, the approach provides examples of explanations with and without autoencoders. The handwritten digits are analysed using a feed-forward convolutional neural network (CNN) trained on training images from the MNIST benchmark dataset. The results from CEM, LRP and LIME were compared with the MNIST dataset to justify the classifications. Similarly, pre-processed fMRI connectivity data from the resting brain state and a real procurement dataset from a large company were used as input to explain the neural networks. The approach describes what is minimally sufficient in the input to justify its classification and what should be minimally and critically absent in the classification. It also distinguishes it from another input that is "closest" to it but would be classified differently. The extraction of pertinent positive and negative aspects by CEM can reduce errors (false positives and false negatives) in such diagnoses.

4.2.5. XAI in enterprise-level applications

XAI approaches are increasingly being used for commercial purposes. For example, the DataRobot platform works on different datasets to automate machine learning and AI applications at an enterprise level. The platform includes a model blueprint that shows the pre-processing steps of each model to draw its conclusions. It also supports interpretable models. Different enterprises have applied DataRobot in their workings. For example, United Airlines applied it to predict which customers are most likely to buy gate-check in bags [122]. With a billion users on its platform, the Google Cloud service added an explainable AI service that evaluates algorithmic models throughout the product lifecycle [123]. It is integrated with Jupyter and Colab notebooks and comes pre-installed on AI Platform Notebooks Tensorflow. H2O Driverless AI is another example of a commercial application that applies XAI during model validation, tuning, selection and deployment [124]. H2O Driverless AI offers machine learning interpretability (MLI) as a core feature. Its offerings include Shapely (which shows how features directly affect the unique prediction of each line), k- LIME (which can generate reason codes and English language explanations for more complex models), surrogate decision trees (which provide a flowchart showing how a model makes decisions based on the original features), and partial dependence plots (which shows the average model predictions and standard deviations for the values of the original features). Watson OpenScale has several model checking features for users [125]. The application provides contrastive explanations for any classification models. In other words, it displays relevant positives and relevant negatives, both of which help explain the behaviour of each model. The cloud computing service Microsoft Azure allows users to build, test, deploy, and manage applications [126]. It provides various programming languages, frameworks, and tools inside and outside the Microsoft ecosystem. Azure's model interpretability provides nine explanation techniques to choose from. This enables the explanation to be matched to the technique used to train the model. For example, if deep learning is used, the SHAP Deep Explainer provides an explanation of how an output has been reached.

4.3. Directions for future research to incorporate XAI in SCORM approaches

While XAI approaches assist in explaining the output of a ML model, from the perspective of explaining the output for better SCORM, future work in the following areas needs to be done:

