



A HYBRID FUZZY APPROACH FOR SELECTING DIGITAL 3PL SERVICE PROVIDERS

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ABSTRACT. Background: The study focuses on identifying the technologies, capabilities, and characteristics that logistics firms must possess during the digital transformation of the supply chain. It addresses the challenge of determining the necessary criteria for selecting a technological or digital third-party logistics service provider (3PL). It aims to develop a structured and hybrid decision-making framework for selecting digital 3PL service providers by integrating subjective and objective weighting methods. The scientific purpose is to bridge the gap in existing research by incorporating Multi-Criteria Decision-Making (MCDM) methods and providing a more comprehensive, empirically validated, and practically applicable model that enhances digital supply chain efficiency.

Methods: The study began with a literature review to identify relevant technological indicators. These indicators were then presented to a group of experts in academia, resulting in the identification of six main criteria and 21 sub-criteria. To determine the weights of these criteria and sub-criteria, MCDM methods were used. Experts with experience in Turkey were selected for the analyses. The study first applied SWARA and Fuzzy Entropy methods, followed by a Bayesian approach.

Results: The findings reveal that the most significant factors influencing the selection of a technological 3PL provider include: Automatic Material Placement and Tracking Technology, Lack of Digital Collaboration, Technology Compatibility, Supplier Compatibility and Use of Augmented and Virtual Reality Technologies. These factors play a key role in ensuring effective digital integration within the supply chain.

Conclusion: This study integrates SWARA, Fuzzy Entropy, and a Bayesian approach to propose a novel decision-making model for selecting digital 3PL service providers. It highlights key criteria such as technology compatibility and augmented reality technologies, emphasizing their importance for seamless digital supply chain integration. SWARA offers a subjective weighting mechanism, Fuzzy Entropy ensures objectivity, and the Bayesian approach balances these methods. The study provides valuable insights into the factors that influence digital transformation in 3PL services and offers actionable policy recommendations to accelerate this transformation in supply chain management.

Keywords: SWARA, fuzzy entropy, digital supplier selection, digital 3PL selection, bayesian approach

INTRODUCTION

The pervasive adoption of Industry 4.0 technologies catalyzes the digitization of traditional supply chains, merging physical processes with digital data to enhance supply chain efficiency. These technological advancements impact all stakeholders, necessitating adaptation by suppliers within the supply chain. The Digital Supply Chain (DSC) integrates physical and digital processes to enhance efficiency and minimize resource

consumption [Queiroz et al., 2019]. Digital supply chains epitomize advancements in the Internet of Things, forming a highly integrated global internet community that connects through a shared network of sensor devices across areas such as order signals, production/warehouse systems, and inventory tracking/delivery, encompassing customers, distributors, manufacturers, and suppliers [Boyson et al., 2022]. Digital technologies (mobile devices, IoT, artificial intelligence, etc.) are transforming supply chains by increasing automation in logistics processes [Büyükoğuzkan & Göçer, 2018b]. Emerging digital technologies are those



currently being developed or anticipated to be developed in the near future, significantly altering the business and social landscape. Digital supply chains have the ability to process large amounts of information and encourage supply chain partners to collaborate and communicate on digital platforms [Agrawal & Narain, 2018]. As supply chains undergo digitalization with Industry 4.0, the proper selection of 3PL has become critical to operational efficiency. The integration of logistics operations within the digital supply chain heightens the need for 3PL providers with robust technological infrastructure. A logistics company's inability to manage this transition effectively can disrupt the digital supply chain and lead to errors in customer-facing processes. Consequently, choosing the right 3PL service provider has become a strategic concern. This study identifies the key criteria that 3PL providers must meet to adapt to digital processes and weights these criteria using a fuzzy logic-based method. The paper includes a literature review, a methodology section, a case study, and results.

Farahani, Meier, and Wilke [2015] identified key technological innovations in digital supply chain management, commonly known as Industry 4.0 components. This 4th Industrial Revolution integrates physical production with cyber technologies through automation and inter-system connectivity. Machines operate simultaneously via the internet and sensors, with data stored in the cloud. Industry 4.0 redefines supply chains and business models, driven by big data analytics, cloud computing, AI, cybersecurity, the IoT, robotics, 3D printing, blockchain, and augmented reality. While existing studies primarily focus on traditional supplier selection or general digital supplier evaluation, they fail to specifically address the selection of technologically advanced 3PL providers. The objective of this study is to develop a hybrid fuzzy-based MCDM model (SWARA + Fuzzy Entropy with Bayesian integration) to identify critical selection criteria and select the optimal digital 3PL provider. Unlike previous models, which remain theoretical, the current study empirically validates the proposed framework by applying it to 10 logistics firms in Turkey, demonstrating its practical effectiveness in real-world scenarios. By bridging the divide between theory and

practice, it provides a robust, data-driven approach to 3PL selection in digitalized supply chains.

