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Enhancing Supply Chain Safety and Security: A Novel AI-Assisted Supplier Selection Method

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ABSTRACT

The "Make or Buy" decision and the supplier selection are critical steps for the efficient operation of companies' supply chains. Safety and security are paramount considerations, especially in industries like logistics, where supply chains are vulnerable to external threats and disruptions. In this scientific article, we present a novel Artificial Intelligence (AI)-assisted supplier selection method that significantly enhances the safety and security of suppliers. During our research project, we have created an expert system and a corresponding knowledge base with the relevant rules to support supply chain decision-makers in selecting logistics service providers for warehousing services. The foundation of the AI-assisted supplier selection method is advanced data analytics and the application of expert systems, enabling companies to evaluate potential suppliers in detail from a safety and security perspective. The applied expert systems can identify potential risks and make predictions about supplier performance in the future. In the turbulent environment of the global supply chain, selecting long-term partners like warehousing services providers is critical for the success of the organization. A wrong supplier selection can hardly be reversed in warehousing services, as the cost of change is usually high. The article demonstrates the practical application of the expert system-assisted supplier selection method in a real-world supply chain environment and thoroughly analyzes the achieved results and advantages. The results show that the expert system-assisted method not only increases supplier safety and security but also contributes to improving the efficiency and sustainability of the supply chain. This article provides valuable guidance and solutions for companies looking to enhance their supplier selection using expert system technologies, thereby increasing the safety and security of their supply chains.

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1. Introduction

Due to the business environment's pace of changes and development, intelligent decisions in business have become a crucial success factor [1–3]. One of the firms' critical decisions in the make-or-buy domain is the outsourcing of logistics [4]. When deciding to outsource, the decision-making firm compares the supplier's cost with its costs for organizing and performing specific logistics processes [5,6]. Outsourcing part of the value creation in the supply chain to logistics service providers (LSP) is a crucial step for a company. There are potential benefits regarding competitiveness [7]. However, there are also considerable drawbacks, such as relationship, asset, and competence risks [8]. The drive behind logistics outsourcing is always the potential gain through access to third-party resources, capabilities, skills, and knowledge. As we are at the tipping point of the digital technology-driven industrial revolution, advanced methods are emerging in the context of supporting business processes [9,10]. There is a broad literature about selecting suppliers, mainly using Technique for Order Preference by Similarity to Ideal Solution method (TOPSIS) [11], analytical hierarchical process (AHP) [12] or goal programming (GP) [13], or multi-criteria decision-making method (MCDM) in the operations research domain [14]. MCDM is a popular approach [15] since the problem is about selecting multiple suppliers in logistics, and the decision needs to satisfy multiple stakeholders, while AHP is used frequently for prioritization and definition of the alternatives ranking [16,17]. AHP and MCDM have certain limitations regarding long-term strategic decisions that must be made relatively quickly [18,19]. Authors may also use hybrid solutions of TOPSIS and Shannon entropy [20]. As well as alternatives to MCDM, like fuzzy multi-criteria decision-making (FMCDM), fuzzy analytic hierarchy process (FAHP), and fuzzy TOPSIS (FTOPSIS) [21]. Alkhatib *et al.,* [22] attempted to find a causal relationship between LSPs' resources and capabilities with the Fuzzy decision-making trial and evaluation laboratory (FDEMATEL) method. However, these techniques are incredibly impactful in the case of less complex problem-solving situations [23].

Our paper utilizes an expert system that creates a novel model for LSP selection. Expert systems are widely used in decision support or recommendation systems [24,25]. During the research project, we developed an expert system by knowledge acquisition and knowledge engineering process [26].

Our model has been tested in real-life outsourcing projects. In this paper, we elaborate on a case about the LSP selection process in Japan for warehousing services. In the logistics outsourcing process, we can distinguish between the different services. Such as transportation, warehousing, fulfilment, customs brokerage [17,27], or other value-added services in the supply chain like additive manufacturing [28]. Warehousing and fulfilment are the most difficult categories regarding long-term decision-making. Once the outsourcing decision is taken and the supplier is selected, it is complicated to change this decision related to warehousing services. In the case of transportation or customs brokerage, the change of the service provider is simple. Typically, these business relationships are also more dynamic. Due to the high stake in choosing the warehousing service provider, we developed a model that focuses on highlighting the options that have a high risk and severe impact on the supply chain [29]. Our knowledge-based model represents the key attributes that must be considered when choosing a service provider, especially for the long term. The associated costs [30], risk, and effort to reverse a supplier selection decision for warehousing services are enormous. So, it is a high-risk decision for a firm aiming to buy the services. However, at the same time, the warehousing services are the minor profit-making businesses of the logistics service providers [31]. These services require capital investments in real estate and machinery. Often, the suppliers are not allowed to terminate warehousing contracts for several years due to the earlier-mentioned risk on the customer side. Customers do not allow the suppliers to terminate the services; therefore, the suppliers' exposure to a potentially harmful relationship is significant.

The market of logistics, and especially for warehousing services, is scattered. There are countless suppliers, global, regional, and local. In warehousing services, there is no significant competitive advantage on the supplier side. Most of the suppliers use the same technology and same processes. Very few of them are at the forefront of digitalization and robotization with minor results yet. Usually, local branches of global logistics service providers control their destiny, e.g., they possess complete control over profit and loss. That means that the local branches make the real difference between the suppliers. In the case of a strong local organization, the service, cost, and reliability are on a higher level compared to another organization whose local branch could be more robust. Therefore, it is a complex decision, especially for a single warehouse operation and a longer time. There are many potential choices with seemingly insignificant differences. However, there are differences between service providers, but those are not easy to identify.

