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Improving supply chain risk assessment with artificial neural network predictions

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Keywords: supply chain risk management, artificial neural network, risk prediction, risk assessment, supply chain.
Abstract: Operational excellence serves as a cornerstone for the success of businesses,and effective risk management is key for minimizing disruptions, and ensuring business continuity. This paper proposes an innovative methodology that harnesses the power of machine learning in supply chain risk assessment to enhance the ability of organizations to identify, predict, and mitigate various risks that can impact their efficiency, effectiveness, and resilience. This study addresses the inherent subjectivity in human assessment which presents a significant challenges and potential biases in the evaluation process. Auditors, who play a crucial role in identifying and assessing risks within an organization's operations, often rely on subjective judgments influenced by their experiences, expertise, and personal biases. To mitigate this issue, we employ a deconstruction approach, breaking down risk factors into sub-factors, and leverage an Artificial Neural Network model as a predictive tool for accurate risk level predictions and enhanced assessment objectivity. Real-world data from a global automotive company specializing in wiring harnesses are utilized to train the Neural Network model, on a dataset of 2100 samples, exhibits good performance of risk prediction as evaluated by appropriate metrics such as Determination Coefficients and Mean Square Error. Overall, this research contributes to the advancement of risk management practices addressing the challenges of subjectivity in human assessment, to more objective by providing a reliable and data-driven framework that supports managers in strategic decision-making and fortifies supply chain operations through an early risk alarm, empowering organizations to proactively manage risks and achieve autonomy in effective risk management.

1 Introduction

Supply chain risk management (SCRM) has become more significant and attracted researchers' attention in comparison to previous years when less attention was given to risk management (RM).Furthermore, the complexity of production processes, huge quantity produced, uncertain demand, unexpected changes, and increase in various disruptions types cause substantial losses.[1] risks in the realm of SC management can be broadly categorized into two main types: strategic uncertainty and operational catastrophes. To illustrate the impact of such risks, consider the recent global phenomenon of the COVID-19 pandemic, which triggered a widespread scarcity of shipping containers and a significant rise in employee absenteeism, resulting in a substantial financial loss of billions of dollars. Additionally, the SC landscape faces inherent risks stemming from geopolitical events, like the Russia-Ukraine war, as well as challenges arising from the lack of synchronization between supply and demand. These factors, as highlighted by [2] contribute to the complexities and vulnerabilities encountered in SCM. Uncertainty, stochasticity, external disruptions, and risks can temporarily or durably impact the performance of the SC, where the need for implementing a well-defined RM process is crucial for mitigating exposure and minimizing disruptions, as it plays a pivotal role in effective RM strategies.

Today auditor's subjectivity can play a role in determining the risk level. It seems to be extremely difficult to assess risk, in the same manner, taking the case of two auditors working on the same organization cannot evaluate the risks equally, as the difference in professional judgment and experience influence their risk assessments and lead to subjective evaluations. The risk assessment subjectivity might cause various problems with severe monetary problems. It can lead to inconsistent evaluations of risks that make it challenging to compare and prioritize risks consistently. also, the subjectivity may lack transparency and fail to provide a clear justification of the factors influencing the risk levels which leaves excessive leeway for managers to understand and evaluate risks on their own in a way that will not interfere with the strategic plans for the company.

As for the impact of subjectivity in the risk assessment process, the primary objective of this research is to minimize the subjective nature of human assessments and achieve a more objective risk evaluation approach using Artificial Intelligence (AI) techniques that can help in addressing some of the subjectivity challenges in the risk assessment process by introducing more objective and data-driven analysis which reduces reliance on subjective judgments and provides a more objective basis for risk assessment.

This study was carried out as the power of AI technologies its significant role in enhancing risk assessment processes due to several reasons and purposes such as the handling of large volumes of data more efficiently than humans and this is particularly important in risk assessment, where numerous variables and factors need to be considered. Further to the human judgment which sometimes can be influenced by biases, emotions. AI can provide consistent and objective analysis, minimizing the impact of human subjectivity and errors, leading to more accurate risk assessments and better-informed decision-making. In addition, AI models can leverage historical data to make predictions about future risks to anticipate potential risks and proactively implement strategies to mitigate them. In summary, AI's capabilities in data processing, analysis, accuracy, and real-time monitoring make it an invaluable tool for enhancing risk assessment across SC.

We propose a methodology with the goal of automating and standardizing the risk assessment process. By deconstructing the risk factors into distinct sub-factors, we systematically examined each component and analysed them collectively as a comprehensive feature vector. This vector serves as input for the machine learning (ML) model, where each numeric parameter conventionally represents the status of each factor in each sub-process. The used data was collected from a real automotive company operating in wiring harnesses worldwide, the type of industry was chosen as it's the pillar of the national economy, further to the widely of concern on SC disruption risk that has been considered in recent years by both business and academic practitioners. As the automotive SC has become increasingly difficult to manage and without effective RM it's almost hardly possible to see its operation normally. The International Automotive Task Force (IATF 16949) reports for 5 years were cleansed and converted to the predefined set of parameters as in Table 1. Audit reports are the result of an audit system assessing the quality management system of the company, verifying risk, defect prevention, process variation, and waste in the SC and production process.

Due to the scarcity of available data, a unique and highly confidential dataset was obtained, which played a pivotal role in training the ML model capable of accurately predicting risk levels within a SC. We trained the model on 80% of the collected data and 20% of a test set of the samples.

Ultimately, the integration of AI into SCRM has introduced new dimensions of complexity and opportunity. However, there are notable research gaps and challenges that require investigation, particularly in the areas of cleansing, integration, and validation of SC data. There are gaps and challenges in AI models that provide interpretable risk assessments, enabling SC professionals to understand risk behaviour. Additionally, gaps exist in AI models that can adapt and update in real-time based on changing risk environments. However, the current research on AI integration in SC lacks models capable of providing probabilistic risk assessments that account for uncertainties and ambiguities in SC risk scenarios.

Furthermore, research could investigate how AI models can effectively collaborate with human experts in making decisions related to SC risk. Additionally, addressing the gap of integrating human knowledge into AI models for SC risk assessment represents our contribution in this paper.

