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# A Novel Integrated Fuzzy-Rough MCDM Model for Assessment of Barriers Related to Smart Logistics Applications and Demand Forecasting Method in the COVID-19 Period

Željko Stević*

*Faculty of Transport and Traffic Engineering*
*University of East Sarajevo, Doboj*
*Republic of Srpska Bosnia and Herzegovina*
*zeljkostevic88@yahoo.com, zeljko.stevic@sf.ues.rs.ba*

Selçuk Korucuk

*Department of International Trade and Logistics*
*Bulancak Kadir Karabaş Vocational School*
*Giresun University, Giresun, Turkey*
*selcuk.korucuk@giresun.edu.tr*

Çağlar Karamaşa

*Department of Business Administration*
*Faculty of Business, Anadolu University*
*Eskişehir, Turkey*
*ckaramasa@anadolu.edu.tr; ckaramasa@gmail.com*

Ezgi Demir

*Department of Management Information Systems*
*Gebze Technical University, Kocaeli, Turkey*
*edemir@pirireis.edu.tr*

Edmundas Kazimieras Zavadskas

*Institute of Sustainable Construction*
*Vilnius Gediminas Technical University, Sauletekio al. 11*
*LT-10223 Vilnius, Lithuania*
*edmundas.zavadskas@vilniustech.lt*

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During the pandemic period, smart logistics applications have rapidly changed the way organizations do business in order to provide competitive products and services while still

*Corresponding author.

remaining flexible. Smart logistics applications and demand forecasting, which have an important place in ensuring customer satisfaction and increasing competitive advantage, came to the fore even more in this period. However, smart logistics applications are often bogged down by several barriers, and then there is the need to choose the most ideal demand forecasting method despite these barriers. The main purpose of this study is to assess the barriers to the smart logistics applications in companies that receive and provide logistics services with corporate identity in Ordu Province, and to choose the most ideal demand forecasting method during the COVID-19 period. This study has the characteristic of a roadmap that helps the construction of smart logistics transformation applications by detecting barriers related to smart logistics applications and determining the most ideal demand forecasting alternative in logistics sector. Fuzzy FUCOM (FUll COnsistency Method)-based interval rough EDAS (Evaluation based on Distance from Average Solution) methodology was used to weight the barriers and to rank and choose the most ideal demand forecasting method during COVID-19 period, respectively.

*Keywords*: COVID-19; smart logistics implementation; demand forecasting methods; fuzzy FUCOM; interval rough EDAS.

## 1. Introduction

The changing expectations and demands of the customer as a result of globalization have led to the proliferation of technology-based elements, thus the differentiation and diversification of the activities need to be carried out.[1] The process of Industry 4.0, which describes the interconnectivity of the period we presently live in, has brought about digital transformation and highlighted smart logistics applications, also known as Logistics 4.0.[2] The concept describes a logistics system with increased flexibility, self-regulation according to market needs, and becoming closer to the customer.[3] Scherf,[4] on the other hand, defined smart logistics as a concept that explains how digitalization and automation in the field of logistics should be shaped and supported, as well as the effects of Industry 4.0 on transportation and cross-functional coordination tasks. According to Kauf,[5] smart logistics is a form of structure used together with advanced artificial intelligence solutions based on new smart technologies, equipped with computer support systems that allow fully automated processes. In other words, smart logistics is smart application that provides real-time communication between people and machines as a result of advanced internet use.[1]

Logistics 4.0, that is, smart logistics applications, are components that aim to increase the efficiency, the effectiveness, and the performance of supply chain members in businesses.[6] Barreto *et al.*[3] desired efficient, powerful, and effective smart logistics applications based on technologies such as resource planning, warehouse management systems, transportation management systems, intelligent transportation systems, and information security. This concept states that the optimal profit that all companies operating in the supply chain obtained as a result of cooperation will exceed the sum of the optimal profit that the companies can achieve on their own.[7]

Czaja[8] defines the purpose of smart logistics applications in terms of effectiveness (flexibility, individualized services, processes, and products), efficiency (transparency, process speed, error reduction, and consolidation), and supply chain partners

(wholesalers, retailers, logistics service providers, and customers) and improved the information and communication technologies with decentralized decision-making structures.

During the duration of the COVID-19 epidemic, smart logistics applications have gained even more prominence especially the incorporation of digital components to achieve an interruption-free supply chain management. In general, the barriers to smart logistics applications in the COVID-19 period have been classified as technological barriers, economical barriers, social barriers, ecological risks, and legal and political risks.

The technological barriers include cyber-attacks on the firm (data-related problems, service frustration, etc.), lack of specialized personnel for smart logistics technology (there is a need to provide continuous education), and the requirement for integration between the technologies used. The economical barriers consist of the high-cost structure of information technology investments, newly developed technologies used in smart logistics investments, and preference level by consumers or other firms. The social barriers include the requirement for fewer people, a low adoption rate of technology usage by older employees, and the negative effects of corporate culture on smart logistics applications.

Ecological risks consist of the increase in energy consumption, expenses related to economic growth in the macrodimension, and not using eco-friendly equipments. Legal and political risks include lack of regulations, lack of incentives, and national climate.

During the COVID-19 period that has been characterized as economic crisis,[9] it is important to identify the barriers to the smart logistics applications mentioned above while still effectively running the supply chain and forecasting demand. According to Görçün,[10] anticipating demands in supply chain management is an issue that needs to be carefully considered in order to manage the supply chain well. Demand forecasting, the determination of which product will be in demand, how much demand will be shown for these products, how long the demand will last, and whether the demand is periodic or not, plays an important role in making the planning realistic. Planning without determining the general and specific characteristics of the demands may fail to reflect the real situation.

The goals of demand forecasting are not limited to the increase in the level of customer service and minimizing logistics costs, but also cover the reduction of investment in the supply chain to acceptable optimum levels.[11] Demand forecasting methods are based on the principle of determining the amount of future demand by using numerical parameters. In other words, a determination is made on the kind of changes expected in future demands based on the current and past sales within the framework of dependent and independent variables of sales in the past periods.[12]

Due to its stated importance and considering the COVID-19 pandemic, demand forecasting methods are vital for both businesses and people. In this context, demand forecasting methods are generally composed of the causal model, time series analysis

method, qualitative approach, simulation method, and machine learning-based forecasting method.

The COVID-19 pandemic has ushered in a new age in the world,[13] so one of the main motivations for this study was to find an effective and applicable solution to the barriers to smart logistics applications of enterprises in the logistics sector during the COVID-19 period as well as to the decision-making problem in the choice of a demand forecasting method.

The authors also demonstrated how criteria and alternatives used in the study related to the COVID-19 outbreak and also identified interdependencies between them. All in all, the study provides a practical roadmap for the logistics industry regarding the barriers to the implementation of smart logistics and demand-forecasting methods. Even though the results of the study are from the logistics sector, the structure of the methodology used allows the study to be replicated in other sectors, hence extending its contribution to the literature.

Based on the expertise, experience, and knowledge of the decision-makers, smart logistics applications have emerged as one of the most promising areas to implement the technological developments that have come out with Logistics 4.0, which are geared toward providing competitive power and customer satisfaction in enterprises that receive and/or provide logistics services. The study was carried out during the COVID-19 period to help identify the barriers to smart logistics applications and to provide a roadmap for the transformation of smart logistics applications and determine the best alternative in demand forecasting. With its complex structure due to the many conflicting criteria and the uncertainties involved, choosing the right and appropriate demand forecasting method is a very difficult process for decision-makers in logistics services.

The fact that smart logistics applications are a new concept may increase the barriers to contain uncertainties, especially during the COVID-19 period. The COVID-19 pandemic period makes it particularly hard to choose a demand forecasting method. The pandemic also expands the list of criteria and alternatives related to the barriers to smart logistics applications and demand forecasting methods. The evaluation of such a large number of contradictory qualitative and quantitative criteria may complicate the choice.

It is thus important to create an effective decision-making model that can overcome the above-mentioned complex alternatives and criteria in order to obtain reliable, logical, and reasonable results. The proposed model, which consists of the fuzzy FUCOM (FUll COnsistency Method) technique and the interval rough EDAS (Evaluation based on Distance from Average Solution) approach, is thought to have many valuable theoretical contributions. In addition to its theoretical contributions, the study has very important implications for decision-makers who receive and/or provide logistics services and others who are interested in the subject. On top of the opportunity to evaluate the barriers to smart logistics applications during the COVID-19 period, the study also pioneers a basic algorithm to choose the optimal alternative in the demand forecasting method. It provides a flexible decision-making environment that takes different views into account. Using the proposed model,

decision-makers can determine a new roadmap for smart logistics and its applications, as well as demand forecasting in a way that takes the COVID-19 period into account. The study also offers a completely updated set of new criteria suitable for real-world decision-making problems encountered in the logistics industry. It can also be inspiring for future researchers and applied in different sectors and industries.

