Horizontal Integration through Knowledge Sharing in the Supply Chain under Uncertainty

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Horizontal Integration through Knowledge Sharing in the Supply Chain under Uncertainty

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***Abstract*—A robust knowledge-sharing network is designed for horizontal integration under disruption risks and epistemic uncertainties by introducing a novel optimization model using fuzzy robust possibilistic programming approach to optimize knowledge sharing among supply chain members with varying knowledge levels. This paper aims to identify an efficient knowledge-sharing network, thereby reducing costs and enhancing suppliers' knowledge levels. By challenging the common assumption that companies with higher knowledge levels are always the primary contributors and have more added value for cooperation, this study highlights their potential inefficiencies and higher sharing costs. The proposed model promotes the integration of diverse knowledge sources within the supply chain, emphasizing the importance of horizontal integration. It advocates for comprehensive knowledge sharing among suppliers and organizations to enhance supply chain efficiency, collaboration, and performance while reducing costs. Quantitative analysis demonstrates that knowledge sharing significantly increases supply chain integration, and the study endorses the use of multi-objective mathematical programming for optimal decision-making in scheduling. The results emphasize the value of collaborating with closely aligned companies to minimize knowledge-sharing costs and enhance broader organizational collaboration. Furthermore, the introduced model proposes practical execution scheduling and knowledge-sharing processes, as evidenced by a case study, leading to effective execution scheduling, reduced costs, improved communication, strengthened collaboration, and increased supply chain efficiency. Overall, this article contributes to research in supply chain management and knowledge sharing models, enabling them to navigate constraints and market dynamics to improve supply chain performance through effective knowledge sharing and collaboration.**

***Index Terms*—Knowledge-Sharing (KS), Horizontal Integration (HI), Fuzzy Robust Possibilistic Programming (FRPP), Supply Chain Integration (SCI).**

I. INTRODUCTION

IN In today's rapidly evolving and unpredictable business landscape, achieving horizontal integration through knowledge sharing is crucial for organizations striving to navigate uncertainty and maintain competitiveness [1], [2], [8]. Horizontal integration has emerged as a powerful strategy for enhancing performance and productivity within the supply chain by promoting the knowledge sharing among various members [15], [16]. This continuous improvement prevents the wastage of time and resources and fosters a collaborative environment for better decision-making and strengthened communication both internally and externally [67], [81], [79].

Within the supply chain, companies at the same level utilize common knowledge for production, but their expertise varies across knowledge fields, with some being experts and others intermediate or novice [35], [62], [87]. Supply chain integration refers to the coordination and synergy among every component and phase of the chain [25], [28], [46]. Integration can occur in two forms: vertical and horizontal [51], [85]. Vertical integration involves coordination between companies and their suppliers and customers, while horizontal integration focuses on collaboration and coordination among peer companies within the supply chain [48]. Horizontal integration, particularly through knowledge sharing, can enhance overall performance and supply chain efficiency [62], [72].

This research aims to identify an efficient scheduling model for knowledge sharing in the supply chain network, thereby reducing costs and enhancing knowledge levels across the chain members by introducing an optimization model using the fuzzy robust possibilistic programming (FRPP) appeoach. The proposed model in this research is capable of addressing the risks of disruption and epistemic uncertainties in horizontal integration.

However, achieving effective horizontal integration faces numerous obstacles and challenges. Recent research highlights several significant issues. Schmoltzi and Wallenburg [62] point to weak collaboration among companies, which can hinder the knowledge-sharing and collaboration processes. Sternberg et al. [70] address technological problems, such as the lack of a systematic decision-making infrastructure to integrate information sharing across companies. Richey et al. [60] identify organizational differences as factors that impede effective coordination and collaboration. These barriers underscore the profound challenges in achieving effective horizontal integration through knowledge sharing [38]. To overcome these obstacles, an efficient approach is needed to improve knowledge sharing and collaboration in the supply chain [40], [46], [47], [82]. A significant gap in the existing literature is the lack of an optimization model for scheduling, managing, and sharing knowledge within the supply chain

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under uncertainty [88], [81], [79]. This gap represents a fundamental barrier to effective horizontal integration, where communication challenges and knowledge-sharing issues create critical challenges [78], [71].

This research is theoretically anchored in the Resource-Based View (RBV) and the Knowledge-Based View (KBV). The RBV asserts that rare and inimitable resources, such as specialized knowledge and expertise, can generate sustainable competitive advantages for organizations [63], [7], [28]. Meanwhile, the KBV posits that knowledge is the primary strategic resource for organizations, and that its effective management and dissemination are crucial for enhancing supply chain productivity and efficiency [64], [69]. Drawing on these theoretical frameworks, this study investigates horizontal integration through knowledge sharing in supply chains under uncertainty. By optimizing the utilization of existing knowledge and resources, the research seeks to achieve effective and efficient horizontal integration. The Robust Fuzzy Possibilistic Programming (RFPP) approach proposed in this research applies the principles of RBV and KBV to help organizations enhance coordination and flexibility through resource optimization and knowledge sharing. This theoretical approach strongly supports the research objectives, presenting a robust model for maintaining sustainability and efficiency in the face of uncertainties and sudden changes within the supply chain.

The contributions of our research can be summarized as follows: First, we introduce a multi-objective mathematical programming model designed to enhance the overall knowledge level of chain members while minimizing costs (including time) and maximizing effective knowledge sharing through suppliers. Second, by incorporating the expertise of industry professionals and addressing the uncertainties caused by epistemic information in their decision-making process, our study presents an FRPP approach to tackle the challenges of disruptions and epistemic uncertainties arising from managerial decisions within the supply chain.Third, another contribution of this research is its emphasis on problem-solving within the supply chain through simulation and detailed graphical outputs, resulting in a systematic scheduling program that fosters horizontal integration.

In addition, contrary to previous assumptions that enhancing knowledge levels in the supply chain necessarily involves companies with the highest knowledge levels [1], [16], [22], [24], [48], our research challenges this notion. By presenting a novel approach to supplier clustering based on knowledge level, we aim to reassess this assumption, emphasizing that such processes can entail significant complexities and costs. Our purpose is to address key questions in knowledge management by narrowing the gap in the literature and tackling the research question: “What, when, how, and among which supply chain members should knowledge be shared, considering the reduction of costs and the enhancement of members' knowledge levels?” This is achieved by optimizing the sharing rate, reducing costs, and enhancing the knowledge levels of supply chain members.

The subsequent sections of this paper are organized as follows: Section 2 presents a systematic literature review and theoretical background. Section 3 defines the problem and introduces a Mixed-Integer Linear Programming (MILP) model. In Section 4, the proposed FRPP model is explained. Section 5 presents numerical results, which are essential for validation and providing insights. Finally, Sections 6, 7, and 8 conclude the paper with a summary of findings and suggestions for future research.

II. Literature Review

A. Supply Chain Integration (SCI) and Knowledge Sharing

The supply chain (SC), which integrates all critical elements required for delivering products or services, relies significantly on effective knowledge management (KM) to enhance flexibility and responsiveness [68]. Sharma et al. [65] assert that KM within the supply chain facilitates collaboration, provides access to external knowledge, and enhances overall competitiveness. This viewpoint is reinforced by Ramanathan [59], and Chauhan et al. [9], who emphasize that supply chain management (SCM) focuses on integration and collaboration to maximize stakeholder value through the coordination of information, physical, and financial flows.

SCM integration not only enhances performance but also reduces costs. A key component of this integration is Supply Chain Integration (SCI), which helps mitigate the "bullwhip effect" [31]. The bullwhip effect refers to the phenomenon where small fluctuations in demand at the retail level lead to progressively larger variations upstream in the supply chain [39], [42]. Effective knowledge sharing (KS) among stakeholders are critical for addressing this issue [44].

In the realm of KM, implementing appropriate knowledge sharing strategies (KSS) and their associated tools is crucial for achieving organizational and supply chain success [51], [52]. Optimal KSS, especially those centered around integration, are essential for sustaining superior performance over time [55], [66]. Nonetheless, there is a need for more in-depth critical analysis of these strategies. While numerous studies underscore the advantages of KM, there is a lack of consensus regarding its impact on supply chain performance [68], [70]. Some researchers contend that the benefits of KM are not evenly distributed across various supply chains or industries, revealing significant gaps and ongoing debates in the literature [76], [79], [82].

B. Vertical and Horizontal Integration in the Supply Chain

Supply chain integration (SCI) encompasses both vertical and horizontal dimensions. Vertical integration involves collaboration between organizations at different levels within the supply chain, such as suppliers and manufacturers, leading to improved coordination, operational efficiency, and cost savings [49], [22]. For instance, manufacturers and suppliers can work closely to optimize processes and shorten lead times [51]. On the other hand, horizontal integration refers to the collaboration between companies at the same level of the supply chain, including those that may be competitors or operate in different product domains [46]. This form of integration focuses on sharing resources such as technology or distribution networks to achieve economies of scale and bolster competitive advantage [11], [38].

Although the significance of knowledge sharing in supply chain integration is well-established, the literature reveals notable gaps and ongoing debates [88]. While KM theoretically offers benefits such as fostering innovation and enhancing decision-making, its practical implementation frequently encounters resistance and alignment challenges [59]. These issues hinder the effective capture and dissemination of knowledge within organizations. To overcome these obstacles, it is essential to develop strategies that address both the technical and human dimensions of KM, thereby fully realizing its potential [51], [56], [58], [83].

The impact of KM varies significantly across industries, emphasizing the crucial role of effective knowledge-sharing networks. High-tech sectors, such as the semiconductor industry, reap considerable benefits from KM practices due to their reliance on cutting-edge knowledge and rapid innovation cycles [22]. In contrast, traditional manufacturing industries frequently encounter challenges with KM implementation, largely due to entrenched practices and resistance to change. For instance, Choi et al. [15] observed that traditional manufacturing firms struggled to cultivate a culture of knowledge sharing, resulting in fragmented information and diminished overall efficiency. This underscores the need for a robust and efficient knowledge-sharing network to address these gaps and enhance organizational performance.

