Roadmap for resilient networks building through artificial intelligence

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Abstract. The business environment around the world continues to face disruptive events of varying magnitude and origin, and as a result, many companies and supply chains often struggle to overcome them. As a solution, resilience has become necessary, not only to be competitive but profitable in the long term. To build resilience, it is critical to define stratagems to enhance its constituent capacities, anticipation, adaptation, and recovery. Recent research studies show that artificial intelligence techniques can be a solution to enhance all these constituent capacities, but implementations are still scarce, and research efforts are dispersed. This work presents a roadmap to help guide research efforts in the quest for resilience, based on a recent literature review.

Keywords: Enterprise Resilience · Supply Chain Resilience · Roadmap · Artificial Intelligence · Disruptive events.

1 Introduction

Resilience is becoming an increasingly relevant capacity for enterprises and supply chains (SC) due to the more and more interconnected and volatile context in which they operate and the occurrence of numerous disruptive events (DEs) such as pandemics (COVID-19), geopolitical conflicts (Russia and Ukraine war), natural disasters, raw material shortages, unexpected changes in demand, and economic crises, among others. Enterprise resilience (ER) is defined as the capacity to anticipate and be prepared for DEs and, if their occurrence is unavoidable, the capacity to recover as quickly and efficiently as possible [1]. Similarly, supply chain resilience (SCR) is the ability to anticipate and recover from a disruption affecting one or more SC entities to maintain operational stability. SCR is essentially decisive, as any disruption that interrupts the flow of products or prevents the delivery of services can have a significantly negative effect on many entities, and thus on the economy as a whole.

Therefore, today's companies and their SC seek to enhance their resilience to proactively anticipate any disruption and, in the event of a disruption, to reactively minimise the negative impacts of the occurring disruptions to guarantee their business continuity and long-term survival. Proactive and reactive actions will enable enterprises and SC to enhance the resilience capacity, as it is not only a short-term need, but an opportunity to work with more robust enterprises and SCs that are prepared to face the challenges of the future. New competitive advantages can arise from a formally implementation of resilience capacity.

To this end, current research is developing approaches that focus on artificial intelligence (AI) to enhance resilience at all levels of the SC, taking advantage of the strong predictive capability that AI has been achieving, and of growing data processing capacity that comes with the latest technology developments.

Thus, the objective of this research is to analyse the current state of research for the enhancement of ER and SCR based on AI approaches to define the roadmap as shown in Figure 3.

The paper is structured as follows. Section 2 shows the review methodology followed by section 3 which offers the literature review providing the main findings related to the objective of this research. Based on the results obtained in the literature review, section 4 shows the roadmap proposal by defining the main steps needed to consolidate and leverage current trends and future lines of research. Finally, section 5 summarises the research of this paper as conclusions.

2 Review methodology

In order to identify current research limitations that will lead to the definition of future research lines for the enhancement of ER and SCR based on AI approaches, a systematic review of recent publications is carried out following the review methodology defined by [2]. Figure 1 shows the review methodology used.

Stage I, planning the review, involves the definition of the research objective that is focused on analysing the current state of research for the enhancement of ER and SCR based on AI approaches. Particularly, the aim of this analysis is to study the current limitations to define further research lines to be targeted to support companies and their supply chains to become more resilient.

Additionally, the proposal for the review is developed by defining the inclusion and exclusion criteria. In this sense, it is worth mentioning that the only exclusion criterion is related to the type of document: conference reviews which were not considered. Then, the review protocol was defined considering that the scrutiny will be based, firstly, on the title and abstract review followed by the full text analysis of the selected publications.

Stage II, conducting a review, is characterized by selecting the search database, which is Scopus, and by defining the search keywords based on the following query: (TITLE-ABS-KEY ("resilien*" OR "disruptive event*") AND TITLE-ABS-KEY ("supply chain*" OR "enterprise*" OR "company*") AND TITLE-ABS-KEY ("artificial intelligence" OR" predictive analytics")) AND PUBYEAR > 2010 AND

PUBYEAR < 2023 AND (EXCLUDE (DOCTYPE , "cr")). The search period involves from 2010 to 2022 taking into account that the keywords search query was performed by November 2022.

