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A Model for Supply Chain Management Maturity Assessment using a Fuzzy Decision-making Approach: An Empirical Study

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A B S T R A C T

This paper presents a model for evaluating the maturity level of supply chain processes in an automobile manufacturer. The model is based on maturity models that are commonly used to evaluate supply chain performance. The study involved 20 industry experts and managers who provided data through a questionnaire. The maturity indices of supply chain processes were identified through a literature review, and the Fuzzy Delphi technique was used to select the most important maturity variables of the supply chain processes. The study identified fifteen indicators across five main dimensions: integration and coordination, strategy, resilience, improvement and development, and agility. To prioritize and identify the relationships among the indicators, a combined approach of Fuzzy DEMATEL and Fuzzy ANP was used. The process survey tools model was then applied to evaluate the maturity level of each process and the entire automobile manufacturer supply chain. The supplier relationship management process scored 3.07, the internal processes scored 2.95, and the customer relationship management process scored 2.68. The overall score of the automobile manufacturer supply chain was 2.92. In conclusion, the research indicates that the automobile manufacturer's supply chain processes are in a good state, but further efforts are needed to achieve maximum customer satisfaction, particularly in the area of customer relationship management.

1. Introduction

In today's business environment, supply chain risks are increasing due to production complexity, price fluctuations, changes in financial markets, and global policies [29,34]. Organizations are striving to reduce costs, improve service quality, and increase operational efficiency to deliver products and services to the market more cost-effectively [51,27]. A supply chain consists of processes that transform raw materials/components into final products and connect suppliers, producers, and consumers [52, 21]. Supply chains operate in complex,

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dynamic, and volatile business environments that require flexibility and agility to meet increasing customer expectations for product diversity and shorter product life-cycles [2,48]. To remain competitive, manufacturers and service providers are seeking new methods and tools to provide faster, cheaper, and better services than their competitors, and thus maintain and enhance their competitive advantage [15,41].

Effective performance evaluation is crucial for the success of a supply chain as it enables organizations to assess the quality of their processes and identify areas for improvement. However, performance evaluation models alone may not provide a comprehensive understanding of the existing gaps and how to bridge them. This is where maturity models come in, as they help organizations to systematically assess the degree of process definition, management, measurement, and continuous improvement.

Supply Chain Council (SCC) Reference (SCOR) model, which was created by the Supply Chain Council (SCC), is a well-known framework for establishing SCM norms. However, the SCOR model does not cover the concept of maturity. Therefore, maturity models have been developed to address this gap, and they have been used to examine the maturity of software processes and identify key approaches for increasing process maturity.

The usefulness of maturity models lies in their ability to systematize the areas and processes of an organization, set precise criteria for achieving different levels of maturity in each area, and recommend methods and techniques for specific levels of the supply chain. For example, a maturity model may include key indicators such as the degree of process standardization, the level of automation, and the degree of integration with suppliers and customers [23].

In this context, this study provides a comprehensive analysis of the maturity level of supply chain processes in an automobile manufacturer, highlighting the critical role played by the automotive industry in the global economy and its connection to various social and economic sectors. The study identifies the most important criteria affecting the maturity of supply chain processes in the automotive industry and analyzes their relationship and relative importance.

The paper proposes a systematic and thorough approach to identifying and analyzing the criteria affecting the maturity of supply chain processes in the automotive industry. This analysis can serve as a useful reference for policymakers and researchers working in this field and help advance the understanding of SCM in the automotive industry.

In this paper, we present a comprehensive model for assessing the maturity of supply chain management within organizations. The primary contribution of this research lies in the development of a structured framework that enables companies to evaluate and benchmark their supply chain management practices effectively. Our model incorporates key dimensions of supply chain management maturity, including strategy alignment, process integration, technology utilization, performance measurement, and collaboration with stakeholders. By assessing these dimensions, organizations can gain insights into their current SCM practices and identify areas for improvement. Furthermore, our model provides a systematic approach to maturity assessment, allowing organizations to progress through different maturity levels and establish a roadmap for enhancing their supply chain capabilities. This structured assessment framework enables companies to identify strengths, weaknesses, and opportunities for growth within their supply chain operations. Overall, the contribution of this paper lies in offering a practical and strategic model that empowers organizations to evaluate, enhance, and optimize their supply chain management practices to achieve higher levels of maturity and competitiveness in today's dynamic business environment.

The article is structured into five sections, starting with the introduction and literature review, followed by the specification of the model and introduction of variables. The third section covers model estimation and analysis of the results, while the final section presents the conclusion and policy proposals. Through this structured approach, the paper provides valuable insights to policymakers and industry leaders, assisting them in understanding and improving the performance evaluation of supply chain processes.

2. Literature review

Garcia Reyes and Giachetti [23] Developed a supply chain maturity model using the Delphi Method with 80 experts in Mexico. The model that was produced offers a guide for companies in Mexico to assess their supply chain operations and create a plan for enhancing them. The model describes supply chain maturity across multiple competency areas and five levels and was validated through experimentation and a pilot test. Chen, et al. [14] conducted research through multiple case studies to investigate the adoption of information and communication technology (ICT) within small and medium-sized enterprises (SMEs) in the Tai-wanese information technology manufacturing sector. The study discovered that the SMEs were in the early stages of developing process maturity in their supply chains. The researchers identified seven types of ICT connections used by the case companies to assist their supply chains, which indicated that most of the companies remained at a lower level of SCM integra-tion and were not utilizing the full advantages of ICT.

Meng, et al. [38] investigated the distinct features of the construction sector and created a maturity model for assessing and enhancing the connections among the primary stakeholders in a construction supply chain. The model adhered to the capability maturity principle and iden-tified four maturity levels of relationships within the construction supply chain. It utilized a matrix layout and provided comprehensive explanations of 24 assessment criteria across eight categories for each of the four maturity levels. Reefke, et al. [49] identified the major decision-making stages of sustainable supply chain management (SSCM) and put forth a mul-ti-layered maturity model for SSCM. Their proposed model presented a guide for attaining sustainable business transformation and was refined through a sustainability modelling and reporting (SMART) system. Dellana and Kros [18] examined differences in quality manage-ment program maturity among industry classes and supply chain positions in the USA. By surveying professionals mainly in sourcing or logistics from the Institute for Supply Man-agement and Council for Supply Chain Management Professionals via email, the researchers found that the level of quality maturity differed depending on the industry and position within the supply chain.

Varoutsa and Scapens [56] aimed to investigate the implementation of SCM and the changing phases of a supply chain as it matures. Through a case study in an aero-manufacturing company, they examined how the minimal structures emerge and evolve during the maturity of a supply chain. Souza, et al. [54] explored the correlation between the maturity level of supply chain process management (SCPM) and the organizational life cycle (OLC) of a company. Data from 228 Brazilian companies were collected through a questionnaire to assess the association between variables. The study found evidence of a relationship between SCPM maturity level and OLC. The maturity level of SCPM was related to capabilities inherent to SCPM, but not to the age or size of a company. The study suggests that management and control of organizational issues can help to develop SCPM maturity, leading to high-quality services. Radosavljevic, et al. [47] conducted research on the necessity of SCM maturity for implementing best practices. They used the Delphi method to adapt a maturity model for Serbian enterprises and found that best practice elements were not widely used. The study identified that all enterprises were at the second and third maturity levels, highlighting the need for continuous improvement and the potential for further development of maturity models with statistical tools.