2 Literature review

Mathematical tools have played a pivotal role in the field of SCRM, enabling advanced analysis, modelling, and decision-making processes. Recently, research has begun to apply additional tools such as AI covering production risk management, and SC risk challenges in complicated environments, and in a specific part of the process.[3] classified the reviewed papers published between 2003 and 2013 on SCRM into four categories, definitions, types, factors, and methods for SCRM.Furthermore, methods are classified for risk management as either qualitative or quantitative depending on their core operations, such as risk detection, assessment, reduction, and monitoring.

[4] centres their investigation on the implementation of intelligence-based tactics to improve the management of SCRs and strengthen overall resilience. The outcomes of their study offer valuable perspectives on the existing landscape of SCRM methodologies and the efficacy of resilience approaches across various sectors. [5] examined the influence of digitization, big data, and Industry 4.0 on their role in mitigating the cascading impact of SC risk. Nevertheless, the researchers highlighted the necessity for further investigation before introducing decision-support systems that incorporate ML and agent algorithms to enhance the optimization of stochastic systems.[6] present a comprehensive model that leverages big data in the planning and process control domains to effectively manage SC risks, this approach involves collecting extensive data from various sensors, both internal and external, which are then meticulously analysed to generate detailed reports for decision-makers, enabling them to make informed decisions regarding SC redesign.

In their research, [7] demonstrate the potential of utilizing SC data analysis not only for pursuing and managing supply risks but also for enhancing supplier performance. This approach empowers global SCs to proactively respond to SC risks rather than adopting a reactive approach, enabling them to take initiative in mitigating potential disruptions and ensuring a more resilient and efficient SC ecosystem. However, their study does not mention a predictive model but only a practical data presentation. Another study by [8] offers a conceptual framework for SCRM using ML techniques and big data without evaluating and implementing the framework, their conclusion suggests that incorporating AI in SCRM processes can potentially enable the discovery of new knowledge. This new found knowledge, when combined with the expertise of decision-makers, has the potential to facilitate optimal decision-making in SCRM processes.

Existing literature reveals that various AI techniques exhibit partial applicability in different contexts of risk management in various stages of the SC. One of the most used AI techniques in various levels of production management is the ANN applied in the area of forecasting, demand planning, inventory management and risk assessment. As the efficacy of forecasts is contingent upon the accuracy of predictions, scholars have redirected their focus to the area of fast-changing data combined with traditional forecasting and AI techniques to generate more accurate predictions of forecasts to improve demand planning.[9] studied the ability of ML in generating more accurate forecasts in comparison to traditional methods.[10] suggest a methodical managerial strategy for investigating the correlation between AI and the bullwhip effect ,their research provides scholars and managers with a fundamental platform for advancing theories on how to alleviate the fluctuations in SC caused by the bullwhip phenomenon. [11] In ordering management ML is used to establish an optimal ordering strategy in several SC levels to evaluate order priority and manufacturing order priority. [12] create an enhanced version of grey neural networks, which can assist businesses in making more accurate forecasts regarding market demand following disruptions in transportation. Subsequently, they conduct an empirical study to validate the practical viability of this improved mode.[13] used a combination of ANNs and auto-regressive integrated moving average (ARIMA) models to forecast the requirements for blood platelets. The intention behind their approach is to minimize uncertainties within the SC associated with blood platelet demands. [14] Their inquiry offers a practical instance where they predict monthly demand for three blood components through the utilization of ANNs. The outcomes of their analysis illustrate that ANN models outperform ARIMA models in the realm of demand forecasting.

From the reviewed existing literature on the AI application in SC, we can see that AI techniques have been used throughout the SC, neural networks have shown their results also in problems related to supplier selection process. [15] In their study, they employed ANN to address the primary challenges associated with case-based reasoning within supplier selection. This was done with the intention of enhancing both the precision in revising stages and the efficiency of the supplier selection process.[16] Their paper aims to put forward a hybrid strategy that melds the Z-number Data Envelopment Analysis (DEA) model with the ANN to improve the process of selecting resilient suppliers. The objective is to refine supplier selection by incorporating two key aspects: an efficiency-centered assessment through Z-number DEA and the predictive potential of ANN, with particular emphasis on the resilience of suppliers.

Enhancing strategies for managing the movement of goods within production logistics systems is a significant aspiration within contemporary industries. Consequently, the investigation of inventory control methods holds exceptional significance. [17] In their proposed methodology, they adopt a state-feedback neural network controller to determine the ideal order quantity, accounting for uncertainties in the deterioration process and adhering to the FIFO issuing policy. [18] develop AI forecasting models for better forecast and inventory management improvement.

[19] Their study elucidate the evolution of deep learning (DL) and ML concepts within the framework of devising a plan for identifying and evaluating SCRs. Their outcomes indicate a notable enhancement in the ability to forecast whether a shipment is destined for export, outperforming numerous other pre-existing ML methodologies.Scholars have increasingly promoted the adoption of Industry 4.0 (I4.0) solutions as a strategy to mitigate supply chain disruptions (SCDs) [20], especially in light of the challenges exposed by the COVID-19 pandemic. In their research [21],they built upon prior work in I4.0 and SCRM, creating 13 projections that delineate how I4.0 technologies will shape Supply Chain Resilience (SCRES) by 2030. Their study evaluates the potential of I4.0 in enhancing SCRES within a post-COVID-19 context. As well,[22] their study seeks to elucidate the role of AI applications in supporting Operations and Supply Chain Management (OSCM) processes, as well as to pinpoint the advantages and challenges associated with their integration. The findings underscored the capacity of AI techniques in OSCM to enhance the competitive edge of companies by diminishing expenses, shortening lead times, and enhancing service levels, quality, safety, and sustainability.[23] examined how AI techniques can enhance SCM through the execution of a structured analysis of existing literature.

In this study, we carefully selected the primary risk factors based on their direct relevance to SC and production organizations. Specifically, our focus was directed toward the critical and potential factors that influence the risk level during auditors' evaluation in each IATF audit. These selected risk factors encompass common types of risk in manufacturing, supply, transport, demand, and information, considering their external and internal interfaces. This selection process served as an initial foundation for creating an additional resource aimed at defining and categorizing the deconstructed risk factors in more detail. The objective is to achieve more accurate risk evaluation from the auditors by placing more emphasis on the sub-factors and enabling a precise assessment of risk factors integrating an ANN model in RM process flow as in Figure 1.