Effective KM necessitates the integration of advanced technologies for the efficient management and dissemination of knowledge [11], [15]. Nevertheless, the integration of such technologies presents several challenges. A case study conducted by Cooper et al. [10] within the construction industry demonstrated that although KM systems can greatly improve information sharing and project management, the initial costs and implementation complexity can be prohibitive for smaller firms. Furthermore, the rapid pace of technological advancement requires ongoing investment and adaptation, which can place significant strain on resources and management focus.

Quantifying the measurement of KM remains a complex and debated issue. While the qualitative advantages, such as enhanced decision-making and innovation, are broadly recognized, translating these benefits into financial terms presents significant challenges [74], [75]. Granz et al. [16] contend that the lack of standardized metrics for assessing KM outcomes hinders its broader adoption. Their research advocates for the development of industry-specific KM metrics to more precisely capture the value generated by these initiatives.

C. *Criteria Selection for Knowledge Assessing*

One of the stages in our proposed method involves establishing criteria for evaluating and comparing knowledge items. During this phase, it is essential to define appropriate criteria to facilitate the comparison of knowledge items. The suggested criteria, compiled from research [67], [58], [78], [24], [2], [3], [33], [52], [53], [40], [4] and expert consultation, are as follows:

Differentiating Organizational Capability [C]: This criterion entails that by acquiring this type of knowledge in one or more fields, an organization gains a competitive advantage over its rivals in the market for its products. It also facilitates the creation of new opportunities for the organization [2], [3], [33], [52], [53], [40].

Generating Greater Value Added (Strategic Value) [V]: Knowledge that yields the most significant impact on enhancing and increasing organizational output, resulting in improved financial value of products and services. This knowledge can also enhance the organization's position by increasing its market share compared to competitors, leading to increased revenue and profits [58], [78], [24], [2].

Addressing Urgent and Critical Organizational Issues [I]: Organizations sometimes face specific and critical challenges that require immediate attention [2]. These challenges can hinder their development and success in the market and potentially lead to their failure. Acquiring knowledge that assists in resolving such organizational issues takes priority [67], [58], [78], [24].

Minimizing External Dependency [D]: Acquiring services from external entities comes with not only costs but also other constraints. These include adhering to the programs and requirements of these external entities [33]. Occasionally, these associations can be expensive and risky for organizations [67], [58], [78], [24]. Due to certain vulnerabilities, organizations might fail to fulfill their commitments to customers and incur substantial losses. Acquiring knowledge in this area can mitigate such consequences [53], [40], [4].

Resource Expenditure Level [R]: Considering that cost and time are important factors in knowledge sharing, and organizations typically face serious constraints regarding these two resources, knowledge that can be shared to the organization with lower cost and time takes priority [52], [53], [40]. The cost and time of knowledge sharing are influenced by various factors, the most significant of which are outlined below:

Availability of Appropriate sharing Infrastructure: By capacity to absorb, we refer to the organization's employees' ability and readiness to absorb, learn, and apply new knowledge [40], [20]. Capacity to absorb involves both ability and motivation [21], [26]. In order to facilitate maximal knowledge absorption within organizational units or among employees, both aspects of capacity to absorb need to be present [78], [24], [84].

D. *Conceptual Model for Knowledge sharing in the Supply Chain*

Song et al. [80] introduced a four-stage spiral model for knowledge sharing in high-tech industry supply chains. Jia and Xu [71] developed a conceptual model for knowledge sharing among members of an industrial cluster, drawing on existing theories of knowledge and its sharing, as well as the Resource-Based View (RBV) and cluster theory from a modern economic perspective. They subsequently assessed this model within the carbon supply chain in southern Germany.

E. Examining Knowledge Networks in the Supply Chain

Another group of studies focuses on knowledge networks within supply chains. Woods et al. [32] analyzed the structural properties of knowledge networks across three industrial clusters using social network analysis. Following this, Malacina and Teplov [37] explored the evolution of knowledge networks in a supply chain by examining the changing roles of various factors at different stages of evolution. Vaez-Alaei et al. [39] investigated the impact of six variables—depth of shared knowledge, regional social-cultural background, knowledge characteristics, breadth of shared knowledge, partner attributes, and network characteristics—on the effectiveness of knowledge networks in supply chains.

F. Optimizing and Designing Knowledge Networks

Nonaka et al. [44] proposed a model for optimizing the sharing of organizational knowledge, focusing on positioning the right individuals at the right time and place. Their model emphasized the correlation between physical parameters of knowledge flow and organizational parameters. Following this, Ganguly et al. [55] analyzed the network of knowledge sharing by considering behaviors, examining interactions among network members, and calculating the optimal knowledge sharing paths. They employed Floyd's shortest path algorithm for optimizing explicit knowledge sharing paths and used social network analysis for implicit knowledge sharing.

Daquin et al. [58] aimed to maximize knowledge sharing among employees by designing an optimized knowledge flow network within an organization. They utilized a mixed-integer programming model for this purpose.

III. Theoretical Background

This research examines horizontal integration through knowledge sharing in the supply chain under uncertainty by leveraging two fundamental theories: the Resource-Based View (RBV) and the Knowledge-Based View (KBV). According to the RBV, organizations can achieve sustainable competitive advantages through the possession of rare and inimitable resources, including specialized knowledge and unique experiences [63], [64]. According to this theory, organizations should focus on identifying and exploiting these resources to maintain their competitiveness in complex and volatile markets. Moreover, the KBV highlights that knowledge is the primary strategic resource for organizations and underscores the importance of effective knowledge management and sharing to enhance supply chain productivity and efficiency [28], [69]. This theory asserts that an organization's ability to generate, retain, and disseminate knowledge is crucial for achieving competitive advantage.

In this paper, we integrate these two theoretical perspectives to explore how to optimally utilize existing knowledge and resources to achieve effective and efficient horizontal integration in the supply chain. The Robust Fuzzy Probabilistic Programming (FRPP) model introduced in this study employs the principles of RBV and KBV to help organizations enhance coordination and flexibility through resource optimization and knowledge sharing. This innovative model not only addresses the limitations of traditional models but also provides a dynamic and adaptable tool for organizations to better handle sudden changes and uncertainties. Our aim in this research is to develop and refine existing frameworks for knowledge and resource management in the supply chain, employing a systematic approach and decision-making based on mathematical modeling to achieve greater coordination and efficiency. By addressing key questions in knowledge management, we strive to enhance knowledge levels among supply chain members, optimize sharing, and reduce costs.

Literature review of the indicates that most studies have adopted a qualitative approach, with only a few employing quantitative methods for knowledge sharing in industrial clusters. Even fewer studies have utilized optimization methods for this purpose. Thus, there is a growing need for research in this area, given the efficiency of optimization techniques. Consequently, this paper focuses on modeling and optimizing knowledge sharing, with the objectives of enhancing organizational knowledge level and reducing knowledge-sharing costs, as identified by managerial perspectives. The Robust Fuzzy Possibilistic Programming (FRPP) approach can effectively be utilized in horizontal knowledge sharing within the supply chain. FRPP, by managing uncertainties and employing fuzzy logic and probabilistic scenarios, facilitates more precise modeling of knowledge sharing among organizations [53], [54]. This method promotes enhanced collaboration, more effective communications, optimized resource allocation, improved decision-making under complex conditions, flexibility in adapting to rapid market changes, risk reduction, and the promotion of diverse knowledge measurement. These aspects collectively contribute to improving overall supply chain performance.

IV. Methodology

To design the optimal knowledge-sharing network within the supply chain, we employed a mathematical modeling method integrated into the quantitative management research paradigm. This modeling approach utilizes a multi-objective optimization method with two objectives: maximizing the overall knowledge level of participating companies in the chain and minimizing the cost of knowledge sharing across the supply chain. The goal is to identify the optimal network for knowledge sharing among supply chain companies, aiming to enhance chain coherence, improve performance, reduce costs, and mitigate discrepancies. The resulting network design provides the most cost-effective means of knowledge sharing among companies within specific time frames, thereby maximizing the knowledge elevation of chain members.

The proposed model in this study is designed for the automotive industry, specifically focusing on the supply chain of automotive spare parts. SAPCO, responsible for the design, engineering, and supply of parts for Iran Khodro, and a subsidiary of Iran Khodro, was chosen for implementing this model due to the complexity of its supply chain, the high level of coordination required between suppliers, manufacturers, and distributors, and the critical importance of knowledge sharing.

The automotive industry, characterized by continuous interactions between companies and the need for sharing technical information and knowledge, provides an ideal setting for optimizing knowledge sharing and cost reduction models. In this industry, knowledge sharing is essential for ongoing innovations and responding to rapid technological changes. The detailed and extensive data available in "SAPCO supply chain" also facilitates the use of complex modeling techniques. Therefore, selecting the automotive industry, and specifically SAPCO, is logical and effective due to its efficient supply chain management and the necessity for improving efficiency and reducing costs.

Given the complexity of the issue, influential factors and variables contributing to the formation of the knowledge-sharing network were identified and formulated into a mathematical planning model. Expert consultation was sought to determine experimental factors, including variables, parameters, and constraints. Following model design, various datasets were scrutinized to validate their accuracy. Expert specifications within relevant domains are outlined in *Table I*.

In this study, the selection of experts for consultation and the determination of experimental factors, including variables, parameters, and constraints, were conducted based on scientific and empirical approaches. The expert selection process and criteria used are as follows:

A. Criteria for Expert Selection

Experts were selected for their dual expertise in knowledge management and the automotive supply chain, ensuring they had both theoretical knowledge and practical experience. The selection focused on professionals with advanced degrees and significant experience in managing knowledge strategies within the automotive industry. Consultants with specialized knowledge in this area and academic professors with strong research backgrounds were also included. From the initial pool, five managers, two consultants, and three professors were chosen based on their ability to meet these criteria. Detailed consultation sessions with these experts helped define key variables and parameters, which were essential in developing the mathematical model and optimization strategy.