1. *Capturing the interdependence among the different features that will impact on the risk class.* In an inter-dependent networked environment such as supply chains, many features or factors may result in the eventuation of a risk event. For informed risk management and to incorporate interpretability, a key requirement is to represent how a feature has contributed to the output and show which other feature/s resulted in this feature in question leading to the risk event. In other words, there is a need to (a) determine the interdependence among different features, and (b) show how the interdependence has evolved over the previous time periods. In SCORM, this will have a significant impact in determining the correct cause/s of a disruption event for which a risk management plan needs to be made. Existing AI or XAI approaches fail to represent such inter-dependability among features and thus cannot represent the analysis as a chain across the past time periods. Future research work needs to address these gaps by using techniques such as knowledge graphs that assist in capturing such dependencies among the different features and over a time period. By representing knowledge in the form of an ontology, knowledge graphs assist in determining how a feature is linked or dependent on other features. This also assists in inferring knowledge on an unknown feature from the features that are linked to it. Kosasih et al. [127] proposed an approach along these lines that attempts to improve visibility in supply chains. The authors utilize graph neural networks (GNNs) that identify the hidden links between the different nodes. However, the utilized techniques are black box in their working nature and only commit to the interpretability factor of XAI. Further research needs to be done that attempts to incorporate other features of XAI, as discussed in Section 2.1.
2. *Identifying the impact of the external factor/s which may influence the output of a risk event.* Supply chains are open-loop systems in which external circumstances may have implications on their operations. Thus, if disruptions arising from these have to be managed, the XAI model should capture the occurrence of such events and then determine their impact on the eventuation of the risk event. Existing XAI models fail in capturing the occurrence of external events and thus only deal with closed-loop systems that are not impacted by external events. This gap needs to be addressed to apply XAI in the risk Management of open-loop systems. Existing research has developed techniques which consider how external events impact on a criterion of a Service Level Agreement (SLA) [128]. However, such impacts need to be mapped down from an SLA criterion to its responsible features. This knowledge can then be used to propagate information to the inter-dependent features to appropriately determine its impact. To achieve this aim, researchers should consider techniques such as complex event processing (CEP) which extracts meaningful information from event streams and maps it to the SLA criterion to which it relates. The relationship between the different features and an SLA criterion then needs to be mapped and joined with compositors such as All, OneorMore and ExactlyOne. These compositors assist in appropriately translating the knowledge determined for a criterion to its dependent features. Future research work needs to done to determine how this information can then be used in knowledge graphs to see how its propagates further and results in the output given by the AI technique.
3. *Representing the output according to the requirements of the risk manager to explain the interpretability of the model.* Personalized risk supervision is the step of risk management in which the determined output is visualized and explained to the risk manager based on their requirements and demands [129]. This requires modelling the mental model of the risk manager [130] and then representing why the shown output is occurring based on that mental model. Existing XAI models are unable to do this and thus have a one-dimensional representation of the output. Future research work should look at addressing this drawback if the aim is for the results to be interpretable by risk managers from different viewpoints.
4. *Integrating different techniques to better capture the interdependency between features.* Researchers should look at the hybridization of different interdisciplinary techniques that attempt to integrate the working of each to intelligently manage supply chain risks [131]. Hybridization allows the integration of multiple algorithms in a single methodology and opens the scope to achieve a unique output which is not possible from using a single approach. For example, transfer learning is a machine learning approach which has been widely used in the literature. It aims to transfer knowledge from one domain to another, for which

no data exist [132]. This technique can be integrated with the use of a knowledge graph to either determine the value of the features for which no data exist or use information about a feature from one knowledge graph to determine its value in another setting. Similarly, can be the case with having a hybridization of different techniques.

We believe that these are some of the directions for future work to incorporate and improve XAI in SCORM. We emphasize that the above directions are not exhaustive and with a change in domain other than SCORM, other advancements too can be incorporated to improve the explainability of a recommended output.

5. Limitation of this study

There are two limitations to this research article. The first, as mentioned in Section 2.2, is that the scope of our analysis in this paper is SCORM. This does not imply that we analysed all the AI techniques that are used for risk management in supply chains. Supply chain management (SCM) consists of different activities, such as inventory management, warehousing, facility location, transportation, etc. Furthermore, risks in supply chains are of different types, such as performance risks, quality risks etc. So, for a complete analysis of the different AI techniques used in SCM and the management of the different risks, a deep analysis of other articles needs to be conducted. Some of these articles relate to the following areas: inventory management and replenishment [133–135], supplier selection [136], transportation [137], manufacturing [138], supply chain design [139,140] etc. It is important to note that this list is not exhaustive and researchers should use a structured approach to define the search query as we did, as detailed in Section 2.2. The second limitation of this paper is that although we pursued the SLR approach, it is still feasible that some papers were missed. However, it seems likely that this might be a small set of papers which would not alter the conclusions and the recommendations.

6. Conclusion

In this paper, we highlighted a shortcoming of the existing AI approaches for SCORM in terms of their lack of explainability. We emphasized that supply chain researchers should explore this potential of AI techniques in realizing proactive, predictive and real-time SCORM. Researchers should move from using a black-box-based technique to a more sophisticated, trustworthy and explainable technique that will assist in making auditable SCORM decisions. Using such techniques, SCORM researchers can monitor the future hazards with accuracy and gain confidence to enhance strategic plans in an explainable way. In our future work, we intend to develop techniques that utilize hybridization and attempt to achieve the features of XAI while SCORM. Our analysis is closely connected to the supply and accessibility of relevant studies.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The first author acknowledges the financial support received from The University of New South Wales for this work. This research was supported partially by the Australian Government through the Australian Research Council's Linkage Projects funding scheme (project LP160100080).

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