In this study, these elements, referred to as components of Industry 4.0, emerge as criteria for the selection of digital/technological 3PL providers. The final decisions regarding the criteria were made by combining a literature review with expert opinions. The selected criteria and their corresponding definitions are as follows.

Technology Infrastructure, which plays a critical role in the digital transformation of supply chains, enhances operational efficiency by preventing disruptions among chain links. This main criterion was examined under three sub-criteria. *Supplier Compatibility* ensures long-term cooperation and performance adequacy, while *Technology Compatibility* refers to the adequacy and integration of technology between the supplier and the chain. *Lack of Technology Integration* highlights deficiencies in the integration of chain members' technologies.

Smart Logistics and Inventory Systems enable warehouse operations to be managed with minimal human labor and are supported by automation systems. This second main criterion comprises five sub-criteria. *Use of Smart Forklifts, Pallet Carriers and Cranes* and *Automatic Material Placement and Tracking Technology* improve efficiency in logistics, while *Real-Time Tracking* allows for continuous inventory monitoring. *Augmented and Virtual Reality* improves business processes, while *Transport Optimization* provides cost and speed advantages.

Digital Competence, designated as the third main criterion and divided into three sub-criteria, reflects a company's ability to digitalize its business processes. *Digital Interaction* and *Lack of Digital Collaboration* address the regulation of interactions with customers and suppliers, while *Customization and Personalization* involves adapting data and personalizing processes.

Management Systems, designated as the fourth main criterion and divided into three sub-criteria, defines organizational culture and structure. *Incorrect Demand Forecasting* and *Advanced Analytics* support accurate decision-making, while *Real-Time Visibility* enables real-time monitoring of processes.

Customer-Centricity, designated as the fifth main criterion and divided into three sub-criteria, prioritizes customer satisfaction. *Flexibility* reflects the ability to adapt to changes, while *Lack of Information Sharing* can lead to disruptions in integrated processes. *Service Support* refers to the ability to quickly resolve technical problems.

Organizational Design, designated as the final main criterion and divided into four sub-criteria, ensures alignment in decision-making processes. *Digital Performance Management* is essential for the effective management of digital processes, while *Online Transparency* fosters trust. *Big Data-Based Quality Management* enhances quality, and finally, *Process Standardization and Automation* reduces error rates and improves operational efficiency.

Figure 1 illustrates the six main criteria and their subcategories.