To ensure dataset accuracy, a thorough review was conducted on 10,000 records from SAPCO's supply chain database, covering knowledge sharing costs and levels from 2020 to 2023. The accuracy of the data was validated by cross-referencing with similar financial systems and identifying anomalies, leading to the removal of records with implausible values (e.g., costs above $10,000 or below $1,000). Missing data, totaling 150 records, were addressed using predictive algorithms and mean imputation. Quality checks revealed a standard deviation of $600 and a mean cost of $4,750, with descriptive and correlation analyses showing a correlation coefficient of 0.78 between knowledge sharing costs and knowledge levels. In the validation phase, a team of ten internal and three external experts reviewed and confirmed the dataset, updating missing values and correcting errors. The model underwent cross-validation with 10 folds, achieving 91% accuracy, and sensitivity analysis, demonstrating stability and high accuracy in predicting and simulating key data variables. All procedures adhered to stringent scientific standards, ensuring reliability and validity.

TABLE I
EXPERT INFORMATION

Experts	*Numbers of experts*	*KM implementation experience (years)*	*Experience in the Vehicle supply chain (years)*
Managers of KM departments	5	17	15
		12	10
		13	12
		14	12
		15	10
KM consultant	2	12	11
		10	10
Professors of KM	3	15	12
		13	10
		20	16

Furthermore, to address parameters characterized by cognitive uncertainty, a possibilistic modeling approach was utilized, incorporating fuzzy robustness methods and FRPP. Subsequently, the final proposed model was implemented within SAPCO's supply chain, and its outcomes were analyzed. Ultimately, these results were validated by experts' endorsement. The steps taken in this research are illustrated in *Fig. 1*. The final proposed model was solved using MATLAB 2021b.

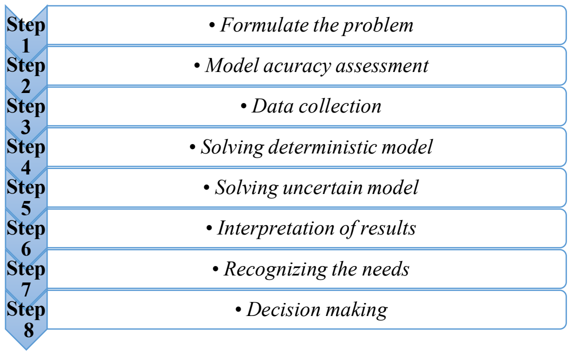

Fig. 1. The stages of the research method.

B. Problem Description and Formulation

Knowledge sharing represents a strategic collaboration at the SC level, ultimately fostering integrity within the SC [57]. Achieving optimal performance in this process necessitates designing the most efficient network among chain members, enabling work to be executed at minimal cost. Companies operating at the same level of the supply chain provide similar products or their components and employ equivalent knowledge for production [61], [63]. Typically, companies vary in their awareness and mastery of different knowledge types. Some companies excel in specific knowledge fields, while others may be intermediate or novice. Through horizontal integration in the SC, these companies can collaborate to knowledge sharing to each other, allowing proficient companies to impart expertise while acquiring necessary knowledge from partners.

To optimize the knowledge sharing process, it is imperative to maximize the total knowledge of companies at this chain level while minimizing costs and adhering to desired timelines [66]. Upon initiating the knowledge sharing program, the knowledge level of each company for all knowledge types should be assessed. Four proficiency levels are defined for each knowledge type: very novice, novice, intermediate, and expert. Companies possessing higher knowledge levels can share their expertise with others in need. The duration of knowledge sharing is determined based on complexity and implicit degree, with more complex knowledge requiring additional information for encoding [67]. Tacit knowledge, residing in individuals' minds, behaviors, and perceptions, poses challenges for sharing, with subjective knowledge being more tacit [68], [72].

Moreover, companies incur knowledge sharing costs based on three factors: sharing duration, distance between companies, and necessary equipment and supplies for employee training, varying by knowledge type [76]. Given that not all knowledge holds equal importance for companies, prioritization of different knowledge types according to their needs and priorities is essential. This ensures that critical knowledge acquisition takes precedence in the knowledge sharing process. Additionally, knowledge should be prioritized concerning the next chain level, giving precedence to knowledge with a more substantial impact on achieving level goals [78], [79], [81].

To maximize the increase in companies' knowledge levels with minimal resources, the problem can be formulated as a mathematical model. By solving this model, the optimal knowledge sharing timing and partners can be determined. Below, we explain the mathematical model, which is a multi-objective mixed-integer programming model, after introducing the assumptions, indices, parameters, and variables.

Based on the problem's characteristics, a set of model assumptions includes:

- *All knowledge comprises four levels: very novice, novice, intermediate, and expert, denoted by 1, 2, 3, and 4, respectively.*
- *The sharing company's knowledge must be at least one level higher than the acquiring company's knowledge.*
- *Each company should not acquire a higher knowledge level from other companies until completing the training period for each knowledge level.*
- *The number of periods and cost required for knowledge sharing from a lower level to a higher level are the same, though these may vary for different knowledge types.*
- *Knowledge level increases by one upon completion of the training period.*
- *Companies have limitations on simultaneous significant knowledge sharing and acquisition abilities.*
- *Companies can simultaneously knowledge sharing to multiple recipient companies.*
- *Horizontal integration is not constrained by budget limitations.*

$$\text{Max Z1} = \sum_{i=1}^{M} \sum_{k=1}^{K} (A_{ik} + B_k) \cdot H_{ik}^t \quad (1$$

$$\text{Min Z2} = \sum_{t=1}^{T} \sum_{i=1}^{M} \sum_{j=1, i \neq j}^{M} \sum_{k=1}^{K} (C_k \cdot D_k \cdot S_{ij}) \cdot X_{ijk}^t \quad (2$$

Subject To:

$$X_{ijk}^t \leq H_{ik}^t - H_{jk}^t + \varphi \cdot (1 - X_{ijk}^t) \qquad i, j = 1, \dots, M; i \neq j; k = 1, \dots, K; \; t < (T - D_k + 1)$$

$$\sum_{i=1}^{M} \sum_{q=t+1}^{t+D_k^{-1}} X_{ijk}^q \leq \left(1 - \sum_{i=1, i \neq j}^{M} X_{ijk}^t\right) \qquad j = 1, \dots, M; k = 1, \dots, K; \; t \leq (T - D_k + 1)$$

$$\sum_{q=T-D_k+1}^{T} X_{ijk}^q \leq 0 \qquad i, j = 1, \dots, M; i \neq j; k = 1, \dots, K$$

$$H_{jk}^{t+1} = H_{jk}^t \qquad j \doteq 1, \dots, M; k = 1, \dots, K; t < D_k \quad (6$$

$$H_{jk}^t = H_{jk}^{t-1} + \sum_{i=1, i \neq j}^{M} X_{ijk}^{t-D_k} \qquad j = 1, \dots, M; k = 1, \dots, K; t > D_k \quad (7$$

$$H_{ik}^t \leq H_{Max} \qquad i = 1, \dots, M \,|; k = 1, \dots, K; t = 1, \dots, T \quad (8$$

$$\sum_{j=1}^{M} \sum_{i=j}^{t+D_k} X_{ijk}^q \leq \theta \qquad i = 1, \dots, M; k = 1, \dots, K; t = 1, \dots, T \quad (9$$

$$\sum_{k=1}^{K} F_{ik}^t \leq W_i \qquad i = 1, \dots, M; t = 1, \dots, T \quad (10$$

$$\left(\sum_{i=1, i \neq j}^{M} \sum_{q=t-D_k+1}^{t} X_{ijk}^q / \varphi \right) \leq F_{ik}^t \qquad i = 1, \dots, M; t = 1, \dots, T \quad (11$$

$$\sum_{k=1}^{K} E_{jk}^t \leq V_j \qquad j = 1, \dots, M; t = 1, \dots, T \quad (12$$

$$\left(\sum_{i=1, i \neq j}^{M} \sum_{q=t-D_k+1}^{t} X_{ijk}^q / \varphi \right) \leq E_{jk}^t \qquad i = 1, \dots, M; k = 1, \dots, K; t = 1, \dots, T \quad (13$$

$$\sum_{i=1, i \neq j}^{M} \sum_{q=t}^{t+D_k} X_{ijk}^q \leq 1 \qquad i = 1, \dots, M; k = 1, \dots, K; t = 1, \dots, T \quad (14$$

In the above model, ***first objective (Eq. 1)*** aims to maximize the knowledge level across all companies within the supply chain (SC) at the desired level. It assigns weights to the knowledge levels based on the perspectives of SC managers at the same level and managers at the next level of the SC. ***Second Objective (Eq. 2)*** on the other hand, seeks to minimize the cost associated with knowledge sharing between companies operating at the desired level of the chain. ***Constraint 3*** show that if the degree of knowledge k of company i is greater than that of company j at the beginning of period t, "X_{ijk}^{t}" can be equal to one, i.e., company i can share knowledge k to company j. ***Constraint 4*** states that if X_{ijk}^{t} equals one at the beginning of period t, company j cannot acquire knowledge k from another company in the next D_{K-1} period. ***Constraint 5*** highlights that knowledge sharing for k should not commence in the last period D_{K-1} of the planning horizon due to insufficient time. ***Constraint 6*** ensures the degree of knowledge k of company j in D_k of the initial period of the planning horizon to be determined according to the initial degree of that knowledge in the company. ***Constraint 7*** shows that the degree of knowledge k of company j can increase by one degree after the sharing period (i.e., the D_k period). ***Constraint 8*** indicates that knowledge level k of company i should not exceed the highest defined level (expert level) in all periods. ***Constraint 9*** shows that the number of companies acquiring knowledge k from company i should not exceed θ. ***Constraints 10 and 11*** control a company's maximum simultaneous knowledge sharing ability. In other words, the number of different knowledge k that company i cannot share to other companies simultaneously in each period is equal to W_i. ***Constraint 12 and 13*** oversee a company's maximum ability to acquire knowledge simultaneously, determining the number of knowledge k the company can receive simultaneously from other companies in each period, which is equal to Vj Finally, ***Constraint 14*** shows that the company should not achieve a higher level of this knowledge from other companies until the end of receiving knowledge k from company i.