Mendes, et al. [37] proposed a theoretical framework to assess the maturity level of a demand-driven supply chain and develop strategies for improvement. The authors used a participatory consensus-building approach to develop the maturity model, which was applied to an international beverage company in Brazil, the United States, and Uruguay. Supply chain executives used the Analytical Hierarchy Process to assign priorities and rank the dimensions of maturity. The results showed that all supply chains were in the early stages of maturity towards becoming demand driven. Broft, et al. [8] examined the factors that facilitate or hinder the implementation of SCM at the lower tiers of the construction supply chain, focusing on col-laboration between main contractors and subcontractors. They created SCM maturity levels and conducted interviews with eight major main contractor and subcontractor organizations in the Dutch construction industry. The study revealed more barriers than enablers to SCM imple-mentation, with organizations struggling to attain a competitive edge through superior value, collaboratively manage costs, and establish continuous improvement within their supply chains. It also highlighted the low SCM maturity of main contractors and their inability to act as supply chain managers, a critical role.

Ferreira, et al. [22] identified the relationship between environmental management ma-turity and green supply chain management (GSCM) practices using an integrative framework and cases. They created a GSCM maturity levels framework and analyzed five companies with high environmental impact. The study classified GSCM maturity levels as reactive, preventive, and proactive, with varying levels of GSCM practice adoption driven by legal restrictions, cost reduction, and competitive advantages. Ward, et al. [57] proposed a three-dimensional ma-turity-based framework to address the gap in exploiting the full potential of the latest manu-facturing technologies. The framework considered technology demonstration, the target product's position in its lifecycle, and the readiness of the supply chain as success factors for industrialization. The study used case studies to illustrate the need for this approach in achieving technology-enabled supply chains.

Roque Júnior, et al. [50] conducted a case study on a Brazilian biotech company to de-termine its level of maturity and complexity in SCM. The study aimed to establish the com-pany's SCM maturity dimensions and serve as a basis for achieving higher competence levels. It also analyzed the relationship between complexity and maturity, and found a clear correlation between the two. The study's results are important for companies in the health services sector, where supply chains play a critical role. Batista, et al. [7] developed a framework to analyze the maturity of KM adoption in SMEs in the food sector for sustainable initiatives. The study highlights potential barriers and makes an original contribution to theory and practice by linking KM maturity levels, perspectives, and processes to sustainable practices. Ho, et al. [30] ex-plored the relationship between SCC mechanisms, maturity levels, and performance outcomes in the textile and garment industry. They used a maturity model to evaluate current practices and measure SCC maturity levels, collecting actual performance data. The research verified the association between Supply Chain Council (SCC) mechanisms and performance, where in-ternal collaboration acted as a mediator and moderator in the correlation between external in-tegration and performance. Büyüközkan, et al. [9] presented a generic model for determining companies' SCA maturity levels. The model's factors were determined through a literature re-view, industry reports, and expert opinions, with weights calculated using Hesitant Fuzzy Linguistic SAW and HFLTS techniques. An application was provided to calculate ABC Company's SCA maturity score, with future perspectives discussed.

Soares, et al. [53] proposed a three-stage approach to measure LSCM maturity based on lean practices and waste elimination. The authors conducted a literature review on MMs and LSCM, validated the review with experts using FDM, and evaluated the proposed model through a multi-case study. Results showed that waste elimination was high across all compa-nies, with logistics management, continuous improvement, and information technology man-agement standing out. The lowest maturity level was found in a company with a make-to-order production policy, potentially hindering the lean supply chain. Peña Orozco, et al. [44] ex-amined the feasibility of implementing a contract model as an integration mechanism for de-cision-making in a decentralized supply chain of small agricultural producers in a developing nation. The findings indicated a high willingness to adopt contracts as an integration mechanism within the studied supply chain of small farmers. Cavalcante de Souza Feitosa, et al. [12] in-troduced a Supply Chain Risk Management (SCRM) maturity model combined with a fuzzy TOPSIS classification method for evaluating organizations. Their approach employs a pre-scriptive methodology based on a theoretical model and a multi-criteria decision technique. The initial test application demonstrated the capability to identify weaknesses and enhance opera-tional and disruption risk management. Caiado, et al. [11] created an Industry 4.0 maturity model (I4.0 MM) for operations and supply chain management (OSCM) using fuzzy logic. They utilized a multi-method approach that included a literature review, interviews, focus groups, and a case study to construct and assess the model. To provide a more accurate eval-uation, they integrated fuzzy logic and Monte Carlo simulation into an I4.0 self-assessment readiness-tool linked with the model architecture. The proposed model was confirmed by conducting an actual application in a multinational manufacturing corporation.

Alidrisi [4] presented a strategic roadmap to address resource allocation in GSCM. The study proposed using supply chain finance (SCF) and the five Vs of big data to determine the role of GSCM practices in improving SCF implementation. The paper employed the fuzzy analytic network process (ANP) and the fuzzy technique for order preference by similarity to ideal solution (TOPSIS) to evaluate GSCM practices. Interpretive structural modeling (ISM) was used to visualize the optimal implementation of GSCM practices. The outcome is a hybrid self-assessment model that measures the environmental maturity of SCF using the Basic Readiness Index (BRI), Relative Readiness Index (RRI), and Strategic Matrix Tool (SMT). Kayikci, et al. [33] presented a conceptual framework for assessing the supply chain sus-tainability and circularity (SCSC) readiness and maturity level of small and medium-sized enterprises (SMEs) in the textile industry in Turkey. The framework took a multi-layered perspective and considered different stakeholders. The study highlighted the importance of approaching readiness and maturity from a systems theory perspective and identified dimen-sions for transitions to Industry 4.0 and circular economy.

Demir, et al. [19] presented a new model called the "Smart and Sustainable Supply chain Readiness and Maturity model (S3RM)" based on the triple-bottom-line approach, with smartness and sustainability dimensions. The TBL of smartness included availability, integrity, and adaptability sub-dimensions, while the TBL of sustainability included social, environ-mental, and economic sub-dimensions. The proposed model calculated the Smart and Sus-tainable Readiness and Maturity Index by averaging sustainability scores' summation and smartness scores' multiplication, with each sub-dimension consisting of items measured by a readiness and maturity scale. The study validated the model by conducting a case study in the automotive industry and provided managerial implications for assessing the readiness and maturity of Industry 4.0 tools and sustainability indicators.

Balouei Jamkhaneh and Safaei Ghadikolaei [5] developed a framework for measuring service supply chain (SSC) maturity. The framework was created by examining ideas and models linked to SSC, business excellence, maturity, and evaluating supply chain performance. The proposed model defined the maturity level of each excellence criterion using a combina-tion of the PDCA cycle and process survey tools maturity model. A questionnaire was designed based on the excellence criteria and their maturity levels to practically measure the proposed framework. Balouei Jamkhaneh, et al. [6] suggested a framework to identify and measure the gaps between evaluation and goal setting in service supply chain (SSC) processes. The pro-posed framework aimed to help plan and develop sustainable tourism that aligns with the ca-pabilities of the firms. The service quality gap model was utilized to examine the gaps between auditors' evaluation and managers' goals in SSC process maturity. The gaps were measured and analyzed using importance-performance analysis (IPA) to determine the strategy and priority for sustainable tourism planning and development. Correia, et al. [16] developed a five-level maturity model aimed at assisting supply chain managers in assessing their engagement with sustainability practices. The model was constructed by combining three perspectives: intra- and inter-organizational sustainability practices, the triple-bottom-line approach, and critical areas for sustainability. The development of the model was based on a thorough literature review, and its effectiveness was supported using case studies to improve, apply, and test the model.