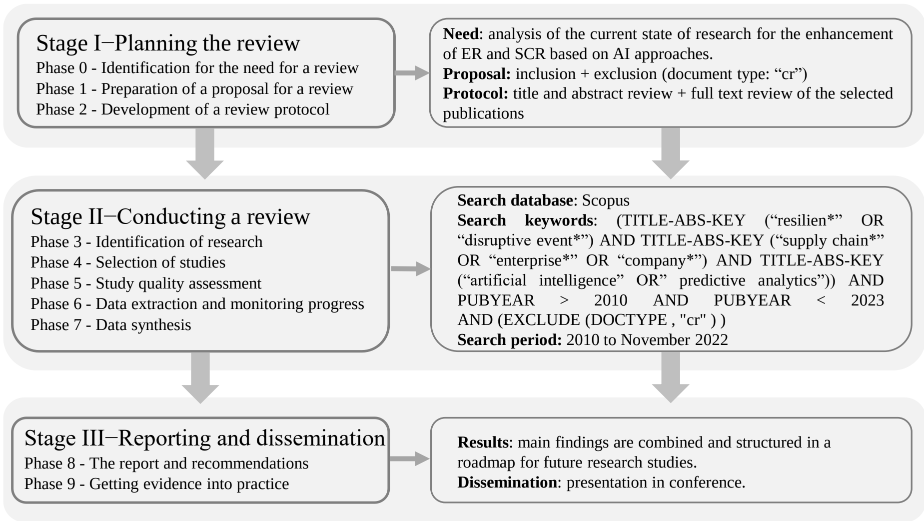


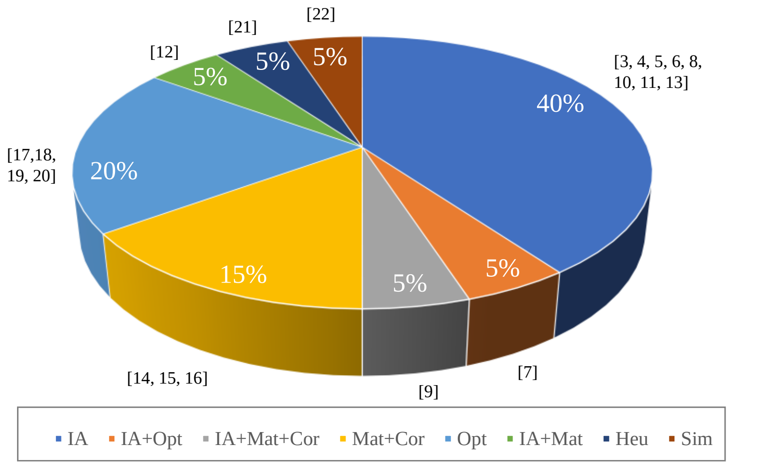
Fig. 1. Review methodology

Stage III, reporting and dissemination, shows the main findings related to the identification of drawbacks, and based on these, the definition of the future directions to bridge the research limitations and gaps. In this sense, a roadmap combining actual trends and main opportunities is defined and structured (see section 4 for the detailed definition of the roadmap proposal).

3 Literature review

The literature review, through the search for keywords defined in the review methodology, identifies 162 papers (excluding literature reviews), of which, after the title and abstract review, only 56 are selected. After analysing, by reading the full text, 20 articles (Figure 2) are identified related to the objective of this research focused on identifying the current limitations to determine future lines of research to enhance the ER and SCR from a mathematical modelling perspective, of which 11 works are supported, mainly, by AI. Figure 2 shows the classification of the approaches used for the enhancement of the resilience capacity of enterprises and supply networks from the selected and analysed 20 articles.

The trend in the application of AI to improve various factors of collaborative networks, including resilience, has grown exponentially during 2022, and it is creating synergies with classical mathematical models. Among the classical methods, matrix correlation models, and optimisation ones are the most widely used approaches.



