Risk Quantification in Cold Chain Management: A Federated Learning-enabled Multi-Criteria Decision-Making Methodology

Abstract

Purpose: In the cold supply chain, effective risk management is regarded as an essential component to address the risky and uncertain supply chain environment in the handling temperature-time-sensitive products. However, existing multi-criteria decision-making (MCDM) approaches greatly rely on expert opinions for pairwise comparisons. Despite the fact that machine learning models can be customised to conduct pairwise comparisons, it is difficult for small and medium enterprises (SMEs) to intelligently measure the ratings between risk criteria without sufficiently large datasets. Therefore, this paper aims at developing an enterprise-wide solution to identify and assess cold chain risks.

Design/methodology/approach: A novel federated learning-enabled multi-criteria risk evaluation system (FMRES) is proposed, which integrates federated learning and the best-worst method to measure firm-level cold chain risks under the suggested risk hierarchical structure. The factors of technologies and equipment, operations, external environment, and personnel and organisation are considered. Furthermore, a case analysis of an e-grocery supply chain in Australia is conducted to examine the feasibility of the proposed approach.

Findings: Throughout this study, it is found that embedding the federated learning mechanism into the MCDM process is effective in acquiring knowledge of pairwise comparisons from experts. A trusted federation in a cold chain network is therefore formulated to identify and assess cold supply chain risks in a systematic manner.

Originality/value: A novel hybridisation between horizontal federated learning and MCDM process is explored, which enhances the autonomy of the MCDM approaches to evaluate cold chain risks under the structured hierarchy.

Keywords – Risk assessment, risk identification, cold chain, federated learning, multi-criteria decision making

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1. Introduction

In recent years, cold chain management has attracted significant attention in the global economy in regard to assuring the quality of temperature-time-sensitive goods, such as fresh produce, seafood and pharmaceuticals, throughout supply chain activities. As such, the number of participants in the global cold supply chain has increased significantly, adding to the complexity and thus vulnerability of the supply network. In the globally connected world, failure at any point in the supply chain (SC) network has repercussions on product freshness, quality and safety (Pereira et al., 2014; Tse et al., 2016). In light of the novel coronavirus (COVID-19), customer behaviours and responses have been changed dramatically, for instance more customers are willing to do online shopping for the necessities and groceries, and the awareness of health and safety has increased substantially. In addition, questions on the effectiveness of existing supply chain risk management (SCRM) to maintain the resilience and robustness of supply chains (SCs) have been raised by academic scholars and industrial practitioners (El Baz and Ruel, 2020). A comprehensive cold chain management system is needed in the industry for effectively managing refrigerated transportation and storage, such as vaccine distribution around the globe, where the SCRM is one of the core components to identify and measure potential risks for eliminating impacts from supply chain risks. In cold chain management, a specific area, namely cold chain risk management (CCRM), is therefore considered to identify, assess, mitigate and control risks that occurr in cold supply chains. Apart from typical risk factors in SCRM, CCRM is required to further consider supply chain visibility, traceability, environmental impact, cost efficiency of adopting refrigeration equipment, and other cold chain-related risk factors. When the new normal in the supply chain management emerges, an improved systematic approach for the CCRM to quantify the risks is required to create a risk-averse and nimble environment in the industry. Among a number of existing methodologies to assess risk in the cold supply chain, multi-criteria decision-making (MCDM) approaches are well-known for evaluating the weights of the concerned risk categories (Dong and Cooper, 2016; Moktadir et al., 2018). However, the most significant weakness on the MCDM approaches, such as analytic hierarchical process (AHP) and the technique for order preference by similarity to the ideal solution (TOPSIS), is to over-rely on a group of domain experts or decision makers to conduct a series of pairwise comparisons. As shown in Figure 1, such methods in the existing supply chain risk evaluation framework solely rely on managers and experts, and thus inevitably contain a certain level of bias and subjectivity. Also, SC firms need to regularly employ appropriate talent for conducting pairwise comparisons, which is not favourable to small and medium enterprises (SMEs). Due to the advancements of machine learning, it is valuable to investigate the synergy between MCDM and machine learning so as to establish an intelligent and automatic risk assessment approach for cold chain management. Since standalone machine learning approaches are also not favourable for SMEs in collecting a vast amount of data for model training and validation, federated learning is deemed to be a promising solution to obtain an aggregated machine learning model for data analytics.

In this study, a novel federated learning-enabled multi-criteria risk evaluation system (FMRES) is proposed, which integrates horizontal federated learning and the best-worst method (BWM) for SC firms, involving the business of cold chain management to quantify cold chain risks in an intelligent and adaptive manner. With the use of horizontal federated learning, an improved global artificial neural network (ANN) model can be obtained in a privacy-persevering way, without disclosing any sensitive information to a third party for model training and validation. Subsequently, the ANN model learns the required knowledge from the decision makers so as to conduct the pairwise comparisons automatically for the deployment of BWM so as to prioritise and rank risk factors. Overall speaking, the study proposes an intelligent decision support system in designated SC firms that can identify, assess and analyse the potential risk factors so as to get rid of the traditional expert-intensive risk assessment process.

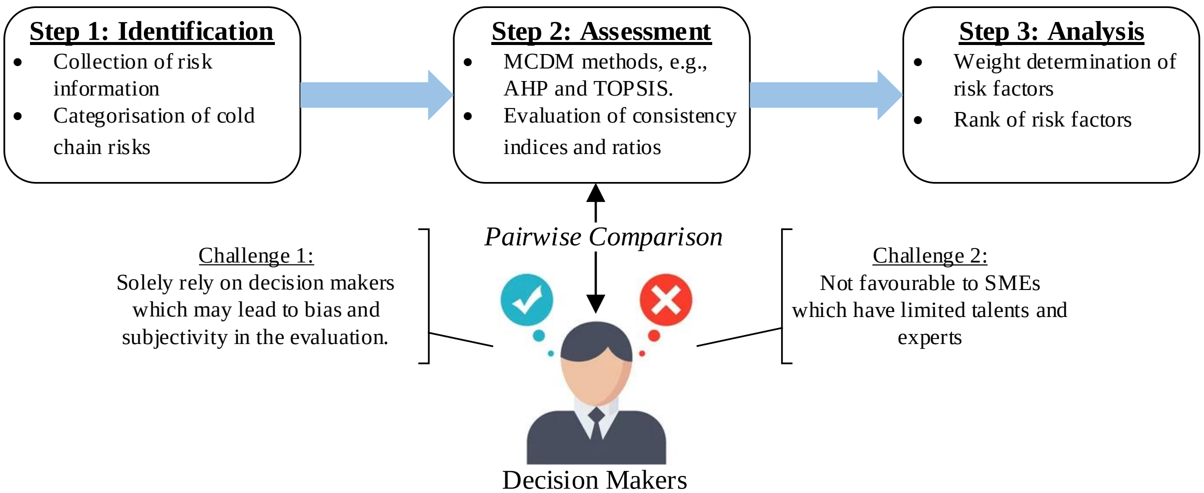

Figure 1. Challenges in the typical supply chain risk evaluation process

This paper is organized as follows. Section 1 is the introduction. In Section 2, the related work of cold chain management, cold chain management risks, and emerging risk assessment methods are reviewed, and thus the hierarchical structure for the cold chain risks can be built accordingly. Section 3 presents the proposed methodology of the FMRES in detail. A case study in implementing the proposed methodology in an Australian SC firm is illustrated in Section 4. Section 5 gives the results and discussion related to the proposed system. Finally, conclusions are drawn in Section 6.

2. Literature review

In this section, a review of cold chain management and cold chain management risks are presented so as to formulate the hierarchical structure for the cold chain risks. In addition, the emerging risk assessment methods are summarised.