Cubo, et al. [17] introduced a novel maturity model (MM) for evaluating the quality management of supply chains (SCQM). The purpose of this MM is to guide organizations in the enhancement and progression of quality in their SCs. The study also aimed to investigate the integration of SCQM and its effect on organizational performance. The paper presented and discussed the proposed SCQM MM, highlighting its potential for promoting SC quality and performance improvements. Pejić Bach, et al. [43] investigated the link between supply chain management maturity (SCMM) and business performance using the balanced scorecard (BSC) framework. The study found a positive relationship between SCMM and business perfor-mance, with industry characteristics such as technological dynamism having a moderating effect.

3. Methodology

This study aims to create a framework that can evaluate the level of maturity of supply chain processes within an automobile manufacturer. The research method used is both descriptive-survey and applied. Both field and library methods were utilized to collect information. The statistical population of the study consists of specialists, experts, and managers in automobile manufacturer and SCM. For the sample, 20 experts were purposively selected. Figure 1 provides a visual representation of the research processes involved in this study.

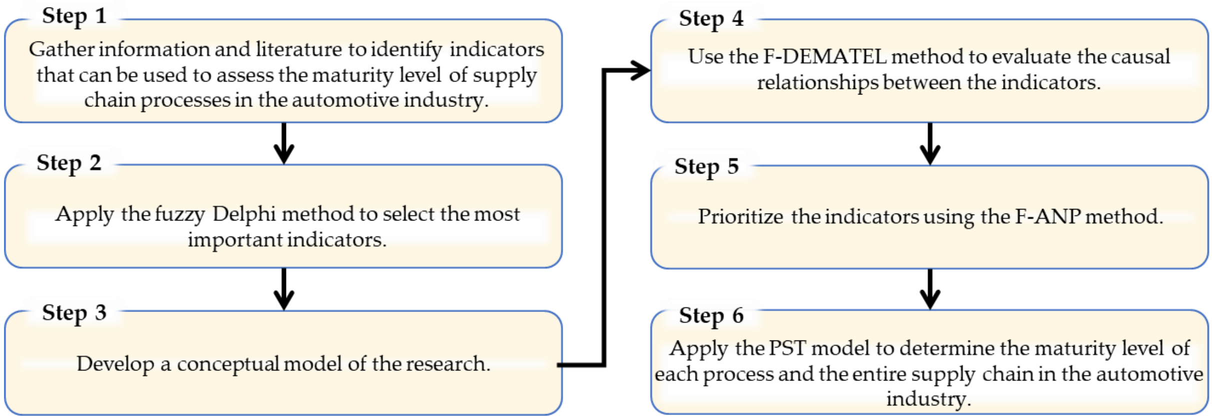

Figure 1. The steps involved in research methodology.

The research followed several stages. Initially, a comprehensive literature review was conducted to extract relevant variables. The fuzzy Delphi technique was then used to localize and select the most critical variables. From this, the initial research model was formulated. The combined approach of fuzzy decision-making trial and evaluation laboratory (F-DEMATEL) and fuzzy analytic network process (F-ANP) was used to identify the relationships and prioritize the indicators. The Super Decisions and Excel software were used for these techniques. Finally, the level of maturity for each supply chain process in the automobile manufacturer was evaluated. Table 1 shows the data collection tools utilized during the various stages of the research.

Table 1. Specifications of data collection tools

No.	Tools	Type of the study	No. of Q	Spectrum used	Purpose (Application)
1	Literature review	Library	-	-	Identification of indicators for supply chain process maturity: 30 indicators were identified.
2	Fuzzy Delphi questionnaire	Field	30	5 Likert options (1-5)	Selection of the most important indicators for supply chain process maturity based on expert opinions: 15 indicators were selected.
3	F-DEMATEL questionnaire	Field	210	5 options (0-4)	Identification of causal relationships between maturity level indicators for supply chain processes.
4	F-ANP questionnaire	Field	71	Hourly range (1-9)	Prioritization of maturity level indicators for supply chain processes.
5	Questionnaire to determine the level of maturity of supply chain processes based on the PST model	Field	15	4options (1-4)	Determination of the maturity level for each process and the entire supply chain in the automobile manufacturer.

3.1. Fuzzy Delphi Method

The Fuzzy Delphi Method (FDM) is an extension of the traditional Delphi method, which is a structured approach for gathering and combining expert opinions to make informed decisions [32]. The FDM adds a level of uncertainty and ambiguity to the Delphi method by allowing experts to express their opinions using linguistic terms instead of precise numerical values. In FDM, experts are asked to provide their opinions in the form of linguistic variables or fuzzy sets [46]. These fuzzy sets represent a range of values or degrees of certainty, which can be combined to form a consensus opinion. The FDM process involves multiple rounds of iteration, where experts are provided with feedback on their opinions and asked to revise them based on the opinions of their peers. FDM is particularly useful when dealing with complex or uncertain problems, where precise numerical values may not be available or appropriate [39]. It allows experts to express their opinions in a more flexible and nuanced way and can help to uncover hidden assumptions or biases that may not be apparent in traditional numerical methods. The steps of the Fuzzy Delphi Method include:

Step 1: Collect and fuzzify expert opinions: The initial stage of the fuzzy Delphi technique involves the gathering and transformation of expert opinions into fuzzy sets. Specifically, the qualitative variables pertaining to the indicators are converted into triangular fuzzy numbers that represent the highest (U), most probable (M), and lowest (L) values. For this study, the conversion of linguistic expressions provided by the experts into fuzzy numbers was based on the triangular fuzzy scale presented in Table 2, as suggested by Özdemir et al. [42].

Table 2. Conversion of verbal variables to triangular fuzzy numbers [42]

Linguistic items	Fuzzy number scale
Equal	(1,1,1)
Very little superiority	(1,2,3)
Slightly superior	(2,3,4)
Superior	(3,4,5)
Good	(4,5,6)
Fair	(5,6,7)
very good	(6,7,8)
Excellent	(7,8,9)
Absolute superiority	(8,9,10)

$$\left(L_1^{(i)}, M_1^{(i)}, U_1^{(i)}\right), i = 1, \dots, n \tag{1}$$

Step 2. Fuzzy aggregation of opinions: Once the opinions have been collected and fuzzified using a suitable fuzzy scale, they need to be aggregated. Various methods have been proposed for aggregating fuzzy opinions from experts. One such method is to compute the fuzzy average of the expert opinions, assuming that they are represented as triangular fuzzy numbers (l, m, u). This is considered a simple and straightforward approach.

$$F_{AVE} = \frac{\sum l}{n}, \frac{\sum m}{n}, \frac{\sum u}{n} \tag{2}$$

In addition to the fuzzy average, other methods are available for aggregating expert opinions in the Fuzzy Delphi Method. These aggregation methods are experimental and have been proposed by various researchers. One such method commonly used for aggregating a set of triangular fuzzy numbers is the minimum l, mean m, and maximum u approach. This method is also known as the L-M-U method and is a conventional approach for aggregating fuzzy sets.