The purpose of the study was to determine the barriers to smart logistics applications in companies that receive and/or provide logistics services with corporate identity in Ordu Province, and to choose the most ideal demand forecasting method in line with these determined barriers. The study proposes a robust, powerful, and practical decision-making model consisting fuzzy FUCOM-based interval rough EDAS that can deal with current uncertainties thereby contributing to the permanent solution of the relevant decision-making problem for the logistics sector at a desirable level. The study seeks to fill the theoretical gaps in the literature by using the advantages of the proposed methods to provide a robust methodological framework.

This paper is arranged as follows. The literature on the barriers to smart logistics applications was examined in Sec. 2. Fuzzy FUCOM and interval rough EDAS methods are explained in Sec. 3. The method of the study was applied to the problem in Sec. 4. Sensitivity and comparison analyses are given in Sec. 5. Discussion and conclusion including future suggestions are presented in Sec. 6.

## 2. Literature Review

There are limited studies in the literature in which the criteria that are effective in determining the barriers to smart logistics applications and/or evaluations, some of them are given as follows. Xie[14] evaluated the status of smart logistics applications in Chinese hazardous chemical logistics and stated that resource support and technical equipment research should be increased to enable modern logistics development. Wen *et al.*[15] focused on how to design an efficient communication and management platform in smart logistics applications of robot swarms and pointed out that it is one of the main problems in the smart logistics industry. Krykavskyy *et al.*[16] examined the reasons for the transition to smart logistics in the study they applied in Ukraine and analyzed the problems encountered in this transition with secondary data surveys. Barczak *et al.*[17] investigated the changes brought by digitalization to logistics management and the resulting macro-environment, functional, and micro-environment risks using a survey method. Karagöz and Doyduk[18] examined the Logistics 4.0 applications within the framework of the logistics sector and found that the logistics enterprises in Turkey are not very open to innovation, and they also see technology investments as a major cost item. Liu *et al.*[19] investigated sustainable risk management in the smart logistics ecological chain and evaluated the elements of technological, governmental, and external stakeholder risks as risk sources. Kodym *et al.*[20] classified the risks in smart logistics applications as economic, social, technological, legal, and political risks and evaluated them.

Studies related to FUCOM can be seen as Table 1.

Table 1. Studies related to FUCOM.

| Author(s) | Methodology | Application |
|---|---|---|
| Cao *et al.*[21] | Grey SWARA (Step-wise Weight Assessment Ratio Analysis)-FUCOM-GRA (Grey Relational Analysis)-EDAS | Selection of the most appropriate contractor for the installation of solar panels |
| Badi and Abdulshahed[22] | FUCOM-AHP (Analytic Hierarchy Process) | Evaluate and compare the performance of four Libyan airlines |
| Fazlollahtabar *et al.*[23] | FUCOM-WASPAS (Weighted Aggregates Sum Product Assessment) | Evaluation and selection of side-loading forklift in a warehouse |
| Stević and Brkovic[24] | FUCOM-MARCOS (Measurement of Alternatives and Ranking According to Compromise Solution) | Evaluation of human resources in an international transport company |
| Prentkovskis *et al.*[25] | Delphi-FUCOM-SERVQUAL | Improving the service quality measurement in an express post company |
| Durmić *et al.*[26] | FUCOM-ROUGH SAW (Simple Additive Weighting) | Sustainable supplier selection for lime production company |
| Nunić[27] | FUCOM-MABAC (Multi-Attribute Border Approximation Area Comparison) | Evaluation and selection of the manufacturers of PVC carpentry |
| Bozanic *et al.*[28] | FUCOM-Fuzzy MABAC | Selecting the most favorable location for the construction of the single-span Bailey bridge |
| Bozanic *et al.*[29] | FUCOM-Z number-MABAC | Selecting a location for a brigade command post during combat operations |
| Božanić *et al.*[30] | D numbers-FUCOM-Fuzzy RAFSI(Ranking of Alternatives through Functional mapping of criterion sub-intervals into a Single Interval) | Selection of the group of construction machines for enabling mobility |
| Pamucar *et al.*[31] | Fuzzy FUCOM-Neutrosophic fuzzy MARCOS | Prioritize the various alternative fuel vehicles for sustainable road transportation in the United States |
| Simić *et al.*[32] | CRITIC (CRiteria Importance Through Intercriteria Correlation)-Fuzzy FUCOM-DEA (Data Envelopment Analysis)-Fuzzy MARCOS | Determining the level of traffic safety on road sections under the conditions of uncertainty |

Table 1. (*Continued*)

| Author(s) | Methodology | Application |
|---|---|---|
| Feizi *et al.*[33] | FUCOM-MOORA (Multi-Objective Optimization on the basis of Ratio Analysis)-MOOSRA (Multi-Objective Optimization on the basis of Simple Ratio Analysis) | Mineral potential mapping in greenfields |
| Erceg *et al.*[34] | ABC-FUCOM-Interval rough CoCoSo (Combined Compromise Solution) | Proposing new model for stock management in the storage system |
| Böyükaslan and Ecer[35] | Fuzzy FUCOM-Bonferroni | Determine the priorities of drivers for investing in crypto-currencies |
| Akbari *et al.*[36] | FUCOM-BWM (Best Worst Method)-AHP | Classify groundwater potential maps in the Sarakhs Plain in north-east Iran |
| Badi and Kridish[37] | FUCOM-CODAS (COmbinative Distance-based ASsessment) | Choosing the appropriate site for the municipal solid waste dumping for the City of Misurata |
| Pamučar *et al.*[38] | FUCOM-MAIRCA (Multi Attribute Ideal-Real Comparative Analysis) | Evaluation of 10 level crossings within the railway infrastructure in the Republic of Serbia |
| Khan *et al.*[39] | Fuzzy FUCOM-QFD (Quality Function Deployment) | Build a resilience-based model on the healthcare sector of Pakistan to combat the COVID-19 and future pandemics in the country |
| Ong *et al.*[40] | FUCOM-VIKOR (VIsekriterijumska optimizacija i KOmpromisno Resenje) | Recycling of cleaning solution in rubber glove manufacturing process |
| Pamucar *et al.*[41] | Fuzzy FUCOM-Dombi-Bonferroni | The selection and prioritization of appropriate Transportation Demand Management (TDM) measures in Istanbul's urban mobility system |

Table 2. Studies related to EDAS.

| Author(s) | Methodology | Application |
|---|---|---|
| Schitea *et al.*[42] | Intuitionistic fuzzy WASPAS-COPRAS(COmplex PRoportional ASsessment)-EDAS | Selecting the best location for hydrogen mobility roll-up site selection in Romania |
| Asante *et al.*[43] | MULTIMOORA(Multi-Objective Optimization by a Ratio Analysis plus the Full Multiplicative Form)-EDAS | Identify and rank the barriers to renewable energy development |
| Kahraman *et al.*[44] | Intuitionistic fuzzy EDAS | Evaluation of solid waste disposal site selection alternatives |
| Karabasevic *et al.*[45] | SWARA-EDAS | Personnel selection in IT industry |
| Stevic *et al.*[46] | Fuzzy EDAS | Select the most suitable manufacturer of PVC carpentry for apartment refurbishing |
| Li *et al.*[47] | Linguistic neutrosophic numbers based EDAS | Property management company selection |
| Keshavarz-Ghorabaee *et al.*[48] | Interval type-2 fuzzy sets based EDAS | Evaluation of suppliers with respect to environmental criteria |
| Gündoğdu *et al.*[49] | Hesitant fuzzy EDAS | Multi-criteria and multi-expert hospital selection problem for organ transplantation |
| Karaşan and Kahraman[50] | Interval valued neutrosophic EDAS | Prioritization of United Nations nationalsustainable development goals |
| Zhang *et al.*[51] | Picture fuzzy EDAS | Green supplier selection |
| Li *et al.*[52] | Q-rung orthopair fuzzy sets based EDAS | Evaluation of alternative household refrigerator |
| Keshavarz-Ghorabaee *et al.*[53] | Fuzzy dynamic approach based on EDAS | Selection of appropriate subcontractors for outsourcing |
| Darko and Liang[54] | Q-rung orthopair fuzzy Hamacher aggregation operators based EDAS | Mobile payment platform selection problem |
| Kundakcı[55] | MACBETH(Measuring Attractiveness by a Categorical-Based Evaluation Technique)-EDAS | Evaluation of steam boiler alternatives that will be used in a dye-house of a textile company |
| Liang[56] | Intuitionistic fuzzy EDAS | Evaluation in green building energy-saving design projects |
| Yanmaz *et al.*[57] | Interval valued pythagorean fuzzy EDAS | Car selection problem |
| Özçelik and Nalkıran[58] | Trapezoidal bipolar fuzzy sets based EDAS | Selection of a medical device |
| Xu *et al.*[59] | Single valued complex neutrosophic sets based EDAS | Green supplier selection |
| He *et al.*[60] | Pythagorean 2-tuple linguistic sets based EDAS | Construction safety assessment |
| Chinram *et al.*[61] | Intuitionistic fuzzy rough EDAS | Evaluation to choose the best optimal power plant for construction activities |
| Yılmaz and Atan[7] | Fuzzy EDAS | Selecting the most appropriate site for a new hospital in İstanbul |