(AI: artificial intelligence; Opt: optimisation; Mat: matrix; Cor: correlation; Heu: heuristics; Sim: simulation)

Fig. 2. Classification of the mathematical approaches

Based on this first analysis, the publications that apply AI, as the main approach to enhance ER and SCR, were selected to study in more detail, examining what the applied models consist of and how they are tested. In addition, this revision evaluated if testing is done with suitability analysis and/or comparison of results, moreover, this aspect is also analysed to identify current limitations of the research. Table 1 summarises the description of the AI models as well as the accuracy of the results obtained.

Table 1. Models' description, and testing and appropriateness of results.

Reference	Model description	Testing and appropriateness of results
[3]	Dynamic bayesian networks (DBN) handling uncertainty to analyse key performance indicators for building resilience strategy. The model allows for expert criteria, along with historical data.	Tested in a consumer goods manufacturing company, with a result of 30% reduction in a specific machine down event. The results show more accurate information, and the model is more robust, adaptable, and resilient compared with automatic bayesian networks.
[4]	Data mining approach for SC risk identification and prediction based en text-mining from Twitter.	Tested with a 200 tweets sample. This test included experimentation with real-time information directly from Twitter.
[5]	Artificial neural networks (ANN) with Levenberg-Marquard back propagation algorithm for SC performance evaluation and optimisation.	Tested in a clothing manufacturing company in China, for 5 years, by using big data. Field research with interviews. The results of the model are reasonable and effective, the error is located inside the objectives.
[6]	A model combining vector autoregressive with exogenous variables (VARX - for time series) with sentiment analysis through natural language processing (NLP) deep learning (DL) models.	Tested with two real situations, based on published news. Both tests got high scores in precision, recall and F1.

Reference	Model description	Testing and appropriateness of results
[7]	Logistic regression with a counterfactual explanation algorithm, integrated to the SC optimisation model. Suitable for transportation scheduling to avoid delay risk.	Tested using a public transportation database, where results show that it is possible to work without delays when coordinating transportation tasks.
[8]	Mix of ML algorithms: (i) for predictive analytics; long short-term memory, and (ii) for prescriptive analytics; term frequency reverse data frequency vectorizer.	Experimentation only in specific cases, such as the datasets of air industries group. There is no comparison of results with other techniques.
[9]	Multi-criteria decision model empowered with AI techniques, specifically with fuzzy wavelets neural networks to evaluate AI techniques for SCR.	Experimentation in a specific company. The model was tested using Pearson correlation tests.
[10]	The model studies if a new product launch would be successful, by using distance similarity scoring and a multithreaded hash-join resilient distributed dataset with prediction classifiers. For the classifiers it is used ML (support vector machine, Naive Bayes, decision trees, and XGBoost).	Experimentation in a dataset of products from e-commerce companies. High precision results and efficient use of computational resources
[11]	Framework combining ML and temporal aggregation mechanisms for intermittent demand forecasting.	Tested in an electronics distribution company. The results were compared to traditional forecasting models using error measures, such as root-mean-square error, mean absolute error and mean absolute scaled error.
[12]	Hybrid ensemble and analytical hierarchy problem (AHP) approach. The ensemble method includes logistic regression, classification and regression trees, and neural network to select resilient suppliers.	Experimentation in a plastic pipe manufacturing company. The results were appropriate according to the statistical indicators measured (gains charts, lift charts and receiver operating characteristic curve).
[13]	Data-analytics approach, which leverages system monitoring data for the ER. A Bias Ordinal SVM with two classifiers; SVM binaries (and sequential) and a biassed SVM for noisy data.	Implementation of the proposed model to real data from a financial services organisation. The model is compared to Logistic AT, Logistic IT and SVM (multiclass). The proposed model got better results than the others, especially in the recall metric.

The most widely used AI approaches for resilience enhancement are based on ML (54.5%), followed by ANN (27.7%). Data mining and NLP are also AI techniques used to build resilient networks, although they have been found to a lesser extent. Moreover, it is worth mentioning that correlation matrix models are mostly focused on decision-making for resilient supplier selection, while AI models have varied applications in the field of resilience. Moreover, few publications combine AI with other mathematical models, in this work, only 27% of the articles that include AI models do this combination.

Based on the models' analysis, different limitations have been identified in each article. In addition, some authors have explicitly mentioned the limitation of their research what is the trigger for defining the future research lines. Table 2 shows both models and research limitations of the selected papers.