$$F_{AGR} = (\min\{l\}, \left\{\frac{\sum m}{n}\right\}, \max\{u\}) \tag{3}$$

Some sources suggest using the geometric mean instead of the simple arithmetic mean for aggregating expert opinions in the Fuzzy Delphi method [58].

$$F_{AGR} = (\min\{l\}, \prod\{m\}, \max\{u\}) \tag{4}$$

Some sources recommend calculating upper and lower bounds using the geometric mean as an alternative to the traditional fuzzy average. The selection of an aggregation method for expert opinions in the Fuzzy Delphi

Method ultimately depends on the researcher's perspective. Fuzzy aggregation methods are preferred over fuzzy mean as they account for the maximum dispersion of individual opinions. Nevertheless, a drawback of these methods is that the opinions of optimists or pessimists can greatly influence the results. To address this issue, experts whose opinions are overly pessimistic or optimistic can be disregarded. Specifically, an expert with u_i less than $\left\{\frac{\sum l}{m}\right\}$ is considered a pessimistic expert, while an expert with l_i longer than $\frac{\sum u}{n}$ is considered an optimistic expert. By eliminating the views of overly optimistic or pessimistic experts, the accuracy and reliability of the results can be further ensured.

Step 3: Defuzzification: Next, the geometric mean of the fuzzy numbers corresponding to each index is calculated. Then, using the center of the surface formula (Equation 2), the fuzzy values are converted into crisp numbers.

$$DF_{ij} = \frac{\left[(u_{ij} - l_{ij}) + (m_{ij} - l_{ij})\right]}{3} + l_{ij} \tag{5}$$

Finally, to eliminate unsuitable indicators, an acceptable limit is set. Indicators that exceed the set limit, as determined by the consensus of experts and after de-fuzzification, are accepted, while those that fall below the limit are eliminated. There is no general rule for determining this limit, and it is based on the researcher's judgment and the consensus of experts. In this study, based on the opinions of expert professors, an acceptable limit of 0.7 has been set.

3.2. F-DEMATEL method

Fuzzy DEMATEL is an extension of the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method that incorporates fuzzy logic [13]. The DEMATEL method is a tool for analyzing complex systems and identifying cause-effect relationships among different elements of the system [40]. It is often used in fields such as engineering, management, and social sciences [45, 60]. Fuzzy logic, on the other hand, is a mathematical framework that allows for the representation of imprecise or uncertain information. By combining these two approaches, fuzzy DEMATEL allows for the modeling of complex systems where the cause-effect relationships are not entirely clear or precise.

In fuzzy DEMATEL, the input data is represented as linguistic variables or fuzzy sets. These fuzzy sets represent the degree of membership of an element in a particular category or group. For example, if we are analyzing the factors that contribute to customer satisfaction, we could use fuzzy sets to represent the degree of satisfaction as "very satisfied", "satisfied", "neutral", "dissatisfied", and "very dissatisfied". Once the input data is represented in fuzzy sets, the fuzzy DEMATEL algorithm can be used to calculate the causal relationships among the different elements. The result of the fuzzy DEMATEL analysis is a matrix that represents the strength of the causal relationships among the different elements of the system. Fuzzy DEMATEL has several advantages over traditional DEMATEL, including the ability to handle imprecise or uncertain data and the ability to model complex systems with multiple causal relationships.

It is a powerful tool for decision-making in complex systems, and it is widely used in fields such as engineering, management, and social sciences.

The steps of the F-DEMATEL Method include:

Step 1: Create a decision matrix: To initiate the decision-making process, a decision matrix is created in Step 1. This matrix consists of rows and columns representing the decision criteria.

In this study, the impact of various factors was measured using a five-level scale proposed by [35] and represented by fuzzy triangular numbers as shown in Table 3.

Table 3. Conversion of linguistic items to triangular fuzzy numbers to determine the effect of variables [35]

Linguistic items	Crisp numbers	Triangular fuzzy numbers
Too much impact	4	(0.75,1,1)
High impact	3	(0.5,0.75,1)
Low impact	2	(0.25,0.5,0.75)
Very little impact	1	(0,0.25,0.5)
Effect less	0	(0,0,0.25)

Step 2: Calculate the fuzzy direct communication matrix: At this stage, each respondent is asked to determine the effect of each criterion on another criterion based on the questionnaire. For each respondent, a matrix $n \times n$ with fuzzy elements is defined, in which $\tilde{a}_{ij}$ is a triangular number as $\tilde{a}_{ij} = (l_{ij}, m_{ij}, u_{ij})$.

$$\tilde{A} = \begin{bmatrix} 0 & \tilde{a}_{12} & \dots & \tilde{a}_{1n} \\ \tilde{a}_{21} & 0 & \dots & \tilde{a}_{2n} \\ \vdots & \vdots & \ddots & \dots \\ \tilde{a}_{n1} & \tilde{a}_{n2} & \dots & 0 \end{bmatrix} \quad (6)$$

Then the fuzzy direct mass communication matrix is created by averaging the opinions of experts according to Equation (3).

$$z = \frac{x^1 + x^2 + x^3 + \dots + x^p}{p} \quad (7)$$

In this context, p refers to the number of experts involved in the decision-making process. X1, X2, and Xp denote the comparison matrix of expert 1, expert 2, and expert p, respectively.

Step 3: Create a normalized fuzzy direct communication matrix: In this step, the fuzzy normalized matrix is obtained by dividing each element in the matrix by the largest sum of the third layer numbers (u in triangular fuzzy numbers) in each row.

$$u = \max_{1 \le i \le n} \left(\sum_{j=1}^{n} u_{ij} \right) \quad (8)$$

$$\tilde{X} = \frac{\tilde{A}}{u} \quad (9)$$

Step 4: Calculate the complete fuzzy communication matrix: To compute the complete correlation matrix, a single matrix is initially formed. This matrix is then subtracted from the normalized matrix, and the resulting matrix is inverted. Finally, the inverse matrix is multiplied by the normalized matrix. The following equations are used to calculate this matrix:

$$\tilde{T} = \tilde{X} + \tilde{X}^2 + \tilde{X}^3 + \dots + \tilde{X}^k \quad (10)$$

Considering $k \to \infty$ we will have all equation (11):

$$\tilde{T} = \tilde{X} + \tilde{X}^2 + \tilde{X}^3 + \dots + \tilde{X}^k = \tilde{X}(I - \tilde{X})^{-1} \quad (11)$$

$$\tilde{T} = \begin{bmatrix} \tilde{t}_{11} & \tilde{t}_{12} & \dots & \tilde{t}_{1n} \\ \tilde{t}_{21} & \tilde{t}_{22} & \dots & \tilde{t}_{2n} \\ \vdots & \vdots & \ddots & \dots \\ \tilde{t}_{n1} & \tilde{t}_{n2} & \dots & \tilde{t}_{nn} \end{bmatrix},$$

$$\tilde{t}_{ij} = (l''_{ij}, m''_{ij}, u''_{ij})$$

$$[l''_{ij}] = X_l \times (I - X_l)^{-1},$$

$$[m''_{ij}] = X_m \times (I - X_m)^{-1},$$

$$[u"_{ij}] = X_u \times (I - X_u)^{-1}$$

Step 5: Defuzzification: In order to convert fuzzy numbers to crisp numbers, the following equation is used:

$$dF_{ij} = \frac{(r_{ij} - l_{ij}) + (m_{ij} - l_{ij})}{3} + l_{ij} \quad (12)$$

Step 6: Draw causal diagram: In this step, the sum of the rows and columns of the previously obtained matrix is computed. Let the sum of rows and columns be represented by D_i and R_i matrices, respectively. The highest sum of rows, D_i, represents the order of criteria that strongly influence the other elements, while the highest set of columns, R_i, represents the order of criteria that are influenced. The superiority matrix, $D_i + R_i$, is obtained by adding these two matrices, and the relational matrix, $D_i - R_i$, is obtained by taking their difference. Once the values of $D_i - R_i$ and $D_i + R_i$ are calculated, a graph is plotted to show the impact intensity and effectiveness. The X-axis represents $D_i + R_i$, indicating the importance of each factor, with higher values indicating greater importance. The Y-axis represents $D_i - R_i$.