According to Table 1, it is seen that FUCOM method has been integrated with a number of different methods such as WASPAS, MARCOS, MABAC, MAIRCA, CoCoSo, CODAS, SAW, AHP, and VIKOR in various environments (fuzzy, rough, grey, D numbers, Z numbers, and neutrosophic). Besides, FUCOM method has been used in several areas such as contractor selection, assessment the performance of airlines, evaluation of human resources, improving service quality measurement, providing sustainable supplier selection, location selection related to bridge construction, construction machines selection, evaluating fuel vehicles in providing sustainable road transportation, proposing new stock management model, crypto-currencies investment decision, traffic safety level determination, mineral and groundwater potential mapping, forming a resilience-based model for healthcare sector, and measurements related to TDM.

Studies related to EDAS are presented in Table 2.

As it can be seen from Table 2, EDAS method has been used in many different environments such as fuzzy, bipolar fuzzy, interval type-2, intuitionistic, hesitant, pythagorean, neutrosophic, q-rung orthopair, and picture. Also, it has been applied with other methods namely MACBETH, SWARA, MULTIMOORA, WASPAS, and COPRAS. Application areas of EDAS method can be summarized as construction safety assessment, green supplier selection, ranking barriers related to renewable energy development, weighting national sustainable development goals, personnel selection, evaluating energy-saving design projects, site selection for a new hospital, and mobile payment platform selection.

In the detailed literature review, the absence of any other study on the assessment of the importance of the barriers related to smart logistics applications and the selection of the most ideal demand estimation method via integrating fuzzy FUCOM with interval rough EDAS is an issue that should be emphasized, but it can also be considered as an overlooked situation. In addition, this study, in which the phenomenon of demand estimation method is pointed out in today's COVID-19 period, is important, and it is thought that the research will contribute to the literature in terms of the method and application area used in the study.

## 3. Methodology

Fuzzy FUCOM considering fuzzy Bonferroni mean (BM) operator in terms of aggregation and interval rough EDAS methods is explained in this section.

### 3.1. *Fuzzy Bonferroni mean (BM) operator*

The values of the interval fuzzy vector of weight coefficients are aggregated using a fuzzy Bonferroni aggregator[62,63] [Eq. (1)], because it allows the representation of the

interrelationships between the aggregation elements.

$$\tilde{a}_{ij} = (a_{ij}^{l}, a_{ij}^{m}, a_{ij}^{u}) = \begin{cases} a_{ij}^{l} = \left( \dfrac{1}{e(e-1)} \displaystyle\sum_{\substack{i,j=1 \\ i \neq j}}^{e} a_i^{lp} \otimes a_j^{lq} \right)^{\frac{1}{p+q}} \\ a_{ij}^{m} = \left( \dfrac{1}{e(e-1)} \displaystyle\sum_{\substack{i,j=1 \\ i \neq j}}^{e} a_i^{mp} \otimes a_j^{mq} \right)^{\frac{1}{p+q}} \\ a_{ij}^{u} = \left( \dfrac{1}{e(e-1)} \displaystyle\sum_{\substack{i,j=1 \\ i \neq j}}^{e} a_i^{up} \otimes a_j^{uq} \right)^{\frac{1}{p+q}} \end{cases}, \tag{1}$$

where $e$ represents the number of experts participating in the research, while $p, q \geq 0$ are a set of non-negative numbers.

### 3.2. *Fuzzy FUCOM method*

This section presents the algorithm of fuzzy FUCOM method[64] through its steps given as follows:

**Step 1.** Creating a set of criteria.

**Step 2.** Ranking the criteria on the basis of experts' preferences by criterion importance.

$$C_{j(1)} > C_{j(2)} > \cdots > C_{j(k)}, \tag{2}$$

where $k$ denotes the ranking of the last-ranked criterion.

**Step 3.** Comparing the criteria using TFNs (triangular fuzzy numbers) and a fuzzy linguistic scale. Specific criterion importance is identified by all experts, so averaged criterion importance is determined using the fuzzy Bonferroni aggregator. Referring to the averaged criterion importance, fuzzy comparative importance $\tilde{\varphi}_{k/(k+1)}$ is obtained using the following equation:

$$\tilde{\varphi}_{k/(k+1)} = \frac{\tilde{\varpi}_{C_{j(k)}}}{\tilde{\varpi}_{C_{j(k+1)}}} = \frac{(\varpi^{l}_{C_{j(k)}}, \varpi^{m}_{C_{j(k)}}, \varpi^{u}_{C_{j(k)}})}{(\varpi^{l}_{C_{j(k+1)}}, \varpi^{m}_{C_{j(k+1)}}, \varpi^{u}_{C_{j(k+1)}})}. \tag{3}$$

Hence, a fuzzy vector of comparative importance for the evaluation criteria is obtained as follows:

$$\tilde{\Phi} = (\tilde{\varphi}_{1/2}, \tilde{\varphi}_{2/3}, \ldots, \tilde{\varphi}_{k/(k+1)}), \tag{4}$$

where $\tilde{\varphi}_{k/(k+1)}$ is the importance of the criterion of $C_{j(k)}$ rank in comparison to the criterion of $C_{j(k+1)}$ rank.

**Step 4.** Calculating the optimal fuzzy weights. The final values of the fuzzy weight coefficients of the criteria $(\tilde{w}_1, \tilde{w}_2, \ldots, \tilde{w}_n)^T$ are obtained. The final values

of the weight coefficients should meet the conditions given by the following equations:

$$\frac{\tilde{w}_k}{\tilde{w}_{k+1}} = \tilde{\varphi}_{k/(k+1)}, \tag{5}$$

$$\frac{\tilde{w}_k}{\tilde{w}_{k+2}} = \tilde{\varphi}_{k/(k+1)} \otimes \tilde{\varphi}_{(k+1)/(k+2)}, \tag{6}$$

$\varphi_{k/(k+1)}$ is the comparative importance of $C_{j(k)}$ and $C_{j(k+1)}$ criteria.

Then, it is required to calculate the values of the weight coefficients of the criteria $(\tilde{w}_1, \tilde{w}_2, \ldots, \tilde{w}_n)^T$ meeting the condition that $|\frac{\tilde{w}_k}{\tilde{w}_{k+1}} - \tilde{\varphi}_{k/(k+1)}| \leq \chi$ and $|\frac{\tilde{w}_k}{\tilde{w}_{k+2}} - \tilde{\varphi}_{k/(k+1)} \otimes \tilde{\varphi}_{(k+1)/(k+2)}| \leq \chi$, with the minimization of $\chi$. Considering the above, the final nonlinear model $(\tilde{w}_1, \tilde{w}_2, \ldots, \tilde{w}_n)^T$ is defined.

$$\begin{aligned}
&\min \chi \\
&\text{s.t.} \\
&\begin{cases}
\left|\dfrac{\tilde{w}_k}{\tilde{w}_{k+1}} - \tilde{\varphi}_{k/(k+1)}\right| \leq \chi, & \forall j \\
\left|\dfrac{\tilde{w}_k}{\tilde{w}_{k+2}} - \tilde{\varphi}_{k/(k+1)} \otimes \tilde{\varphi}_{(k+1)/(k+2)}\right| \leq \chi, & \forall j \\
\displaystyle\sum_{j=1}^{n} \tilde{w}_j = 1, & \\
w_j^l \leq w_j^m \leq w_j^u, & \\
w_j^l \geq 0, & \forall j \\
j = 1, 2, \ldots, n &
\end{cases},
\end{aligned} \tag{7}$$

$\tilde{w}_j = (w_j^l, w_j^m, w_j^u)$ and $\tilde{\varphi}_{k/(k+1)} = (\varphi^l_{k/(k+1)}, \varphi^m_{k/(k+1)}, \varphi^u_{k/(k+1)})$.