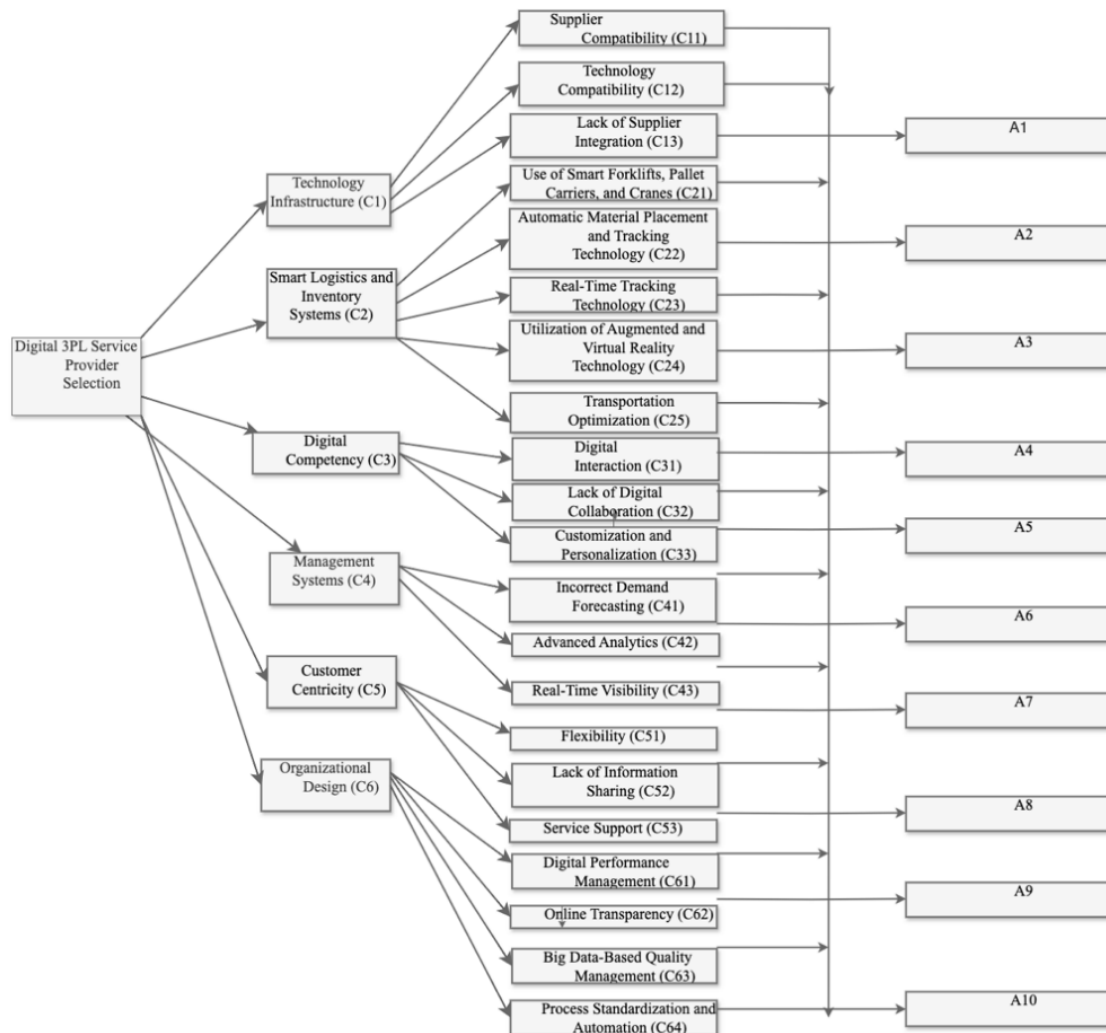


Fig. 1. Criteria Used to Select Digital Third-Party Logistics (3PL) Service Providers

BACKGROUND

The selection of digital suppliers has been widely explored in the literature, particularly in the context of Industry 4.0 and digital transformation. Various multi-criteria decision-making (MCDM) approaches have been applied to evaluate suppliers based on their technological capabilities, operational efficiency, and sustainability factors. However, most studies focus on general supplier selection rather than the specific evaluation of 3PL providers in digital supply chains.

Previous studies have employed IT2F-TOPSIS [Özbek & Yildiz, 2020], IVIF AHP & ARAS [Büyükoçkan & Göçer, 2018a], SWARA & WASPAS [Sharma & Joshi, 2020], and Fuzzy Entropy & COPRAS [Xie et al., 2022] to assess supplier selection criteria. These methodologies emphasize key factors such as technology infrastructure, supplier compatibility, flexibility, digital competence, and automation systems. Other works have highlighted real-time visibility, smart inventory management, IoT-enabled logistics, and AI-driven optimization as critical elements in supplier evaluation [Tavana et al., 2021; Dolatabad et al., 2023].

In addition to technological aspects, sustainability and digitalization have gained attention in recent studies. Wang et al. [2022] and Ali et al. [2023] investigate environmental and social dimensions, considering factors like carbon footprint tracking, green logistics, and workforce digital skills in supplier selection models. Similarly, Krstić et al. [2022] evaluate the adaptability of Industry 4.0 technologies in reverse logistics, emphasizing cost efficiency, modular integration, and regulatory compliance.

Despite advancements in digital supplier selection, the specific evaluation of digital 3PL providers remains underexplored. Existing models primarily focus on manufacturing suppliers or general logistics partners without addressing the unique technological and operational requirements of digital 3PL firms. While SWARA and Fuzzy Entropy are widely used, their integration with Bayesian methods for

digital 3PL selection has not been explored in detail. This study fills this gap by introducing a hybrid decision-making model that merges subjective (SWARA) and objective (Fuzzy Entropy) weighting methods, further enhancing reliability through Bayesian inference. By addressing the inherent uncertainty in criteria evaluation and incorporating decision-makers' expertise, this innovative framework ensures a more balanced and comprehensive selection process. Furthermore, unlike previous research, the proposed model is empirically validated through its application to 10 logistics firms in Turkey, demonstrating its real-world applicability in digital supply chain environments and contributing a novel perspective to the existing body of literature.

This literature review underscores the need for an advanced, structured approach to digital 3PL selection, positioning the study as a significant contribution to the evolving landscape of Industry 4.0-driven supply chain management.

MATERIALS AND METHODS

Based on the literature review, key technological and digital indicators in logistics firms were identified. A panel of experts refined these indicators, reaching a consensus on 6 main criteria and 21 sub-criteria. The conceptual framework outlining the research process is shown in Figure 2.

For 3PL provider selection in Turkey, firms were chosen based on their technological adaptability, Logistics 4.0 transition, e-commerce experience, and digital investments. To handle decision-making uncertainty, a hybrid MCDM approach was applied, integrating SWARA and Fuzzy Entropy.

SWARA enabled expert-driven weighting of criteria, ensuring decision accuracy, while Fuzzy Entropy enhanced objectivity by evaluating uncertainty in the criteria. This hybridization effectively combined subjective and objective insights, offering a comprehensive evaluation model for digital 3PL selection.