C. Uncertainties in Model

When applying systematic and operational mathematical programming to horizontal integration for scheduling, the primary challenge lies in creating a solution that is resilient to the uncertainty of the data. Solutions that are stable in the face of such uncertainty fall under the category of "Robust" optimization. The state of uncertainty in knowledge-sharing networks is stochastic, indicating that the uncertainties are not necessarily independent.

Proposed Fuzzy Robust Possibilistic Programming (F.R.P.P)

In the domain of horizontal integration scheduling using systematic and operational mathematical programming, the primary challenge is to develop a solution that remains robust against inherent data uncertainties. Such solutions must exhibit stability, thereby aligning with "Robust" optimization principles. To address the issue of imprecise model parameters, possibilistic programming is employed to handle epistemic uncertainty, characterized by ambiguous or vague parameters. This method utilizes possibilistic distributions, integrating both limited objective data and the decision maker's subjective experience. Additionally, flexible programming is incorporated to accommodate varying target values for objectives and constraints, incorporating fuzziness through imprecise boundaries or subjective fuzzy sets. These approaches are fundamental to fuzzy mathematical programming methodologies [54], [47], [48].

The model presented in this paper involves two parameters, both subject to cognitive uncertainty and determined by an expert. These parameters entail the significance of knowledge kk from the perspective of the next level of the chain (B_k) and the importance of knowledge kk for the company at the desired level of the chain (A_{ik}).

In recent years, various methods grounded in possibility theory have emerged to tackle imprecise coefficients in objective functions and constraints. Proposed by researchers like Torabi and Hassini [77], Luhandjula [36], Lai and Hwang [27], Inuiguchi and Ramik [19] methods significantly contribute to effectively managing uncertainties within mathematical programming models.

Primary knowledge of Robust Possibilistic Programming (R.P.P) Models

The SRSCND model, with the exception of the second objective function, can be succinctly presented as *Eq. 15*, simplifying its processing [54]:

$$
\begin{aligned}
&\text{Minimization} \quad z = \varphi y + \upsilon x \qquad (15\\
&\text{s.t. } \partial x \geq d,\\
&\qquad \eta x = 0,\\
&\qquad \rho x \leq \omega y,\\
&\qquad \phi x \leq 1,\\
&\qquad \leq \{0,1\}, x \geq 0,
\end{aligned}
$$

The vectors $\boldsymbol{\varphi}$, $\boldsymbol{\upsilon}$, and $\boldsymbol{d}$ correspond to fixed production costs, opening costs, variable transportation, and demands, respectively. Matrices $\boldsymbol{\partial}$, $\boldsymbol{\eta}$, $\boldsymbol{\omega}$, $\boldsymbol{\rho}$, and $\boldsymbol{\phi}$ represent the coefficients of the constraints. Additionally, the vector $\boldsymbol{x}$ denotes the continuous variables, while the vector $\boldsymbol{y}$ represents the binary variables. Given that the second objective function can be handled similarly to the first objective function without sacrificing generality, it is excluded from the concise formulation.

Now, let's consider that vectors $\boldsymbol{\varphi}$, $\boldsymbol{\upsilon}$, and $\boldsymbol{d}$, along with coefficient matrix $\boldsymbol{\phi}$, which represents the facility capacities, are the uncertain parameters in the concise formulation of the SRSCND problem. To construct the fundamental possibilistic chance-constrained programming model, as outlined in [53], [54], we utilize the expected value operator to formulate the objective function. In this context, trapezoidal possibility distributions (refer to Fig. 2) are employed to characterize uncertain parameters, defined by their four key points, such as $\tilde{\xi}=(\xi_{(1)},\xi_{(2)},\xi_{(3)},\xi_{(4)})$. It's worth noting that when $\xi_{(2)}= \xi_{(3)}$, the corresponding trapezoidal possibility distribution simplifies to a triangular one.

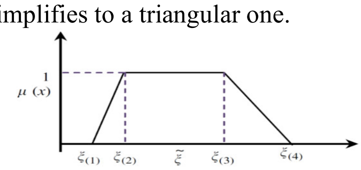

Fig. 2. Schematic of fuzzy parameter $\tilde{\xi}$ in the frame of trapezoidal possibility distribution.

Formulation (16) indicate the BPCCP (Basic Possibilistic Chance-Constrained Programming) model as follows:

$$\begin{array}{ll} Minimization & E[z]=E[\tilde{\varphi}]y+E[\tilde{v}]x \\ s.t. & Nec\{\partial x\geq\tilde{d}\}\geq\alpha \\ & \eta x=0 \\ & Nec\{\rho x\leq\tilde{\omega}y\}\geq\beta \\ & \phi x\leq 1, \\ & y\in\{0,1\}, x\geq 0 \end{array} \qquad (16$$

In Eq. 17, the relationships are categorized into two classes: the first class comprises uncertain parameters characterized by trapezoidal possibility distributions, such as the first and third sets of constraints, while the second class encompasses crisp parameters, including the remaining constraints. Following the works of [29], [32], [24], [19], Eq. 17 represents the equivalent crisp model derived from the aforementioned.

$$(17$$

$$\begin{aligned} &Minimization\ E[z]=\left(\frac{\varphi_{(1)}+\varphi_{(2)}+\varphi_{(3)}+\varphi_{(4)}}{4}\right)y+\left(\frac{v_{(1)}+v_{(2)}+v_{(3)}+v_{(4)}}{4}\right)x \\ &s.t.\quad \partial x\geq(1-\alpha)d_{(3)}+\alpha d_{(4)}, \\ &\eta x=0, \\ &\rho x\leq\left[(1-\beta)\omega_{(2)}+\beta\omega_{(1)}\right]y, \\ &\phi x\leq 1, \\ &y\in\{0,1\}, x\geq 0. \end{aligned}$$

In Equation 17, under the assumption of a confidence level higher than 0.5, denoted as (α, $\boldsymbol{\eta}$ > 0.5), the conditions are satisfied.

In this context, uncertainty becomes more accurately defined as the decision maker (DM) subjectively assigns different initial values to each confidence level. Subsequently, through an interactive process, a specific experiment that closely aligns with the DM's preferences is chosen as the final value. It's important to emphasize that this final value is inherently subjective, and there is no guarantee that it represents the optimal choice for every confidence level. This approach can be classified as reactive or, at best, interactive, resembling sensitivity analysis where the DM varies parameter values (i.e., confidence levels of chance limits) and observes their impact on the analysis model's outcomes.

Furthermore, as the number of chance constraints increases, the number of trials needed to determine suitable confidence level values should increase exponentially. Consequently, employing highly intricate and time-consuming simulation tests becomes necessary.

Robust Possibilistic Programming (R.P.P) model

It is assumed in this phase that only $\boldsymbol{\varphi}$, $\boldsymbol{v}$, and d are vectors containing imprecise parameters, in addition to acknowledging the inaccuracy of the coefficient matrix N. Consequently, the RPP model, derived from the BPCCP model, is formulated as *Eq. 18* [54]:

$$(18$$

$$\begin{array}{ll} \text{Minimization E}[z] & +\gamma(z_{\max}-z_{\min})+\delta\left[d_{(4)}-(1-\alpha)d_{(3)}-\alpha d_{(4)}\right] \\ \text{s.t.} & \partial x\geq(1-\alpha)d_{(3)}+\alpha d_{(4)}, \\ & \eta x=0 \\ & \rho x\leq\omega y \\ & \phi x\leq 1, \\ & \leq\{0,1\},\ x\geq 0{,}0.5<\alpha\leq 1. \end{array}$$

In the following step, as depicted in Formulation 19, it is important to note that this model does not address deviation; rather, its objective is solely to minimize the expected value (average) of the objective function. The focus on this approach arises from the importance of the decision maker's (DM) perspective. The decisions made by the DM consistently have significant and far-reaching consequences in certain practical scenarios, posing heightened risks for the DM.

$$(19$$

$$\begin{aligned} &\text{Maximization } \textstyle\sum_{i=1}^{M}\sum_{k=1}^{k}\left(\frac{A_{ik}^{1}+A_{ik}^{2}+A_{ik}^{3}+A_{ik}^{4}}{k}+\frac{B_{k}^{1}+B_{k}^{2}+B_{k}^{3}+B_{k}^{4}}{k}\right) \\ &\qquad +\gamma(Z_{\max}-Z_{\min})+ \\ &\delta[\alpha W_{i}^{1}+(1-\alpha)W_{i}^{2}] \\ &s.t: \end{aligned}$$

$$(20$$

$$\textstyle\sum_{k=1}^{k}F_{ik}^{t}\leqslant\alpha W_{i}^{1}+(1-\alpha)W_{i}^{2} \qquad \textit{(Modified constraint of the deterministic model)}$$

The crucial aspect of the aforementioned model lies in the parameters Aik and Bk. These parameters signify the significance of knowledge k for the company at the desired level of the SC and the importance of knowledge k from the perspective of the next level of the SC, respectively. Given that these parameters are subjectively determined by an expert and lack precise and definitive values, the presented model incorporates cognitive uncertainty. Additionally, according to expert input, the parameter Wi also exhibits cognitive uncertainty. Therefore, due to the cognitive uncertainty associated with these parameters, the FRPP approach is utilized to address them and stabilize the proposed model.

Mitigating Inaccuracies in the Coefficient Matrix N through Robust Possibilistic Programming (R.P.P) Model

To address the inaccuracies present in the coefficient matrix N, the Robust Possibilistic Programming (R.P.P) model employs a systematic approach that integrates both robust optimization and possibilistic programming techniques. This approach is particularly valuable in scenarios where parameters such as λ, μ, and d are represented by vectors with imprecise values, and N also exhibits imprecision.

In the R.P.P model, derived from the Basic Possibilistic Coefficient Programming *(BPCCP)* model, the imprecision in N is addressed by treating it as a range of possible values rather than a fixed quantity. This reflects the inherent uncertainty and cognitive biases associated with these parameters. By incorporating possibilistic constraints, the model integrates these uncertainties directly into the optimization process. The R.P.P model addresses the inaccuracy in the coefficient matrix N by focusing on minimizing the expected value of the objective function rather than addressing specific deviations. Specifically, Equation (35) aims to reduce the mean expected value of the objective function, thereby helping the model mitigate the overall impact of inaccuracies in the coefficient matrix N and provide a stable solution. This approach is particularly chosen due to its effectiveness in managing significant practical decision-making consequences, which may involve substantial risks.