### 3.3. *Interval rough EDAS*

Interval rough EDAS consists of the following steps[65]:

**Step 1.** After defining input parameters, which include defining $m$ alternatives and $n$ criteria, it is necessary to model a group decision-making process by forming a group of $k$ experts who will evaluate the alternatives, considering each criterion individually.

**Step 2.** Transformation of individual decision matrices into a group interval rough matrix as shown in the following equation:

$$IRN(X_{ij}) = \begin{array}{c} \\ A_1 \\ A_2 \\ \ldots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \ldots & C_n \end{array} \\ \begin{bmatrix} IRN(x_{11}) & IRN(x_{12}) & \ldots & IRN(x_{1n}) \\ IRN(x_{21}) & IRN(x_{22}) & & IRN(x_{2n}) \\ \cdots & \cdots & \cdots & \cdots \\ IRN(x_{l1}) & IRN(x_{l2}) & \ldots & IRN(x_{ln}) \end{bmatrix}_{m \times n} \end{array}. \tag{8}$$

**Step 3.** In this step, it is necessary to calculate an average solution by forming an $IRN(AV_j)$ matrix (9)

$$IRN(\mathrm{AV}_j) = [av_j^L, av_j^U], [av_j^{L'}, av_j^{U'}]_{1\times n}, \tag{9}$$

by applying the following equation:

$$\sum_{i=1}^{m} \frac{IRN(x_{ij})}{m} = \sum_{i=1}^{m} \left[\frac{IRN(x_{ij}^L)}{m}, \frac{IRN(x_{ij}^U)}{m}\right], \quad \sum_{i=1}^{m} \left[\frac{IRN(x_{ij}^{L'})}{m}, \frac{IRN(x_{ij}^{U'})}{m}\right]. \tag{10}$$

**Step 4.** Calculation of positive distance $IRN(PDAij)$ (11) and negative distance $IRN(NDAij)$ (12) in relation to the average solution $IRN(AVj)$ for all criteria.

$$IRN(PDA_{ij}) = [pda_{ij}^L, pda_{ij}^U], [pda_{ij}^{L'}, pda_{ij}^{U'}]_{m\times n}, \tag{11}$$

$$IRN(NDA_{ij}) = [nda_{ij}^L, nda_{ij}^U], [nda_{ij}^{L'}, nda_{ij}^{U'}]_{m\times n}. \tag{12}$$

In order to obtain the elements of these matrices, it is necessary to take into account the type of criteria, so if it is necessary to be maximized, i.e., if it belongs to the benefit group, the following equations are applied:

$$\begin{aligned} IRN(PDA_{ij}) &= [pda_{ij}^L, pda_{ij}^U], [pda_{ij}^{L'}, pda_{ij}^{U'}] \\ &= \left[\frac{b_{ij}^L}{av_j^{U'}}, \frac{b_{ij}^U}{av_j^{L'}}\right], \left[\frac{b_{ij}^{L'}}{av_j^U}, \frac{b_{ij}^{U'}}{av_j^L}\right] \\ IRN(B_{ij}) &= [b_{ij}^L, b_{ij}^U], [b_{ij}^{L'}, b_{ij}^{U'}] \\ &= \max(0, [x_{ij}^L - av_j^{U'}, x_{ij}^U - av_j^{L'}], [x_{ij}^{L'} - av_j^U, x_{ij}^{U'} - av_j^L]), \end{aligned} \tag{13}$$

$$\begin{aligned} IRN(NDA_{ij}) &= [nda_{ij}^L, nda_{ij}^U], [nda_{ij}^{L'}, nda_{ij}^{U'}] \\ &= \left[\frac{b_{ij}^L}{av_j^{U'}}, \frac{b_{ij}^U}{av_j^{L'}}\right], \left[\frac{b_{ij}^{L'}}{av_j^U}, \frac{b_{ij}^{U'}}{av_j^L}\right], \\ IRN(B_{ij}) &= [b_{ij}^L, b_{ij}^U], [b_{ij}^{L'}, b_{ij}^{U'}] \\ &= \max(0, [av_j^L - x_{ij}^{U'}, av_j^U - x_{ij}^{L'}], [av_j^{L'} - x_{ij}^U, av_j^{U'} - x_{ij}^L]), \end{aligned} \tag{14}$$

As can be seen, the difference is in the calculation of $IRN(Bij)$. If the criterion needs to be minimized, i.e., if it belongs to the cost group of criteria, the following equations are applied:

$$\begin{aligned} IRN(PDA_{ij}) &= [pda_{ij}^L, pda_{ij}^U], [pda_{ij}^{L'}, pda_{ij}^{U'}] = \left[\frac{b_{ij}^L}{av_j^{U'}}, \frac{b_{ij}^U}{av_j^{L'}}\right], \left[\frac{b_{ij}^{L'}}{av_j^U}, \frac{b_{ij}^{U'}}{av_j^L}\right] \\ IRN(B_{ij}) &= [b_{ij}^L, b_{ij}^U], [b_{ij}^{L'}, b_{ij}^{U'}] = \max(0, [av_j^L - x_{ij}^{U'}, av_j^U - x_{ij}^{L'}], \\ &\quad [av_j^{L'} - x_{ij}^U, av_j^{U'} - x_{ij}^L]), \end{aligned} \tag{15}$$

$$\begin{aligned} IRN(NDA_{ij}) &= [nda_{ij}^{L}, nda_{ij}^{U}], [nda_{ij}^{L'}, nda_{ij}^{U'}] \\ &= \left[\frac{b_{ij}^{L}}{av_{j}^{U'}}, \frac{b_{ij}^{U}}{av_{j}^{L'}}\right], \left[\frac{b_{ij}^{L'}}{av_{j}^{U}}, \frac{b_{ij}^{U'}}{av_{j}^{L}}\right], \\ IRN(B_{ij}) &= [b_{ij}^{L}, b_{ij}^{U}], [b_{ij}^{L'}, b_{ij}^{U'}] \\ &= \max(0, [x_{ij}^{L} - av_{j}^{U'}, x_{ij}^{U} - av_{j}^{L'}], [x_{ij}^{L'} - av_{j}^{U}, x_{ij}^{U'} - av_{j}^{L}]). \end{aligned} \tag{16}$$

The formulas previously created require additional constraints due to the nature of interval rough numbers. Precisely due to the nature of the IRN, i.e., the existence of the lower and upper limits, the following situations related to the *IRN*(*Bij*) calculation are possible:

(1) if the sum of the lower and upper limits of the interval rough number is less than zero, then the following equation is applied:

$$\text{if } [b_{ij}^{L} + b_{ij}^{U}], [b_{ij}^{L'} + b_{ij}^{U'}] \leq 0 \quad \text{then } IRN(B_{ij}) = 0. \tag{17}$$

(2) if the sum of the lower and upper limits is greater than zero and each element of the IRN is greater than zero, then the value of that IRN number is retained in the *IRN*(*Bij*) as shown by the following equation:

$$\begin{aligned} &\text{if } [b_{ij}^{L} + b_{ij}^{U}], [b_{ij}^{L'} + b_{ij}^{U'}] > 0 \quad \text{and if } [b_{ij}^{L} > 0, b_{ij}^{U} > 0], [b_{ij}^{L'} > 0, b_{ij}^{U'} > 0] \\ &\quad \text{then } IRN(B_{ij}) = IRN(B_{ij}) \end{aligned} \tag{18}$$

(3) if the sum of the lower and upper limits is greater than zero, and the lower limit of IRN is less than zero, then the absolute value of that number is taken, i.e., *IRN*(*Bij*) as follows:

$$\begin{aligned} &\text{if} [b_{ij}^{L} + b_{ij}^{U}], [b_{ij}^{L'} + b_{ij}^{U'}] > 0 \quad \text{and if } [b_{ij}^{L} < 0, b_{ij}^{U} > 0], [b_{ij}^{L'} < 0, b_{ij}^{U'} > 0] \\ &\quad \text{then } IRN(B_{ij}) = IRN|B_{ij}| \end{aligned} \tag{19}$$

**Step 5.** Multiplying the interval rough matrix *IRN*(*PDAij*) and *IRN*(*NDAij*) by the weight values of the criteria, Eqs. (20) and (21).