2.1 Review of Cold Chain Management

The cold Chain has been well-defined as a particular SC to control and monitor temperature-time-sensitive products, or so-called perishables, throughout a series of SC activities and processes (Shashi et al., 2018). The integrity and quality of perishable products, such as pharmaceuticals, fresh produce, and dairy items, must be preserved in the cold chain management. The channel of the cold supply chain is characterized by the complex geographic, economic and legislative spread of the participating entities, exposing multiple points of delay and disruption of production, transportation, temperature control, services of third-party logistics providers, contamination transmitted via manual product handling, spoilage and quality problems (Nakandala et al., 2017). In practice, the cold supply chain can be distinguished from the general supply chain by the following characteristics (Yang et al., 2017):

(i) Shelf life: The shelf life is referred to the perishability of food products, in which a limited timeframe is defined for supply chain activities from the suppliers to end customers.

(ii) Seasonal production: Some food products can only be farmed and produced in a specific season, and therefore such products cannot be sold throughout the entire year.

(iii) Refrigerated transport and storage: To ensure high food quality throughout the whole supply chain, refrigeration and other cold chain equipment are applied in transportation and storage so as to provide designated environmental conditions to food products.

(iv) Small or zero inventories: Due to the effect of shelf life and demand fluctuation, the inventory policy in regard to perishable food is to keep a small or even zero amount of stock in the supply chain.

(v) Food traceability: Since food products are perishable and sensitive to the surrounding environmental conditions, tracking and tracing the food products along the supply chain is necessary for all relevant stakeholders.

(vi) Stochastic process yields: Process yields of food products in quantity and quality are subject to biological variations, seasonality, weather, pests, and other biological hazards.

2.2 Related studies of Cold Chain Management Risks

Generally speaking, risks are conceptualized as a “set of triplets”, which consists of a risk scenario, likelihood of that scenario, and consequences. The “set of triplets” characterizes the quantification of the likelihood and resulting consequence of risk scenarios and in extending to a supply chain, such risks can impact on multiple entities operating within the supply network, not just one individual or organization. Ho et al. (2015) differentiated supply chain risks into operational and catastrophic aspects where a risk event can trigger varying severity of consequences that significantly threaten normal business operations of the multiple firms in the supply chain. However, supply chain risks are directly related to how operations and processes are performed across various entities within the entire network. As such, risk identification and assessment extend beyond the boundaries of one firm, and thus the situation is far more complex. Risks are identified as events with the potential of negatively impacting on supply chain performance objectives, like network-wide service levels, responsiveness and efficiency (Kumar et al., 2018). Therefore, in designing a high performing supply chain as a whole, integrated risk management forms an indispensable core to minimise harmful impacts from risks. Regarding the effective management of supply chain risks, a variety of typologies and/or taxonomies of supply chain risks have been proposed in the literature to differentiate supply chain risks from other business risks. Firstly, equipment malfunction is deemed to be the most critical risk in cold chain management, which affects the environmental control of the perishables in SC activities and processes (Guo et al., 2018). Second, standardised processes and infrastructure are essential to prevent operational errors during transportation and storage, so as to maintain the high integrity and quality of the products. Although a short food supply chain is advocated to reduce the geographical distance and social relations between producers, processors, and consumers, supply chain risks, such as order fulfilment risk and supply risk, are not completely eliminated (Paciarotti and Torregiani, 2020). There is a room to further enhance the cold chain risk management in order to establish a risk-averse and nimble cold chain environment. Differing from the typical SC, cold chain risks may not only result in poor supply chain coordination, but also affect the integrity and quality of the temperature-time-sensitive products. Based on the above considerations, a firm-level risk management framework for each SC needs to be developed in the industry.

2.3 Emerging Risk Assessment Methods

In the field of SCRM, multi-criteria decision-making approaches are promising for evaluating the risk levels of defined risk criteria under a standardised hierarchical structure. Khan et al. (2019) adopted a fuzzy analytic hierarchical process to identify risk elements in the Halal food supply chain. It was reported that such a MCDM approach highly relies on experts' subjective judgements, and thus the sensitivity analysis to the prioritisation is considered when using MCDM approaches. Junaid et al. (2020) combined the neutrosophic AHP and TOPSIS to conduct supply chain risk assessment in the automotive industry in order to deal with complexity, uncertainty, and vagueness in the decision-making process. In recent years, some studies started exploring hybrid approaches, which integrated the existing MCDM approaches and other advanced data science methodologies. Chand et al. (2017) integrated the analytical network process and multi-objective optimisation by rational analysis methods to select the best SC with the minimum risks, where the robustness of the MCDM approaches was further enhanced. Further, Baryannis et al. (2019) summarised various artificial intelligence (AI)-based methods in the context of supply chain risk management, including stochastic programming, robust optimisation, fuzzy programming, network-based approaches, agent-based approaches, reasoning, machine learning, and big data. Particular to machine learning approaches, a designated input-output model can be formulated to gain capability of risk estimation under different scenarios. However, modelling the non-linear relationship between risk criteria and risk levels in a mathematical expression is complicated. Although machine learning approaches are widely adopted in the supply chain risk assessment, a pitfall in consolidating a sufficiently large dataset by a single organisation exists, particular for SMEs. Therefore, federated learning, which refers to machine learning approaches across decentralised edge devices without exchanging users' data, is considered to formulate a global machine learning model within a federation of trusted organisations. In view of the above situations, the integration of MCDM and federated learning is therefore explored in this study in order to formulate a data-rich SCRM for the cold chain management.

2.4 Federated Learning and its Applications

Although some AI approaches have been developed to assist supply chain risk management, such approaches are not easily deployed in small and medium enterprises (SMEs) due to the challenges of the data island and concerns on data privacy and security (Kim et al., 2019). Without inputting a sufficiently large dataset to the AI approaches, it is difficult to obtain an effective AI application, including supply chain risk management. To address the above challenges, federated learning (FL) with a decentralised, collaborative and privacy-preserving mechanism is developed from the foundation of machine learning algorithms (Yang et al., 2019; Li et al., 2020). Generally speaking, FL is categorised into three types, namely horizontal federated learning, vertical federated learning, and federated transfer learning, subject to the overlap of feature and sample spaces. Instead of merely applying data to train local machine learning models, a secure protocol in FL is established to derive a global model, where the federated averaging (FedAvg) is the most common method according to the computation of the average of local stochastic gradient descent updates. According to the work (Li et al., 2020), most of the FL-based applications analytics in recent years are deployed in the areas of mobile devices, industrial engineering, and healthcare to enhance the capability of existing machine learning models. To our best knowledge, since the FL is still at in under exploration and preliminary stage, limited research study has considered FL in logistics and supply chain management. In recent years, some scholars determined the value of incorporating machine learning models into multi-criteria decision-making methodologies (Özkan and İnal, 2014; Hassan and Hamada, 2017). Subsequently, there is a room to further explore the role of FL in multi-criteria decision-making methodologies, and enhance the accuracy and reliability of the results. FL has a great potential to improve the capability of deiciosn support functionalities, such as risk management, in logistics and supply chain management (Lim et al., 2020). Therefore, the synergy of FL and BWM can be further investigated in the area of cold chain risk management.