3.3. Fuzzy ANP method

The Fuzzy Analytic Hierarchy Process (ANP) method is a decision-making tool that combines the benefits of the ANP method and fuzzy logic [36]. The ANP method is a multi-criteria decision-making (MCDM) technique that allows decision-makers to make complex decisions by breaking down the problem into smaller, more manageable parts [24]. Fuzzy logic, on the other hand, allows for uncertainty and ambiguity in the decision-making process. The Fuzzy ANP method works by first identifying the criteria and sub-criteria of the decision problem [20]. Next, the decision-makers assign weights to the criteria and sub-criteria based on their importance. These weights are then combined to form a weighted matrix. The next step involves the use of fuzzy logic to handle the uncertainty in the decision-making process. Fuzzy logic uses linguistic variables, such as "very important" or "somewhat important," to represent the weights assigned to the criteria and sub-criteria. These linguistic variables are then converted into fuzzy numbers, which are used to calculate the weighted matrix. Finally, the weighted matrix is used to calculate the final scores of the alternatives being considered. The alternatives are compared to each other based on their scores, and the one with the highest score is chosen as the best option. The Fuzzy ANP method has several advantages over traditional decision-making methods. It allows for uncertainty and ambiguity in the decision-making process and can handle complex, multi-criteria decision problems. Additionally, the method provides a systematic and structured approach to decision-making, making it easier for decision-makers to make informed decisions.

Step 1: Build the model and structure the problem: Initially, the ANP network includes all criteria and sub-criteria, and all relationships between them are established.

Step 2: Obtain fuzzy pair-wise comparison matrices: In the second step, after creating the ANP network, pair-wise comparison matrices containing fuzzy numbers and obtained from the questionnaire are created and the criteria comparison matrices with respect to the target and the sub-criteria comparison matrices with respect to the main criteria are formed. The elements to be compared in pairs are usually in a cluster. Each pair-wise comparison is performed using linguistic terms. Each linguistic expression is represented by a triangular fuzzy number ($L_1^{(i)}$، $M_1^{(i)}$، $U_1^{(i)}$). After forming the pair-wise comparison matrix, it is necessary to calculate the degree of incompatibility of each matrix. For each fuzzy ANP questionnaire there is a level of incompatibility that should be less than 0.1. In the present study, in order to calculate compatibility, Gogus and Boucher method was used and confirmed [25].

Step 3: Averaging from the point of view of experts and calculating the weight of the criteria (special vector): The third step involves consolidating the viewpoints of the experts by computing the geometric mean of the pairwise comparisons made by the respondents. Using Equations (13) and (14), the weight of each criterion is then determined.

$$r_i = [\prod_{j=1}^{n} a_{ij}]^{\frac{1}{n}} = [a_{i1} \otimes a_{i2} \otimes \ldots \otimes a_{in}]^{\frac{1}{n}} \tag{13}$$

$$w_i = r_i \otimes [\sum_{j=1}^{n} r_j]^{-1} = \frac{r_i}{r_1 \otimes \ldots \otimes r_n} \tag{14}$$

Step 4: Convert fuzzy value to crisp value: In the fourth step, the fuzzy priority values are presented as fuzzy numbers, and therefore, it is necessary to convert them to crisp values. There are multiple methods available for defuzzification, but for this study, the district center method, as described in Equation (10)[10], was employed.

$$X(N_i) = \frac{\int_{n_1}^{n_2} x\mu_N(x)dx}{\int_{n_1}^{n_2} \mu_N(x)dx} = \frac{\int_{n_1}^{n_2} \left(x\frac{x-n_1}{n_2-n_1}\right)dx + \int_{n_1}^{n_2} \left(\frac{n_3-x}{n_3-n_2}\right)dx}{\int_{n_1}^{n_2} \left(\frac{x-n_1}{n_2-n_1}\right)dx + \int_{n_1}^{n_2} \left(\frac{n_3-x}{n_3-n_2}\right)dx} = \frac{(n_1+n_2+n_3)}{3} \tag{15}$$

In Equation (15), $X(N_i)$ represents the value of the triangular fuzzy mean of the number $N_i = (n_1, n_2, n_3)$.

Step 5: Formation of the super-matrix: In the fifth step, the fuzzy values of the weights of the criteria and sub-criteria are subtracted, and the resulting crisp values are inserted into the super-matrix. This matrix is divided into parts, with each part representing the relationship between two components or clusters within the system. The super-matrix is constructed by arranging the targets, main criteria, sub-criteria, and options in the rows and columns of the matrix [55].

Step 6: Normalize the super-matrix: In the sixth step, the matrix must be stochastic, so column normalization is applied to obtain a weight super-matrix. Normalization involves dividing each element in the super-matrix by the sum of the corresponding column.

Step 7: Bounded super-matrix and final weight criteria: In the seventh step, the bounded super-matrix is obtained by raising the weight super-matrix to a power. This process ensures that the weight super-matrix is strong enough to converge, and all the columns of the bounded super-matrix become identical. The values in this matrix represent the desired limit or final values of the decision network elements. Lastly, the sub-criteria are ranked based on the priority of their importance in achieving the goal [10].

3.4. A PST maturity model

Process Survey Tools (PSTs) are instruments used to assess various aspects of an organization's processes. PSTs typically consist of a set of questions or statements that are designed to evaluate different aspects of a process. These tools provide indicators that measure how processes can improve and reach the next level of maturity. To assess the maturity of supply chain processes using PST, two preparation steps are necessary. The first step is to identify the desired processes, and the second step is to translate the objectives into performance objectives and sub-performance indicators. The PST maturity model consists of four levels:

- *Level one - Informal:* This level refers to the absence of formal procedures and processes, resulting in unpredictable quality and supply. Keywords at this level include informal, unpredictable, and demand-supply imbalances.
- *Level two - Functional*: The performance areas of the supply chain optimize their tasks without reference to what is happening in other areas of the business. Processes are usually performed sequentially, and tasks are directed towards the optimization of the organization's performance in cost and asset management, and customer satisfaction. Keywords at this level include inactive, monthly processes, and standard services.
- *Level three - Integrated:* Processes at this level are cross-functional and optimized for the entire organization. Processes are performed in parallel by cross-functional groups, and information flows freely across the organization. At this level, the organization demonstrates integrated operational processes,

continuous improvement, and performance with alignment at all sub-processes and management levels. Keywords at this level include flexibility, responsiveness, reactivity, different services, and interdisciplinary decisions.