Multiplying the interval rough matrix by the weight values of the criteria yields the following equations:

$$\begin{aligned} IRN(VP_{ij}) &= [vp_{ij}^{L}, vp_{ij}^{U}], [vp_{ij}^{L'}, vp_{ij}^{U'}]_{m\times n} \\ &= [pda_{ij}^{L} \times w_{j}^{L}, pda_{ij}^{U} \times w_{j}^{U}], [pda_{ij}^{L'} \times w_{j}^{L'}, pda_{ij}^{U'} \times w_{j}^{U'}], \end{aligned} \tag{20}$$

$$\begin{aligned} IRN(VN_{ij}) &= [vn_{ij}^{L}, vn_{ij}^{U}], [vn_{ij}^{L'}, vn_{ij}^{U'}]_{m\times n} \\ &= [nda_{ij}^{L} \times w_{j}^{L}, nda_{ij}^{U} \times w_{j}^{U}], [nda_{ij}^{L'} \times w_{j}^{L'}, nda_{ij}^{U'} \times w_{j}^{U'}]. \end{aligned} \tag{21}$$

**Step 6.** Calculation of the sum of previously weighted rough interval matrices, as follows:

$$IRN(SP_{i}) = [sp_{i}^{L}, sp_{i}^{U}], [sp_{i}^{L'}, sp_{i}^{U'}] = \sum_{i=1}^{n} IRN(VP_{ij}), \tag{22}$$

$$IRN(SN_i) = [sn_i^L, sn_i^U], [sn_i^{L'}, sn_i^{U'}] = \sum_{i=1}^{n} IRN(VN_{ij}). \tag{23}$$

**Step 7.** Calculation of normalized values for matrices from the previous step for all alternatives, as follows:

$$IRN(NSP_i) = [nsp_i^L, nsp_i^U], [nsp_i^{L'}, nsp_i^{U'}] = \frac{IRN(SP_i)}{\max IRN(SP_i)} = \left[\frac{sp_i^L}{\max sp_i^{U'}}, \frac{sp_i^U}{\max sp_i^{L'}}\right], \left[\frac{sp_i^{L'}}{\max sp_i^U}, \frac{sp_i^{U'}}{\max sp_i^L}\right], \tag{24}$$

$$IRN(NSN_i) = [nsn_i^L, nsn_i^U], [nsn_i^{L'}, nsn_i^{U'}] = 1 - \frac{IRN(SN_i)}{\max IRN(SN_i)} = 1 - \left[\frac{sn_i^L}{\max sn_i^{U'}}, \frac{sn_i^U}{\max sn_i^{L'}}\right], \left[\frac{sn_i^{L'}}{\max sn_i^U}, \frac{sn_i^{U'}}{\max sn_i^L}\right]. \tag{25}$$

**Step 8.** Calculation of the values of all alternatives $IRN(ASi)$ and their ranking in descending order, as follows:

$$IRN(AS_i) = [as_i^L, as_i^U], [as_i^{L'}, as_i^{U'}] = \left[\frac{IRN(NSP_i) + IRN(NSN_i)}{2}\right]. \tag{26}$$

## 4. Results

In this study, criteria and subcriteria related to the barriers of smart logistics applications which are determined according to the depth literature review and expert opinions are presented in Table 3.

Besides related criteria are determined by making a pilot study with expert group consist of managers working in firms that receive and/or provide logistics services and academicians in the field. According to the views of expert group, related criteria set is constructed and applied to firms that receive and/or provide logistics services.

The significance of the criteria and subcriteria for the barriers to smart logistics applications is determined via fuzzy FUCOM method by taking into account the views of 10 experts (4 managers working in firms that receive logistics services, 4 managers working in firms that provide logistics services, and 2 academicians in the field). The experts considered consist of individuals who have more than 10 years of work experience in companies that receive and/or provide logistics services, and who understand the importance of smart logistics practices and demand forecasting, and also have industry experience in managerial positions. The two academicians are a group working in the field of production and operation management, supply chain, and logistics management and have many international publications in the relevant field.

### 4.1. *Determining the significance of the criteria using the fuzzy FUCOM method*

This section presents the calculation of the weight values of the criteria using the fuzzy FUCOM method. A total of $10 \times 6$ models were formed and each was solved

Table 3. Criteria and subcriteria related to the barriers of smart logistics applications.

| Criteria | Subcriteria | References |
|---|---|---|
| C1 — Technological barriers | C11 — Cyber-attacks on the firm (data-related problems, service frustration etc.) | 3, 66 |
| | C12 — Lack of specialized personnel for smart logistics technology (there is a need to provide continuous education) | 19, 67 |
| | C13 — Requirement for integration between the technologies used | 19, 68, 69 |
| C2 — Economical barriers | C21 — High-cost structure of information technology investments | 7, 18, 70, 71 |
| | C22 — Newly developed technologies used in smart logistics investments | 20, 72 |
| | C23 — Preference level by consumers or other firms | 20, 73 |
| C3 — Social barriers | C31 — Requirement for fewer people | 20, 74 |
| | C32 — Low adoption rate of technology usage by older employees | 20, 75 |
| | C33 — Negative effects of corporate culture on smart logistics applications | 20 |
| C4 — Ecological risks | C41 — Increase in energy consumption | 3, 66 |
| | C42 — Expenses related to economic growth in the macro dimension | 19, 68 |
| | C43 — Not using eco-friendly equipments | 71, 77 |
| C5 — Political and legal risks | C51 — Lack of regulations | 20, 71 |
| | C52 — Lack of incentives | 20, 77 |
| | C53 — National climate | 20, 77 |

separately using the fuzzy FUCOM method, and for each group, aggregation was performed using the fuzzy Bonferroni mean operator. An example of the first expert for technological barriers group and the model formed using Eq. (7) in the fuzzy FUCOM method is given as follows:

$$\min \chi$$

$$\begin{cases} \left(\frac{w_2^l}{w_3^u} - 1.10\right) \le \chi; \quad \left(\frac{w_2^m}{w_3^m} - 1.15\right) \le \chi; \quad \left(\frac{w_2^u}{w_3^l} - 1.20\right) \le \chi; \quad \left(\frac{w_3^l}{w_1^u} - 1.25\right) \le \chi; \\ \left(\frac{w_3^m}{w_1^m} - 1.52\right) \le \chi; \quad \left(\frac{w_3^u}{w_1^l} - 1.64\right) \le \chi; \\ \left(\frac{w_2^l}{w_1^u} - 1.38\right) \le \chi; \quad \left(\frac{w_2^m}{w_1^m} - 1.75\right) \le \chi; \quad \left(\frac{w_2^u}{w_1^l} - 1.96\right) \le \chi; \\ (w_1^l + 4 \cdot w_1^m + w_1^u)/6 + (w_2^l + 4 \cdot w_2^m + w_2^u)/6 + (w_3^l + 4 \cdot w_3^m + w_3^u)/6 = 1; \\ w_1^l \le w_1^m \le w_1^u; \quad w_2^l \le w_2^m \le w_2^u; \quad w_3^l \le w_3^m \le w_3^u; \quad w_1^l, w_2^l, w_3^l, \ge 0. \end{cases}$$

The same calculations that have been performed for main criteria and the results for 10 experts are shown in Table 4.

Table 4. Weights for main criteria obtained using fuzzy FUCOM method.

| | C1 | C2 | C3 | C4 | C5 |
|---|---|---|---|---|---|
| DM1 | (0.25,0.27,0.27) | (0.14,0.18,0.19) | (0.17,0.2,0.21) | (0.14,0.19,0.19) | (0.14,0.19,0.19) |
| DM2 | (0.17,0.2,0.2) | (0.25,0.27,0.27) | (0.14,0.18,0.18) | (0.19,0.22,0.22) | (0.13,0.16,0.16) |
| DM3 | (0.21,0.24,0.25) | (0.26,0.27,0.27) | (0.16,0.18,0.19) | (0.13,0.16,0.16) | (0.14,0.17,0.17) |
| DM4 | (0.25,0.26,0.26) | (0.2,0.23,0.24) | (0.14,0.17,0.17) | (0.16,0.19,0.2) | (0.13,0.17,0.17) |
| DM5 | (0.27,0.29,0.29) | (0.16,0.19,0.19) | (0.14,0.18,0.18) | (0.18,0.21,0.22) | (0.12,0.15,0.15) |
| DM6 | (0.17,0.2,0.2) | (0.25,0.27,0.27) | (0.14,0.17,0.17) | (0.19,0.22,0.22) | (0.12,0.16,0.16) |
| DM7 | (0.26,0.3,0.3) | (0.16,0.19,0.19) | (0.19,0.21,0.21) | (0.14,0.18,0.18) | (0.12,0.14,0.14) |
| DM8 | (0.24,0.25,0.25) | (0.16,0.19,0.19) | (0.18,0.2,0.21) | (0.19,0.23,0.23) | (0.13,0.16,0.17) |
| DM9 | (0.19,0.23,0.23) | (0.24,0.25,0.25) | (0.18,0.2,0.21) | (0.16,0.19,0.19) | (0.13,0.16,0.17) |
| DM10 | (0.24,0.25,0.25) | (0.18,0.2,0.21) | (0.13,0.16,0.17) | (0.19,0.23,0.23) | (0.16,0.19,0.19) |
| FINAL | (0.22,0.25,0.25) | (0.2,0.22,0.22) | (0.15,0.18,0.19) | (0.17,0.2,0.2) | (0.13,0.16,0.17) |

Weights for subcriteria for all 10 experts are shown in Table 5.