3. Hierarchical Structure of Managing Cold Chain Risks

To establish effective cold chain risk management, SC firms should classify the potential risks into two aspects, namely known and unknown risks (Bailey et al., 2020). Regarding the unknown risks, their impact on SCs might be severer than known risks, but it is difficult and challenging to foresee and quantify the occurrence of such unknown risks. The primary measure to minimise the impacts from unknown risks is to formulate various layers of defence in the risk-aware SC culture. Apart from the unknown risks, known risks are relatively imaginable and measurable, and require an effective risk management framework to determine a set of metrics for assessing the risks. Therefore, the assessment and quantification of known risks are the primary focus in this study, where the hierarchical structure of the cold chain risks with suggested measurement metrics are proposed in this section. Referring to Zhang's work, a hierarchical structure for agricultural products cold chain logistics risks was proposed, while the risks were measured in the aspects of technical equipment, commodity distribution, external environment, and personnel organisation (Zhang et al., 2017). The above study provides a solid foundation to construct an improved hierarchical structure of modern cold chain risks at the firm-level in SCs. Zheng et al. (2020) illustrated the operational risks for the cold chain logistics system, in which processing packaging, transportation, warehousing and information management are four core perspectives. Due to the recent pandemic situation from the novel coronavirus (COVID-19), the regulatory compliance on quality, environment, health and safety in SCs have become stricter and more essential, such that shipments are safely distributed in the supply chain network (Kecinski et al., 2020). The risks of carrying any novel virus and contaminating the shipment itself should be considered.

In view of the above modern concerns on cold chains, an integrated hierarchical structure for modern cold chain risks is formulated, as shown in Figure 2. It consists of four primary criteria, namely (i) technologies and equipment (C1), (ii) operations (C2), (iii) external environment (C3), and (iv) personnel and organisation (C4). The detailed descriptions of the above four aspects are summarised in Table I, which are modelled to assess cold chain risks at the firm-level in cold chains. The criteria also have their corresponding sub-criteria to facilitate the risk quantification process, in which sets of measurement metrics are defined to assess the sub-criteria. In total, four primary criteria with sixteen sub-criteria are considered to formulate the hierarchical structure in this study. In C1, the essential technologies and equipment in the cold chain management are considered, including temperature control equipment in storage and transportation, monitoring and detection equipment, and traceability system. Effective temperature excursion management is guaranteed through the use of the above technologies and equipment to assure product quality throughout the cold chains. In C2, operational aspects, covering process packaging, refrigerated transportation, cold warehousing and storage, supply stability, and process stability, are considered to assess the internal capability of cold chains. Undesirable operational incidences, such as chain disruption and supply shortage, should be avoided in cold chains. In C3, external forces to the cold chains, including regulatory control on quality, environment, health and safety, environment impact, and market demand stability, are determined, which highly influence SC's business environment. SCs with high adaptability to the macro-economic business environment are preferred. In C4, firm-internal factors on personnel and organisation, including operational expertise, human resource management, and financial healthiness, are also considered. A human-centric and stable working environment is favourable to the development of cold chain businesses. Although the sub-criteria of cold chain risks are measured in a quantifiable manner through the set of metrics, as in Table I, the relative importance between the sub-criteria in the hierarchical structure is not effectively investigated. Therefore, this study proposes to implement federated learning in regard to acquiring the behaviour of experts in cold chains on the process of pairwise comparison, based on the measurement metrics. Through analysing the pairwise comparisons in the selected MCDM approach, the above risk criteria can be prioritised effectively so as to establish and revise the risk mitigation and contingency plan to minimise the impact from the cold chain risks.

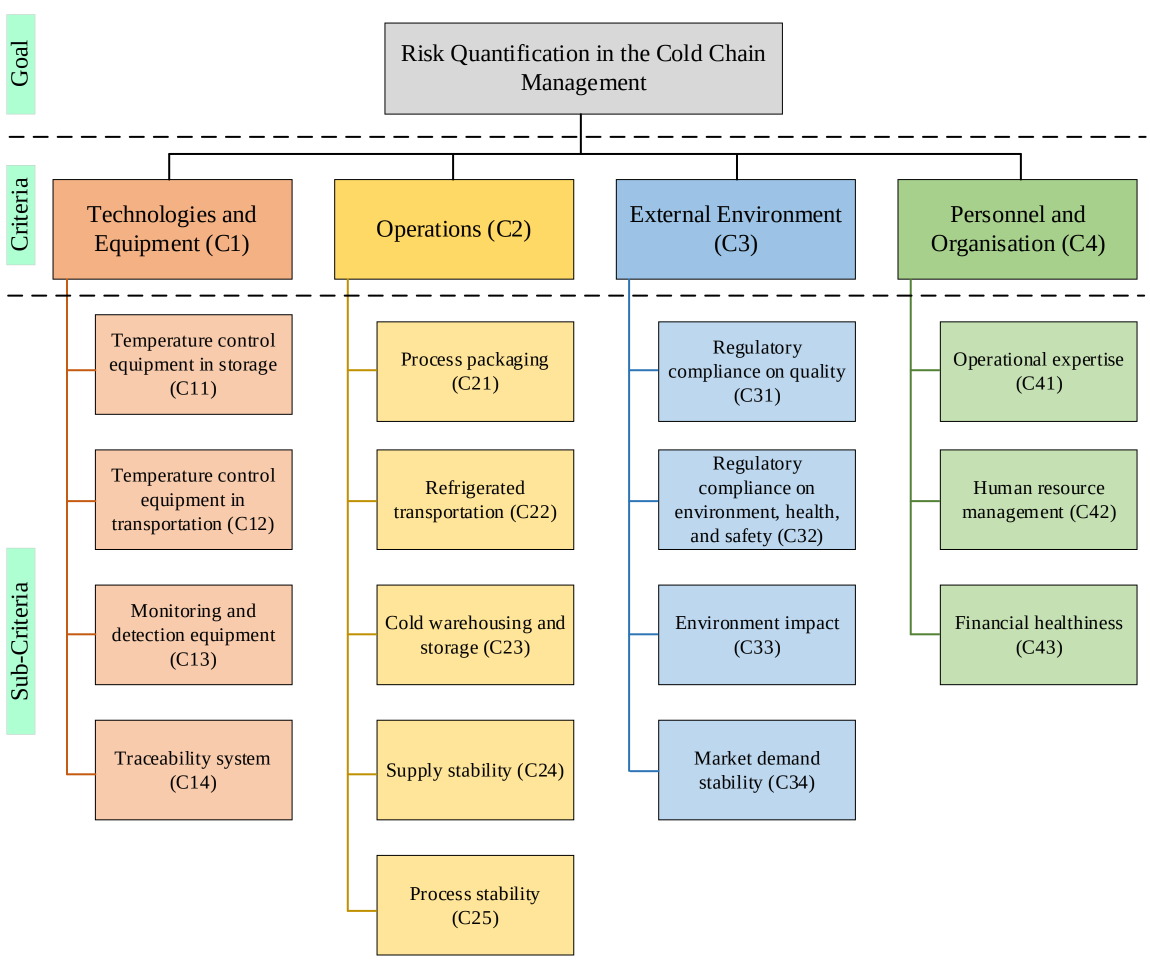

Figure 2 Hierarchical structure for the firm-level CCRM

Table I Criteria and measurement metrics of cold chain risks

Risk criteria	**Descriptions**	**Metrics**	**Unit**
Temperature control equipment in storage	Malfunction or breakdown of the temperature control equipment in cold storage facilities	Frequency of temperature excursion in storage (v_1)	Frequency
Temperature control equipment in transportation	Malfunction or breakdown of the temperature control equipment in refrigerated trucks	Frequency of temperature excursion in transportation (v_2)	Frequency
Monitoring and detection equipment	Improper calibration and connectivity error of monitoring and detection devices	Errors in monitoring and detection devices (v_3)	Frequency
Traceability system	Incomplete and incorrect product traceability records	Errors of product traceability (v_4)	Frequency
Process packaging	Inappropriate use of cold chain packaging during SC activities	Errors in mishandling process packaging (v_5)	Frequency
Refrigerated transportation	Handling errors to cause shipment delay and damages	Number of damaged cargos (v_6)	Frequency
Cold warehousing and storage	Handling errors to increase complexity in order fulfilment and quality deterioration	Storage capability (v_7)	Cubic metre (CBM)
Supply stability	Fluctuations on the supply of raw materials to SCs	Variation in supply (v_8)	Coefficient of variation (CV)
Process stability	Fluctuations on the production process to SCs	Variation in production process (v_9)	Coefficient of variation (CV)
Regulatory compliance on quality	Breach of quality requirements and promised service levels	Violation of regulatory compliance on quality (v_{10})	Frequency
Regulatory compliance on environment, health, and safety	Breach of binding regulations on environment, health, and safety	Violation of regulatory compliance on environment, health, and safety (v_{11})	Frequency
Environment impact	Criticism of the sustainability and corporate social responsibility of SCs	Wastage in SC activities (v_{12})	Carbon dioxide equivalent (CO_2eq)
Market demand stability	Fluctuation on the market demand to SCs	Variation in market demand (v_{13})	Coefficient of variation (CV)
Operational expertise	Lack of professional workforce to supervise and monitor SC operations	Proportion of professional talents (v_{14})	%
Human resource management	Instable workforce and work environment in SCs	Turnover rate of manpower(v_{15})	%
Financial healthiness	Fragile financial situations to sustain SCs	Amount of free cash flow (v_{16})	AUD