The R.P.P model is designed to minimize the expected average value of the objective function, as detailed in Equation (19). This method is selected to mitigate the overall impact of inaccuracies in NN, focusing on reducing the average expected impact rather than addressing specific deviations from expected values. By emphasizing the minimization of the expected average, the model aims to deliver a stable solution despite potential imprecision in the coefficient matrix. Instead of explicitly addressing deviations, the model targets the reduction of expected values, as outlined in Formulation (20), aligning with the decision maker's goal of minimizing potential adverse effects. Robust optimization techniques are employed to maintain solution effectiveness amidst imprecision. To address cognitive uncertainties in parameters like A_{ik}, B_k, and W_i, which are often subjectively derived, the Fuzzy Robust Possibilistic Programming (FRPP) method is utilized. This approach integrates fuzzy robustness to handle the imprecise nature of these parameters, ensuring that the solutions remain resilient and effective despite inherent uncertainties.

D. Solution Procedure

The formulated model (*Equations 18-31*) clearly represents a nonlinear 0-1 integer programming model. In this model, the solution space is determined by parameters *i, j* (representing member companies of an SC level), *k* (indicating the number of knowledge sharing between companies), and *t* (denoting the time periods for knowledge sharing between companies).

As the number of member companies within a supply chain tier increases, it is evident that the solution space expands exponentially. Consequently, the task of selecting team members often becomes NP-hard, making it impractical to solve using conventional techniques alone [19], [27].

While standard enumeration methods may suffice for scenarios with limited dimensions, tackling more complex challenges necessitates the application of metaheuristic algorithms. Examples of such algorithms include Genetic Algorithms (GA), Gray Wolf Optimization Algorithm (GWO), Particle Swarm Optimization algorithm (PSO), and Crystal Structure Algorithm (CryStAl), among others. These algorithms collectively offer innovative and effective strategies to address intricate problems.

Metaheuristic algorithms were selected due to their advanced capabilities and effectiveness in exploring large and complex search spaces. These algorithms leverage AI-based optimization strategies to tackle NP-hard problems and provide near-optimal solutions. To ensure consistency and objectivity in determining final parameter values, an interactive process involving multiple stages of validation and result alignment was implemented. During this process, various algorithms were tested and evaluated using input data and problem conditions to verify the accuracy and reliability of the results. Additionally, standard criteria for comparing and analyzing algorithm performance, including normalized deviation assessments, were employed to maintain objectivity and ensure result validity. These measures ensure that the final selection is scientifically and systematically derived, and the results obtained are credible and reliable.

In the subsequent section, these metaheuristic algorithms were employed to solve the presented model in both deterministic and uncertain states. The performance outcomes of these algorithms are illustrated in *Fig. 3*. Particularly noteworthy, as demonstrated by the findings of Talatahari et al. [112], is the superior performance of the CryStAl algorithm compared to its counterparts. This highlights its suitability for solving the model outlined in this article, which focuses on knowledge sharing within the supply chain.

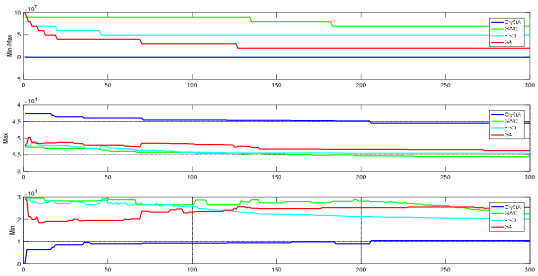

Fig. 3. *The assessment of algorithms performance is evaluated concerning the normalized deviation in deterministic mode.*

E. Fitness Calculation

Parameter tunning for the proposed algorithm to solve the minimization model

The Taguchi method was chosen for parameter optimization of the CryStAl algorithm due to its efficiency in reducing the number of experiments required compared to traditional methods. This method, based on fractional factorial design, allows for the simultaneous assessment of multiple parameters and helps identify the optimal parameter combinations with fewer experimental runs. For our proposed model, we explored three different values for each parameter, resulting in the design of 27 experiments using the Taguchi method. The use of the Taguchi method enabled us to efficiently determine optimal parameters and enhance the model's performance with greater precision.

It was employed to attain the best possible solution for the objective function in the previously mentioned model. In this modeling approach, the population size is set at 150, and the number of iterations equals 50.

V. CASE STUDY

In the automotive industry, the value chain includes distinct roles such as standards creators, material suppliers, component specialists, integrators, assemblers, and distributors. Car manufacturers, as primary standards creators, engage in market research, vehicle concept development, component design (including core platforms and systems), and significant investment in engineering R&D. Increasingly, this role operates within extensive supply networks involving close collaboration with suppliers. First-tier suppliers, who often help define standards, work alongside car manufacturers to design essential components and modules. Material suppliers provide a wide range of raw materials to both car manufacturers and parts specialists, who produce components according to the manufacturers' specifications. These components are then supplied to assemblers or integrators for final assembly. Within this framework, a distinction is made between first-tier suppliers, who deliver parts directly to final assemblers, and lower-tier suppliers, who produce simpler components for higher-tier suppliers. These higher-tier suppliers manufacture parts to order for car manufacturers and also produce components under their own brand for the broader market.

According to Jiang et al. [22], approximately 40-70% of the added value within the global automotive value chain is dedicated to integration processes. The added value contributed by each stage of the automotive industry's value chain is depicted in *Fig. 4*.

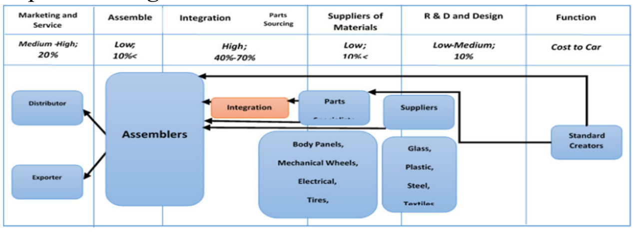

Fig. 4. The global value chain of the car and the maximum share of parts manufacturing in the earned value[22].

Spare parts manufacturing facilities have a vast product range, encompassing over 340 different types of parts varying in type, packaging, dimensions, and application. These factories collectively produce more than 63,000 pieces daily, making them readily available for distribution within the network of distributors. These 23 companies employ a total of 15,000 personnel directly, with an average of approximately 450 individuals per factory (ranging from a minimum of 180 to a maximum of 3,000 employees).

Regarding horizontal integration through knowledge sharing at the chain producer level, 12 critical knowledge fields have been selected for collaboration based on the insights and expertise of departmental managers and experts. In the subsequent phase, the level of proficiency in these 12 fields of knowledge is established for the companies before integration takes place. Experts assess the initial competence level for each knowledge category.

Prioritizing these 12 fields of knowledge is considered from two perspectives. One perspective involves the prioritization from the producers' standpoint, where company managers assign weights (A_{ik}) to knowledge areas based on their individual company's circumstances and objectives. The other perspective involves prioritization from the viewpoint of the downstream chain level (distributor). In this regard, distributor company managers assign priority by determining appropriate weights (B_k) based on how valuable the desired knowledge is in meeting the distributor's objectives.

The duration required for any knowledge sharing hinges upon the intricacy and implicit nature of that knowledge. Generally, the more complex and tacit the knowledge, the longer it takes to share. Within this supply chain, considering the type of knowledge to be shared and expert opinions, knowledge is categorized into four groups based on complexity and tacitness. Consequently, the duration for sharing each knowledge type falls within a range of 1 to 15 periods.

The cost associated with each knowledge sharing between two companies is determined by considering three key factors: the type of knowledge, the equipment and facilities necessary for the share, the duration of knowledge sharing, and the physical distance between the companies. Notably, shorter distances between companies result in lower knowledge sharing costs, primarily due to reduced expenses related to employee travel and missions. To calculate the entitlement of employees in the companies within this supply chain level, *Table II* is employed to establish the distance factor.

Table II.

DETERMINING THE DISTANCE COEFFICIENT ACCORDING TO THE DISTANCE BETWEEN COMPANIES

Distance (Km)	***1-300***	***300-600***	***600-900***	***900-1200***	***1200-1500***	***1500-1800***	***More than 1800***
Distance factor S_{ij}	*1*	*1.15*	*1.25*	*1.35*	*1.45*	*1.55*	*1.65*

The simultaneous ability to knowledge shairing is considerable and acquire multiple knowledge is limited for each company *(Fig. 5)*.

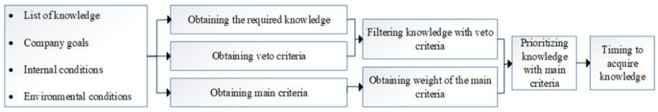

***Fig. 5.** The process of determining time intervals for knowledge sharing among supply chain members.*

It is determined according to factors such as the number of employees, their level of education and experience, the company's facilities, and the opportunity the company allocates for training. At this level of the chain of producers, this ability is determined for each company based on its specifications, in intervals between 3 and 20. The parameter's value is determined based on the available hardware and software facilities for training.

Classification of Companies Based on Knowledge Level

By classifying partner companies based on their knowledge and expertise, organizations can leverage data mining techniques to identify valuable patterns and insights, which support informed decision-making. This process facilitates the selection of appropriate strategic partners and the prediction of new companies' classifications based on known attributes. Classification, achieved through methods such as cluster analysis—whether demographic, psychological, transactional, or promotional—enables organizations to group companies into clusters with similar characteristics, optimizing communication and collaboration. Data-driven classification, utilizing statistical and data mining techniques, reveals customer demographics and achieves specific industry goals. Clustering techniques, including K-means, fuzzy K-means, and specialized neural network algorithms, are employed to classify companies into optimal clusters. This article evaluates the CVIDR model, using fuzzy K-means and K-means algorithms to determine parameter weights and classify companies into four main categories based on their knowledge levels.