- *Level Four - Developed:* Organizations at this level have a high level of internal and external integration, and supply chain member organizations are growing and evolving in all operations. Working with companies ranging from suppliers to customers, the organization can provide specific services to its customers and focus on value creation. Keywords at this level include pivotal event, timely production system, and customized services.

Figure 2 depicts the main levels of the proposed maturity project model.

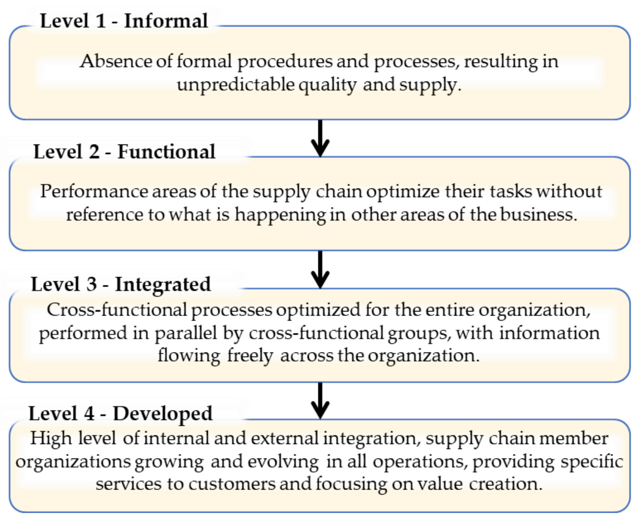

Figure 2. Proposed maturity model

4. Case study

Based on the descriptive statistics, we can determine that 35% of the participants in this study are faculty members of the university, while the remaining 65% are experts, specialists, and managers from the automobile manufacturer.

All participants hold a university degree, with 60% at the master's level and 40% at the doctoral level. The age range of the participants falls between 38 and 56 years, with work experience ranging from 10 to 22 years, and an average of 16 years.

4.1. Determination of critera: Using Fuzzy Delphi

In order to enhance the precision of the conceptual framework in this research, an exhaustive exploration of pertinent scholarly sources was initially carried out. As a result, 30 discernible markers were identified that could be employed to evaluate the degree of development attained by the supply chain procedures of the automotive manufacturer. These 30 markers are presented comprehensively in Table 4.

Following the identification of the 30 indicators utilized for assessing the degree of advancement of supply chain processes in the automotive manufacturer, the study proceeded to employ the fuzzy Delphi technique to ascertain the most pivotal indicators. The outcomes of this examination are elucidated in Table 5.

Table 4. Indicators for assessing the maturity level of supply chain processes in the automobile manufacturer.

Criteria	Sub-criteria	References
Integration and coordination	Existence of information system Process ownership Order time cycle Software networking (information flow and materials) Leadership Financial support required Simultaneous engineering	Salami et al. (2022); Gorji (2023); Salari et al., (2022)
Strategy	Existence of process strategy The fit of the process strategy with the strategy of the organization Strategy efficiency Innovation-based strategy Reduction in startup time	Abazari et al. (2021); Oh et al., (2022); Ehsani et al., (2023)
Resilience	Stability Capacity (assets and resources of the organization) Recovery Adaptation Compatibility	Aghsami et al., (2023); Abbaspour et al., (2023)
Improvement and development	Teaching and learning Innovation Update customer relationship management Quality and performance development Cooperation based on competencies Improving manpower	Cho et al., (2022); Gu et al., (2023)
Agility	Flexibility Accountability speed Competence Design and integration of processes Proportional planning Sensitivity and responsiveness to the market	Abazari et al., (2021); Gu et al., (2023); Cho et al., (2023)

Table 5 depicts the outcomes of the fuzzy Delphi method implemented to discern the foremost markers for evaluating the degree of maturity of supply chain processes in the automobile manufacturer.

According to this analysis, 15 indicators with a crisp value surpassing 0.7 were identified as the most pivotal. Subsequently, the conceptual model of the research, founded on these findings, is visually represented in Figure 3.

Table 5. Results of screening indicators

Indicators	Outcome	Crisp value	Fuzzy average
Existence of information system	Acceptance	0.842	(0.709,0.868,0.95)
Process ownership	Rejection	0.578	(0.414,0.605,0.716)
Order time cycle	Rejection	0.476	(0.291,0.473,0.664)
Software networking (Information flow and materials)	Acceptance	0.756	(0.605,0.773,0.891)
Leadership	Acceptance	0.767	(0.609,0.786,0.905)
Financial support required	Rejection	0.526	(0.313,0.741,0.525)
Simultaneous engineering	Rejection	0.557	(0.425,0.587,0.658)
Existence of process strategy	Acceptance	0.790	(0.623,0.814,0.932)
The fit of the process strategy with the strategy of the organization (Strategic alignment)	Acceptance	0.921	(0.818,0.945,1)
Strategy efficiency	Acceptance	0.712	(0.577,0.727,0.832)
Innovation-based strategy	Rejection	0.516	(0.336,0.518,0.695)
Reduction in startup time	Rejection	0.544	(0.345,0.55,0.736)
Stability	Rejection	0.576	(0.289,0.654,0.785)
Capacity (assets and resources of the organization)	Acceptance	0.858	(0.732,0.882,0.959)
Recovery	Acceptance	0.936	(0.845,0.964,1)
Adaptation	Rejection	0.418	(0.245,0.414,0.595)
Compatibility	Acceptance	0.936	(0.845,0.964,1)
Teaching and learning	Acceptance	0.921	(0.823,0.95,0.991)
Innovation	Acceptance	0.873	(0.75,0.891,0.977)
Update	Acceptance	0.835	(0.691,0.855,0.959)
Customer relationship management	Rejection	0.451	(0.291,0.445, 0.618)
Quality and performance development	Rejection	0.613	(0.325,0.634,0.634)
Cooperation based on competencies	Rejection	0.671	(0.458, 0.741,0.814)
Improving manpower	Rejection	0.695	(0.577,0.727,0.781)
Flexibility	Acceptance	0.883	(0.759,0.909,0.982)
Accountability speed	Acceptance	0.842	(0.709,0.868,0.95)
Competence	Rejection	0.684	(0.550,0.701,0.801)
Design and integration of processes	Acceptance	0.797	(0.632,0.818,0.941)
Proportional planning	Rejection	0.492	(0.327,0.491,0.659)
Sensitivity and responsiveness to the market	Rejection	0.564	(0.373,0.568,0.75)

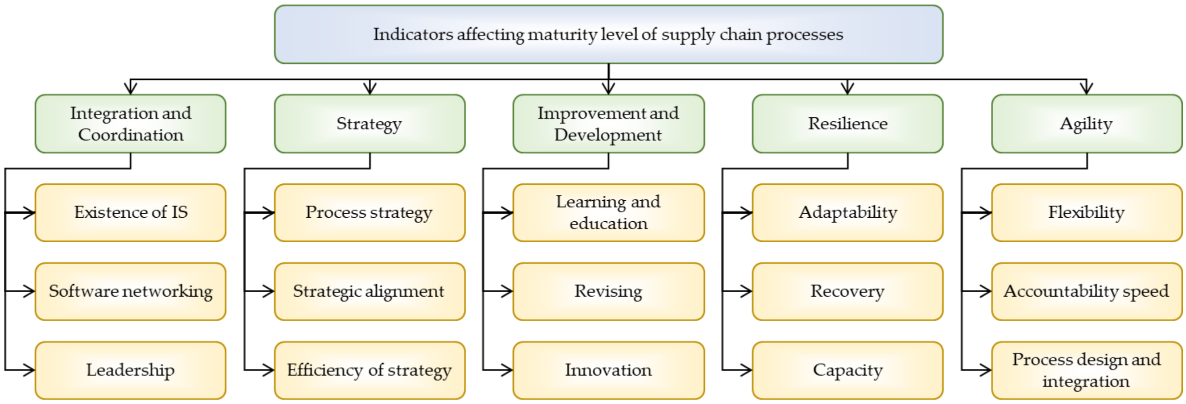

Figure 3. Supply chain process of project maturity assessment model.