4. Design of a Federated Learning-enabled Multi-Criteria Risk Evaluation System (FMRES)

To effectively evaluate cold chain risks in the supply chain network, this study integrates federated learning into the best worst method, which is a well-known and effective multi-criteria decision-making approach, so as to establish an intelligent risk evaluation mechanism in the industry. As shown in Figure 3, the proposed system consists of three major tiers, namely (i) data collection based on the hierarchical structure, (ii) acquisition of expert knowledge in pairwise comparisons, and (iii) multi-criteria decision-making process by the best worst method.

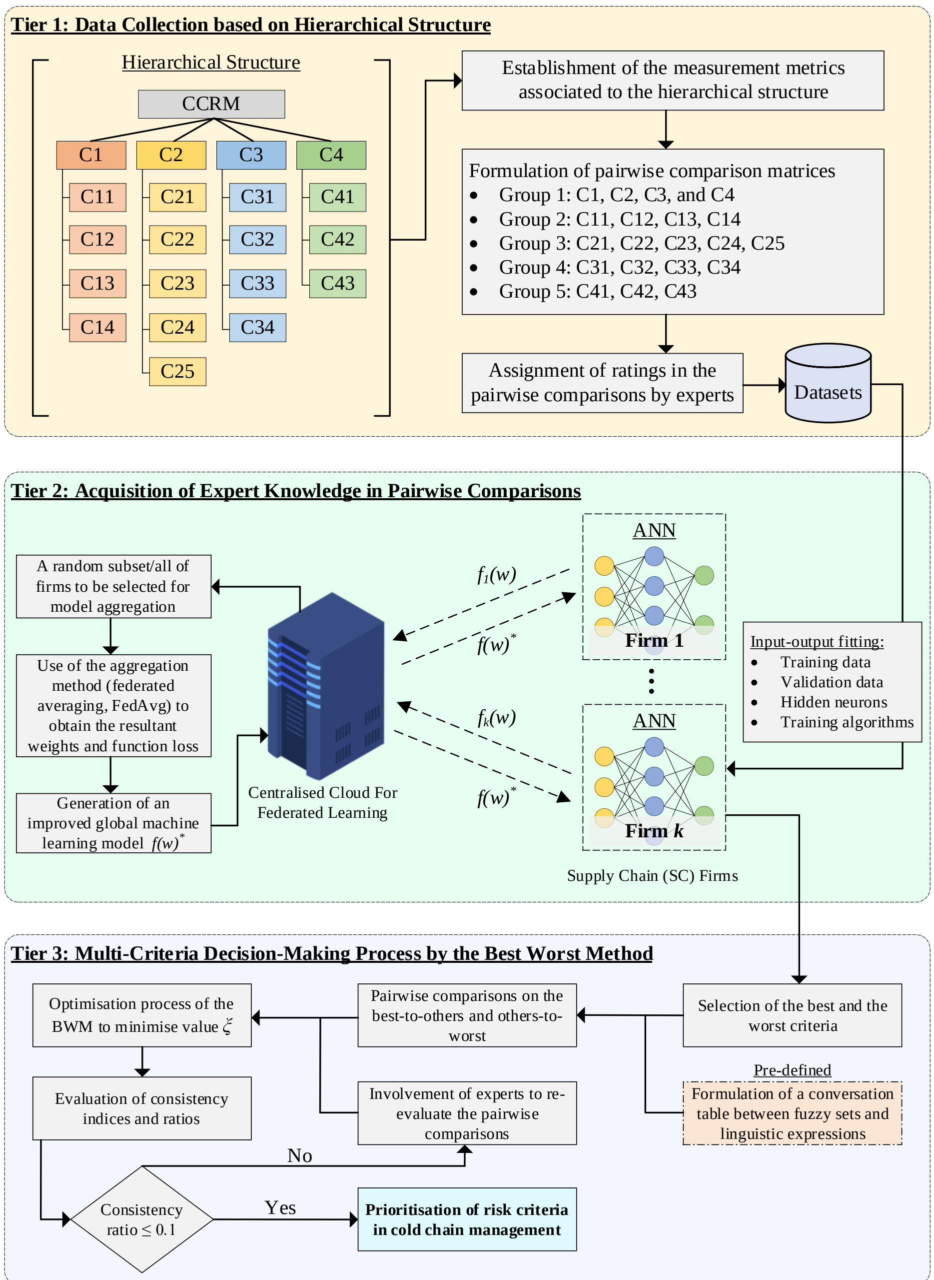

Figure 3 Systematic framework of the FMRES

4.1 Tier 1: Data Collection based on the Hierarchical Structure

According to the previous section, the hierarchical structure for managing cold chain risks has been established, while the corresponding 16 evaluation matrices are suggested as the references to conduct pairwise comparisons in the MCDM method. Regarding pairwise comparisons, there are five groups in accordance with the hierarchical structure as shown in Figure 2, namely the comparisons (i) between C1, C2, C3, and C4, (ii) between C11, C12, C13, and C14, (iii) between C21, C22, C23, C24, and C25, (iv) between C31, C32, C33, and C34, and (v) C41, C42, and C43. Mathematically, the matrix of the pairwise comparison $\boldsymbol{P}$ for n criteria can be formulated as in equation (1), where the weights in the matrix's diagonal is equal to 1, and the weights in the upper triangular matrix except the diagonal are the reciprocal of the weights in the lower triangular matrix. Subsequently, a group of decision makers at the specific SC firm, who are managers and experts in cold chain management, are invited to assign the rating in the lower triangular matrix of pairwise comparisons based on the given hierarchical structure and evaluation matrices. Thus, dataset $\boldsymbol{D}$ is separated into training dataset $\boldsymbol{D_T}$ and validation dataset $\boldsymbol{D_V}$ in the formulation of five independent ANN models (baseline) based on five groups of pairwise comparisons, where number of pairwise comparisons of each group is $n(n-1)/2$, and n denotes the number of criteria to be considered. Consequently, based on the proposed hierarchical structure in this study, there are sixteen evaluation metrics as input to estimate twenty-five ratings between [0, 10] of the pairwise comparisons.

$$\boldsymbol{P} = (p_{ij})_{n\times n} = \begin{bmatrix} \emptyset & \cdots & \varphi_{n1}^{-1} \\ \vdots & \ddots & \vdots \\ \varphi_{n1} & \cdots & \emptyset \end{bmatrix} \tag{1}$$

4.2 Tier 2: Acquisition of Expert Knowledge in Pairwise Comparisons

After structuring the input (i.e. sixteen evaluation metrics) and output (i.e. twenty-five pairwise comparisons) based on the hierarchical structure, the SC firm can formulate a local ANN model to assist the process of pairwise comparisons, where the number of hidden neurons N_h is determined by using equation (2), and m denotes the number of input neurons (Sheela and Deepa, 2013). With the selection of an appropriate training algorithm, the local ANN models for all SC firms can be initiated.

$$N_h = \frac{4m^2+3}{m^2-8} \tag{2}$$

In order to obtain a global ANN model in the cold chain network, particularly to benefit SMEs which do not have sufficient training and validation datasets, federated learning with deploying federated averaging (FedAvg) as the aggregation method is applied (Hao et al., 2019; Li et al., 2020). By deploying the FL mechanism, multiple cold chain stakeholders can collaboratively formulate the global ANN model through effectively aggregating local model updates to assist the pairwise comparisons in the BWM through a privacy-preserving protocol. Compared with typical ANN models trained by local data, the FL mechanism is more effective in obtaining an industry-wide ANN models such that the perception on cold chain risk management from different stakeholders can be synthesized. Therefore, the FL-enabled ANN is formulated in this study as follows.