3 Methodology

3.1 Risk management process flow with ANN integration

In Figure 1, we detail the methodology employed to integrate an ANN model in the RM process for risk prediction purpose, to mitigate and reduce SC disruptions and control risks in advance. The initial phase involves the identification of potential risks that could impact the organization, followed by risk factors deconstruction into sub factors to get more precision on the risk elements. The identified risk factors are evaluated in terms of their severity, impact, and probability. Gathered and cleaned data is used to train the model to predict risk level of the potential risks that may disrupt the SC, foreseeing risks helps in prioritizing and providing strategies to mitigate the risks, decisions can vary in their approach, ranging from accepting the entire risk without implementing any actions for low-risk events, to implementing a series of preventive measures for high-risk events. A regular RM process review ensures that new potential and suspected risks are remains up-to-date and introduced in the model to be verified and assessed if they occur. Figure 1 depicts the risk assessment flow integrating the ANN model.

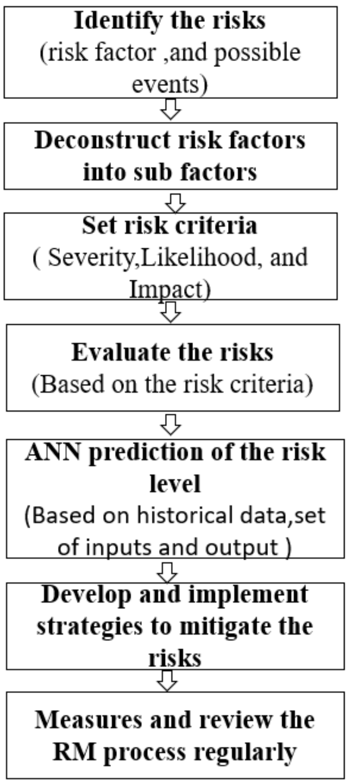

Figure 1 Risk assessment process flow with integration of ANN

3.2 Neural network model for risk assessment

In order to initiate the development of our proposed methodology of applying ML tools in SC risk assessment an exhaustive list of parameters was selected, covering most of the operational risks, from a reel audit report of an automotive company that covers the results of IATF certification following regulations and automotive standards. We focused on a research sample consisting of 30 automotive production sites operating in wiring harnesses word wide. Findings and audit results of 5 years were converted in accordance with the selected operational risks which were observed as parameters and a major risk of the selected automotive company. The selected parameters of the model which represents the risk factors in this research are mainly based on their relevancy to the automotive SC. The selected risks cover external and internal risks in different node of the SC, covering supply,demand,manufacturing,process,financial,macro,in ventory,information,payement and transport risks. Moreover, the inputs include the results and feedback from different OEMs (Original Equipment Manufacturers) and tier 1 suppliers. Audit reports were employed as the dataset containing risk factors and served as the input layer for the ANN used in training the predictive model for future risk estimation.The model underwent training using a dataset consisting of 2100 samples. The risk data is highly classified business information that is publicly unavailable. Attaining the data from an automotive manufacturing company for the purpose of risk prediction was a challenging goal and a unique opportunity to gain insights using confidential business information.

Table 1 List of parameters

No	Parameter	Literature
1	Leadership and commitment	[24,25,26,27,28]
2	Products/services requirements	[29]
3	Performances evaluation	[30]
4	Continuous improvement	[31]
5	Demand Uncertainty/Variability	[32,33]
6	Manufacturing risk	[22,34]
7	Delivery/Transport delay	[35]
8	Supplier dependency	[36]
9	Information system	[37]
10	Financial risk	[38]
11	Inventory control	[39,40,41]
12	Payment control	[42]
13	Purchase orders	[43]
14	Macro risk	[44]

We converted the findings of 150 IATF audit reports, produced in 2018-2023, in accordance with the exhaustive selected risk factors from the IATF standards that are most relevant for the selected automotive company, specific and unique risk factors were neglected as their low probability of occurrence in the results of the audits. The focus was on the most relevant and probable risk factors assessed and reported during several audit reports with a high impact on the operational business.

Auditor's risk assessment practice is an investigation based on experience and risk knowledge way of saying and assessing the risks, auditors do not have a well-defined result for each parameters deviation linked to the IATF standards and regulations basics, parameters are not evaluated in the same way for all auditors. In order to get an easy, objective, quantitative, and accurate risk assessment each of the selected risk factors is broken down

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into their sub-factors and the results are fit as an input vector to train the ML model.

Regarding the numerical evaluation of the audit results for each assessed parameter, auditors assign a risk level of high, low, or medium to indicate the severity of the risk associated with that parameter. However, it's worth emphasizing that the final audit results are subjective assessments made by the auditors based on their judgment and interpretation of the assessment.

The deconstruction of risk factors into sub-factors is crucial to achieve a more accurate assessment of the selected parameters. To accomplish this, each sub-factor of every parameter was assigned a value based on its performance level. A value of 0 indicates a neutral level of compliance with standards and regulations, -1 indicates a weakness in adhering to the standards and regulations, and 1 indicates an appropriate level of compliance. Additionally, each compiled report was assigned a risk probability value, ranging from 0 to 1, representing the likelihood of risk for each company. To obtain an assessment for each specific evaluated risk and gain a comprehensive understanding of the most influential factors in the overall risk probability assessment for each company, it is important to identify the key impacting factors. This knowledge is particularly valuable as the reports are derived from the same company with consistent standards applied across various sites.

While it may not be immediately evident, the selection of parameters from the IATF 16949 standard, as related to the topics in Table 1, is undertaken with a specific aim. These parameters are chosen based on their alignment with factors derived from quality management standards. These factors hold essential roles in establishing the quality management requirements expected of automotive manufacturers and suppliers. This research aims to assess the automotive industry's capability to manage risks. The careful organization of these selected parameters is designed to evaluate an organization's risk exposure and compliance with the IATF standard. By considering these factors collectively, we contribute to a comprehensive understanding of their impact on organizational performance and overall success (Table 2).