Our two research questions focused on finding the critical factors and variables from which we can develop a comprehensive theoretical framework for LSP selection and how AI techniques can support decision-making in vendor selection problems in a complex commodity. In our research project, we build a unique knowledge base and the corresponding rules for vendor selection problems in the warehousing services domain. We test the results in a real-life large-scale project of setting up a new distribution center in Japan. Contrary to the existing literature, we decided not to explore another MCDM method but to use the ID3 algorithm and decision tree in our decision support system. That is a novel approach to the vendor selection problem. Hence, our solution can handle a higher level of complexity than the traditional methods.

Our research process followed the logic of Saunders *et al.,* [32] related to applied research as per Figure 1.

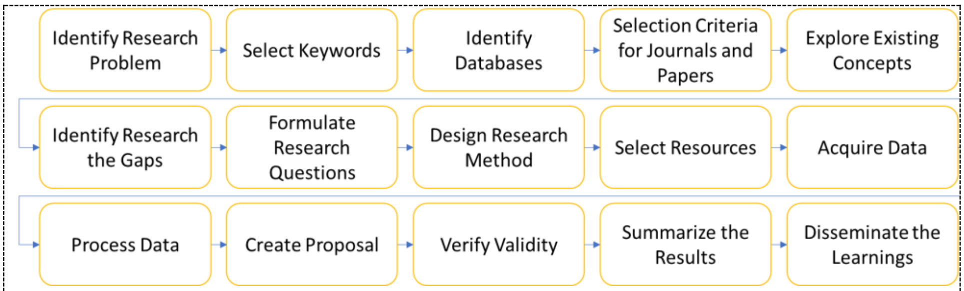

Fig. 1. Applied research process

The following sections of the paper will consist of a comprehensive literature review of the topic, the research gap identification, the data collection and research method, the results and the discussion parts, and lastly, the limitations of the research as well as future research direction that addresses it.

2. Literature review and conceptual framework

The literature review aimed to search for existing knowledge in vendor selection, precisely supplier selection in the logistics service provider commodity, and the existing solutions for decision support in that field. Our objective was to see how supply chain and logistics experts' knowledge could be synthesized into the decision-making process, as the LSP selection for warehousing is a complex problem.

We began our literature review by identifying the critical journals from Scopus, Web of Science, and Google Scholar. We used keyword combinations for search such as LSPor for example

"Knowledge Representation AND Cognitive Bias AND Supplier Selection", as well specifically "Logistics Service Provider Selection AND Expert Systems". Based on the findings, we identified 42 journals that may have relevant papers, and after studying them in detail, we have selected 30 journals.

Based on the expert interviews and our initial hypothesis of utilizing an expert system to solve this complex problem, we found four critical concepts: 1) LSP Selection, 2) Knowledge Representation, 3) Expert System, and 4) Decision-taking. During the literature review, we studied 83 papers from the selected journals and identified 55 as relevant to our research problem. The papers can be seen in Table 1, sorted according to the identified categories.

Table 1
Concept matrix

Source	Concept			
	LSP Selection	Knowledge Representation or Acquisition	Expert System	Decision making
Development of a case-based intelligent customer-supplier relationship management system			X	
Development of a decision support system for supplier evaluation and order allocation				X
A decision support system for strategic issues management of logistics	X			
A decision support system for supplier selection and order allocation in stochastic, multi-stakeholder and multi-criteria environments	X			
A fuzzy-Bayesian model for supplier selection	X			
A knowledge-based experts' system for evaluation of digital supply chain readiness			X	
A logistics provider evaluation and selection methodology based on AHP, DEA and linear programming integration.	X			
A model of a decision support system based on case-based reasoning for third-party logistics evaluation				X
A new trend for knowledge-based decision support systems design.				X
A novel technique for evaluating and selecting logistics service providers based on the logistics resource view	X			
An approach and decision support tool for forming Industry 4.0 supply chain collaborations				X
An Empirical Taxonomy for Logistics Service Providers	X			
An improved model for supplier selection under capacity constraint and multiple criteria	X			
Application of decision-making techniques in supplier selection: a systematic review of literature	X			
Categorization of knowledge graph-based recommendation methods and benchmark datasets from the perspectives of application scenarios: A comprehensive survey		X		
Deciding how to decide				X
Decision support for risk analysis on dynamic alliance			X	
Deriving knowledge representation guidelines by analyzing knowledge engineer behavior		X		
Detecting mismatches among experts' ontologies acquired through knowledge elicitation			X	

Source	Concept			
	LSP Selection	Knowledge Representation or Acquisition	Expert System	Decision making
Developing a decision support system for logistics service provider selection employing fuzzy MULTIMOORA & BWM in mining equipment manufacturing	X			
Explainability in supply chain operational risk management: A systematic literature review			X	
How additive manufacturing drives business model change: The perspective of logistics service providers	X			
If-then scenarios: Smart decisions at SMEs				X
Integrating (rules, neural networks) and cases for knowledge representation and reasoning in expert systems		X		
Intelligent decision making for service providers selection in maintenance service network: An adaptive fuzzy-neuro approach	X			
Knowledge Acquisition for Expert Systems: A Practical Handbook		X		
Knowledge-based expert systems: User interface implications			X	
Knowledge engineering: Principles and methods		X		
Knowledge acquisition in the fuzzy knowledge represen tation framework of a medical consultation system		X		
Leveraging global sources of knowledge for business model innovation		X		
Logistics provider selection for omnichannel environment with fuzzy axiomatic design and extended regret theory	X			
Logistics service provider selection decision making for healthcare industry based on a novel weighted density-based hierarchical clustering	X			
Logistics Service Providers (LSPs) evaluation and selection: Literature review and framework development	X			
Logistics Service Providers and Value Creation Through Collaboration: A Case Study	X			
Model-driven decision support systems: Concepts and research directions				X
Modelling expert knowledge.		X		
New trends on e-Procurement applying semantic technologies: Current status and future challenges				X
New research directions for data and knowledge engine ering: A philosophy of language approach		X		
Outsourcing modelling using a novel interval-valued fuzzy quantitative strategic planning matrix (QSPM) and multiple criteria decision-making (MCDMs)	X			
Personal Knowledge		X		
Reductive reasoning				X
Risk knowledge modelling for offer definition in customer-supplier relationships in Engineer-To-Order situations			X	
Selection criteria for providers of third-party logistics services: an exploratory study	X			