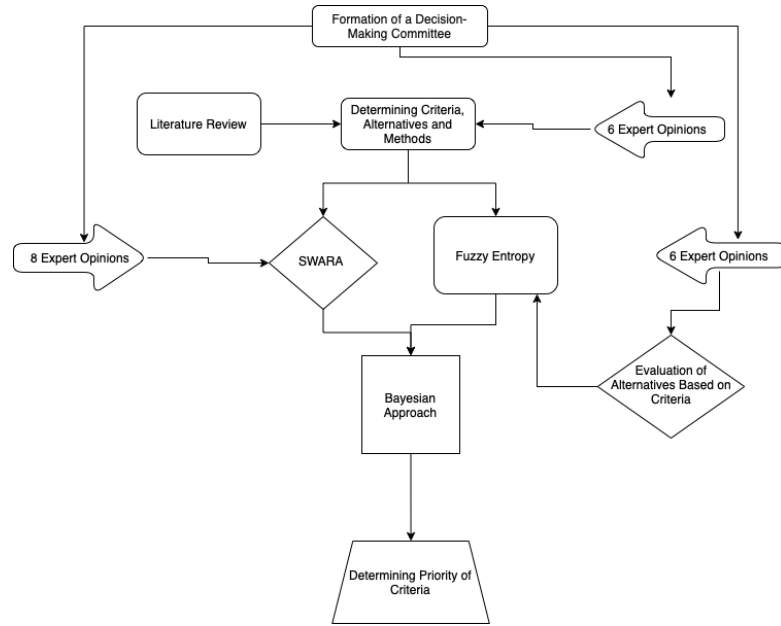


Fig. 2. The conceptual framework

SWARA (Step-Wise Weight Assessment Ratio Analysis) Method

The fundamental characteristic of the SWARA method is the ability to estimate the opinions of experts or stakeholders regarding the importance of attributes in determining the weights. Its steps are as follows [Keršulienė et al., 2010]:

Step 1: Experts rank the criteria in order of importance, starting with the most important criterion.

Step 2: Starting from the second criterion, each criterion i is compared to the criterion immediately before it, $i - 1$, to determine its relative importance. Based on these comparisons, importance values are calculated for all criteria except the first. The relative importance of each criterion is expressed as s_i , a value derived using multiples of 0.05.

Step 3: The k_i coefficient is calculated using Equation (1).

$$k_i = \begin{cases} 1 & i=1 \\ s_i + 1 & i>1 \end{cases} \quad (1)$$

Step 4: The corrected weight value (q_i) is calculated using Equation (2).

$$q_i = \begin{cases} 1 & i=1 \\ \frac{q_{i-1}}{k_i} & i>1 \end{cases} \quad (2)$$

Step 5: Using Equation (3), the criterion weight (w_i) is obtained.

$$w_i = \frac{q_i}{\sum_{i=1}^n q_i} \quad (3)$$

Step 6: If multiple decision makers are used in solving the problem, the final criterion weights are obtained by taking the geometric mean of all w_i values.

Fuzzy Entropy Method

Shannon entropy is widely used in MCDM to determine criterion weights objectively, especially when decision-maker preferences are unavailable. It quantifies disorder in a system, assigning higher weights to criteria with greater variation across alternatives and lower weights to those with minimal differences. This method ensures an unbiased, data-driven approach by deriving weights directly from the performance matrix. The original Shannon entropy process can be outlined in several steps [Kacprzak, 2017]:

If there is an uncertain decision matrix $\tilde{X}$ resulting from the evaluation of m alternatives

for n criteria, with elements represented as $\tilde{x}_{ij} = (l_{ij}, m_{ij}, u_{ij})$, then the score of the i th alternative for the j th criterion is as shown in Equation (4):

$$\tilde{X} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix} \quad (4)$$

Step 1: To compute the normalized fuzzy decision matrix $\tilde{Z} = (\tilde{z}_{ij})$:

$$\tilde{z}_{ij} = \left(\frac{l_{ij}}{\sum_{i=1}^m l_{ij}}, \frac{m_{ij}}{\sum_{i=1}^m m_{ij}}, \frac{u_{ij}}{\sum_{i=1}^m u_{ij}} \right) \quad (5)$$

Step 2: The Shannon entropy vector $\tilde{e} = (\tilde{e}_1, \tilde{e}_2, \dots, \tilde{e}_n)$ is calculated according to Equation (6):

$$\tilde{e}_j = \left(-\frac{1}{\ln m} \sum_{i=1}^m l_{ij} \ln l_{ij}, -\frac{1}{\ln m} \sum_{i=1}^m m_{ij} \ln m_{ij}, -\frac{1}{\ln m} \sum_{i=1}^m u_{ij} \ln u_{ij} \right) \quad (6)$$

Here, if l_{ij} , m_{ij} or u_{ij} equals 0, then $l_{ij} \ln l_{ij}$, $m_{ij} \ln m_{ij}$ or $u_{ij} \ln u_{ij}$, respectively, are defined as 0.