Table 2. Models and research limitations.

Reference	Model limitations	Research limitations
[3]	No data available for the comparison with other models.	Partially manual model. Considerable effort for data preparation.
[4]	Small sample. Only one social network (Twitter).	The model is implemented with a small tweet collection. The model only uses single keywords.
[5]	The model is more complex than the classical SC performance evaluation models.	No limitations explicitly mentioned.
[6]	The model was tested after the events happened. Focused only on pharmaceutical companies.	The VARX model, which is more limited than several ML models. Two sequential models were proposed but how the error propagates from the first model to the second was not measured.
[7]	Not suitable for large models.	No limitations explicitly mentioned.
[8]	Small sample, only for specific cases.	No limitations explicitly mentioned.
[9]	Tested in only one company.	The input data provides just a quick overview of the sample because this is an exploratory study. The authors do not recommend generalising the results. They suggest that each company should personalise the input data to analyse their specific SC.
[10]	The model was not tested for specific new product launches. Only tested in e-commerce.	No limitations explicitly mentioned.
[11]	The model was tested in only one company.	No limitations explicitly mentioned.
[12]	Tested in only one company of one specific industry sector.	No limitations explicitly mentioned.
[13]	Tested in only one company of one specific industry sector. The performance metrics to evaluate the model are precision, recall, F1, and AUC.	Limited amount of real-world data with few incidents. Significance testing or comparisons with deep learning models were not done.

The main limitation seems to be that resilience-enhancing approaches are only applied to particular cases in specific sectors, followed by the lack of data availability. Other limitations found in the studies reviewed include the complexity of the solutions developed and the emphasis on reactive mechanisms rather than proactive models.

From an overall research perspective, the most important limitations focus on the large efforts in data processing, the limited automation of the developed solutions, the lack of error estimation to analyse accuracy, the lack of generalised solutions, the scarcity of tests with real data, the lack of comparison studies among solutions, and the lack of longitudinal studies, among others.

In order to define the roadmap that will propose future research steps for ER and SCR enhancement, the positive aspect of the current research and the proposed further research of the selected articles are summarised in Table 3.

Table 3. Contributions' positive aspects and further research.

Reference	Positive aspects	Further research
[3]	The information content is significantly higher than with automatically created DBN. It allows for expert criteria and uncertainty.	To reinforce the use of DBNs by means of multi-channel data pipelines.
[4]	The consideration of modern attributes, such as, real time data gathering, risk identification and severity estimation, and continuous monitoring.	To transform the methodology in a continuous monitoring tool to spot new threads.
[5]	The use of big data and the strengths of ANN.	No future research explicitly mentioned.
[6]	High precision results, even for very short time series.	To extend the analysis to social media contents. To analyse online news through potential use of text vector representations (text embeddings).
[7]	Innovative due to the integration of a ML and an optimisation technique. Interdependency of ML features are considered in the integrated model.	To use other ML models in this integration. To analyse other disruptions and risk, besides the delay. To consider 3 and 4 echelon SC models and the ripple effect.
[8]	Up to date techniques.	No future research explicitly mentioned.
[9]	Uncertainty is handled better when comparing to other multi-criteria decision models. It runs in a regular capacity computer.	To explore the patterns identified in AI-technique adoption for SCR-building through longitudinal studies. To consider the interrelationships between AI techniques in supporting SCR strategies.
[10]	Faster performance in processing data when compared to similar methods. Better forecasting precision (11%).	To improve the model to make real-time streaming forecasts through an API that considers customer suggestions, references and surveys from different online sites.
[11]	Better indicators of the proposal than the traditional approaches tested.	To extend a variety of demand forecast problems for smart production. To integrate it with other AI technologies for different forecast problems in different contexts. To develop instruments to acquire inputs from domain experts and business insights to support demand forecasts.
[12]	Powerful combination of AI and multi-criteria models.	To develop metrics to measure the resilience of the suppliers, where these metrics must measure the impacts of supplier's vulnerability and recoverability in the presence of DEs. To include in future models the impacts of time to supply failure and financial losses.
[13]	Data-analytics approach instead of expert-centric approach for resilience in computer systems.	To incorporate the feedback mechanism to the model. To study time-series features to consider temporal information for the predictive model to proactively detect incidents.