Source	Concept			
	LSP Selection	Knowledge Representation or Acquisition	Expert System	Decision making
Semantic multi-agent system to assist business integration: An application on supplier selection for shipbuilding yards				X
Smart Decisions: DoctuS chooses a CLO Managerial Challenges of the Contemporary Society			X	
SPARTA II: Further development in an expert system for advising on stocks of spare parts			X	
Strategic supplier selection using multi-stakeholder and multi-perspective approaches	X			
Supplier Selection with Shannon Entropy and Fuzzy TOPSIS in the Context of Supply Chain Risk Management☆	X			
The dark side of logistics outsourcing–unravelling the potential risks leading to failed relationships	X			
The relative importance of cost and quality in the outsourcing of warehousing	X			
The search for knowledge, contexts, and case-based reasoning.		X		
Third-party logistics selection problem: A literature review on criteria and methods	X			
Third-party reverse logistics provider selection: A computational semantic analysis-based multi-perspective multi-attribute decision-making approach	X			
Trends in expert system development: A longitudinal content analysis of over thirty years of expert system case studies			X	
What drives the choice of a third-party logistics provider?	X			

In the third phase of the literature review, we aimed to identify the research gap. According to [33], there are six potential gaps: “methodological conflict," “contradictory evidence," “knowledge void," “action-knowledge conflict," “evaluation void," and “theory application void." In Table 2, we listed the potential knowledge gaps and identified two based on the rigorous literature review process.

Table 2
Types of research gaps

Types of research gaps	Localization Strategy
Knowledge void	Analyse literature with regard to theoretical concepts (e.g., using the chart method) and look for specific gaps or under-researched areas of research.
Evaluation void	Analyse if research findings have been evaluated and empirically verified.

Based on the studied scientific papers, there is a gap when it comes to the existing theoretical concepts of logistics service provider selection by using advanced techniques, especially when it comes to original decision making; for instance, rule-based reasoning based on tacit knowledge of experts [34]. There are papers about case-based reasoning models [35–37]. See below Figure 2, showing that the knowledge-based expert systems need more representation in the existing literature, based on the keywords and concepts that previously explained in the literature review section.

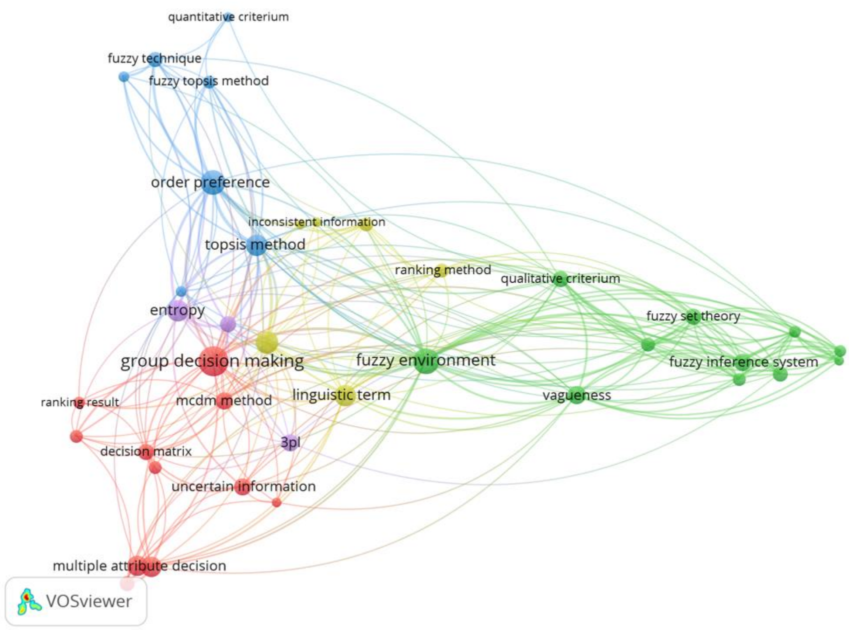

Fig. 2. Literature review – network visualization based on co-occurrence of keywords.