Step 3: The degree of separation $\tilde{d}_j$ for each criterion C_j is found.

$$\tilde{d}_j = \left(1 - \frac{1}{\ln m} \sum_{i=1}^m l_{ij} \ln l_{ij}, 1 - \frac{1}{\ln m} \sum_{i=1}^m m_{ij} \ln m_{ij}, 1 - \frac{1}{\ln m} \sum_{i=1}^m u_{ij} \ln u_{ij} \right) \quad (7)$$

Step 4: The fuzzy weight vector $\tilde{w} = (\tilde{w}_1, \tilde{w}_2, \dots, \tilde{w}_n)$ is calculated using Equation (8).

$$\tilde{w}_j = \left(\frac{1 - \frac{1}{\ln m} \sum_{i=1}^m l_{ij} \ln l_{ij}}{\sum_{j=1}^n \left(1 - \frac{1}{\ln m} \sum_{i=1}^m l_{ij} \ln l_{ij} \right)}, \frac{1 - \frac{1}{\ln m} \sum_{i=1}^m m_{ij} \ln m_{ij}}{\sum_{j=1}^n \left(1 - \frac{1}{\ln m} \sum_{i=1}^m m_{ij} \ln m_{ij} \right)}, \frac{1 - \frac{1}{\ln m} \sum_{i=1}^m u_{ij} \ln u_{ij}}{\sum_{j=1}^n \left(1 - \frac{1}{\ln m} \sum_{i=1}^m u_{ij} \ln u_{ij} \right)} \right) \quad (8)$$

Step 5: The Center of Area (COA) defuzzification technique is used to obtain a numerical result from triangular fuzzy numbers. For a triangular fuzzy number $\tilde{A}(x) = (c_A^L, c_A^M, c_A^U)$, the COA $\tilde{A}(x)$ formula is expressed as follows:

$$COA_{\tilde{A}} = \frac{(c_A^U - c_A^L) + (c_A^M - c_A^L)}{3} + c_A^L \quad (9)$$

Bayesian Approach

The Bayesian approach can be employed to integrate the weights of evaluation criteria and derive a singular optimal weight score in studies utilizing both objective and subjective weighting methods. This approach is implemented using equations (10) and (11), as provided below [Vinogradova - Zinkevič et al., 2018]:

$$W\left(\frac{R_j}{X}\right) = \frac{\left[w(R_j) w\left(\frac{X}{R_j}\right) \right]}{\left[\sum_{j=1}^m w(R_j) w\left(\frac{X}{R_j}\right) \right]} \quad (10)$$

$$\alpha_j = \frac{w_j W_j}{\sum_{j=1}^m w_j W_j} \quad (11)$$

$w(R_j)$ = w_j : Initial Weight (jth criterion R_j)

X : Event (when the weights of new evaluation criteria are obtained)

$W\left(\frac{X}{R_j}\right)$ = W_j : New Criterion Weight

α_j : Recalculated Criterion Weights

Decision Making Tool

Criteria weights were determined using the SWARA method based on expert opinions. Eight professionals, including academics, industry employees, managers, and consultants with expertise in digital logistics, participated in the study. To maintain consistency, six experts were consulted for company evaluations, selected through criterion sampling to ensure reliability. Ten firms, considered as alternatives, were

evaluated based on these criteria to determine the most suitable digital 3PL provider.

Experts completed a questionnaire to rank and compare criteria, followed by online meetings for further assessment. Evaluations were conducted using linguistic expressions, later converted into triangular fuzzy numbers [Chen, 2000]. Tables 1 and 2 provide details on expert profiles and corresponding fuzzy number conversions.

Table 1. Titles and Number of Participants comprising the study group

Title	Number of Participants
Academic	1
Industry Employee	1
Manager	4
Consultant	2

Table 2. Linguistic Expressions and Corresponding Triangular Fuzzy Numbers

Linguistic Expressions	Triangular Fuzzy Number Equivalents
Very Low (VL)	(0,0,1)
Low (L)	(0,1,3)
Moderately Low (ML)	(1,3,5)
Reasonable (R)	(3,5,7)
Moderately High (MH)	(5,7,9)
High (H)	(7,9,10)
Very High (VH)	(9,10,10)

RESULTS

Calculation of Criterion Weights Using the SWARA Method

The weights calculated using the SWARA steps for the six main criteria evaluated by eight decision-makers are as follows:

Table 3. Final Weights of the Main Criteria

	DM1	DM2	DM3	DM4	DM5	DM6	DM7	DM8	Final Criterion Weight
C1	0.19	0.24	0.22	0.18	0.29	0.44	0.19	0.14	0.240
C2	0.12	0.13	0.14	0.12	0.17	0.10	0.23	0.19	0.155
C3	0.23	0.20	0.24	0.16	0.19	0.23	0.18	0.13	0.206
C4	0.03	0.10	0.11	0.15	0.08	0.14	0.13	0.12	0.107
C5	0.37	0.18	0.13	0.26	0.14	0.03	0.12	0.25	0.166
C6	0.06	0.15	0.17	0.13	0.13	0.06	0.15	0.17	0.127

When examining the table resulting from the reordering of the main criteria, the criterion named C1, "Technology Infrastructure," stands

out as the most important. Criterion C3, "Digital Competency," is in second position, while criterion C5, "Customer Centricity," is in third position. They are followed by "Smart Logistics

and Inventory Systems," "Management Systems," and "Organizational Design."