Step 1: For *i*-th SC firm, an initial model parameter $f(\omega_t)$, namely weights between nodes and node biases, in the ANN is received from the federated learning cloud, as the baseline setting at time *t*.

Step 2: By using the initial model parameter $f(\omega_t)$, the gradient ∇f_{it} of the local ANN model is computed by using the training $\boldsymbol{D_{Ti}}$ and validation $\boldsymbol{D_{Vi}}$ datasets of the *i*-th SC firm. Subsequently, a local update on the ANN model is conducted as $f_i(\omega_t) \leftarrow f(\omega_t) - \eta \cdot \nabla f_{it}$, where η is the learning rate.

Step 3: Step 2 is repeated according to the number of epochs *E* defined in this federated learning model, and therefore finalised model parameter $f_i(\widetilde{\omega}_t)$ is sent to the federated learning cloud for further aggregation.

Step 4: The federated learning cloud collects all model parameters from *k* SC firms, namely $f_1(\widetilde{\omega}_t), \dots, f_k(\widetilde{\omega}_t)$, in the cold chain network, and the weight average of the model parameters is computed as $f^*(\omega_t) \leftarrow \frac{1}{\sum_{i=1}^{k} n_i} \sum_{i=1}^{k} [n_{it} \cdot f_i(\widetilde{\omega}_t)]$, where n_{it} represents the number of data rows considered in building the local models at time *t*.

Step 5: An improved global ANN model with the parameter $f^*(\omega_t)$ is built accordingly, which is then disseminated to all SC firms in the network for conducting pairwise comparisons between defined criteria. The above steps 2 to 5 are repeated for obtaining another improved model with the parameter $f^*(\omega_{t+1})$ at the next time stamp *t*+1.

Consequently, at time *t*, the global ANN model is therefore obtained with high privacy-preserving functionality in the cold chain network such that the SC firms can effectively estimate twenty-five ratings of the pairwise comparisons. Knowledge from experts and managers in the field of cold chain management can be acquired in the above federated learning approach so as to facilitate the MCDM process according to the hierarchical structure.

4.3 Tier 3: Multi-Criteria Decision-Making Process by the Best Worst Method

Among a number of MCDM methods, AHP and its variants have been widely applied to identify and assess supply chain risks (Butdee and Phuangsalee, 2019; Vishnu et al., 2019). However, some drawbacks in using AHP-based solutions, such as high complexity in pairwise comparisons and difficulty in maintaining consistency, have been revealed. Rezaei (2015) proposed a novel MCDM method, called best worst method (BWM), which outperforms the AHP-based solutions in term of practicality and reliability. Therefore, the BWM is selected in this study to evaluate cold chain risks, while the pairwise comparisons are extracted from the results of the global ANN model.

Step 1: The *i*-th SC firm requires to select the best and worst criteria for group *j* of pairwise comparisons, and thus vectors of best-to-others $V_{ij}^{b} = (v_{ij1}^{b}, \dots, v_{ijn}^{b})$and others-to-worst $V_{ij}^{w} = (v_{ij1}^{w}, \dots, v_{ijn}^{w})$ are formulated.

Step 2: The ratings $\boldsymbol{R} = (r_1, \ldots, r_{25})$ obtained from the global ANN model are inputted to the vectors of best-to-others and others-to-worst. For example, C2 and C4 are selected as the best and worst criteria, respectively, in group 1. As shown in Figure 4, the upper triangular matrix of the matrix P is filled by the reciprocal of the corresponding rating between two criteria. Subsequently, the vectors of best-to-others and others-to-worst (from row to column) are built, where v_{i12}^{b} and v_{i14}^{w} are null, and v_{i14}^{b} is exactly equal to v_{i12}^{w}.

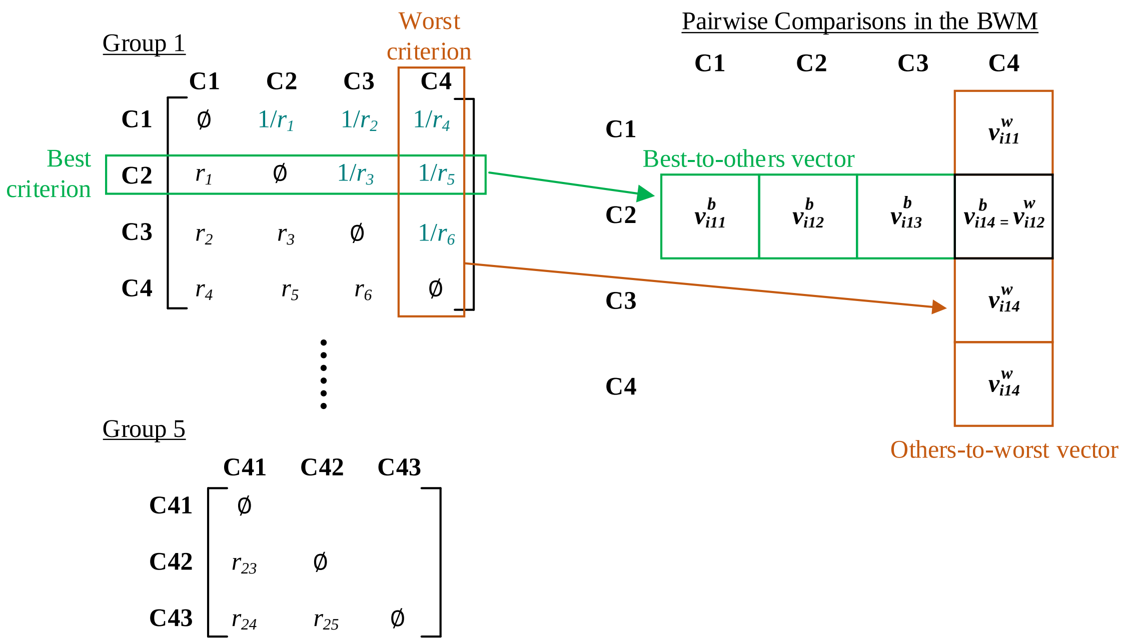

Figure 4. Example of extraction of ratings to the pairwise comparisons for the BWM

Step 3: The optimisation problem, as in equations (3) to (7), is formulated to minimise the absolute gap ξ between w_b/w_k and triangular fuzzy number of the best criterion V_{ij}^{b}, and between w_k/w_w and triangular fuzzy number of the worst criterion V_{ij}^{w}. The values w_b, w_w, w_k represent the weights of best, worst, and other k criteria, respectively. Except for the examination of the absolute gap, the sum of weights for all criteria is restricted to be 1, and non-negativity constraint is considered for the weights and absolute gap.

$$\text{Min. } \xi \tag{3}$$

Subject to:

$$\left| \frac{w_{ijb}}{w_{ijk}} - v_{ijk}^{b} \right| \leq \xi \tag{4}$$

$$\left| \frac{w_{ijk}}{w_{ijw}} - v_{ijk}^{w} \right| \leq \xi \tag{5}$$

$$\sum_{k=1}^{n} w_k = 1 \tag{6}$$

$$w_k, \xi \geq 0 \tag{7}$$

Step 4: By solving the above optimisation problem, the optimal weight w_{ijk}^{*} ($\forall k = 1, \ldots, n$) with the optimal absolute gap ξ^{*}.