Table 2 Selected parameter is derived from a set of sub-parameters

Leadership and commitment were compiled from the following sub-parameters	**Products/services requirements were compiled from the following sub-parameters:**	**Supplier dependency**	**Delivery/Transport delay**
(1) is the company taking responsibility for the effectiveness of the quality management system? (2) Are the quality management system requirements integrated into the organization's business processes? (3) Is the organization promoting the use of the process and risk-based approaches? (4) Is the organization incentivizing, guiding, and supporting persons to contribute to the effectiveness of the quality management system? (5) Does the organization promote improvement? 6) The priority of increasing customer satisfaction is maintained by the organization? 7) Are the customer's requirements understood and met? **Payment control**	(1) Is the communication with customers include: (a) the provision of information relating to products and services? (b) the treatment of consultations, contracts, or orders, including amendments? (c) obtaining feedback from customers regarding products and services, including their complaints? Any applicable legal and regulatory requirements? (2) Does the organization use appropriate means to identify output elements where it is necessary to ensure compliance with products and services? (3) Does the organization preserve the output elements during production and service provision to an extent sufficient to ensure compliance with the requirements? NOTE: The preservation may include identification, handling, contamination control, packaging, storage,	Alternative supplier in case of major supplier stoppage Long-term relationships with reliable suppliers Supplier monopoly Selection of the wrong partner Low technical reliability **Information system** Information infrastructure System Integration Information transparency Information delays Compatibility in IT platforms Back up procedures **Demand Uncertainty/Variability** Forecasting errors Market change Bullwhip effect distortion **Continuous improvement** Does the organization continuously improve the relevance, adequacy, and effectiveness of the quality management system? Does the organization consider the results of the analysis and evaluation, as well as the outputs of the	Natural Accidents (Fire, Earthquake) Abnormal Accidents(Manmade Disaster/Terrorism attack) Packaging and shipping quality issues Safety stock unavailability Custom clearances Transportation breakdown Damages in transport No transport solution alternatives Lack of outbound effectiveness **Purchase orders** Purchase process control through the ERP system Purchase procedures and documents follow up **Inventory control** Regular warehouse inspection Warehouse inspection according to procedures Inventory system update **Financial risk** Exchange rate fluctuations Loss of contrast Market growth Profit margin Price fluctuations

Presence of sufficient control mechanisms ensuring alignment between a certificate of receipt and the corresponding invoice. Appropriate measures in place to ensure effective control over payments **Performances evaluation** (1) Does the company determine: (a) what needs to be monitored and measured? (b) the monitoring, measurement, analysis, and evaluation methods to ensure the validity of the results? c) when monitoring and measurement should be carried out? 2) Customer satisfaction: Is the organization actively monitoring and assessing customers' perceptions regarding the extent to which their needs and expectations are being met? Does the organization analyze and evaluate the level of customer satisfaction?	transmission, or transport and protection. **Manufacturing risk** Unstable manufacturing process Employee accidents Insufficient maintenance Lack of experience/training Production capabilities Product inflexibility Machine breakdown, Quality problems Design changes Technological changes	management review, to determine if there are needs or opportunities to consider as part of continuous improvement?	 **Macro risk** Political instability Economic downturns External legal issues Sovereign risk Regional instability Social and cultural grievances Natural Accidents (Fire, Earthquake) Abnormal Accidents(Manmade Disaster/Terrorism attack)

3.3 ANN model application on real database

A stable database was formed from the audit reports conducted for 5 years to create a consistent database to train the model. For example, we chose 2 IATF audits reports of 2 sites audited in 2022. Table 3 shows how the risk factors and their risk sub-factors were converted into a table of parameters as a sum of each graded {-1,0,1} parameter.

The probabilities by the auditors were given by text that reflects the level of the risk as low, medium, or high (Table 3). These are transformed to represent low: [0 – 0.3], medium: [0,4 – 0,7], and high: [0,8 – 1]. In the example, Site 1 was assigned a probability value of 0.3, indicating a relatively low level of risk. Conversely, Site 2 and Site 3 received probability values of 0.4 and 0.5, respectively, indicating moderate levels of risk.

Table 3 Risk factors and their risk sub-factors

Parameters	Site 1	Site 2	Site 3	Details
Continuous improvement	1	1	1	Site 1,2,3: The organization has a high adequacy and effectiveness of the quality management system, continuously improving. The organization has a good consideration for the outputs of the management review to determine needs and opportunities for continuous improvement.
Leadership and commitment	1	0	-1	Site 1: The company has a high responsibility for the effectiveness of the quality management system and requirements are integrated into the organization's business processes and customer's requirements as well as the applicable legal and regulatory requirements are determined, understood, and met continuously in a good level. The company maintains customer satisfaction and promotes improvement. Site 2:

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				The company has a responsibility for the effectiveness of the quality management system and requirements are integrated into the organization's business processes. Customer requirements are determined and understood, regulatory requirements are not determined, and either. The company maintains the customer satisfaction and promotes improvement. understood. Site 3: The company has a very low responsibility for the effectiveness of the quality management system and requirements are not integrated into the organization's business processes and customer requirements are not determined and either understood. Customer satisfaction is not met and improvement is very low
Total risk probability	0.3	0.4	0.5	

4 Results and discussion of the ANN model

ANNs are crucial in ML and AI, mimicking biological neural structures. ANNs consist of interconnected layers of artificial neurons that process input, learn from data through weight adjustments, and excel in tasks like pattern recognition and prediction across domains. This learning ability empowers researchers to create intelligent systems capable of understanding complex phenomena.

In the context of this work, the dataset comprises 2100 samples, each consisting of 150 observations, characterized by 14 parameters with values {-1, 0, 1} and a score within the range [0, 1] representing total risk probability. This distinctive dataset configuration necessitates ANNs to master regression tasks. To enable a robust evaluation, the data is partitioned into training (80%) and testing (20%) subsets. Additionally, the model's performance evaluation employs k-fold cross-validation, which partitions the dataset into subsets for both training and testing, yielding reliable performance assessments across multiple iterations.