Comparison of clustering performance

The results of applying clustering algorithms to a dataset can vary significantly depending on the chosen algorithm parameters. The aim of cluster validation is to identify the clusters that most accurately correspond to the data. Various definitions based on the distance between members are scrutinized in depth to gauge intra-cluster homogeneity and inter-cluster heterogeneity. Subsequently, using these definitions, criteria for assessing the clustering quality have been formulated.

Measuring the distance between clusters

To calculate the heterogeneity between clusters, different distance criteria have been defined, some of the most common criteria for measuring the distance between two clusters are:

A. The minimum possible distance between elements of clusters:

If O^n is the set of members of cluster n and C_i is the members of nth cluster, and O^m is the set of members of cluster m and C_j is the members of mth cluster, the distance between cluster n and m is:

$$d(m,n) = Min\left(Dist\left(c_i, c_j\right)\right), c_i \in O^n, c_j \in O^m \quad (21$$

B. The maximum possible distance between the elements of two clusters:

The distance between cluster n and m is:

$$d(m,n) = Max\left(Dist\left(c_i, c_j\right)\right), c_i \in O^n, c_j \in O^m \quad (22$$

C. The average values of all possible distances between the elements of two clusters:

The distance between cluster n and m is:

$$d(m,n) = \frac{1}{\|O^n\| \times \|O^m\|} \sum_{c_i \in O^n} \sum_{c_j \in O^m} Dist\left(c_i, c_j\right) \quad (23$$

D. The distance between the centers of two clusters:

If the members of the clusters are discrete variables, the closest member to the middle of the cluster is used to measure the distance, and if these members are continuous, the middle is used. If C^n is the center of the nth cluster and C^m is the center of the mth cluster. The distance between cluster n and m is:

$$d(m,n) = Dist\left(c^n, c^m\right) \quad (24$$

E. Cluster quality measurement criterion

As mentioned, clustering is better where the distance between the clusters is the smallest and the distance between the clusters is the largest. One of the methods of evaluating the clustering performance is the intra-cluster density measurement method. This measure shows the degree of cluster density when the number of clusters is fixed. In this criterion, the variables must be in the same range. Considering that in this research, the data are discrete, to calculate the density of a cluster, the distance of the data within a cluster should be measured with the center of the cluster. The density of the nth cluster, I_n, is defined as follows:

$$I_n = \sum_{c_i \in O^n} Dist\left(c_i, c^n\right) \quad (25$$

Then F(K) for K cluster is equal to:

$$F(K) = \frac{1}{K} \sum_{n=1}^{k} \sum_{c_i \in O^n} Dist\left(c_i, c^n\right) \quad (26$$

In fact, F(K) is the mean squared Euclidean distance between each observation and the median of the corresponding cluster. The lower F(K) indicates that the clusters are denser and the clustering has been done better. The smaller the above criterion, the smaller the distance between the members of each cluster and the center of that cluster, and the greater the distance between the centers of the clusters. To measure the quality of clustering, in which intra-cluster homogeneity and extra-cluster heterogeneity are simultaneously defined and calculated as follows:

$$Q(K) = \frac{1}{K}\left(\frac{IntraDist}{ExtraDist}\right) \quad (27$$

IntraDist is the sum of the largest distance of the members within each cluster:

$$IntraDist = \sum_{n=1}^{k} Max\left(Dist\left(c_i, c_j\right)\right), c_i, c_j \in O^n \quad (28$$

and ExtraDist is the sum of the shortest distances between clusters:

$$ExtraDist = \sum_{n=1}^{k}\left(Min_{1 \le m \le K, m \ne n}\left(Dist\left(c_i, c_j\right)\right)\right), c_i \in O^n, c_j \in O^m \quad (29$$

F. Calculate the value of each cluster in the CVIDR model

The value of each knowledge can be determined based on *Differentiating Organizational Capability (C), Generating Greater Value Added (V), Addressing Urgent and Critical Organizational Issues (I), Minimizing External Dependency (D) and Resource Expenditure Level (R)* to each company as follows:

$$V(c_i) = W^c \times C(c_i) + W^V \times V(c_i) + W^I \times I(c_i) + W^D \times D(c_i) - \quad (30$$

Where $C(C_i)$, $V(C_i)$, $I(C_i)$, $D(C_i)$, and $R(C_i)$ are respectively the scores of C_i company according to *C,V,I,D* and *R* criteria. W^C, W^V, W^I, W^D and W^R show the weighted importance for *C, V, I, D* and *R* criteria, respectively. We also have the following relationships:

$$W^C + W^V + W^I + W^D + W^R = 1 \quad (31$$

The profitability of the O^n cluster is obtained by calculating the average value of all companies in the nth cluster. It can be defined through the following equation:

$$V(O^n) = W^C \times C(O^n) + W^V \times V(O^n) + W^I \times I(O^n) + W^D \quad (32$$

$$C(O^n) = \frac{\sum_{c_i \in O^n} C(c_i)}{\|O^n\|} \quad (33$$

$$V(O^n) = \frac{\sum_{c_i \in O^n} V(c_i)}{\|O^n\|} \quad (34$$

$$I(O^n) = \frac{\sum_{c_i \in O^n} I(c_i)}{\|O^n\|} \quad (35$$

$$D(O^n) = \frac{\sum_{c_i \in O^n} D(c_i)}{\|O^n\|} \quad (36$$

$$R\left(O^{n}\right)=\frac{\sum_{c_i \in O^{n}} R\left(c_{i}\right)}{\left\|O^{n}\right\|} \quad (37$$

where $C(O^n)$, $V(O^n)$, $I(O^n)$, $D(O^n)$, and $R(O^n)$ are the scores of the nth cluster according to the criteria of C,V,I,D and R.

After extracting the values of the variables from the database (related to the companies investigated in this article), they are sub-standardized.

$$C\left(C_{i}\right)=\frac{\left(Q^{C}-Q_{\min}^{C}\right)}{\left(Q_{\max}^{C}-Q_{\min}^{C}\right)} \quad (38$$

$$V\left(C_{i}\right)=\frac{\left(Q^{V}-Q_{\min}^{V}\right)}{\left(Q_{\max}^{V}-Q_{\min}^{V}\right)} \quad (39$$

$$I\left(C_{i}\right)=\frac{\left(Q^{I}-Q_{\min}^{I}\right)}{\left(Q_{\max}^{I}-Q_{\min}^{I}\right)} \quad (40$$

$$D\left(C_{i}\right)=\frac{\left(Q^{D}-Q_{\min}^{D}\right)}{\left(Q_{\max}^{D}-Q_{\min}^{D}\right)} \quad (41$$

$$R\left(C_{i}\right)=\frac{\left(Q^{R}-Q_{\min}^{R}\right)}{\left(Q_{\max}^{R}-Q_{\min}^{R}\right)} \quad (42$$

G. Knowledge leveling of companies based on the CVIDR model

After calculating the variables, using K-means and fuzzy K-means algorithms, the studied companies are clustered based on the level of knowledge. In order to compare the clustering quality of two algorithms with each other and also to determine the optimal number of clusters from 15 to 36, we will perform the following steps using MATLAB (2021.b).

Table III

COMPARISON OF CVIDR MODEL CLUSTERING ALGORITHMS.

Based on the results presented in Table III and IV, incorporating the two parameters—time of first purchase and average order time—reveals that the fuzzy K-means algorithm creates denser clusters compared to the K-means algorithm. Additionally, clustering with 7 clusters demonstrates superior quality.

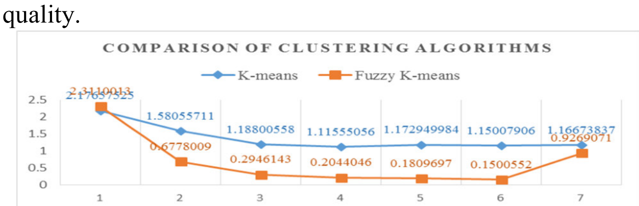

Fig. 6. Clustering density of CVIDR model algorithms

Table IV

CORRELATION OF CVIDR MODEL VARIABLES

	C	V	I	D	R
R	-0.43523	0.081548	-0.64007	0.01773	1
D	-0.79451	0.078569	0.041632	1	
I	0.034529	0.5573	1		
V	-0.68719	1			
C	1				

The integration of the time of first purchase and average order time into the Fuzzy K-means algorithm leads to the formation of denser clusters compared to the K-means algorithm due to the inherent properties and mechanisms of these clustering methods.

The Fuzzy K-means algorithm, unlike the traditional K-means, allows for partial membership of data points to multiple clusters rather than assigning each point to a single cluster definitively. This characteristic enables the Fuzzy K-means algorithm to better handle the variability and imprecision inherent in real-world data (see fig. 6). By incorporating additional parameters such as the time of first purchase and average order time, the Fuzzy K-means algorithm gains a more nuanced understanding of the data distribution, leading to a more refined clustering outcome.

The time of first purchase and average order time provide temporal dimensions that offer valuable insights into customer behavior and ordering patterns. When these temporal factors are included, the Fuzzy K-means algorithm can differentiate between clusters with more granularity, resulting in clusters that more accurately represent the underlying data patterns. Consequently, this leads to denser and more meaningful clusters.

The comparison of clustering quality, as demonstrated in the results (*Table IV*), shows that the addition of these parameters improves the clustering density in Fuzzy K-means. The superior performance of the Fuzzy K-means algorithm, particularly with seven clusters, is indicative of its enhanced capability to capture the intricacies of the data when temporal factors are incorporated. This improvement in clustering density reflects a more effective clustering process that is better suited to the complexities of the data.

Number of clusters	*Fuzzy K-means*	*K-means*
2	2.3110013	2.17657525
3	0.6778009	1.58055711
4	0.2946143	1.18800558
5	0.2044046	1.11555056
6	0.1809697	1.172949984
7	0.1500552	1.15007906
8	0.9269071	1.16673837

H. Cluster Analysis

Determination of Variable Weights:

The weights of variables were established based on expert opinions. Specifically, the variable "Organizational Capability" (C) was assigned a higher weight of 0.3 due to its critical importance. Other variables were weighted as follows: "Generating Greater Value Added" (V) and "Addressing Urgent and Critical Organizational Issues" (I) were each given a weight of 0.2, "Resource Expenditure Level" (R) was assigned a weight of 0.3, and "Minimizing External Dependencies" (D) was given a weight of 0.1. These weights were integrated into Equation (26) to calculate the value of each cluster.