Similar calculations were conducted for each sub-criterion of the main criteria. The evaluation results for the sub-criteria are presented below (Table 4).

After the subjective weighting method, SWARA, the aim was to weight the same criteria using an objective weighting method, the Fuzzy Entropy method.

Calculation of Criterion Weights Using the Fuzzy Entropy Method

Before proceeding to the fuzzy entropy solution steps, linguistic expressions provided by

the experts were converted into triangular fuzzy numbers, as shown in Table 2. Separate matrices were prepared for the main criteria and sub-criteria. The evaluations of the six decision-makers were averaged to form the main decision matrix, and the analysis was carried out based on this main matrix. Each decision-maker was asked to evaluate 10 logistics companies according to these criteria (alternatives without evaluations are indicated by "-" in the table). Subsequently, an arithmetic mean was calculated to create a single main matrix. The steps were performed sequentially and weights for the main criteria were determined (Table 5).

Table 4. Final Weights of Sub-Criteria

	DM1	DM2	DM3	DM4	DM5	DM6	DM7	DM8	The Final Criterion Weight
C11	0.19	0.45	0.39	0.32	0.21	0.53	0.32	0.43	0.348
C12	0.37	0.30	0.33	0.47	0.47	0.29	0.39	0.31	0.372
C13	0.44	0.25	0.28	0.21	0.32	0.18	0.29	0.26	0.280
C21	0.16	0.16	0.11	0.15	0.15	0.13	0.17	0.13	0.152
C22	0.24	0.20	0.23	0.18	0.22	0.08	0.19	0.15	0.184
C23	0.29	0.31	0.30	0.22	0.17	0.26	0.28	0.28	0.268
C24	0.14	0.11	0.19	0.13	0.14	0.04	0.15	0.19	0.132
C25	0.17	0.22	0.17	0.31	0.33	0.49	0.21	0.25	0.264
C31	0.29	0.32	0.44	0.31	0.32	0.29	0.41	0.47	0.364
C32	0.55	0.41	0.27	0.24	0.47	0.54	0.27	0.32	0.380
C33	0.15	0.27	0.29	0.46	0.21	0.17	0.32	0.21	0.256
C41	0.15	0.23	0.17	0.46	0.47	0.30	0.29	0.32	0.310
C42	0.29	0.35	0.50	0.31	0.21	0.50	0.32	0.16	0.344
C43	0.55	0.42	0.33	0.24	0.32	0.20	0.39	0.21	0.347
C51	0.53	0.32	0.29	0.24	0.47	0.16	0.39	0.22	0.326
C52	0.28	0.41	0.15	0.32	0.32	0.55	0.28	0.46	0.347
C53	0.19	0.27	0.55	0.44	0.21	0.29	0.33	0.33	0.327
C61	0.16	0.24	0.18	0.22	0.20	0.25	0.19	0.26	0.219
C62	0.23	0.28	0.10	0.18	0.37	0.10	0.25	0.21	0.205
C63	0.19	0.17	0.33	0.26	0.16	0.17	0.27	0.33	0.236
C64	0.41	0.31	0.39	0.34	0.27	0.48	0.30	0.19	0.340

Table 5. Weights of Main Criteria According to the Fuzzy Entropy Method

	C1	C2	C3	C4	C5	C6
w_j	0.246	0.391	0.207	0.089	0.032	0.034

Upon reviewing this ranking, it can be seen that "Smart Logistics and Inventory Systems" is ranked first, followed by "Technology Infrastructure" in second place, and "Digital

Competency" in third place, indicating that these criteria are the most important.

The same process was repeated for the sub-criteria of each main indicator.

Table 6. Weights of Sub-Criteria

Criteria	C11	C12	C13	C21	C22	C23	C24	C25	C31	C32	C33	C41	C42	C43	C51	C52	C53	C61	C62	C63	C64
w_j	0.35	0.34	0.29	0.24	0.38	0.02	0.30	0.03	0.24	0.53	0.21	0.25	0.30	0.43	0.35	0.55	0.09	0.32	0.27	0.14	0.25

The weights obtained from the objective weighting method and the results of the subjective weighting method were later recalculated using the Bayesian approach.

Recalculation of Weights Using the Bayesian Approach

The elements of the matrix consist of either expert evaluations of criteria for various

alternatives or data that statistically fluctuates over time. The criteria weights and the probabilities of random values range from 0 to 1. In the context of Bayes' theorem applied to criterion weights, when different criterion weights are obtained from different groups of experts or through alternative evaluation methods, these weights must be recalculated.