4.2. Determining causal relationships: Using Fuzzy DEMATEL

The next step involved using the fuzzy DEMATEL technique to determine the causal relationships between the evaluation indicators of supply chain processes. Table 6 displays the results of this method.

Table 6. Values of $\widetilde{D}$, $\widetilde{R}$, $\widetilde{D}+\widetilde{R}$, $\widetilde{D}-\widetilde{R}$

Criteria	$\widetilde{D}-\widetilde{R}$	$\widetilde{D}+\widetilde{R}$	$\widetilde{R}$	$\widetilde{D}$
Process strategy	0.113	3.285	1.586	1.699
Strategic alignment	2E-04	3.394	1.697	1.697
Efficiency of strategy	-0.113	3.425	1.769	1.656
Learning and education	0.229	3.484	1.627	1.857
Revising	-0.058	3.579	1.818	1.76
Innovation	-0.171	3.588	1.88	1.708
IS	0.059	3.495	1.718	1.777
Software networking	-0.113	3.259	1.686	1.573
Leadership	0.054	3.525	1.736	1.789
Adaptability	-0.056	3.067	1.561	1.506
Recovery	-0.19	2.893	1.541	1.351
Capacity	0.246	2.804	1.279	1.525
Flexibility	0.093	3.524	1.716	1.808
Accountability speed	-0.071	3.486	1.778	1.707
Process design and integration	-0.022	3.404	1.713	1.691

Indicators that have a positive $\widetilde{D}$-$\widetilde{R}$ according to Table 6 influence other factors, while factors with negative $\widetilde{D}$-$\widetilde{R}$ are influenced by other factors. A cause-and-effect diagram of the indicators is shown in Figure 4, where points with coordinates $\widetilde{D}$+$\widetilde{R}$ and $\widetilde{D}$-$\widetilde{R}$ are plotted based on the $\widetilde{T}$ matrix in a Cartesian coordinate system.

4.3. Determining the importance of criteria: Using Fuzzy ANP

In this section, the F-ANP approach is used to prioritize evaluation indicators related to supply chain processes. The F-DEMATEL technique generates a complete relations matrix, which is then used as input for the F-ANP method.

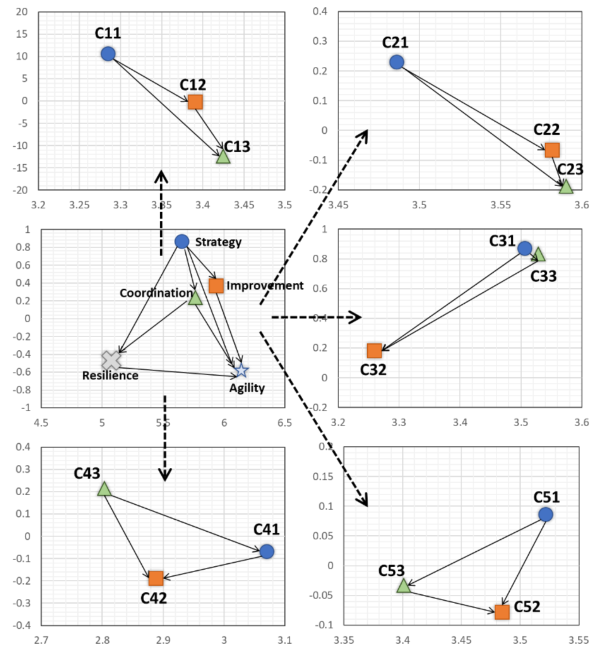

Figure 4. Causal diagram and network map between the main and sub-factors

Table 7. Weight and rank of indicators for assessing the maturity level of supply chain processes.

Weight and priority of the main factors		Sub-criteria	Code	Relative weight and pri		Final weight and priority of sub-criteria	
Strategy C1	0.169 (5)	Process strategy	C11	0.308	3	0.0522	15
		Strategic alignment	C12	0.346	2	0.0585	13
		Efficiency of strategy	C13	0.346	1	0.0586	12
Improvement and development C2	0.199 (2)	Learning and education	C21	0.296	3	0.059	11
		Revising	C22	0.346	2	0.0687	6
		Innovation	C23	0.358	1	0.0712	4
Integration and coordination C3	0.194 (3)	IS	C31	0.333	2	0.0647	9
		Software networking	C32	0.325	3	0.0631	10
		Leadership	C33	0.342	1	0.0664	8
Resilience C4	0.193 (4)	Adaptability	C41	0.365	1	0.0706	5
		Recovery	C42	0.35	2	0.0676	7
		Capacity	C43	0.286	3	0.0549	14
Agility C5	0.245 (1)	Flexibility	C51	0.323	3	0.079	3
		Accountability speed	C52	0.35	1	0.0857	1
		Process design and integration	C53	0.327	2	0.0799	2

Table 7 indicates that the "Accountability speed" factor holds the highest weight and is given first priority in the evaluation. Other factors such as "process design and integration", "flexibility", "innovation (improvement)", "adaptability", and "updating (revision)" hold two to six priorities out of 15 factors, which amount to approximately 45.40% of the total weight of factors. This highlights the significant importance of these sub-factors. Additionally, Figures 5 and 6 illustrate the weight chart of the main criteria used to assess the maturity level of supply chain processes in the automobile manufacturer.

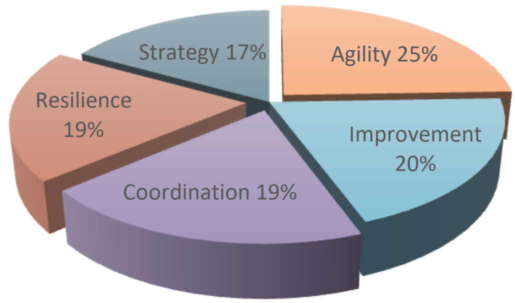

Figure 5. The weight of the main criteria for assessing the maturity level of supply chain processes.