Calculation of Cluster Characteristics:

Utilizing Equations (27-31), the freshness, repetition, and monetary value of each cluster's sales were computed. These parameters were essential for a comprehensive assessment of each cluster's status and quality (table V).

Table. v.
THE VALUE OF THE FORMED CLUSTERS

NUMBER CLUSTER	*VALUE OF EACH CLUSTER*	*THE NUMBER OF MEMBERS OF EACH CLUSTER*
3	8.375014	*9*
6	6.483674	*3*
4	6.350609	*7*
7	4.874912	*6*
2	3.867405	*4*
5	3.371083	*5*

Clusters were analyzed and categorized based on five variables: "Novelty," "Repetition," "Monetary Value," "Time of First Purchase," and "Average Order Time." This analysis led to the classification of clusters into four main skill levels:
Level 1: *Exprt companies (cluster 3)*
Level 2: *Intermediate companies (cluster 4 and 6)*
Level 3: *Novice companies (cluster 2 and 7)*
Level 4: *Very Novice companies (cluster 5)*

With the analysis done, the status of the studied supply chain companies is categorized as follows (Fig. 7).

The results from the cluster calculations and classifications were validated using standard criteria and compared with real-world data to ensure accuracy and reliability. This included analyzing deviations and aligning results with practical conditions.

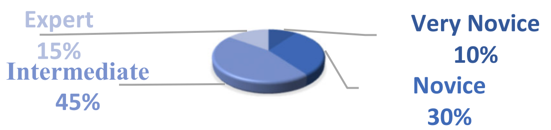

Fig. 7. The initial level of 12 knowledge fields in manufacturing companies before horizontal integration.

VI. RESULTS AND DISCUSSION

The model was executed on a computer system equipped with 8 GB of RAM and a CPU operating at a speed of 2.2 GHz to address the test problems. By relying on the proposed model, the solution procedure, and a comprehensive data analysis, it becomes evident that in scenarios where there are no time constraints, orchestrating 345 instances of knowledge sharing among companies would result in each of them achieving expertise across all knowledge fields. This finding is visually depicted in Fig. 8, offering a graphical representation of the number of sharing required for each knowledge type. Ultimately, this approach ensures that all companies reach an expert level in these knowledge fields.

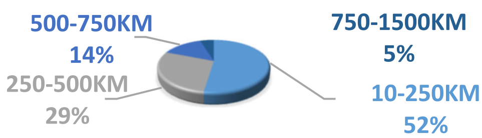

Fig. 10. Percentage of knowledge sharing by the distance between companies

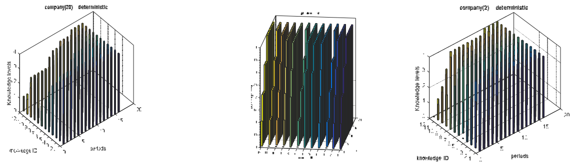

Fig. 8. Improving knowledge in supply chain members in the studied companies

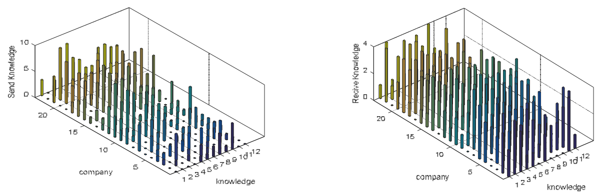

Fig. 9. The number of knowledge sharing required for each knowledge in full integration and their sharing companies

As shown, prior to the initiation of supply chain integration through knowledge sharing, 10 companies held the highest level of expertise within the supply chain. Surprisingly, by conducting only 11 knowledge-sharing instances, all these companies achieved expert status. Conversely, knowledge areas 11 and 12 had the lowest levels of expertise among supply chain members, with a requirement of 20 knowledge-sharing activities each to attain expertise in these two specific domains. Fig. 9 provides a visual representation of the firms involved in sharing each knowledge type to other members within their respective supply chain level and the extent of their involvement.

For instance, consider the sharing of knowledge 1 with other members of the SC. In this context, companies 3, 4, 7, 9, 10, 11, 12, 13, 15, 16, 17, 18, 21, and 23 (highlighted in color within the first row of Fig. 9) play central roles. Furthermore, each of these companies bears responsibility for sharing knowledge 1 at varying rates, which are 5, 7, 3, 5, 4, 3, 7, 6, 8, 7, 9, 6, 7, and 6, respectively (indicating the intensity of knowledge sharing). Additionally, Fig. 9 provides an overview of the initial proficiency level of each knowledge within the companies involved at the outset of the integration process.

Furthermore, as depicted in Fig. 10, it becomes evident that the process of integration involves knowledge sharing responsibilities not solely limited to companies initially possessing expert-level knowledge. Companies at intermediate and novice knowledge levels also play an active role. As they acquire knowledge and advance to higher levels, they gain the capability to share their knowledge with other companies and actively participate in this collaborative effort. When it comes to sharing knowledge to other members at the same level within this chain, companies with varying expertise levels are involved, comprising 37% with expert-level knowledge, 46% at the intermediate level, and 17% at the novice level.

Allowing companies with different knowledge levels to engage in integration efforts can effectively lower the expenses linked to knowledge sharing. This approach becomes feasible as each company can access knowledge from nearby chain members, reducing the costs tied to employee travel and mission expenses. The results of this strategy are prominently displayed in *Fig. 10*. It's evident that a significant 85% of knowledge sharing occurs among companies located within a maximum distance of 500 kilometers, leading to a substantial reduction in integration costs.

In addition to maximizing the knowledge level of companies in SC integration, minimizing the cost of knowledge sharing is also considered. To minimize its cost, each company must get the knowledge it needs from the nearest company with the ability to sharing that knowledge. Also, to analyze the objective function and find the optimal solution of the above model from Crystal Structure Algorithm (CryStAl). The results of solving the model are shown in Fig. 11.

The important parameters in the above model are the A_{ik} and B_k. Since these parameters respectively indicate the importance of knowledge k for the company at the desired level of the chain and the importance of knowledge k from the point of view of the next level of the SC, and since these parameters are determined by an expert and cannot be determined with certainty and exact value Also did, in the presented model, according to experts, the Wi parameter (Constraint 10) also has cognitive uncertainty. Therefore, since these parameters have cognitive uncertainty, we will use the FRPP approach to solve it in the presented model in order to stabilize the proposed model. according to the explanation, the parameters with uncertainty are quantified based on the above and through the possible values determined by the expert. The robust formation is examined again in the following.

The standard deviation of the robust model is always better than the deterministic programming model. Also, the increase in fines causes an increase in the deviation of the standards; however, the supremacy and superiority of FRPP model are always maintained.

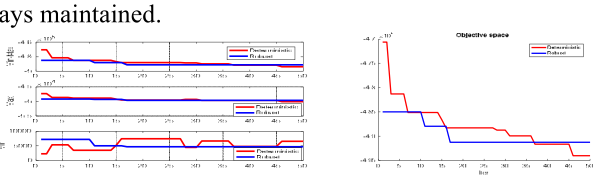

Fig. 11. Graphical representation of the average costs of the objective functions of the models under simulation

As seen in *Fig. 11*, the average robust possible planning shows a better performance than the possible planning model. Increased fines make it more reasonable to use risk-averse models such as the proposed *FRPP* model. Due to the level of risk aversion created by the *FRPP* model, its outputs face less risk and violations than the deterministic planning models under high fines.

It appears there is a contradiction regarding the role and involvement of companies with higher levels of knowledge in the knowledge-sharing process. Specifically, the conventional assumption that companies with higher expertise are the primary contributors to knowledge sharing has been challenged by this research. The study reveals that companies with higher levels of knowledge do not necessarily participate more in knowledge sharing than others and may incur higher knowledge sharing costs. Thus, contrary to common assumption, companies with higher expertise do not always lead in knowledge sharing within the supply chain.

Our model addresses this issue by optimizing the knowledge-sharing process within the supply chain, considering four different levels of expertise among companies. Designed specifically for the scenario under investigation, the model demonstrates how to leverage optimal knowledge sharing while minimizing the high costs associated with more knowledgeable companies. In other words, our model is optimized to configure the knowledge-sharing process so that companies with varying levels of expertise can sharing knowledge effectively and efficiently, thereby reducing sharing costs.

Consequently, the model clearly shows that the best approach to managing knowledge sharing within the supply chain cannot rely solely on the knowledge level of companies. Instead, it requires a comprehensive and optimized approach that considers all dimensions of cost and participation.

The possibility of participation of companies with different degrees of knowledge in integration reduces the knowledge sharing cost because it is possible for each company to acquire knowledge from the closest member of the SC (in terms of distance) so that the cost of the mission and travel of employees is minimized; this result of such work can be seen in *Fig. 9 and 10*. As seen, *85%* of knowledge sharing is between companies with a maximum distance of *500* km, significantly reducing the integration cost.

Crucial for fostering knowledge sharing within the supply chain is the capability to sharing and acquisition knowledge among member companies. This capacity is characterized by the parameters W_i and V_j in the model under consideration. Importantly, increasing this capacity does not impact the cost associated with knowledge sharing, but it significantly streamlines the achievement of the optimal knowledge-sharing level within a more efficient planning timeframe. Within this specific scenario (*Fig. 12.A*), the effects of varying the α_{1-4} value within the range of 0% to 30% can be assessed. Additionally, it's possible to abbreviate the planning horizon by permitting a slight deviation from the ideal level, as demonstrated in *Fig. 12.B*.

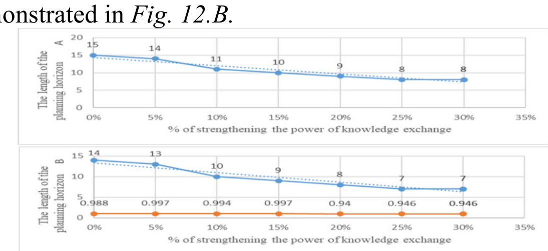

Fig. 12. Evaluating the knowledge acquisition and sharing capabilities (Wi and Vj) of member companies within the supply chain.