Even though the proportion of publications including AI models is small, it is important to highlight the fact that these models are obtaining good results in different ER or SCR dimensions. Recent articles show how AI is leveraging the use of big data, and the application of very different techniques to solve problems, or potential problems, generated by DEs. In this sense, now it is more common to find research studies using AI techniques ranging from ML to deep learning to minimise the impact of similar DEs, and according to the further research proposed in the articles studied, this trend will keep growing, searching for the best mechanisms to face each DE. Most of the future research lines proposed can be summarized in that authors intend to test their models in more complex environments, and to include more AI techniques in their models to make them more robust. While achieving the proposed goals, ER and SCR will be getting stronger.

4 ER and SCR roadmap based on AI

Based on actual research trends and future research projections regarding the use of AI techniques to enhance resilient networks, we propose a roadmap to guide and clarify the path to achieve this goal. This blueprint contains six steps, divided into two stages. Stage 1 aims to configure the research study, by defining the roadmaps dimensions, while stage 2 is the implementation scope definition. Both stages are composed by the elements shown in Table 4.

Table 4. Stages and detailed steps of the proposed roadmap.

Stage	Dimensions	Description	Trends
Dimensions definition	D1. SC complexity	This dimension involves the level and/or scope to which the research study is going to be limited (e.g. -intra: a company, -inter: a SC, and -extra: SC with external entities such as governments…) to define the number of echelons in the SC structure.	The trend derived from the future lines of research is to start analysing one organisation and, after the objectives are achieved, to go further and test the model in a SC, considering its complexity, defined by the number of stages. The last step is applying the model in SCs with relationships with external entities.
	D2. Resilience dimension	The objective of each research study must be clear, and this starts by selecting the resilience dimension to analyse; detection, prediction, adaptation or recovery. The mathematical model must be directly related to this dimension.	The trends indicate that itis recommended to start with one resilience dimension, and after successful results, to include the next correlated dimension. Although all the resilience dimensions are related to each other, it is recommended to cover them in their regular sequence (as stated in the description column) since the first two dimensions can avoid or at least minimise the financial impact of the corrective actions needed for the last two dimensions.

Stage	Dimensions	Description	Trends
	D3. DEs type	It is essential to define the specific DE to study, since there are many different DEs from different origins. The first division is between internal and external events, meaning that some events occur within the SC and others are created outside the SC.	Since different modelling approaches are needed to cope with different DEs, the trends recommend solving the problem for one DE at a time, and when significant improvements are achieved, study another DE from the same type (internal or external). When several DEs from one type have been controlled, it would be the moment to analyse the other type of events.
	D4. Modelling approach	Selecting the right mathematical model according to the defined problem can be time-consuming, but it is a key step to obtain solid results. AI approaches should be classified to clarify the objectives and uses in each research work. This classification should include at least: Level 1: ML or DL. When level 1 is ML, level 2 should specify if it is a classification or a regression problem and the data type. Level 3 should detail the specific techniques used. When level 1 is DL, level 2 should specify the type of ANN, such as convolutional NN, recurrent NN, transformers, or graph NN. Like the first case, level 3 should detail the specific techniques used.	The trends indicate that using more AI techniques is the recommended method; first including individual algorithms, and after several tests, scaling up with a combination of various AI techniques. Combining AI techniques with other mathematical approaches (such as optimisation and simulation) is recommended if AI methods do not find an efficient solution to the problems defined based on the above dimensions.
Implementation scope	Validation path	This work shows many different styles of model validation, thus is it very important to choose one; a least to define the data sources and the implementation depth (for example, defining if the model should be tested in a laboratory, in a company or in many companies). Also, it is important to specify if the validation includes tests at different moments within a specified horizon.	Research trends recommend upgrading from public data sets to actual companies' data (preferably from many organisations). If the study can be tested in different industry sectors and at different moments, it is advisable to do so since that would enhance successful implementations.
	Deployment level	It is a must to define how the model will be deployed, and this can range from model coding to run some tests to applications development.	The trends advise to start from the basis (programming and testing the model), and when the model has shown valid results, to develop an application with a friendly user interface. One of the main features to define in developing an application is whether it will be web-based or not.