Table 7. Integration of Objective and Subjective Weights for Main Criteria

Criteria	SWARA	F – Entropy	a_j
C1	0.240	0.246	0.325
C2	0.155	0.391	0.334
C3	0.206	0.207	0.236
C4	0.107	0.089	0.052
C5	0.166	0.032	0.029
C6	0.127	0.034	0.024

Table 8. Integration of Objective and Subjective Weights for Sub-Criteria

Criteria	SWARA	F – Entropy	a_j
C11	0.348	0.357	0.370
C12	0.372	0.344	0.381
C13	0.280	0.299	0.249
C21	0.152	0.242	0.222
C22	0.184	0.384	0.426
C23	0.268	0.029	0.047
C24	0.132	0.307	0.245
C25	0.264	0.038	0.061
C31	0.364	0.248	0.258
C32	0.380	0.539	0.586
C33	0.256	0.213	0.156
C41	0.310	0.255	0.235
C42	0.344	0.305	0.312
C43	0.347	0.439	0.453
C51	0.326	0.352	0.340
C52	0.347	0.558	0.573
C53	0.327	0.090	0.087
C61	0.219	0.322	0.284
C62	0.205	0.278	0.230
C63	0.236	0.148	0.141
C64	0.340	0.252	0.345

The determination of the final weights established the importance levels of the criteria. The most crucial criterion to consider when

selecting a technological/digital 3PL service provider is "Automatic Material Placement and Tracking Technology." The second most important is "Lack of Digital Collaboration." According to decision-makers, a company that

does not embrace digital collaboration should not be pursued further. The criterion of "Technology Compatibility," which indicates the compatibility of technological tools/software used within the supply chain, ranks third. In fourth place is the criterion of "Supplier

Compatibility," indicating that supplier compatibility with digital/technological processes is among the most critical criteria. All criteria and their weights are shown below (Figure 3).

Table 9. Calculation of Final Weights for Criteria

Main Goal	Main Criteria	Main Criteria Weights	Sub-Criteria	Direction	Sub-Criteria Weights	Overall Weight
Technological 3PL Service Provider Selection	C1	0.325	C11	Benefit	0.370	0.120
			C12	Benefit	0.381	0.124
			C13	Cost	0.249	0.081
	C2	0.334	C21	Benefit	0.222	0.074
			C22	Benefit	0.426	0.142
			C23	Benefit	0.047	0.016
			C24	Benefit	0.245	0.082
			C25	Benefit	0.061	0.020
	C3	0.236	C31	Benefit	0.258	0.061
			C32	Cost	0.586	0.138
			C33	Benefit	0.156	0.037
	C4	0.052	C41	Cost	0.235	0.012
			C42	Benefit	0.312	0.016
			C43	Benefit	0.453	0.024
	C5	0.029	C51	Benefit	0.340	0.010
			C52	Cost	0.573	0.017
			C53	Benefit	0.087	0.003
	C6	0.024	C61	Benefit	0.284	0.007
			C62	Benefit	0.230	0.005
			C63	Benefit	0.141	0.003
			C64	Benefit	0.345	0.008

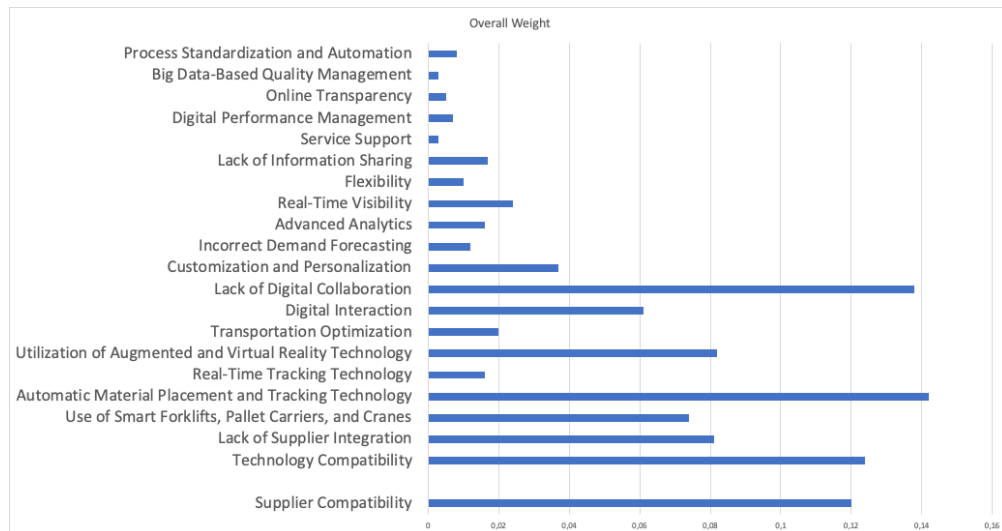


Fig. 3. Graph of Weights for the Selection of Technological 3PL Service Provider According to a Bayesian Approach

DISCUSSION

The extant literature on the implications of technological advancements within the logistics sector elucidates a broad spectrum of issues, spanning the identification of technological tools their respective advantages and disadvantages, their areas of application, and their effects. The dynamic evolution of technological/digital enterprises, encompassing customers, suppliers, warehouses, factories, vehicles, software, business models, and operations, continually generates novel research inquiries. The transformative processes engendered by the digital supply chain and their outcomes form the foundational basis of this research. Specifically, this study examines the key characteristics and selection criteria for 3PL service providers offering digital supply chain integration.