The physical distance (S_{ij}) between companies is a factor that can be enhanced to enhance the model's outcomes (β). If managers at various levels of the chain can introduce initiatives aimed at reinforcing inter-company relationships, this can lead to a reduction in knowledge sharing costs within the chain. In essence, the closer the bond between member companies within the examined chain, the more affordable knowledge sharing becomes. As depicted in Fig. 13, strengthening inter-company relationships by 25% results in a 13% decrease in the cost of knowledge sharing.

The enhancement of inter-company relationships by 25% was assessed using the parameter S_{ij}, which measures the physical distance and interaction level between companies. Initially, the physical distance and interaction levels between each pair of companies were evaluated. By adjusting the S_{ij} values to reflect a 25% increase in interactions and collaboration, and a 25% reduction in effective physical distance, strengthened relationships were simulated. These adjusted values were incorporated into the model to optimize the processes of knowledge sharing and acquisition among companies. These improvements were achieved through initiatives that facilitated knowledge sharing, improved communication channels, strategic partnerships, cross-training programs, skill development, and the creation of policy and incentive structures.

These measures resulted in significant cost reductions and efficiency improvements. The enhanced relationships reduced redundancies and increased the efficiency of knowledge sharing, leading to faster and more accurate dissemination of knowledge. Strengthened local collaborations reduced travel and mission costs associated with knowledge sharing. Additionally, more efficient use of resources and reduced risks related to knowledge sharing further lowered overall costs. These results demonstrate that improving inter-company relationships directly impacts the efficiency and cost-effectiveness of the supply chain, resulting in a 13% reduction in costs.

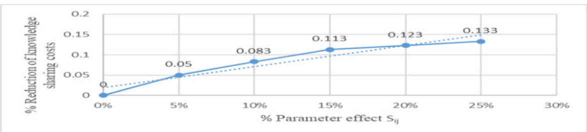

Fig. 13. Evaluating the physical distance (Sij) between companies

Consequently, given the evaluations discussed above, it can be inferred that the presented model has produced coherent findings and is capable of suggesting a wide range of valuable solutions for knowledge-sharing networks within horizontal integration scenarios.

A. Theoretical implications

This article discloses essential academic contributions to the literature on supply chain integration and horizontal integration through knowledge sharing using multi-objective mathematical modeling. Our research is grounded in the Resource-Based View (RBV) and Knowledge-Based View (KBV), which emphasize the crucial role of effective knowledge management and sharing in achieving competitive advantage and enhancing supply chain efficiency; therefore, we further add to contributions made by Agostini et al. [2], Peng [3], Barney [7], Grant [5], Acedo et al. [14] and Choi et al. [15].

The proposed model in this research facilitates more effective coordination and collaboration among organizations and supply chain members. This research advances theoretical discussions by providing evaluation criteria and knowledge level assessment of supply chain members, clustering and cluster management in knowledge sharing, and practical solutions based on mathematical programming for improving supply chain productivity and efficiency through proposed scheduling aligned with organizational strategic approaches. therefore, we further add to contributions made by Bahinipati et al. [6], Asmussen et al. [4], Guo et al. [17] and Cozzolino et al. [11].

Since without considering uncertainty in the mathematical modeling presented in Section 4.6, systematic scheduling for knowledge sharing would undoubtedly face significant challenges [19], [24], [29](e.g., in any decision-making system, the decision-maker (DM) plays a crucial role in making decisions or weighting criteria, and since human judgment is prone to cognitive biases), using robust and risk-averse approaches to mitigate these biases in modeling is essential. Thus, the proposed FRPP approach in this study was employed to address this challenge, and based on the results of this research, it has performed well in this area and neglecting our proposed framework would hinder an effective and optimize knowledge sharing in supply chain.

Furthermore, mobilized knowledge resources may be directed inefficiently, particularly if the scheduling horizons are long-term or if many companies and participants are involved in knowledge sharing. A key aspect of this research is the solution method for the proposed model, which has successfully identified the optimal solution to the problem under consideration (Fig. 15).

We also expanded upon the academic discussion related to Krylova et al. [26], Mazloomi and Jolly [41], Mehdikhani and Valmohammadi [42] and Lee [30], strategic programming for effective knowledge sharing among supply chain members requires clustering and differentiating them based on their knowledge levels. Our research is founded on this principle and aids in understanding the prerequisites for appropriately utilizing clustering methods in this domain for business models. The approach presented in Section 5.2 of the study substantiates this claim.

Therefore, the presented model narrows the gap in the literature, addresses the proposed research question ("what, when, how, and among which supply chain members knowledge should be shared by considering reducing costs, and enhancing knowledge levels among supply chain members?"), and thus plays a vital role in guiding the supply chain managers (see Fig. 8 and 9). Furthermore, it makes a crucial contribution to the theory and will help future researchers build upon findings to position themselves and to further drive academic discussion.

B. Practical implications

Despite numerous studies identifying the factors influencing knowledge sharing to achieve supply chain integration, a systematic approach that can be implemented in organizational platforms has not yet been presented. The model proposed in this paper can pave the way for the implementation of this method in various organizations. Given the importance of optimal and efficient use of organizational resources, this approach can replace managers who do not know how to leverage systematic methods to enhance productivity. Therefore, it is essential for supply chain managers, policymakers, and organizational leaders to prepare for future challenges and actively seek new opportunities and tools to ensure long-term success for their companies.

The framework presented in this study highlights the criteria for classifying company knowledge, such as Differentiating Organizational Capability, Generating Greater Value Added, Addressing Urgent and Critical Organizational Issues, Resource Expenditure Level, Minimizing External

Dependency, and Availability of Appropriate Sharing Infrastructure. These criteria are key for evaluating and categorizing organizational knowledge. Management teams can utilize the approach proposed in this paper to cluster these companies for effective management.

The multi-objective mathematical model proposed in this research provides managers with the ability to manage optimally (with a focus on reducing knowledge sharing costs) and efficiently (using the most effective approach to enhance the knowledge level of the supply chain) in the foreseeable future, while monitoring the status. This capability essentially serves as a decision support system. we further add to contributions made by Abdelwhab et al. [1], Castañer and Oliveira [8] and Asmussen et al. [4], have reached similar conclusions.

Overall, strategic management must adopt a reliable approach to uncertainty, particularly in decision-making processes where managers face cognitive uncertainties due to insufficient data in various conditions. The use of the Robust Fuzzy Possibilistic Programming approach can significantly aid managers in mitigating decision-making errors and reducing risk.

VII. Conclusion

Supply chain integration plays a pivotal role in promoting collaboration among its stakeholders, resulting in a host of benefits such as improved performance within the SC, cost reduction, and the effective dampening of the disruptive "bullwhip effect." Integration can take shape both horizontally and vertically, fostering cooperation across operational, tactical, and strategic levels within the SC. At the strategic echelon, horizontal integration involves the knowledge sharing among members operating within a specific chain tier.

This article introduces an innovative mathematical model with the primary aim of optimizing knowledge sharing among members, thereby enhancing collaboration at the chain level, all while endeavoring to minimize costs attributable to resource constraints. The model's practical application was exemplified within the context of horizontal integration involving manufacturers in an auto spare parts supply chain comprising 23 distinct companies. Throughout this endeavor, the allocation of 12 critical knowledge components among these SC-level participants was thoroughly scrutinized.

Notably, this research introduces a multitude of pioneering elements, most notably the groundbreaking mathematical modeling of the knowledge sharing process. This intricate process was addressed through robust optimization, employing the FRPP method. Among the salient findings is the strategic approach taken by companies to mitigate integration costs, involving cooperation with geographically proximate counterparts for efficient knowledge acquisition. Consequently, companies positioned at greater distances from their peers exhibited diminished involvement in the integration process.Next, even companies with an increased level of knowledge in the training process could teach other companies. In addition to reducing the costs of knowledge sharing, this issue expanded cooperation between more companies and obtained more and more benefits from horizontal integration.

By having a larger workforce and better-equipped facilities for carrying out the integration process, it becomes possible to shorten its duration. Thus, company managers can determine the appropriate timeframe based on the resources at their disposal and their strategic priorities.

The implementation of the integration process included two types of costs, the direct costs related to the process and the indirect costs resulting from the allocation of a part of employees and facilities to the process; during the implementation period of the integration process, they are left out of the direct flow of production, causing a reduction in the company's production and in turn reducing its income. Therefore, using fewer employees and facilities increases the implementation period of the integration process; however, due to the limited resources, the sum of the above analyses increases the managers' knowledge of the problem and obtains accurate insight to make the best decisions in the integration process.

A. Limitations and future research

This study utilized the well-established CVIDR framework to identify the determinants of knowledge sharing. Within this framework, the sharing process between knowledge owners and recipients was explored, incorporating factors such as the willingness and ability of knowledge owners to share, the motivation and capacity of recipients to absorb knowledge, and the shared opportunities for knowledge sharing. However, previous research [13], [20], [22] has underscored additional influential factors in knowledge sharing, including interaction frequency, power dynamics, and various personality traits. These factors could potentially enhance the proposed model in future investigations. For instance, integrating interaction frequency could involve introducing a multiplier in the knowledge-sharing equation to adjust the collective sharing capacity, with techniques like Social Network Analysis (SNA) aiding in estimating this multiplier.

In forthcoming studies, it may be beneficial to examine the costs of knowledge sharing from both

Future research could expand the model by exploring the costs of knowledge sharing from both direct and indirect perspectives, optimizing communication among units, and applying dynamic planning methods or cooperative game theory to solve the model. Additionally, focusing on vertical integration in supply chain knowledge sharing may offer alternative research avenues. While the current model aims to maximize knowledge levels, minimize sharing costs, and enhance collaboration within the supply chain, future studies could pursue objectives like maximizing profits, reducing sharing time, or improving stakeholder compatibility. Moreover, transitioning from a static to a dynamic approach could enable the development of long-term strategies in knowledge management and resource allocation by accommodating changing parameters and inputs through dynamic simulations.

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