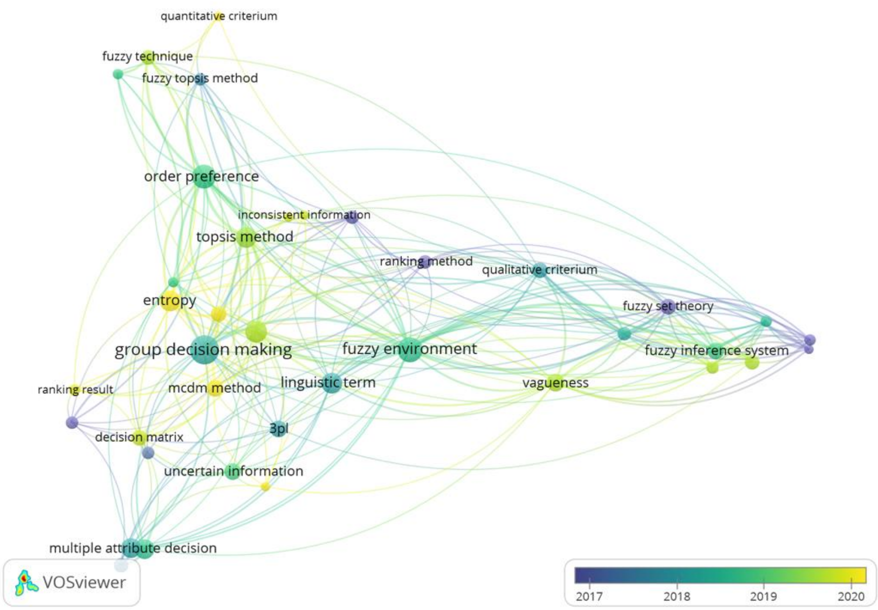

Fig. 3. Overlay visualization based on co-occurrence of keywords

In Figure 3, it is visible that the identified keywords from the literature that have at least 4 cases of co-occurrence changed over the last years. Towards 2020 and beyond, the results are lower and they are about entropy and MCDM, as well as showing the cyclical nature of these research projects. The difference between Figure 2 and Figure 3 is that in Figure 3 we can see the temporal distribution of the existing concepts in the literature, while on Figure 2 the network of the concepts based on co-occurrence.

We identified the need for empirical data from the field. Theoretical concepts must be verified with real-life empirical data to confirm or reject the corresponding theories. To address that topic, we completed a case study to provide the necessary empirical evidence [38]. Employing AI systems in decision-making is relatively new, which makes case studies an appropriate method to gain insights and understand the phenomenon [39].

Based on the above-identified gaps, we have formulated the research questions and designed the research to address these topics.

Q1: What are the key factors and variables that should be considered in developing a comprehensive theoretical framework for logistics service provider selection using AI, and how can these factors be structured and integrated to enhance decision-making processes?

Q2: How can the application of advanced AI techniques be leveraged to create a predictive model for logistics service provider selection that not only optimizes cost and efficiency but also considers dynamic factors such as real-time market conditions, supplier performance, and sustainability criteria?

3. Data and Method

To answer the Q1 research question, we have prepared a knowledge acquisition process. Knowledge acquisition is a critical process in the creation of the expert system. At the same time, it is a challenging task due to the difficulty of making transparent and understandable the various representations- and the different forms of knowledge [40–43]. There are many ways of acquiring expert knowledge. It can be done in the form of interviews that collect attributes and the corresponding values and create the if-then rules between the attributes [34, 44, 45], or using Matlab’s fuzzy input analyser [46]. We designed the method to collect the sub-symbolic information from experts and apply that information into a pre-defined shell system that organizes the attributes and values into tables, the rules into matrixes, and form a decision tree based on the most powerful attribute on a level when it comes to information gain.

To address the Q2 research question, we decided to test the system in an LSP selection project in Japan. The project was a supplier selection case in which the test company aimed to open a new warehouse in Tokyo, Japan, in a relatively short timeline (3 months) with no disruption of customer deliveries. We defined the criteria for success as follows:

i. The system can support decision-making in the supplier selection process.
ii. The company does not select a supplier not recommended by the system.
iii. The project was delivered on time and without process quality defects.
iv. We requested short ‘post-mortem’ feedback from the key stakeholders:
    a. Head of Market Operations, Asia-Pacific-Japan Region
    b. Head of Market Operations, Market Unit Japan
    c. Transformation Manager
    d. Head of Global Distribution
    e. Warehouse Manager
    f. Sourcing Manager - Japan

Besides the Japan project members, we have completed an interview (Table 3) with the Sourcing Manager who ran a similar project previously in Brazil, in which a traditional scorecard was used for supplier selection.

Table 3
Company Stakeholder Interviewees

ID	Role	Service years at the company	Service years in the current role
HMOAPJ	Head of Market Operations Asia-Pacific-Japan Region	15	2
HMOJP	Head of Market Operations, Japan	13	2
TM	Transformation Manager	25	11
HGD	Head of Global Distribution	20	5
WM	Warehouse Manager	18	10
SM1	Sourcing Manager – Japan case	5	5
SM2	Sourcing Manager – Brazil case	27	12

4. Result

In the case study, we used an expert system based on the ID3 (Iterative Dichotomiser 3) algorithm [47]. ID3 is based on Shannon's information theory. The ID3 algorithm, widely employed for classification tasks, relies on Shannon's entropy to quantify uncertainty in datasets with respect to class labels. The ID3 algorithm creates decision trees iteratively by selecting features with the highest information gain at each node. Entropy, a core concept in information theory forms the basis for decision-making in the ID3 algorithm. The reduction of entropy while splitting dataset based on specific feature develops the information gain.

Shannon's entropy is expressed as H (X), it quantifies information or surprise associated with a random variable X. In the context of ID3, entropy is used to measure uncertainty in datasets. The formula is the following $H(X) = -\sum_{i=1}^{n} P(x_i) \cdot \log_2\big(P(x_i)\big)$ where $P(x_i)$ represents the probability of each class label x_i in the dataset. Information gain (IG) is calculated for dataset D and feature $F = \{v_1, v_2, \ldots, v_m\}$, as $IG(D,F) = H(D) - \sum_{j=1}^{m} \frac{|D_j|}{|D|} \cdot H(D_j) \cdot \log_2\big(P(x_i)\big)$. It calculates the difference in entropy before and after splitting the dataset based on the given feature.