Step 5: The consistency ratio (CR) of the MCDM process is computed, where the optimal absolute gap is divided by the consistency index (CI), as in equation (8). The value v_{ij} is the largest rating assigned in the pairwise comparisons, and thus the largest positive root of CI is obtained to measure the CR. If the consistency is greater than 0.1, experts/managers in the SC firms can fine tune the pairwise comparison, and steps 3 and 4 are repeated until the consistency ratio is less than 0.1.

$$CR = \frac{\xi^{*}}{CI}, \text{ where } CI^2 - \left(1 + 2v_{ij}\right)CI + \left(v_{ij}^2 - v_{ij}\right) = 0 \tag{8}$$

Step 6: According to the resultant weights of risk criteria determined by the BWM, the most vulnerable criteria between C1, C2, C3, and C4 can be discovered. Similarly, the most vulnerable sub-criteria out of the sixteen criteria can be evaluating through multiplying the weights of the corresponding risk category and the weight, namely $\widetilde{w}_{iqk}{}^{*} \leftarrow w_{i1(q-1)}{}^{*} \times w_{iqk}{}^{*}, \forall q \in \{2, \ldots, 5\}$, in this study.

5. Case Analysis of a Cold Chain Network in Australia

In this section, a case analysis of deploying the proposed FMRES in the cold chain network in Australia is conducted. It consists of (i) industrial background and motivation, and (ii) implementation roadmap of the FMRES.

5.1 Industrial Background and Motivations

In this study, a case study on e-grocery supply chains in Australia was conducted, where the e-fulfilment on temperature-time-sensitive products to end customers is provided. Regarding the e-grocery supply chain management, it is classified as a branch of the cold chain that manages material flow, information flow, and capital flow between suppliers, refrigerated distribution centres, e-commerce platforms, and online-to-offline (O2O) stores. End customers can place their orders in the e-commerce platforms for grocery commodities and fresh produce, while the orders are fulfilled by either home delivery or pick-up at O2O stores. An effective cold chain system from raw suppliers until the last mile delivery is thus established to assure product quality through the entire supply chain journey. In order to ensure high service level and product quality in the cold chain, e-grocery firms are eager to have a comprehensive and effective risk identification and assessment approach for mitigating the effects of supply chain vulnerability. After discussing with the industrial practitioners, it is found that most e-grocery firms in the industry know that there are a number of risk identification and assessment methodologies, including the MCDM method. However, such methods require specialised talent and experts to quantify the potential risk factors, which are not favourable to the SMEs in the e-grocery business. They are eager to seek an automated and intelligent solution to evaluate cold chain risks for their business, and therefore the proposed system is deemed to be an effective way to strengthen the capability on the cold chain risks management. Under the mechanism of federated learning, sensitive and confidential data are not required to be disclosed to competitors or a third-party company. Only the model parameters are shared in the federated learning cloud, which enhance the data security and privacy in the establishment of enterprise-wide intelligence for the risk quantification.

In view of the above motivation, five Australian e-grocery firms as a federation were successfully invited to illustrate the implementation of the proposed system in the period between January 2020 and June 2020. A global ANN model is therefore established to acquire the knowledge of pairwise comparisons from the experts. The expert reliance on the MCDM method can be reduced, and therefore the whole risk assessment process can become more objective and systematic. Therefore, the five e-grocery firms can consistently evaluate cold chain risks in a daily manner to spot any vulnerable elements in their cold chain management through the intelligent system.

5.2 Implementation Roadmap of the FMRES

Following with the proposed system shown in Figure 3, the entire implementation is divided into two separate stages, namely (i) establishment of federated learning, and (ii) risk quantification by the BWM. In addition, the proposed system is built in the Python environment to achieve the data acquisition, federated learning, and computations on the BWM as a whole.

5.2.1 Stage 1: Establishment of Federated Learning

Firstly, according to the defined hierarchical structure and evaluation metrics, five e-grocery firms provided the datasets on the 16 metrics of the hierarchical structure (input) and 25 ratings of pairwise comparisons (output). The datasets were extracted from the historical records when conducting pairwise comparisons to assess the cold chain risks in their supply chain activities. In this case analysis, each e-grocery firm provided 50 rows of data, which are only stored in their local storage with any sharing protocols. Since the five e-grocery firms are doing similar business in the e-fulfilment of grocery products, but customer pools are different in their e-commerce platforms as each store has its own competitive edge and advantages. Consequently, the horizontal federated learning proposed in the FMRES is appropriate to synthesize the model parameters to generate an improved global ANN model, as shown in Figure 5. With the initial model parameters disseminated by the federated learning cloud, the local ANN models are then trained and validated by the e-grocery firms, where the number of hidden neurons used in the model is 4.14, determined by equation (2), and thus five hidden neurons are set. Moreover, the Levenberg-Marquardt training algorithm is adopted to evaluate the performance of mean square errors in the validation datasets, which has been widely applied to construct an efficient ANN solution (Du and Stephanus, 2018). In the e-grocery firms, a weekly review by experts and managers on the cold chain risks according to the hierarchical structure is performed, where additional datasets about the pairwise comparisons can be collected. Under the monthly aggregation in the supply chain network, there are four epochs for the e-grocery firms to evaluate the updates on their models with the learning rate at 0.5, which are separately managed to await the centralized aggregation in the federated learning cloud. After performing local updates in the four epochs, the updates of the model parameters, namely (i) weights between nodes and (ii) bias values at nodes, are uploaded to the cloud for aggregation. In the federated learning cloud, the FedAvg method is applied to aggregate the model parameters by calculating the weighted average, in which the weights used in the calculation of the weighted average are referred to the row of datasets considered in the local updates. Consequently, the global ANN model is updated and disseminated back to the e-grocery firms for the daily cold chain risk evaluation practice. The firms can solely rely on the global model to conduct the pairwise comparisons and risk assessment in a daily timeframe, based on the latest evaluation metrics. The role of experts and managers in the risk assessment is therefore refined so as to concentrate on regular review and amendments on the datasets, instead of frequently conducting manual pairwise comparisons in daily operations. With the aid of the proposed system, the frequency of the risk evaluation in the cold chain management can be increased, resulting in better supply chain resilience and risk awareness.