Then, the fuzzy Bonferroni mean operator was applied to obtain the final criteria weights. An example of calculation for the C11 is as follows:

$$BM^{p=1,q=1}\left\{\begin{array}{l}(0.22,0.23,0.28),(0.25,0.27,0.31),(0.35,0.35,0.35),\\(0.25,0.27,0.31),(0.41,0.46,0.48),(0.38,0.38,0.40),\\(0.38,0.41,0.43),(0.40,0.46,0.47),(0.29,0.29,0.29),\\(0.25,0.27,0.31)\end{array}\right\}$$

$$=\left\{\begin{array}{l}\varpi^{\,l}_{C_{1(1)}}=\left(\dfrac{1}{10(10-1)}\displaystyle\sum_{\substack{i,j=1\\ i\neq j}}^{10}\varpi^{\,lp}_{C_{1(1)}i}\varpi^{\,lq}_{C_{1(1)}j}\right)^{\frac{1}{1+1}}\\ =(0.01(0.22^1\cdot 0.25^1+0.22^1\cdot 0.35^1+0.22^1\cdot 0.25^1+\cdots\\ \qquad +0.25^1\cdot 0.29^1))^{\frac{1}{1+1}}=0.313,\\ \varpi^{\,m}_{C_{1(1)}}=\left(\dfrac{1}{10(10-1)}\displaystyle\sum_{\substack{i,j=1\\ i\neq j}}^{10}\varpi^{\,mp}_{C_{1(1)}i}\varpi^{\,mq}_{C_{1(1)}j}\right)^{\frac{1}{1+1}}\\ =(0.01(0.23^1\cdot 0.27^1+0.23^1\cdot 0.35^1+0.23^1\cdot 0.27^1+\cdots\\ \qquad +0.27^1\cdot 0.29^1))^{\frac{1}{1+1}}=0.336,\\ \varpi^{\,u}_{C_{1(1)}}=\left(\dfrac{1}{10(10-1)}\displaystyle\sum_{\substack{i,j=1\\ i\neq j}}^{10}\varpi^{\,up}_{C_{1(1)}i}\varpi^{\,uq}_{C_{1(1)}j}\right)^{\frac{1}{1+1}}\\ =(0.01(0.28^1\cdot 0.31^1+0.28^1\cdot 0.35^1+0.28^1\cdot 0.31^1+\cdots\\ \qquad +0.31^1\cdot 0.29^1))^{\frac{1}{1+1}}=0.360.\end{array}\right.$$

Table 5. Weights for subcriteria obtained using fuzzy FUCOM method.

| | C11 | C12 | C13 | C21 | C22 | C23 | C31 | C32 | C33 |
|---|---|---|---|---|---|---|---|---|---|
| DM1 | (0.22,0.23,0.28) | (0.39,0.41,0.43) | (0.35,0.35,0.35) | (0.43,0.51,0.52) | (0.19,0.24,0.26) | (0.27,0.27,0.27) | (0.28,0.28,0.28) | (0.42,0.48,0.5) | (0.2,0.25,0.29) |
| DM2 | (0.25,0.27,0.31) | (0.34,0.34,0.34) | (0.37,0.39,0.41) | (0.38,0.41,0.42) | (0.31,0.31,0.31) | (0.25,0.28,0.32) | (0.34,0.34,0.34) | (0.37,0.39,0.41) | (0.25,0.27,0.31) |
| DM3 | (0.35,0.35,0.35) | (0.23,0.25,0.3) | (0.38,0.4,0.42) | (0.29,0.29,0.29) | (0.4,0.46,0.47) | (0.22,0.27,0.29) | (0.3,0.3,0.3) | (0.39,0.43,0.45) | (0.24,0.27,0.32) |
| DM4 | (0.25,0.27,0.31) | (0.34,0.34,0.34) | (0.37,0.39,0.41) | (0.31,0.31,0.31) | (0.38,0.41,0.42) | (0.25,0.28,0.3) | (0.24,0.29,0.32) | (0.38,0.43,0.44) | (0.29,0.29,0.29) |
| DM5 | (0.41,0.46,0.48) | (0.21,0.26,0.28) | (0.29,0.29,0.29) | (0.31,0.31,0.31) | (0.38,0.41,0.42) | (0.25,0.28,0.3) | (0.33,0.33,0.33) | (0.36,0.38,0.39) | (0.27,0.29,0.33) |
| DM6 | (0.38,0.38,0.4) | (0.38,0.38,0.38) | (0.23,0.24,0.28) | (0.25,0.27,0.31) | (0.38,0.41,0.43) | (0.32,0.32,0.32) | (0.25,0.29,0.32) | (0.37,0.4,0.42) | (0.31,0.31,0.31) |
| DM7 | (0.38,0.41,0.43) | (0.24,0.27,0.31) | (0.32,0.32,0.32) | (0.38,0.43,0.44) | (0.25,0.28,0.32) | (0.29,0.29,0.29) | (0.31,0.31,0.31) | (0.38,0.41,0.42) | (0.25,0.28,0.32) |
| DM8 | (0.4,0.46,0.47) | (0.29,0.29,0.29) | (0.22,0.27,0.29) | (0.31,0.31,0.31) | (0.25,0.28,0.32) | (0.38,0.41,0.42) | (0.25,0.28,0.32) | (0.38,0.41,0.42) | (0.31,0.31,0.31) |
| DM9 | (0.29,0.29,0.29) | (0.22,0.27,0.29) | (0.4,0.46,0.47) | (0.21,0.25,0.28) | (0.28,0.28,0.28) | (0.41,0.48,0.51) | (0.34,0.34,0.34) | (0.37,0.39,0.4) | (0.25,0.28,0.31) |
| DM10 | (0.25,0.27,0.31) | (0.32,0.32,0.32) | (0.38,0.41,0.43) | (0.27,0.29,0.33) | (0.36,0.38,0.39) | (0.33,0.33,0.33) | (0.41,0.48,0.49) | (0.21,0.26,0.29) | (0.27,0.27,0.27) |
| FINAL | (0.31,0.34,0.36) | (0.29,0.31,0.33) | (0.33,0.35,0.36) | (0.31,0.34,0.35) | (0.32,0.34,0.36) | (0.29,0.32,0.33) | (0.3,0.32,0.33) | (0.36,0.4,0.41) | (0.26,0.28,0.31) |
| | C41 | C42 | C43 | C51 | C52 | C53 | | | |
| DM1 | (0.36,0.36,0.38) | (0.36,0.36,0.36) | (0.27,0.28,0.31) | (0.38,0.38,0.38) | (0.38,0.38,0.4) | (0.21,0.22,0.27) | | | |
| DM2 | (0.36,0.38,0.39) | (0.33,0.33,0.33) | (0.27,0.29,0.33) | (0.39,0.44,0.45) | (0.3,0.3,0.3) | (0.23,0.27,0.3) | | | |
| DM3 | (0.34,0.34,0.34) | (0.25,0.27,0.31) | (0.37,0.39,0.41) | (0.38,0.38,0.38) | (0.38,0.38,0.4) | (0.21,0.22,0.27) | | | |
| DM4 | (0.36,0.36,0.38) | (0.27,0.28,0.31) | (0.36,0.36,0.36) | (0.4,0.44,0.46) | (0.22,0.25,0.29) | (0.31,0.31,0.31) | | | |
| DM5 | (0.32,0.32,0.32) | (0.39,0.42,0.43) | (0.23,0.26,0.31) | (0.36,0.36,0.38) | (0.36,0.36,0.36) | (0.27,0.28,0.31) | | | |
| DM6 | (0.39,0.42,0.43) | (0.23,0.26,0.31) | (0.32,0.32,0.32) | (0.38,0.38,0.38) | (0.38,0.38,0.4) | (0.21,0.22,0.27) | | | |
| DM7 | (0.35,0.35,0.37) | (0.35,0.35,0.35) | (0.27,0.29,0.33) | (0.39,0.42,0.43) | (0.32,0.32,0.32) | (0.23,0.26,0.31) | | | |
| DM8 | (0.31,0.31,0.31) | (0.38,0.41,0.42) | (0.25,0.28,0.32) | (0.27,0.28,0.31) | (0.36,0.36,0.38) | (0.36,0.36,0.36) | | | |
| DM9 | (0.38,0.41,0.42) | (0.31,0.31,0.31) | (0.25,0.28,0.32) | (0.27,0.29,0.33) | (0.36,0.38,0.39) | (0.33,0.33,0.33) | | | |
| DM10 | (0.35,0.36,0.38) | (0.29,0.32,0.35) | (0.32,0.32,0.32) | (0.35,0.35,0.35) | (0.39,0.41,0.43) | (0.22,0.23,0.28) | | | |
| FINAL | (0.35,0.36,0.37) | (0.31,0.33,0.35) | (0.29,0.31,0.33) | (0.36,0.37,0.39) | (0.35,0.35,0.37) | (0.26,0.27,0.3) | | | |