Our expert system has two solutions, Rule-Based-Reasoning and Case-Based-Reasoning [36, 48, 49]. Rule-based reasoning is useful for original decision-making when we do not have enough data or cases to apply case-based reasoning [50]. There are hybrid solutions as well that use rule- and case-based reasoning at the same time [51]. To set up a rule-based system, we must go through the knowledge acquisition and knowledge engineering process. The general knowledge engineering process is visible in Figure 4. The goal of knowledge engineering is to create information that an algorithm can process, and field experts can understand [52].

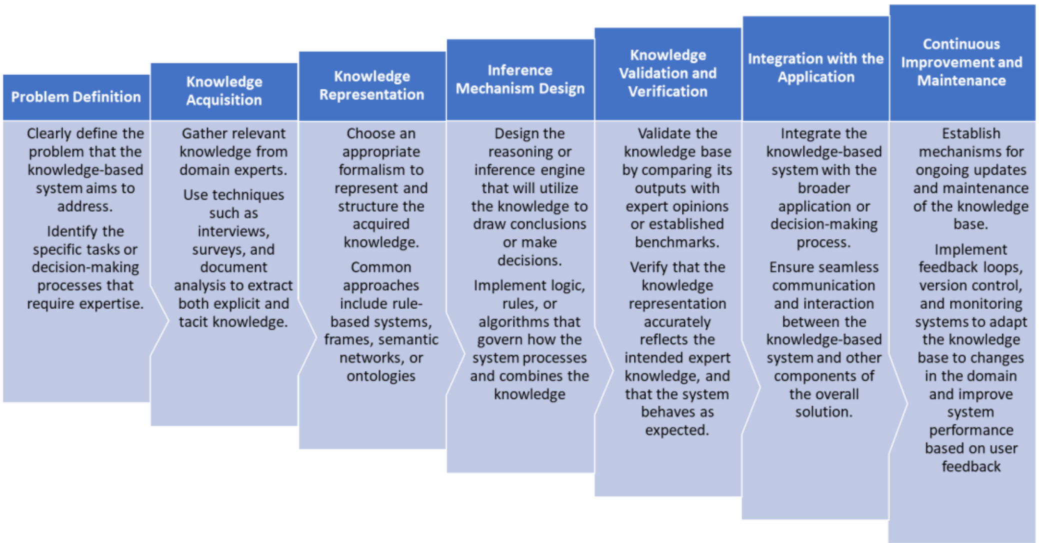

Fig. 4. Generic Knowledge Engineering Process

The basics of supplier selection strategy are usually straightforward, like Technology – Quality – Cost – Delivery Performance [53]; however, in the case of services sourcing, there is a need for a more complex approach. We have selected experts from three groups for the interviews to build our knowledge base and system of rules, see Table 4. Group 1 consists of two interviewees who have an academic career, and besides that, both work part-time at a consulting firm in the logistics market. In Group 2, we have one interviewee who works as Head of Global Sourcing in Logistics and participates in a Ph.D. course. The last two interviewees have over 20 years of experience in logistics and supply chain, and currently, one of them is heading a factory logistics team. The other one is leading the supply chain organization at his respective company. We aimed to deliver primarily external knowledge to the pilot firm of the case study, which has its limitations. However, according to von [54], it may have a positive impact on innovation of existing business practices.

Table 4
Expert Interviewees

Group	Interview ID	Age	Education	Occupation	Work Experience	Academic Experience
1	1	47	PhD	Assistant Professor	20+ years	Researcher, Lecturer
	2	35	PhD	Assistant Professor	10+ years	Researcher, Lecturer
2	3	42	PhD Candidate	Head of Global Sourcing (Logistics)	20 years	Researcher
3	4	45	Masters	Head of Logistics	20+ years	NA.
	5	42	Masters	Head of Supply Chain	20 years	NA.

During the interview, we went through a structured format that first asked about the most important attributes when selecting the LSPs for a three-year contract period. Second, we asked the interviewees to define values for the attributes from worst to best in the expert system [55]. After this part had been completed, we worked on the gathered information and built the combined attribute and value matrix. Once the matrix had been completed, we worked with the interviewees to define the “If-Then” rules between the attributes [56].

The target variable of the expert system was to define if a supplier (for warehousing services for three years) is “not recommended," “acceptable with risk," or “recommended." For this purpose, we identified thirty attributes. The thirty attributes are:

- i. Total Cost of Ownership (TCO)
- ii. Minimum conditions
    - a. Quality Assurance minimum
        - i. Quality Assurance – Audit Results
        - ii. Historical Data
- iii. Administrative minimum
    - a. Risk Assessment result
        - i. Personal Risk
            1. Acquisitions and Takeovers
            2. Labor Attrition
        - ii. Financial Risk
            1. Financial Stability
            2. Ownership
            3. Compatibility
        - iii. Business Risk
            1. Spend and Revenue
            2. Supplier and Customer size
    - b. System Audit result
    - c. Qualifications
- iv. Capacity minimum
    - a. Equipment Capacity
    - b. Human Capacity
    - c. Logistical Capacity
        - i. Material Handling Capacity
        - ii. Customer Service Capacity
        - iii. Storage Capacity
- v. Reliability
    - a. Coordination Capability
    - b. Punctuality
- vi. Investment Cap vs. Solution

The attributes have different values that the interviewees define. We must use the terminology of the experts, so it is suitable to synthesize the knowledge of multiple experts into a single knowledge base. That makes the system powerful in dealing with complex problems. In the rule-based setup, the experts with the knowledge engineer must define the root node that is the starting point of the decision tree based on a criterion that maximizes information gain based on entropy. In the case of the decision support system presented in our case study, the "which(s)" attribute dependencies mean to allocate for each attribute on which other attributes it depends. To construct a hierarchy of attributes called a Rule-Based (or deductive) Graph (Figure 5). In the present application, drag-and-drop is used to construct the graph.