The architecture of the neural network is thoughtfully designed through hyper-parameter tuning, with the number of hidden layers strategically selected based on problem complexity. The specific configuration comprises seven layers, commencing with 14 inputs and culminating in a single output, employing the sigmoid function to ensure values within the [0, 1] range. The choice of 100, 80, 70, 60, and 50 neurons across hidden layers is meticulously calibrated to optimize model performance. The model's optimization employs Adam as the optimizer and Mean Squared Error as the loss function, implemented using TensorFlow 2.10.0 library.

After inputting the data into the network, we employed two suitable evaluation metrics, Mean Squared Error (MSE) and R^2 (coefficient of determination), to assess the model's predictive performance for both cases. Case N1 involved predicting the overall risk probability for each company, while case N2 focused on predicting the risk probability for individual factors across all company sites. These evaluations helped us identify the effectiveness of the model in predicting the total risk probability and determining which factors have the most significant impact on the company's overall risk profile.

In Figure 2, the Mean Squared Error (MSE) values between the desired target values and estimated model outputs for training data are plotted against different epochs for case N1. The horizontal axis represents the progression of the model over time, while the vertical axis represents the MSE values, which range between 0.002 and 0.004. The graph shows that the MSE values decrease over epochs, indicating that the model is improving its predictions and reducing errors during the training phase.

Similarly, in Figure 3, the MSE values for testing data are depicted over different epochs for case N2. The graph illustrates the performance of the model in predicting the risk probability for each factor across all company sites. The MSE values also exhibit a decreasing trend, indicating that the model's predictions are becoming more accurate and closer to the desired target values during the testing phase.

Overall, the observed trends in Figure 4 demonstrate that the neural network model is performing well, continuously learning from the data, and effectively reducing errors over time, leading to achieving the lowest MSE values possible.

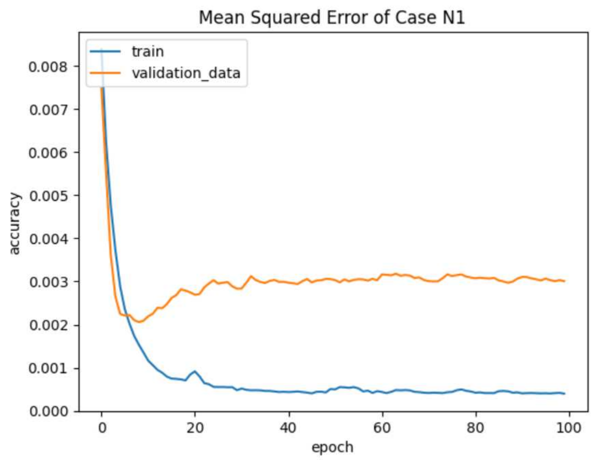

Figure 2 Mean Squared Error of case N1

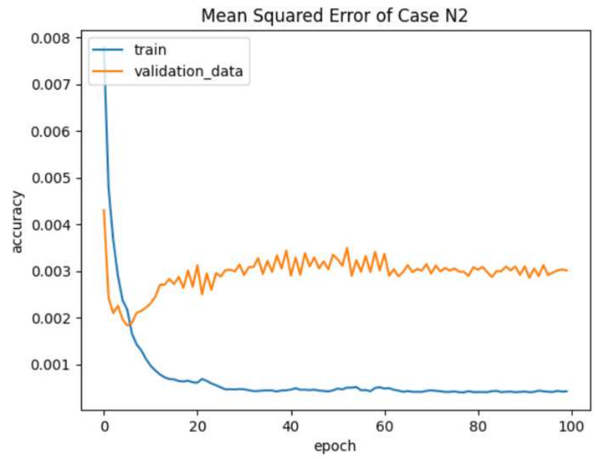

Figure 3 Mean Squared Error of case N2

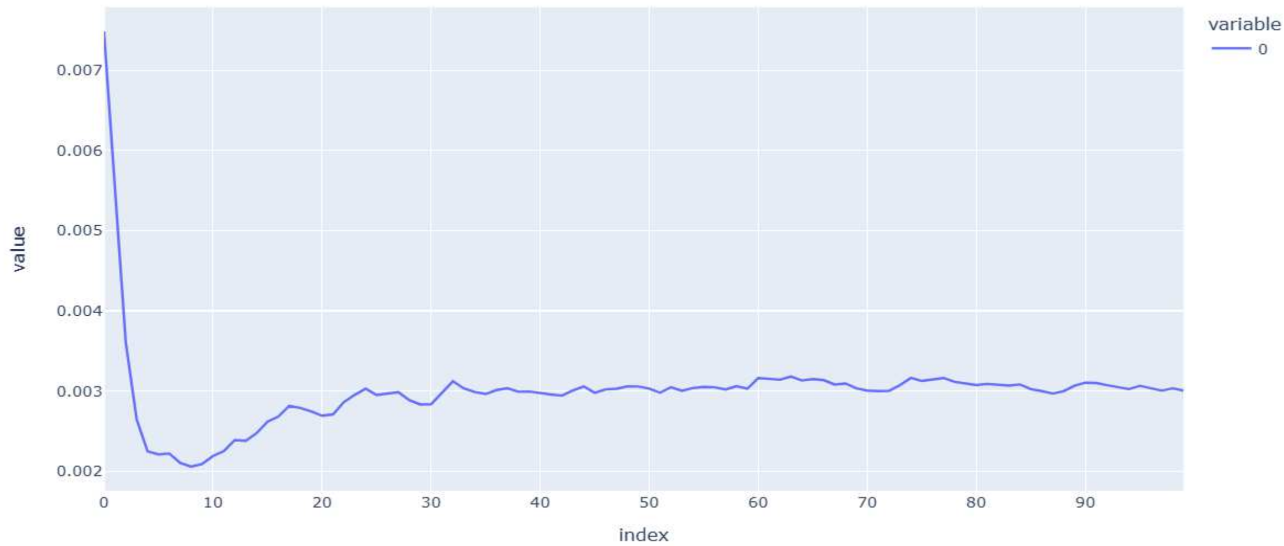

Figure 4 Mean Squared Error Trend over time of case N1

In Figure 5, the determination coefficient (R^2) values are plotted against different epochs to measure the goodness of fit for the training data. The horizontal axis represents the progression of the model over time, while the vertical axis represents the R^2 values, ranging from 0 to 1. The graph shows how well the model predicts the outcome by indicating the proportion of variability explained by the model. As the epochs progress, the R^2 values increase, indicating that the model's predictions are becoming more accurate and explaining a larger proportion of the variance in the variables.