All the steps included in the roadmap are meant to be generic, so they can be applied in different ER and SCR studies. Moreover, these steps are equally important, since they together enhance the synergy to drive research efforts toward timely solutions that can be implemented in many companies and SCs. Figure 3 shows the main features of the proposed framework.

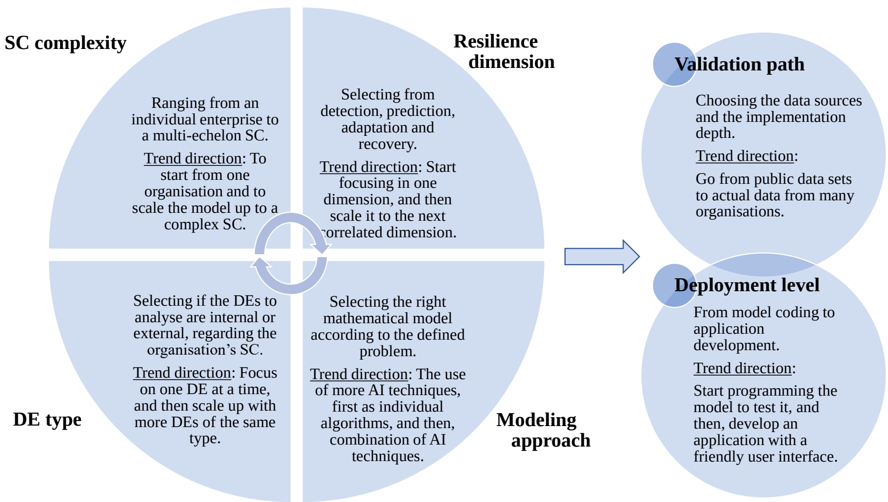


Fig. 3. Framework for research studies aiming to build ER and SCR using AI.

The related roadmap, specifying the recommended flow is shown in Figure 4.

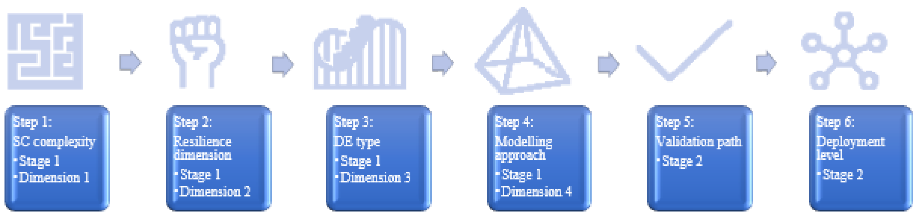


Fig. 4. Proposed roadmap

5 Conclusions

The low resilience capacity shown by enterprises and SCs when facing DEs during the last few years has driven a significant increase in formal research studies in this field. The attempts to enhance resilience dimensions through mathematical modelling have also been increasing, mainly powered by AI techniques, and this trend represents a solid opportunity to achieve the related objectives. Even though general solutions and results are still scarce since most research works adopt a case study approach regarding a specific problem or test, the proposed mathematical models with public datasets are still not a suitable solution for companies. It is a positive fact that many researchers are concentrating their efforts on proposing solutions to the problem of low resilience levels. It is even more positive that they are including powerful AI techniques to solve resilience related problems. Still, despite these efforts, there is not a clear roadmap to guide research studies in a coordinated way to find efficient solutions that can be implemented in various companies and SCs, based on experimentation applied in similar entities. Grounded on the mentioned findings, this work presents a proposal for a roadmap to lead the way to ER and SCR; by means six steps covering from problem definitions and settings to implementation scope. A straightforward roadmap, like the one mentioned above, can help coordinate efforts and accelerate solutions suitable for companies and SCs seeking to be more resilient. A coherent future line of work is to apply the proposed roadmap to analyse how to detect and predict a prioritised set of DEs based on individual or combined AI techniques to strengthen the resilient capacity of organisations. Another important line of research is to categorise the validated AI models according to their expected impact facing specific DEs and relating their contributions to the higher-level objectives of resilient networks.

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