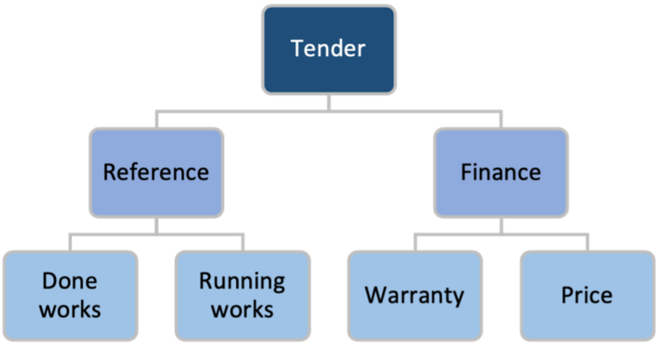

Fig. 5. The Rule-Based Graph

In the case-based reasoning approach, the algorithm itself can compute entropy and select the root node and continue to split the data based on the best criteria.

When we have finished the matrix of the attributes and their values, we have built the decision tree, as shown in Figure 6.

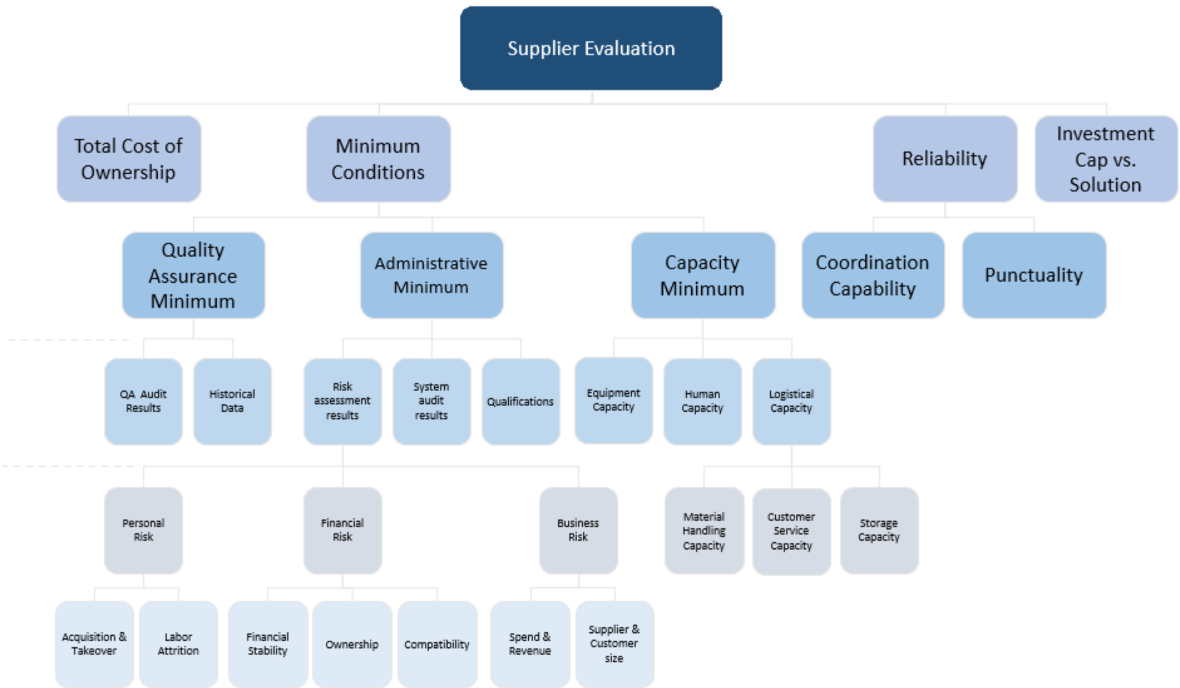

Fig. 6. Decision Tree of Logistics Service Provider Selection

Once the decision tree (Figure 6) had been built, we continued the work with the experts to define the rules. In the expert system, the rules shall give clear direction when multiple attributes merge into one branch. In this current expert system, we have defined 181 “IF Then” rules (Table 5). The table shows that the supplier's rating is based on "TCO", "Minimum Requirements", "Investment Cap", and "Reliability". The supplier is "Not recommended" if the "TCO" is high and "Reliability" is low. According to the rules of the decision maker, the supplier is suitable if the "TCO" is low, meets the "Minimum requirements", the "Investment Cap" is under, and its "Reliability" is also good. If the

"TCO" is high, the "Minimum requirements" can be improved, the "Investment cap" is low, and the "Reliability" is good, then the supplier can be considered acceptable with risk. It can be seen from the rules (Figure 5) that the "Minimum requirements" attribute is a decisive attribute because if it does not take the expected value, then all other attributes can take any value.

As a comparison, in the past, the company used a scorecard to evaluate suppliers' offers in the Request for Quotation (RfQ) process. Several stakeholders, including different organizational functions, filled out the scorecards, and the responsible sourcing manager consolidated the results. Each stakeholder had equal influence on the decision with his or her scoring. The traditional company scorecard from a previous project in Brazil included the following attributes, followed by the weight of each attribute in brackets:

i. Scope Coverage
   a. Understanding of the scope (6%)
   b. Covered all areas of the scope (7%)
ii. Capabilities
   a. Warehousing Toolset (6%)
   b. Warehousing Operations (6%)
   c. Warehouse Facility (6%)
iii. Reporting (10%)
iv. Customer Service (6%)
v. Track Record / Experience (4%)
vi. Contract Compliance
   a. Payment Term Compliance (3%)
   b. Liabilities Compliance (3%)
   c. Financial Consequences Compliance (3%)
   d. General Terms Compliance (3%)
   e. Adherence to Pricing and Understanding (1%)
vii. Strategic Fit
   a. In line with Client's strategy and business model (3%)
   b. Flexibility/Ease of Doing Business With (3%)
   c. Ease of Transition (10%)
   d. Pricing (20%)