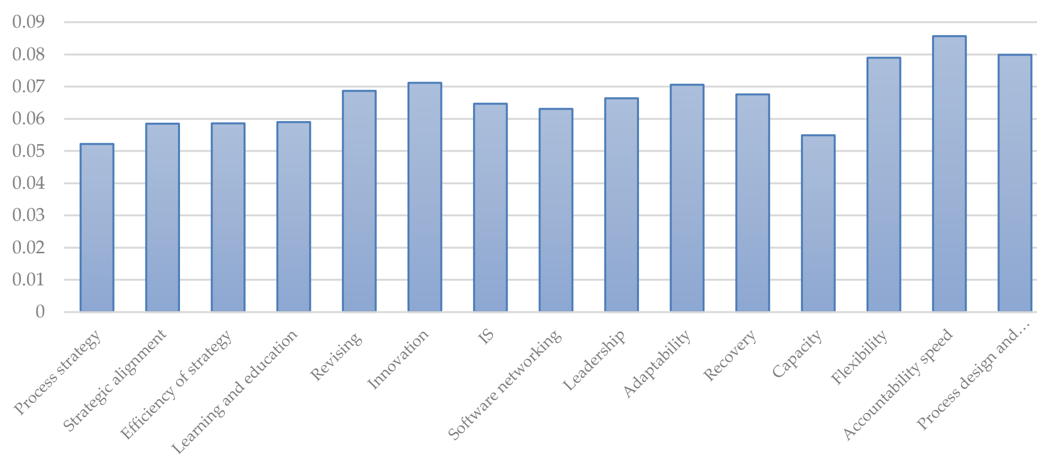

Figure 6. Weight of sub-criteria for assessing the maturity level of supply chain processes.

4.4. Assess the maturity level of supply chain processes based on the PST model and managerial insight

The maturity level of industry supply chain processes was assessed by evaluating the responses of field experts to a maturity level questionnaire. The questionnaire consisted of maturity level assessment indicators of industry supply chain processes identified in previous stages, which were evaluated on four levels: informal, functional, integrated, and developed.

Experts assigned one of these levels to each of the 15 sub-criteria identified, and final scores were determined using the fuzzy method. The indicators were then classified into three categories: customer relationship management, internal processes, and supplier relationship management. Table 8 displays the results of implementing the maturity model for these three categories.

Table 8. Results of PST model implementation in automobile manufacturer

Processes / maturity level	Level 1 (Informal)	Level 2 (Functional)	Level 3 (Integrated)	Level 4 (Developed)	Process maturity score
Customer relationship management	2.94	27.23	69.14	0.69	2.68
Internal processes	0	13.4	78.23	8.35	2.95
Supplier relationship management	0	9.9	73.22	16.84	3.07
The total score of the industry supply chain maturity					2.9

Table 8 presents an overview of the supply chain process maturity levels attained by an automotive manufacturer, indicating the highest scores in customer relationship management, internal processes, and supplier relationship management at the integrated level (level 3). The total supply chain score was computed as the average of the maturity scores, which amounted to 2.9. These findings illustrate that the maturity level of the industry's supply chain processes is currently at the integrated level (level 3). Therefore, it is recommended that the industry align its processes with the corresponding maturity level achieved at this stage.

4.5. Managerial insights

Here are some managerial insights related to your paper on evaluating the maturity level of supply chain processes in an automobile manufacturer:

- **Importance of Maturity Models**: The paper underscores the importance of using maturity models as a tool for assessing and improving supply chain processes. Maturity models provide a structured framework for understanding where an organization stands in terms of process maturity and what steps are needed for improvement. This insight highlights the relevance of maturity models in supply chain management across various industries.
- **Identification of Key Dimensions**: The paper identifies five main dimensions for assessing supply chain maturity: integration and coordination, strategy, resilience, improvement and development, and agility. This categorization highlights that supply chain maturity is a multi-dimensional concept, and managers should consider these aspects when evaluating and enhancing their supply chains.
- **Fuzzy DEMATEL and Fuzzy ANP**: The use of Fuzzy DEMATEL and Fuzzy ANP techniques for prioritizing and identifying relationships among indicators is a notable methodological approach. Managers can learn from this and consider employing advanced analytical techniques to gain deeper insights into their supply chain processes, especially when dealing with complex and interrelated factors.
- **Focus on Customer Relationship Management**: The research findings indicate that customer relationship management is an area where improvement is needed. This underscores the importance of customer-centricity in supply chain management. Managers should prioritize efforts to enhance customer relationships and satisfaction as it can have a significant impact on overall supply chain performance.
- **Knowledge Sharing:** Effective knowledge sharing with supply chain partners is suggested as a critical step towards improving customer relationship management. This emphasizes the role of collaboration and information exchange in supply chain excellence. Managers should invest in strategies and technologies that facilitate knowledge sharing among supply chain stakeholders.
- **Limitations and Generalizability**: The paper acknowledges the limitations of its research, particularly its non-generalizability to other industries or countries. This highlights the need for managers to consider the uniqueness of their industry or region when applying supply chain evaluation models. It's essential to adapt and customize approaches to specific contexts.

5. Conclusion

The primary objective of supply chain evaluation models across various industries, including the automotive industry, is to ensure the effectiveness and efficiency of supply chain processes while meeting the end consumer's needs. Among the various evaluation models, maturity models serve as a basis for comparing, evaluating, and enhancing supply chain processes. This study aimed to present a model to evaluate the maturity level of supply chain processes in the country's automotive industry. The research collected data using a questionnaire from 20 experts. Based on the research objectives, experts' opinions on supply chain maturity indicators were gathered, and 15 indicators were selected, categorized into five main dimensions: integration and coordination, strategy, resilience, improvement and development, and agility. The research then utilised fuzzy DEMATEL and fuzzy ANP approaches to prioritize relationships and indicators. Based on the findings, "responsiveness speed" was identified as the most crucial factor, followed by "process design and integration," "flexibility," "innovation (improvement)," "adaptability," and "updating (reviewing)." The maturity level of each process and the entire supply chain of the automotive industry were assessed based on the PST model.

The results showed that the supplier relationship management process had the highest maturity score, while the customer relationship management process had the lowest among the industry supply chain processes. Although the overall score for the industry supply chain was 2.9, improvements were required in customer relationship management to elevate all supply chain processes to maturity level 4. Effective knowledge sharing with supply chain partners was suggested as a crucial step towards achieving this goal.

However, the study's non-generalizability to other domestic industries or the automotive industry in other countries is a limitation. This is because the structure of the automotive industry in Iran is unique, and it may not be applicable to other industries or countries. Therefore, other industries are recommended to utilize maturity models to self-assess their current supply chain processes and strive to improve continuously. Additionally, using a larger number of questionnaires to evaluate and monitor the maturity level would enhance the credibility of the results alongside the self-declaration method used in this study.

One limitation of the proposed model for supply chain management maturity assessment is the potential challenge of generalizability. The model may have been developed based on specific industry contexts or organizational settings, which could limit its applicability to a broader range of industries or diverse organizational structures. Future research may be needed to validate the model across different sectors to ensure its generalizability. Another limitation is the inherent subjectivity involved in assessing supply chain management maturity. The interpretation of maturity levels and the scoring of different dimensions may vary based on individual perceptions or biases of assessors. This subjectivity could introduce inconsistencies in the assessment process and impact the reliability and validity of the results.

Therefore, for future studies could focus on validating the proposed supply chain management maturity assessment model across a diverse range of industries. Investigating how the model performs in various sectors could provide valuable insights into its applicability and effectiveness in different organizational contexts. Also, Given the rapid advancement of technologies such as block chain, artificial intelligence, and Internet of Things in supply chain management, future studies could explore how the integration of these technologies impacts supply chain maturity levels. Investigating the role of emerging technologies in enhancing supply chain capabilities and maturity could provide valuable insights for organizations seeking to stay competitive.

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

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