Similarly, in Figure 6, the R^2 values for the validation data are depicted over different epochs. The graph illustrates how well the model generalizes its predictions to new, unseen data. As the epochs progress, the R^2 values for the validation data also increase, indicating that the model is performing well in capturing the underlying patterns and variability in the data.

Overall, the observed trends in both Figure 5 and Figure 6 demonstrate the improvement of the model's predictions over time, as indicated by the increasing R^2 values. These results indicate that the model is effectively capturing the relationships between the variables and explaining a significant proportion of their variance, leading to a good fit between the predicted outcomes and the actual data.

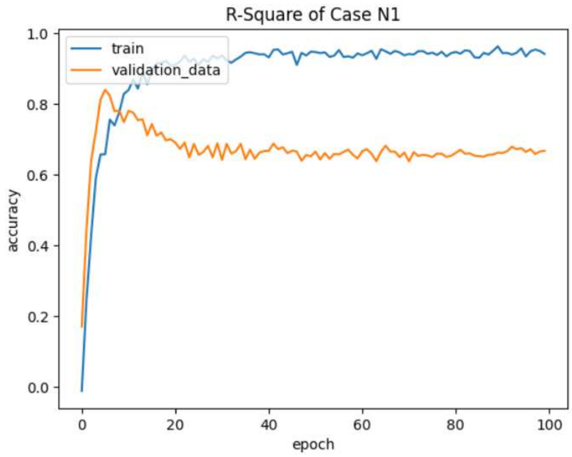

Figure 5 R-Squared of case N1

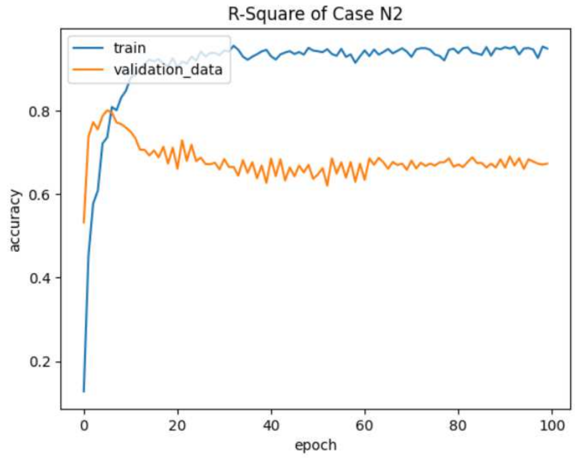

Figure 6 R-Squared of case N2

For both cases, the R-squared values for the model's predictions range between 0.5 and 0.85. This indicates that the model is able to explain a significant portion of the variance in the dependent variable. The proximity between the training and validation R-squared values suggests that the model's performance is consistent across different datasets, indicating its generalization ability.

In case N1, the developed model demonstrates an explanatory power of approximately 85% in terms of the variance in the dependent variable. This means that the model is able to account for 85% of the variability observed in the risk assessment. However, there is still 15% of the variance that remains unexplained by the model.

In case N2, the model shows an explanatory power of approximately 70% in relation to the variance in the dependent variable. This indicates that the model can explain 70% of the variability observed in the risk assessment. However, there is 30% of the variance that remains unexplained by the model.

Overall, the increasing trends of the R-squared values and their proximity to 1 demonstrate the model's ability to capture and explain a substantial portion of the variance in the data, indicating its effectiveness in predicting the outcomes for both cases.

It's important to note that the remaining unexplained variance may be attributed to various factors such as inherent complexity in the risk assessment process, external influences, or other unaccounted variables that were not included in the model. The aim of the model is to capture as much of the variability as possible and provide a standardized and objective assessment of risk, but there will always be some level of unexplained variance.

To ensure that the developed ANN model avoids overfitting or overtraining problems, two key parameters need to be carefully adjusted: the number of epochs and the number of neurons in each hidden layer.

In this study, the optimum size of epochs and the appropriate number of neurons for each hidden layer were determined through experimentation and evaluation. The goal was to strike a balance where the model achieves good performance without overfitting the training data. For example, when comparing the performance of the model with 100 epochs to the model with 150 epochs, it was observed that increasing the number of epochs led to a decrease in performance for both statistical measures: R-squared (with a higher percentage of unexplained variance) and MSE (with greater distance between the training and validation test values).This indicates that the model with 100 epochs achieved better results in terms of capturing the variability in the dependent variable and minimizing the prediction errors. It suggests that increasing the number of epochs beyond a certain point may lead to overfitting, where the model becomes too specialized in the training data and fails to generalize well to unseen data.