Table 5
The "IF Then" rules

	Reliability	Low	Low	Average	Average	Good	Good
	Investment Cap	Above	Under	Above	Under	Above	Under
TCO	Minimum Requirements						
High	NOK	Not Recommended	Not Recommended	Not Recommended	Not Recommended	Not Recommended	Not Recommended
High	Improvable	Not Recommended	Not Recommended	Not Recommended	Acceptable with Risk	Not Recommended	Acceptable with Risk
High	OK	Not Recommended	Not Recommended	Not Recommended	Acceptable with Risk	Not Recommended	Acceptable with Risk

	Reliability	Low	Low	Average	Average	Good	Good
Low	NOK	Not Recommended	Not Recommended	Not Recommended	Not Recommended	Not Recommended	Not Recommended
Low	Improvable	Not Recommended	Acceptable with Risk	Not Recommended	Acceptable with Risk	Not Recommended	Acceptable with Risk
Low	OK	Not Recommended	Acceptable with Risk	Acceptable with Risk	Acceptable with Risk	Acceptable with Risk	Recommended

According to the Sourcing Manager, the challenge with the scorecard is that many of the attributes have binary values, e.g., the suppliers' offers are either compliant with the requested payment term or they are not. Also, stakeholders may need to be fully aware of how the suppliers understood the scope, as only some stakeholders are engaged to the deepest level in the RFQ process. In the project mentioned above, according to the SM2 "the selected supplier suffered for more than one year after the inauguration of the new warehouse to meet the operational targets and had to complete constant organizational changes during that ramp-up period of one year". According to SM2, "the main reason behind was the selected LSP's lack of experience of running warehousing operation of this customer and business, hence underestimating the required efforts." The entire RfQ process took over six months, yet the selected LSP needed help to ramp up the warehouse operation. "By difficulties, I mean that the operational Key Performance Indicators (KPIs) were not met for a long period, and the LSP had to make two key changes in the leadership team and several changes in the organization of the warehouse in order to be able to meet the KPIs" – SM2.

Anderson *et al.,* [57] completed an extensive research project about the critical attributes of selecting third-party logistics providers. They interviewed 309 managers in charge of the procurement of logistics services in multiple industries and regions around the world. They came up with ten attributes as shown in Table 6:

Table 6
Key attributes for selecting third-party logistics providers.

Attribute	Description
Reliable performance	Consistent "on time" delivery without loss or damage of shipment
Delivery speed	Amount of time from pickup to delivery
Customer service	Prompt and effective handling of customer requests and questions
Track & trace	Transparency and "up to the minute" data about the location of shipments end-to-end
Customer service recovery	Prompt and empathetic recovery and resolution of errors or problems concerning customers.
Supply chain flexibility	ability to meet unanticipated customer needs, e.g., conduct special pickups and seasonal warehousing.
Professionalism	Employees exhibit sound knowledge of products and services in the industry and display punctuality and courtesy in how they interact and present to the customer.
Proactive innovation	This activity refers to providing supply chain services to provide new solutions for the customer.

Attribute	Description
Supply chain capacity	the ability to cope with significant changes in volumes, e.g., demand surges, and deliver through multi-modal transport services, including international express and domestic, by air, ocean, and land
Relationship orientation	characterized by the sharing of information and trust in the exchange partner.

Source: Own design based on "What Drives the Choice of a Third-Party Logistics Provider?" [57]

In the case of our trial project, the RfQ process took three months to complete. The primary reason is the enormous time pressure on the project team to set up the new distribution center before the end of the first quarter of the calendar year 2022. The RfQ process started in October 2021. Due to the urgency, the usual six months' time had to be reduced to three months. Therefore, it included a limited number of suppliers. Supplier #1 is the most significant global player in logistics, with broad coverage of services globally. Supplier #2 is one of the top five players in the global market but not the largest one; however, it manages most of the customer's warehousing services portfolio globally. Supplier #3 is the existing supplier in the Japanese market; it is an original Japanese firm. Supplier #3 provides a simplified logistics service in the Japanese market for the customer and has yet to gain experience in providing distribution services, which is the scope of this project.

During the RfQ process, the three suppliers provided two solutions, one for each round of the RfQ. The first proposal was submitted in the first round of the RfQ. It aimed for a high-level solution and cost estimation. The second submission by the suppliers included the final solution and best price level. The different rounds of the RfQ aim to reduce the number of participants in the process to simplify the selection process. In this RfQ, the project could not reduce the number of suppliers after the first round, so all three LSPs submitted an offer in the second round. After the second round, the core team of the RfQ (consisting of HMOJP, HGD, WM, and SM1) evaluated the submissions [58] to record the details of the submissions in the designed expert system. Each submission has been evaluated according to the values of the 30 attributes. After the evaluation, Supplier #1 was eliminated from the further stages of the RfQ. There were two main reasons: first, their price level and second, their need for more expertise in distribution in general in the region, as well as related to the customer's business, despite them being the most significant player in the industry. Supplier #1 had low results in TCO, Quality Assurance, and Capacity Minimum.

At the last stage of the RfQ, with the two remaining suppliers, the Sourcing Manager 1 completed a final negotiation round based on the recommendations of the expert system. The recommendation from the expert system was to choose Supplier #2 over Supplier #3. Even though Supplier #3 had the best price level, they had an excellent connection with the customer's local organization. The lack of expertise in running the distribution business of the customer and using the warehouse management system and warehousing processes of the customer in any other location made their solution less desirable than Supplier #2. Based on the system recommendations, in the last negotiation round, the aim was to negotiate Supplier #2 price level to at least match Supplier #3. As that was not too much higher, Supplier #2 was able to lower their offer, while Supplier #3 could not further decrease the offer.