The final criteria weights are obtained by multiplying the weights of the main criteria and subcriteria.

$$
\begin{aligned}
w_{11} &= (0.070, 0.083, 0.089), & w_{12} &= (0.066, 0.077, 0.081),\\
w_{13} &= (0.074, 0.086, 0.091), & w_{21} &= (0.061, 0.075, 0.079),\\
w_{22} &= (0.062, 0.077, 0.081), & w_{23} &= (0.058, 0.071, 0.075),\\
w_{31} &= (0.047, 0.059, 0.063), & w_{32} &= (0.056, 0.073, 0.078),\\
w_{33} &= (0.041, 0.052, 0.058), & w_{41} &= (0.059, 0.072, 0.075),\\
w_{42} &= (0.053, 0.066, 0.070), & w_{43} &= (0.049, 0.061, 0.067),\\
w_{51} &= (0.047, 0.061, 0.065), & w_{52} &= (0.045, 0.058, 0.061),\\
w_{53} &= (0.034, 0.044, 0.050),
\end{aligned}
$$

Weights of criteria/subcriteria are given in crisp form as Fig. 1.

According to Fig. 1, while the technological barriers (C1) criterion was found as the most important barrier related to smart logistics applications, the political and legal risks (C5) criterion was acquired as the least important one. In terms of subcriterion while the requirement for integration between the technologies used (C13) was obtained as the most important one, national climate (C53) was found as the least important subcriterion related to the barriers of smart logistics applications.

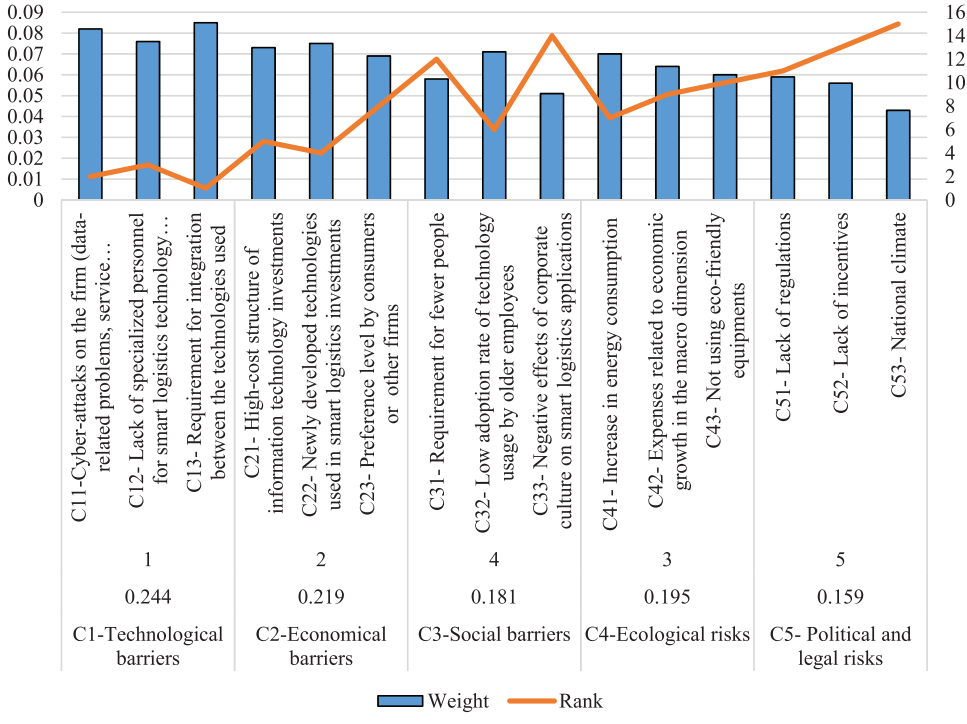



Fig. 1. Weights of criteria/subcriteria related to the barriers to smart logistics applications.

Table 6. Demand forecasting methods as alternatives.

| Mark | Alternatives | Explanation | References |
|---|---|---|---|
| A1 | Causal model | Finding out the strength of the relationships between variables and how these variables affect each other | 10, 78, 79 |
| A2 | Time series analysis method | A conceptual model for predicting future events based on previously known events | 10, 80, 81 |
| A3 | Qualitative approach | A process of holistic examination of events and phenomena in a realistic environment | 10, 82, 83 |
| A4 | Simulation method | A technique that evaluates the properties and behavior of a dynamic system by using computers | 10, 83, 84 |
| A5 | Machine learning based forecasting method | A method that allows learning from data and generalization of learned information | 10, 85, 86 |

### 4.2. *Evaluation of alternatives using the IRN EDAS method*

In this section, we have shown details about the application of the IRN EDAS method for the evaluation of demand forecasting methods. Demand forecasting methods which are determined according to the depth of literature review and expert opinions are given in Table 6.

After evaluating the alternatives according to the criteria by 10 experts, it is first necessary to transform the values of individual decision-makers' responses in group decision-making. Initial interval rough matrix is shown in Table 7.

Table 7. Initial interval rough matrix for the IRN EDAS method.

| | A1 | | A2 | | ⋮ | A5 | |
|---|---|---|---|---|---|---|---|
| $C_{11}$ | [3.87, 5.6] | [4.04, 6.21] | [3.62, 6.06] | [4.49, 6.55] | | [4.31, 6.37] | [5.15, 6.95] |
| C12 | [3.62, 5.03] | [4.09, 5.46] | [2.61, 4.77] | [3.12, 5.62] | | [3.93, 6.58] | [4.32, 6.62] |
| C13 | [4.59, 6.29] | [5.24, 7.01] | [3.37, 6.02] | [3.89, 6.74] | | [3.01, 4.46] | [3.19, 5.29] |
| C21 | [3.02, 5.77] | [3.9, 6.56] | [2.93, 4.35] | [3.66, 4.84] | | [3.69, 5.71] | [4.2, 6.47] |
| C22 | [4.51, 6.49] | [4.89, 6.94] | [4.01, 5.46] | [4.4, 6.2] | | [4.13, 5.64] | [4.46, 6.29] |
| C23 | [3.87, 5.8] | [3.91, 6.2] | [3.02, 5.56] | [3.48, 6.48] | | [3.05, 5.62] | [3.86, 6.03] |
| C31 | [2.94, 4.62] | [3.31, 5.31] | [3.44, 5.32] | [4.31, 5.86] | | [4.29, 5.93] | [4.96, 6.87] |
| C32 | [2.86, 5.2] | [3.79, 5.89] | [4.31, 5.85] | [4.48, 6.21] | | [3.46, 5.53] | [3.76, 5.92] |
| C33 | [2.87, 5.36] | [3.49, 5.95] | [4.21, 6.31] | [4.49, 6.38] | | [3.54, 6.03] | [3.82, 6.53] |
| C41 | [3.36, 6.11] | [3.69, 6.7] | [3.26, 4.57] | [3.82, 5.22] | | [3.36, 5.15] | [3.85, 6.08] |
| C42 | [2.59, 4.67] | [3.2, 5.22] | [3.1, 5.05] | [3.38, 5.58] | | [4.46, 6.16] | [4.94, 6.82] |
| C43 | [3.68, 5.56] | [4.49, 6.39] | [4.69, 6.79] | [5.28, 7.45] | | [4.27, 6.38] | [4.64, 7.13] |
| C51 | [3.47, 6.18] | [4.16, 6.36] | [3.11, 5.19] | [3.69, 5.83] | | [3, 5.33] | [3.58, 6.1] |
| C52 | [3.82, 5.91] | [4.52, 6.65] | [3.7, 5.3] | [4.12, 5.84] | | [2.86, 5.36] | [3.41, 5.4] |
| C53 | [2.94, 4.38] | [3.94, 5.38] | [3.6, 5.54] | [3.63, 5.73] | | [3.71, 5.41] | [4.25, 6.24] |