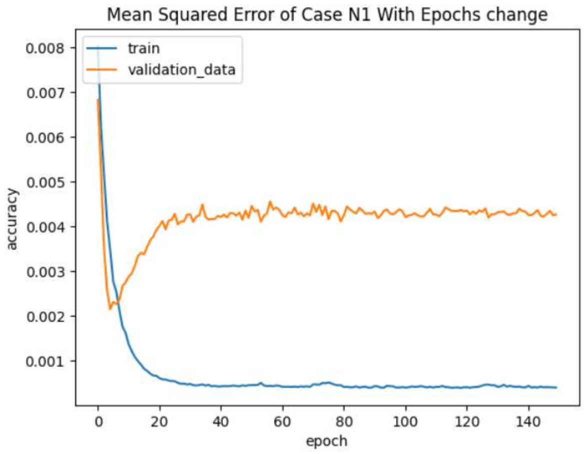

Figure 7 MSE of case N1 with epochs change

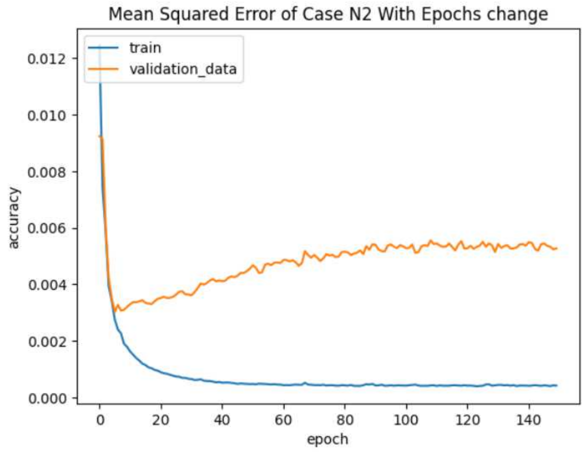

Figure 8 MSE of case N2 with epochs change

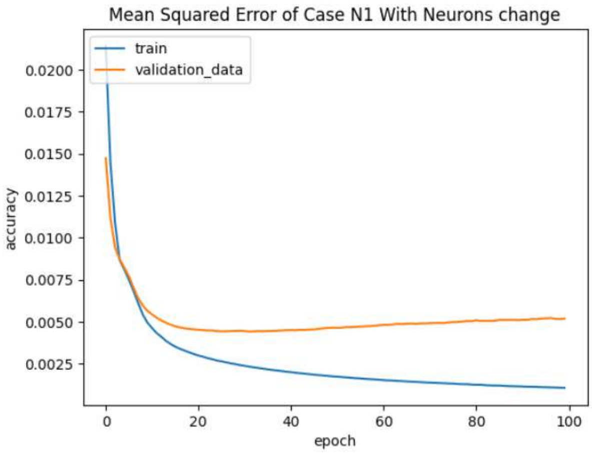

Figure 9 MSE of case N1 with neurons change

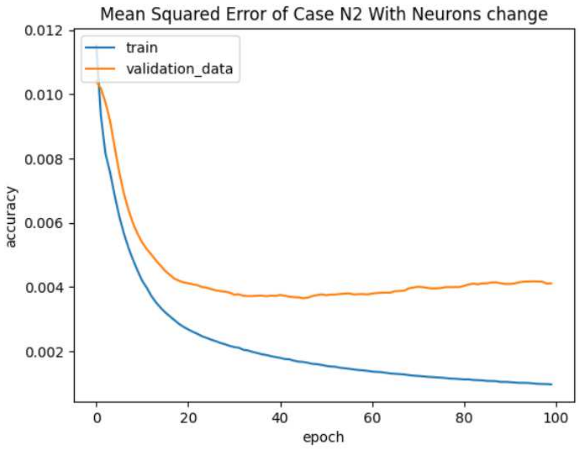

Figure 10 MSE of case N2 with neurons change

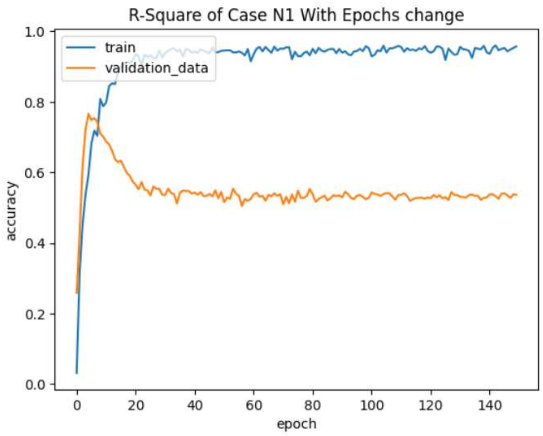

Figure 11 R-Square of Case N1 with Epochs change

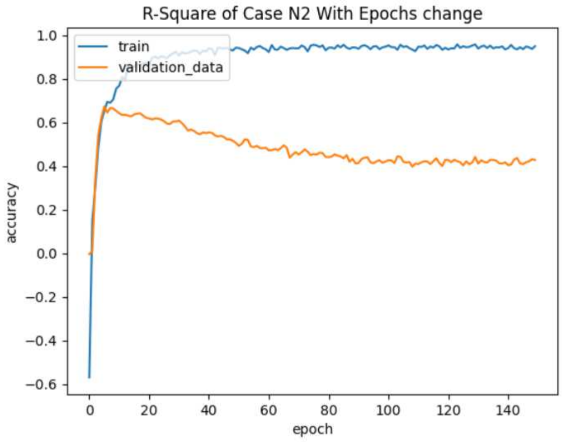

Figure 12 R-Square of Case N2 with Epochs change

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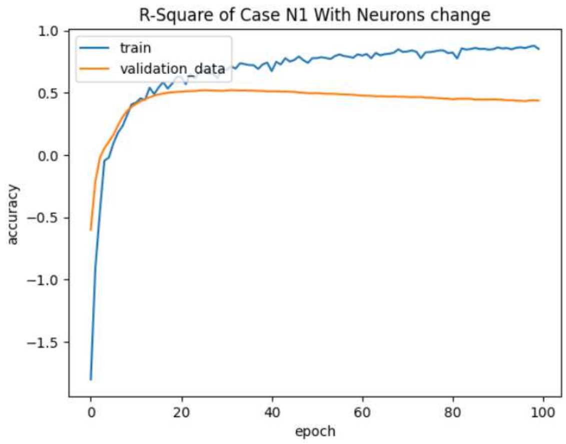

Figure 13 R-Square of Case N1 with Neurons change

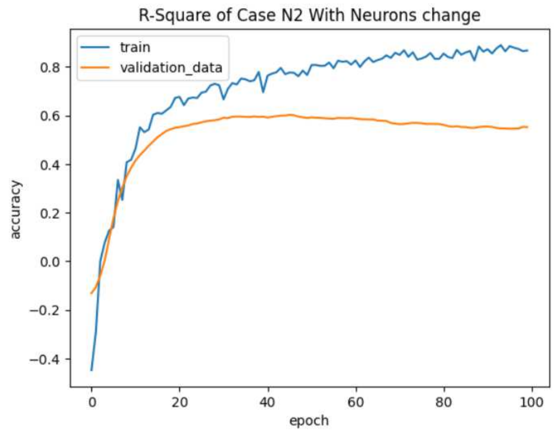

Figure 14 R-Square of Case N2 with Neurons change

To optimize the model's performance and improve R-squared and MSE, adjustments were made to the number of epochs, (Figure 7, Figure 8), and the number of neurons in the hidden layers. By fine-tuning these parameters, we aimed to achieve higher values of R-squared and lower values of MSE.Through this adjustment and parameter tuning process, it was determined that R-squared and MSE can vary significantly depending on the number of epochs and neurons in the hidden layers. The model's structure, including the configuration of hidden layers and the number of neurons, has a direct impact on the predicted values and overall performance of the model. The predicted values of the model align with the scale range of the training dataset, as shown in Table 4. This implies that the model's predictions are consistent with the data it was trained on. Specifically, the predicted values consistently fall in the middle of the scale range, indicating that the predicted risk level aligns with the risk level observed in the trained dataset. Furthermore, the computed risk probabilities generated by the model exhibit a good fit with the assessed risk levels determined by the auditors. This positive indication confirms that the model has successfully learned and captured the patterns and relationships present in the training data.