Once both suppliers completed the final offers, SM1 prepared a proposal for the decision board that consisted of HMOAPJ, HMOJP, TM, HGD, WM, and SM1. The proposal contained final offers and solutions by Suppliers #2 and #3. The recommendation of SM1 has been based on the result of the expert system outcome, which, based on the preset rules, favored Supplier #2 over Supplier #3.

Contrary to using the traditional scorecard method, where stakeholders shall not provide any reasoning as to why they scored certain suppliers' offers higher or lower than the others, the expert system results are explainable by the preset rules and the level of informativity of certain attributes. The decision committee has made a unanimous decision and selected Supplier #2 for the new distribution center in Tokyo. Explainability is a critical feature in the employment of AI, especially in decision support [59-61].

As for verifying the expert system result, we monitored the three-month-long implementation project of the new warehouse. The schedule was tight; the new distribution center projects usually take six to eighteen months. Supplier #2 has established a strong project team that consists of their project management experts, as well as experts from the customer's existing distribution centers in the Netherlands and China that are also managed by Supplier #2. The project has been delivered on time and without any setbacks. On the 7th of March 2022, the new distribution center opened in Tokyo, Japan. This new distribution center project in Japan has been the fastest and most successful project in the last ten years, according to the experts who participated in the steering group of the project (HMOAPJ, HMOJP, TM, HGD, WM).

We have asked the participants to write short feedback notes about their experience, and what would they address to a supplier:

"It was nice first visiting/site acceptance last Friday for us. I felt enthusiasm and huge possibility from all of the on-site workers, including many staff who are receiving training from the leader. I appreciate you and all of the Supplier #2 members for the sufficient preparation/setting toward go-live. Thank you." (HMOJP)

"I would like to thank Supplier #2 team for the great work and commitment to the project's success!! Let's keep it up!" (TM)

"I would like to add my thanks to those of my colleagues. Great to see your teamwork in action... Many thanks again for your great work to date." (HGD)

"Many Thanks to the Supplier's team for a great job done under tremendous time pressure!" (HMOAPJ)

"Congratulations, Supplier #2 and all!" (WM)

Based on the interviews after the RfQ process, we distinguish between two kinds of participants' experiences. First, the APJ regional and Japanese local teams heavily supported Supplier #3 as they had an existing relationship with that supplier. The rest of the participants were neutral with the suppliers but expected that Supplier #2 could manage the project on time, as they are managing similar operations globally for the customer. Therefore, the regional-local teams were very positively surprised by the outstanding performance of the selected supplier. According to the feedback that we have received from the customer's team of experts, during the time between the 7th of March 2022 and the 29th of October 2023, "there was not any major problem with the operation, and the KPIs have been met by the supplier the whole time" (WM). As a result of our research project, we can say that the expert system is an excellent support in case of complex problems, it is able to synthetize several experts knowledge into a single knowledge base, it can recommend or not recommend certain choices in an RfQ process in an explainable way. Supply chain security, to minimize risk and increase resilience is at the forefront of the supply chain management leadership teams' agenda, in which such AI-based solution is essential to take the right decisions. Quantitative methods and AI-based methods exist to support decisions. However, this paper aims to highlight that the human factor cannot be completely excluded in hybrid systems. In addition to quantitative methods, AI-based methods are also effective decision-support methods, but it is essential to recognize when and which method is useful for the dilemma that arose. For practitioners, the AI-based expert system, which uses the expert's knowledge then and there, is a tool that makes thinking transparent, which helps to support decisions and make them accepted.

Furthermore, it can be seen from the literature that quantitative methods are the focus of research when selecting suppliers. However, hybrid systems are based on human-machine interaction. Knowledge-based expert systems can make decision-makers thinking processes transparent by highlighting the attributes on which they have made their decisions. We believe that our case is primarily not about a tool or an algorithm, but it is about the culture that strives for nearly perfect decisions for the medium or long-term by leveraging the best available knowledge from internal and external experts. It is indeed a cultural change of decision making to leverage the benefits of such technologies.

5. Future Research Directions

The research aims to introduce a novel AI-assisted method for supplier selection for logistics service providers. The project focused on a specific solution for a specific problem and built the knowledge base accordingly. Naturally, this knowledge base can be reused in other LSP selection projects for warehousing and similar commodities in the strategic sourcing field, where firms buy relationships instead of transactions. However, very different commodities would require another knowledge base and approach. According to Malone [62], there are four types of AI: tool, assistant, peer, and manager. It is important to carry out further research about the different roles of AI in business processes and management decisions. Our expert system can be interpreted in multiple levels of using AI. It could be a peer or manager as well, depending on the organization layer who is using it. It requires further research, especially considering the contemporary dynamics of the global economy and how we can use AI to deal with complex problems, primarily in decision-making processes.

Author Contributions

Conceptualization, J.P.; methodology, Z.B.; software, T.Z.; validation, A.H., Z.B. and J.P.; formal analysis, A.H.; investigation, J.B.-S.; resources, J.P.; data curation, T.Z.; writing—original draft preparation, J.P.; writing—review and editing, J.P. and J.B.-S.; visualization, J.P.; supervision C.M. and S.R.; project administration, J.P.; funding acquisition, J.P. All authors have read and agreed to the published version of the manuscript. Authorship must be limited to those who have contributed substantially to the work reported.

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Data Availability Statement

Data supporting reported results can be found at the authors, subject to approved request from the requestors.

Conflict of Interest

The authors declare no conflict of interest.

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