What attributes should such a 3PL service provider possess, and what selection model can be constructed based on these attributes? These questions have been methodically addressed through a model employing SWARA and Fuzzy Entropy methodologies. The findings reveal that the five most pivotal criteria for selecting a technological/digital 3PL service provider are: "Automatic Material Placement and Tracking Technology," "Lack of Digital Collaboration," "Technology Compatibility," "Supplier Compatibility," and "Use of Augmented and Virtual Reality Technology." Logistics firms should be evaluated according to these criteria to ensure their success as integral members of a technological supply chain.

Winkelhaus & Grosse [2020] defined the core dimensions of Logistics 4.0, emphasizing the critical role of digitalization, automation, and efficiency in logistics processes. Similarly, this study identifies technology compatibility and lack of digital collaboration as key determinants in selecting technological 3PL service providers. The prominence of "Automatic Material Placement and Tracking Technology" as the most crucial criterion aligns with Winkelhaus & Grosse's findings on the impact of warehouse management and automation systems in logistics. Additionally, the significance of supplier compatibility and technology integration in this study reflects the essential role of digitalization in ensuring seamless supply

chain operations, reinforcing the conclusions drawn by Winkelhaus & Grosse regarding the transformative effects of Logistics 4.0. Similarly, Dolatabad et al. [2023] utilized Fuzzy Cognitive Maps and VIKOR to evaluate digital supplier selection across economic, environmental, and social dimensions. Their study emphasized technology capability, cost optimization, and quality improvement through smart technologies—key aspects that align with this study's findings on digital 3PL selection. Furthermore, Tavana et al. [2021] applied F-BWM, F-MULTIMOORA, F-COPRAS, and F-TOPSIS to evaluate supplier selection in digital supply chains, emphasizing real-time visibility, advanced analytics, and digital collaboration. Their study aligns with this research by recognizing that firms lacking digital collaboration face significant disadvantages. However, unlike Tavana et al., this study makes use of a Bayesian approach to merge subjective and objective weighting, ensuring a more robust and balanced evaluation framework.

The Digital Technology Affordance for Intralogistics Systems framework by Albrecht et al. [2024] assessed the impact of digital technologies on logistics processes across four affordance layers: data, manual tasks, goods/assets, and decision management. Their study underscores how digital transformation enhances supply chain efficiency, reinforcing this study's argument that automatic material placement and tracking technology is a pivotal factor in selecting 3PL providers.

A key difference between this study and previous works is its empirical validation. Unlike many theoretical models, this study applies the proposed SWARA-Fuzzy Entropy-Bayesian model to 10 logistics firms in Turkey, demonstrating its practical applicability in real-world digital supply chain environments.

In summary, this study aligns with existing research in recognizing the role of digitalization and automation in logistics, while distinguishing itself by introducing a hybrid decision-making framework that incorporates subjective and objective weighting, Bayesian integration, and empirical validation. The findings provide a novel contribution to the field, offering a structured approach to digital 3PL selection that

can be adapted for various logistics environments. It should be noted that the findings are based on expert judgments and a specific set of companies; thus, the weighted criteria might change if another sample or data from a different country were used. However, the model is flexible and can be applied to various contexts.

CONCLUSION

As the digitalization of the supply chain progresses, it is increasingly crucial for each component to exhibit technological robustness and for technologically advanced 3PL companies to be integrated into the supply chain. Consequently, companies are prioritizing the most salient criteria and making selections based on these parameters when choosing technological 3PL providers. The model developed in this study aims to illuminate the most critical criteria and provide a structured approach for selecting 3PL companies based on these benchmarks. Utilizing this model, supply chain members can identify the optimal 3PL provider, thereby enhancing operational efficiency, securing a competitive edge, and succeeding in the digitalization process. Moreover, the establishment of objective criteria for selecting technological 3PL companies is anticipated to contribute to the formulation of industry standards and the propagation of best practices, ultimately bolstering supply chain management and enhancing industry competitiveness.

This study is limited to the Turkish logistics sector, and the findings may not be directly generalizable to other regions. Future research could extend the proposed model to international markets or explore additional criteria to enhance its applicability.

Future studies could apply this decision model to diverse decision-making contexts or employ different methods to refine and expand the criteria identified in this study, thereby developing new models. Given that the data utilized in this research is rooted in the experiential insights and opinions of experts, the results may exhibit variability contingent on the decision-maker's perspective. Future studies could adopt a more objective approach by leveraging precise data, thereby further

validating and extending the applicability of the findings. Additionally, future studies could explore the applicability of this model in global supply chain networks or employ machine learning methods to enhance decision-making accuracy. Moreover, future research should incorporate larger expert panels to enhance the robustness and generalizability of the findings.

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