In Figures 9-14, we explored the effect of decreasing the number of hidden layers and neurons in the ANN model. Specifically, we transitioned from a model architecture with 5 hidden layers and 100, 80, 70, 60, and 50 neurons for each hidden layer to a simpler architecture with only 1 hidden layer consisting of 50 neurons.

The observed trend in the performance of the model is that as we decreased the number of hidden layers and neurons, there was a decrease in performance metrics such as R-squared and MSE. This is reflected in the greater distance between the training and validation values, indicating a higher level of prediction errors.

The alignment between the predicted values and the actual risk levels, as well as the confirmation through evaluation metrics, provides confidence in the model's ability to generalize and make accurate predictions for unseen data. It suggests that the model has effectively learned from the training data and can apply its understanding to new instances, enabling it to provide reliable risk-level assessments.

Table 4 Predicted and trained values risk level comparison

Predicted Values	Probability Range	Predicted Risk Level	Trained Values	Predicted Risk Level
0.58	[0.4, 0.7]	Medium	0.6	Medium
0.52	[0.4, 0.7]	Medium	0.6	Medium
0.41	[0.4, 0.7]	Medium	0.5	Medium
0.40	[0.4, 0.7]	Medium	0.4	Medium
0.33	[0.0, 0.3]	Low	0.3	Low

5 Conclusion

The overarching goal of this study was to establish a methodology serving in the risk assessment process in the industry. Our suggested work tries to formally conceptualize the risk assessment process practice consisting to objectify the risks instead of their subjectivity, as the interviews conducted with expert auditors indicated a prevailing absence of educational programs or professional accountability standardizing the way of assessing the risk, this lack of formal methodology is one of the main factors of subjectivity leading auditors to look at risks differently. The subjective nature of auditor risk assessment introduces uncertainty in risk measurement. To address this issue, we proposed a measurable risk approach based on risk levels assessed by the auditors. Risks were categorized into specific ranges and assigned a percentage of occurrence. This quantifiable approach aims to provide a more objective and standardized assessment of risk, reducing the inherent subjectivity in the evaluation process and making more precise and consistent risk measurement. The suggested method comprised the entire risk assessment process, from engaging the firm with a clearly defined set of criteria for evaluation, which were deconstructed to their sub-risk factors, for an accurate risk evaluation instead of a general risk factor assessment, then utilized as a feature vector for the input layer of the neural network model which return and predict a computed risk probability aiming to centralize the risk in its perimeter. The used data was collected from a real automotive company presented word wide and operating in the same activity sector, audit reports of 5 years served as input of the model they were cleansed and transformed from textual written into the predefined deconstructed risk factors, the selected data is resulted in a small, confidential but a highly valuable data.

Indeed, the implementation of the neural network model in risk assessment can significantly reduce the impact of auditor subjectivity and improve the reliability and consistency of risk assessment. The continuous learning process of the neural network allows it to improve its predictions over time by reducing errors and adjusting its internal parameters. This leads to achieving acceptable Mean Squared Error and R-squared values in both cases N1 and N2.

The acceptable MSE values indicate that the predicted risk probabilities are close to the auditor's risk level assessment, values range between 0.002 and 0.004, the MSE values decrease over epochs, indicating that the model is improving its predictions and reducing errors during the training phase. Furthermore, the model's performance in terms of capturing the variability in the dependent variable is reflected in the R-squared values by achieving approximately 85% and 70% respectively for case N1 and N2.

By having the predicted risk values within the scale range, it provides a means to evaluate and quantify risk using the model's predictions. This enables stakeholders to make informed decisions based on the risk assessment results generated by the neural network model. The alignment between the predicted values and the risk level scale enhances the model's usability and applicability in real-world risk assessment scenarios. The method we recommend has the capability to provide practical benefits as a tool for companies and organizations. that are looking to evaluate and manage their risk as by addressing the subjectivity in risk assessment, organizations can benefit from more reliable and consistent risk assessments, which can aid in strategic decision-making and enhance the overall risk management process.

However, the study is not free of limitations. The research findings strongly support the notion that ML is highly effective in both reducing the time needed for risk assessment feedback and improving the accuracy and objectivity of the risk assessment itself. The returned outputs from the trained model allow us to take the model as a basic step and attempt to expand it by introducing inputs from various sensors providing data from different points. The used dataset comprised 150 IATF audit reports for a defined automotive company, it might be the case that other companies from the same activity sector provide different audit results which will differentiate the dataset aspects as well as the outputs that will also be changed. Furthermore, the number of selected parameters may be changed in case of several companies' dataset presence as each company has a strategy and policy to manage its business. Secondly, the process of transforming the data from written reports into categorized parameters involves a certain degree of manual work that needs to be formed in a manner to get results automatically to speed up the process of collecting data, in addition to the subjectivity in evaluating the risk level assessed by the auditors to transform it to a risk percentage, this assessment may keep a degree of subjectivity, it would be preferable to have this assessment by the auditors instead of their general judgment. Moreover, exploring the relationships between specific risk factors that may have a low individual risk but still influence the overall risk in the SC should be a focal point for future directions. Additionally, conducting interviews with auditors to gather their insights and feedback on the methodology would enable adjustments to the model based on their needs and help address any subjectivity in the risk assessment process. Taking these perspectives into account, we will consider and incorporate them into our future research endeavours.

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