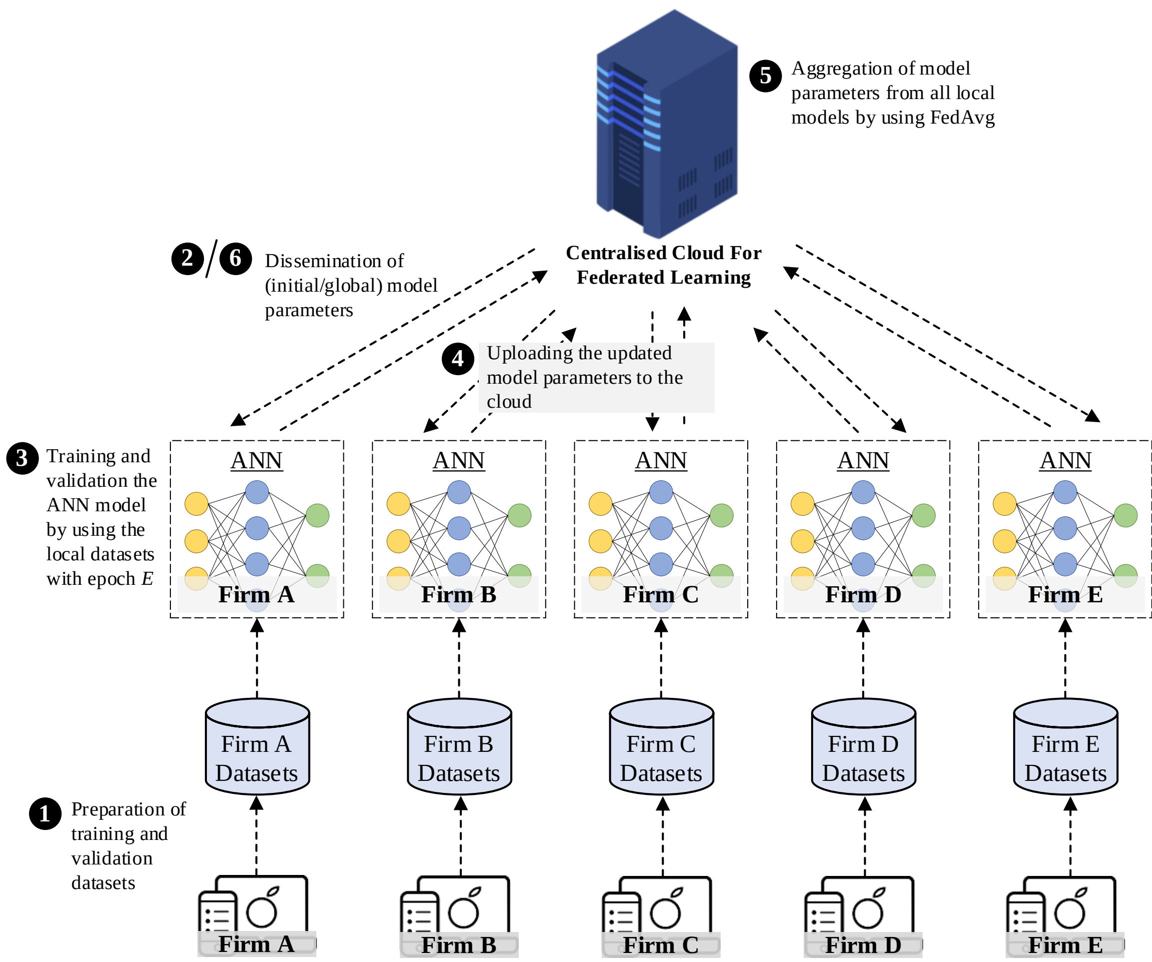

Figure 5. Graphical illustration of the horizontal federated learning in the e-grocery supply chain network

5.2.2 *Stage 2: Risk Quantification by the BWM*

When the global ANN model is disseminated by the federated learning cloud, the pairwise comparisons based on the current risk performance metrics can be conducted such that the ratings are assigned for the analysis of the BWM, as shown in Figure 6. The global ANN model defines 80 weights between the input and hidden neurons, 125 weights between hidden and output neurons, 5 bias values at hidden neurons, and 25 bias values at output neurons. Subsequently, the five metrics of pairwise comparisons from group 1 to group 5 are established, in which the ratings refer to the level of risks and vulnerability on the designated areas. Each e-grocery firm is required to define the best criterion (i.e., the most vulnerable factor), and the worst criterion (i.e., the least vulnerable factor). For instance, firm A selects C3 and C4 as the best and worst criteria, respectively, in group 1; C12 and C11 as the best and worst criteria, respectively, in group 2; C24 and C23 as the best and worst criteria, respectively, in group 3; C34 and C33 as the best and worst criteria, respectively, in group 4; C43 and C42 as the best and worst criteria, respectively, in group 5. By applying the BWM, the pairwise comparisons can be analysed to generate the weights on the criteria and sub-criteria defined in the proposed hierarchical structure of cold chain risks. The proposed approach not only considers the preferences of the e-grocery firms in prioritising the risk criteria, but also the facts and knowledge obtained in the cold chain network.

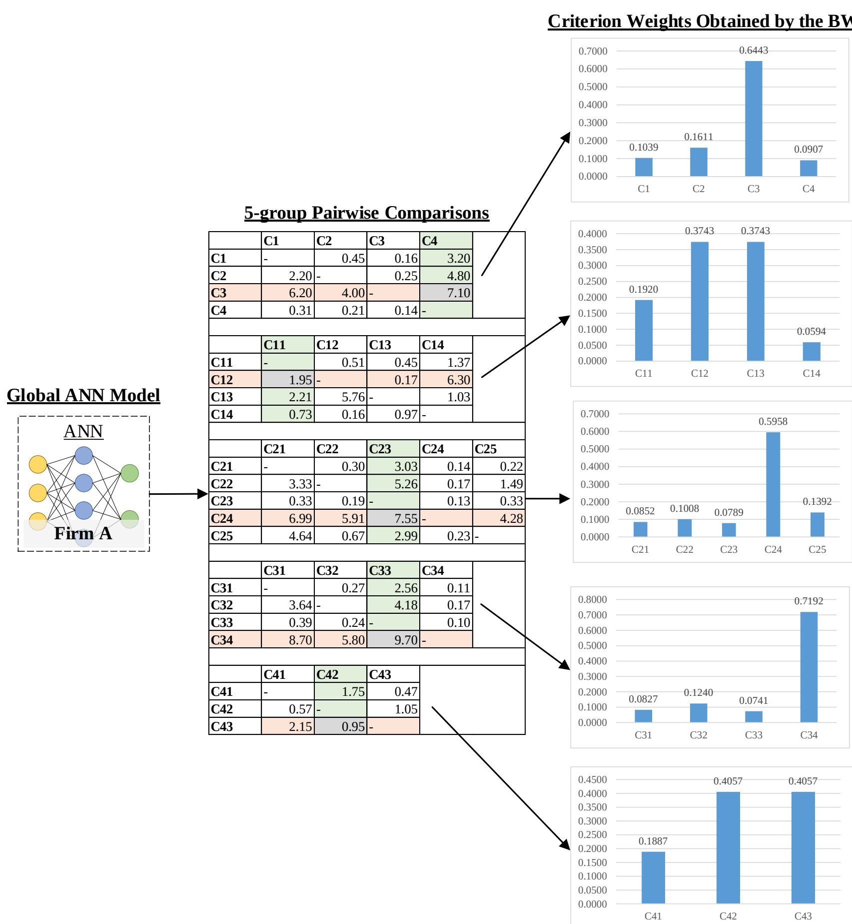

Figure 6. Graphical illustration of the automatic BWM deployment

Consequently, the weights of the criteria and sub-criteria are combined together to obtain the resultant weights on each sub-criterion, which refers to the level of severity of cold chain risk criteria. The results of the composited weights for sixteen risk criteria are summarised in Table II. For firm A, it is found that the criteria C34 (market demand stability), C24 (supply stability), and C32 (regulatory compliance on environment, health, and safety) are measured as top three risk factors in its cold chain management system. During the period of the first half year in 2020, the emergence of the novel coronavirus (COVID-19) caused serious disruptions on supply chain activities, including the e-grocery businesses. On the one hand, the proposed model correctly reflects the fluctuations in demand and supply, where the grocery supply is always under tension and shortage. Besides, more and more end consumers tend to purchase daily necessities and grocery items via e-commerce platforms, instead of shopping in person, and thus the demand was highly varied in the examined period of time. On the other hand, the serious epidemic situation influences consumers' awareness on food safety, personal health, and environmental impact, and therefore additional regulations and advice are introduced to the cold chain businesses. Generally speaking, the proposed system is effective in identifying and assessing cold chain risks in the supply chain network, while appropriate risk mitigation strategies and contingency plans can be established to eliminate the impact from the risks.

Table II Summary of composited weights of cold chain risk criteria

Criteria	Sub-criteria	Weights of Criteria	Weights of Sub-criteria	Composited Weights
C1	C11	0.1039	0.1920	0.0199
	C12		0.3743	0.0389
	C13		0.3743	0.0389
	C14		0.0594	0.0062
C2	C21	0.1611	0.0852	0.0137
	C22		0.1008	0.0162
	C23		0.0789	0.0127
	C24		0.5958	**0.0960**
	C25		0.1392	0.0224
C3	C31	0.6443	0.0827	0.0533
	C32		0.1240	**0.0799**
	C33		0.0741	0.0478
	C34		0.7192	**0.4634**
C4	C41	0.0907	0.1887	0.0171
	C42		0.4057	0.0368
	C43		0.4057	0.0368

6. Results and Discussion

After illustrating the proposed system in the above case analysis, the top three risk factors for the cold chain management are identified and assessed successfully. The hybridization of federated learning and BWM is theoretically and practically achievable. To discuss the results obtained from the proposed system, the performance validation and managerial implications are covered in this section.

6.1 Validation of the Proposed System in Solving MCDM Problems

In this study, the inclusion of federated learning aims at providing an intelligent and automatic BWM to solve the MCDM problem of cold chain risk assessment. In order to validate the proposed system, except the measurement of consistency ratios stated in Section 4.3, the minimum variation (MV), and total deviation (TD) are considered to compare the performance between the (i) proposed system, (ii) ANN-based BWM, and (iii) traditional BWM. For the proposed system and ANN-based BWM, the machine learning model plays the role of respondent to conduct pairwise comparisons according to the hierarchical structure. For the traditional BWM, the experts and managers (sample size = 30) were invited to conduct the pairwise comparisons based on their knowledge and experience. Regarding the MV, the occurrence of the violation between the pairwise comparisons and finalized ranking of risk criteria is calculated as in equation (9). The value MV_u for the expert u who conducts the pairwise comparisons can be therefore computed, while the value of MV_u refers to the level of inconsistency between pairwise comparisons and finalized weights of risk criteria. Consequently, small values of MV_u are preferred in the MCDM process.

$$MV_u = \sum_{i=1}^{n} \sum_{j=1}^{n} \frac{V_{uij}}{2n-3}, \text{ where } V_{uij} = \begin{cases} 1 & \text{if } \varphi_{ij} < 1 \text{ and } \widetilde{w}_i^* > \widetilde{w}_j^* \\ 0.5 & \text{if } \varphi_{ij} = 1 \text{ and } \widetilde{w}_i^* \neq \widetilde{w}_j^* \\ 0.5 & \text{if } \varphi_{ij} \neq 1 \text{ and } \widetilde{w}_i^* = \widetilde{w}_j^* \\ 0 & \text{Otherwise} \end{cases} \tag{9}$$

Regarding the TD, the square of the absolute distance between the proportion between $\widetilde{w}_i^*$ and $\widetilde{w}_j^*$, and the corresponding rating φ_{ij} is measured, as in equation (10). Generally speaking, a small value of *TD* is preferred in the MCDM process such that the final prioritization and ranking results relatively match the pairwise comparisons. By applying the above three validation approaches, the proposed system is therefore validated in terms of CR, MV and TD, as shown in Table III. For the proposed system and ANN-based BWM, pairwise comparisons in five defined groups are performed, and thus five samples of the pairwise comparisons are collected for the validation. On the other hand, 30 respondents produce 150 samples of pairwise comparisons in total. It is found that the proposed system performs well in terms of MV and TD, while its CR is close to the result of using the traditional BWM. In addition, the values of CR are less than 0.1, which implies that the BWM is effective in generating consistent results in assessing risk criteria. To sum up, it shows that the proposed system has good capability in assigning consistent and accurate ratings on the pairwise comparisons.

$$TD = \sum_{i=1}^{n} \sum_{j=1}^{n} \left| \varphi_{ij} - \frac{\widetilde{w}_i^*}{\widetilde{w}_j^*} \right|^2 \tag{10}$$

Table III Validation results between the proposed system, ANN-based BWM, and traditional BWM

	N	**CR**		**MV**		**TD**	
		Average	S.D.	Average	S.D.	Average	S.D.
The proposed system	5	0.0553	0.0181	0.0167	0.0304	3.3481	2.0519
ANN-based BWM	5	0.0916	0.0449	0.0261	0.0498	5.0329	4.6450
Traditional BWM	150	0.0549	0.0203	0.0193	0.0333	3.5267	2.7051

6.2 Managerial Implications

With the aid of the proposed system, the deployment of risk identification and the assessment process for SC firms becomes effective and convenient. Since traditional MCDM approaches requires extensive involvement of experts and managers, uncontrolled subjectivity and uncertainty cannot be prevented. Further, managing a large group of experts and managers to frequently conduct pairwise comparisons is difficult to justify from the firms' perspective. It is always a challenging task for the SC firms to plan and deploy the execution of the MCDM process to estimate the risk levels. Particularly for cold chain management, an effective risk management approach is essential to the survival and competitiveness of SC firms. Therefore, the proposed system offers a novel solution which combines federated learning and one of the MCDM approaches, namely BWM, to automate the process of pairwise comparisons, which traditionally is regarded as a tedious and challenging task. Business intelligence on the pairwise comparisons of risk quantification is acquired, which enables better adaptability and practicality in real-life situations. More frequent risk identification and assessment can be conducted to timely control and monitor any disruptions in the cold chain network. For reaching the post-pandemic era, supply chain resilience and risk awareness have drawn considerable attention, which aligns to this study. In near future, when the new normal emerges, an intelligent risk quantification mechanism will become a core component to avoid and prevent significant disruptions to supply chain operations.

Since the proposed method opens up a new research synergy in combining FL and MCDM methods, another theoretical implication is derived from this study in extending the existing MCDM-based applications. In the field of supply chain management, MCDM techniques have been widely applied instead of cold chain risk management, for example performance evaluation, assessment of competitive advantages, and supplier selection (Uygun and Dede, 2016; Pang et al., 2017; Wu et al., 2017). The autonomy of the above MCDM-based applications can be further strengthened through the adoption of the proposed method in this study. The reliability, accuracy and measurement consistency of the results can be improved, resulting in positive impact on decision-making process.

7. Concluding Remarks

In this study, a federated learning-enabled multi-criteria risk evaluation system (FMRES) is proposed, which enables the federated learning scheme in the BWM, so that an intelligent and automatic risk quantification process is established. Prior to the system design, a hierarchical structure to model firm-level cold chain risks is synthesized with a set of corresponding evaluation metrics. In order to acquire knowledge in pairwise comparisons, the federated learning scheme is implemented in the formulation of the global

ANN model, which is used to automatically assign the ratings for pairwise comparisons as being an intelligent agent. Furthermore, the proposed system was successfully implemented in a case study in Australia to identify and assess cold chain risks in the defined hierarchical structure, where the top three risk criteria, namely market demand stability, supply stability, and regulatory compliance on environment, health, and safety, are determined. Overall speaking, the contribution of this study can be summarised into two aspects: First, a firm-level risk hierarchical structure in the cold chain management is proposed with considering four essential dimensions, namely technologies and equipment, operations, external environment, and personnel and organisation. The research literature related to the cold chain risk management is thus enriched through this study. Secondly, a novel hybridisation of federated learning and BWM is formulated to embed the intelligence and automatic mechanism in the process of BWM, resulting in better adaptability and practicality of the risk identification and assessment in cold chains. To explore further possibilities in digitalising the MCDM approaches, future research may focus on decentralised federated learning with the use of blockchain technology in the formulation of intelligent MCDM mechanisms. Compared with managing the model parameters in the centralised federated learning cloud, the privacy-preserving feature of the proposed method is further strengthened.

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