Then, in the third step, using Eqs. (9) and (10), the average solution is calculated forming a matrix:

$$IRN(AV_j) = \begin{bmatrix} [3.87, 5.67] & [4.49, 6.32] \\ [3.57, 5.78] & [4.07, 6.31] \\ [3.61, 5.53] & [4.03, 6.07] \\ [3.51, 5.38] & [4.19, 6.14] \\ [3.83, 5.93] & [4.28, 6.37] \\ [3.42, 5.43] & [3.89, 6.01] \\ [3.41, 5.48] & [4.01, 6.2] \\ [3.42, 5.43] & [4.05, 5.9] \\ [3.63, 5.92] & [4.11, 6.32] \\ [3.3, 5.49] & [3.71, 6.12] \\ [3.41, 5.4] & [3.84, 6] \\ [3.68, 5.6] & [4.36, 6.45] \\ [3.16, 5.41] & [3.81, 5.98] \\ [3.55, 5.6] & [4, 5.97] \\ [3.65, 5.47] & [4.18, 6.06] \end{bmatrix},$$

$$\sum_{i=1}^{m} \frac{IRN(x_{ij})}{m} = \begin{bmatrix} \left[\frac{[3.87 + 3.62 + 3.06 + 4.51 + 4.31]}{5}\right] = 3.87 \\ \left[\frac{[5.60 + 6.06 + 4.10 + 6.22 + 6.37]}{5}\right] = 5.67 \\ \left[\frac{[4.04 + 4.49 + 3.92 + 4.84 + 5.15]}{5}\right] = 4.49 \\ \left[\frac{[6.21 + 6.55 + 5.06 + 6.85 + 6.95]}{5}\right] = 6.32 \end{bmatrix}.$$

After that, a positive distance matrix $IRN(PDAij)$ and a negative distance matrix $IRN(NDAij)$ for the average solution $IRN(Avj)$ are calculated for all criteria. Since this research includes the criteria that belong to the benefit group, Eqs. (11)–(14) and Eqs. (17)–(19) are applied.

An example of calculation for the element $(pda_{11}) = [0.0, 0.00], [0.29, 0.60]$ is the following:

$$(pda_{11}) = \left[\frac{0.00}{6.32}, \frac{0.00}{4.49}\right], \left[\frac{1.63}{5.67}, \frac{2.34}{3.87}\right],$$

$$(B_{11}) = [0.00, 0.00], [1.63, 2.34] = \max(0, [3.87 - 6.32, 5.60 - 4.49], \times [4.04 - 5.67, 6.21 - 3.87]).$$

The calculation of the element $(nda_{11}) = [0.0, 0.00], [0.20, 0.63]$, is performed as follows:

$$(nda_{11}) = \left[\frac{0.00}{6.32}, \frac{0.00}{4.49}\right], \left[\frac{1.11}{5.67}, \frac{2.45}{3.87}\right],$$
$$(B_{11}) = [0.00, 0.00], [1.11, 2.45] = \max(0, [3.87 - 6.32, 5.60 - 4.49], \times [4.04 - 5.67, 6.21 - 3.87]).$$

In the fifth step, the interval rough matrices $IRN(PDAij)$ and $IRN(NDAij)$ are multiplied with the weight values of the criteria using Eqs. (20) and (21).

$$(vp_{11}) = [0.00, 0.00], [0.02, 0.05]$$
$$= [0.00 \times 0.082, 0.00 \times 0.082], [0.29 \times 0.082, 0.60 \times 0.082],$$
$$(vn_{11}) = [0.00, 0.00], [0.02, 0.05]$$
$$= [0.00 \times 0.082, 0.00 \times 0.082], [0.20 \times 0.082, 0.63 \times 0.082].$$

In the sixth step, the sum of previously weighted rough interval matrices is calculated using Eqs. (22) and (23), respectively.

$$sp_1 = \begin{bmatrix} [0+0+0.02+0+0.02+0+0+\cdots+0] = 0.04 \\ [0+0+0.05+0+0.04+0+0+\cdots+0] = 0.09 \\ [0.02+0.02+0+0.02+0.01+0.02+0+\cdots+0.01] = 0.20 \\ [0.05+0.04+0.08+0.06+0.06+0.06+0+\cdots+0.02] = 0.65 \end{bmatrix},$$

$$sn_1 = \begin{bmatrix} [0+0+0+0+0+0+0.02+\cdots+0] = 0.06 \\ [0+0+0+0+0+0+0.03+\cdots+0] = 0.10 \\ [0.02+0.01+0+0.02+0+0.02+0.01+\cdots+0] = 0.21 \\ [0.05+0.06+0+0.07+0+0.04+0.06+\cdots+0.04] = 0.67 \end{bmatrix}.$$

Then, normalization for the matrices from the previous step is performed for all alternatives using Eqs. (24) and (25), respectively.

$$(nsp_1) = [0.05, 0.36], [1.57, 10.74] = \left[\frac{0.04}{0.82}, \frac{0.09}{0.24}\right], \left[\frac{0.20}{0.12}, \frac{0.65}{0.06}\right],$$
$$(nsn_1) = [-6.51, -0.23], [0.49, 0.93] = 1 - \left[\frac{0.06}{0.77}, \frac{0.10}{0.19}\right], \left[\frac{0.21}{0.17}, \frac{0.67}{0.09}\right].$$

In the eighth step, the values of all $IRN(Asi)$ alternatives are calculated using Eq. (26) and they are ranked in descending order, as shown in Table 8.

$$(as_1) = [-3.23, 0.07], [1.03, 5.84]$$
$$= \left[\frac{0.05 + (-6.51)}{2}, \frac{0.36 + (-0.23)}{2}\right], \left[\frac{1.57 + 0.49}{2}, \frac{10.74 + 0.93}{2}\right]$$

The results presented in Table 8, obtained using the original developed Fuzzy FUCOM — IRN EDAS model, show that A4 — simulation method has the best

Table 8. Final results and ranking obtained using the IRN EDAS method.

| | $IRN(AS_i)$ | Rank |
|---|---|---|
| A1 | [ −3.23, 0.07],[1.03, 5.84] | 4 |
| A2 | [−3.13, 0.16],[1.18, 5.71] | 3 |
| A3 | [−3.82, −0.02],[0.78, 4.42] | 5 |
| A4 | [−2.89, 0.11],[1.46, 7.27] | 1 |
| A5 | [−2.75, 0.11],[1.07, 6.36] | 2 |

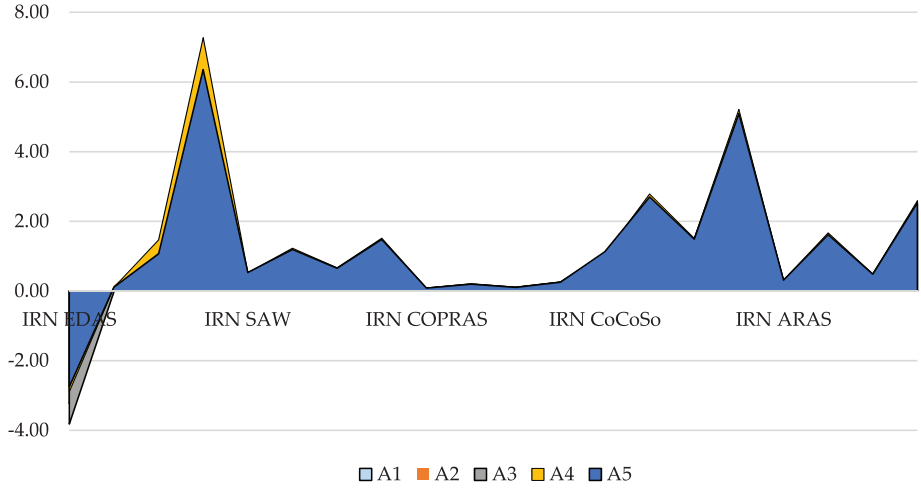
characteristics out of the set of alternatives considered in this research. On the other hand, the A3-qualitative approach was found as the least important demand forecasting method. The demand forecasting methods can be ranked as A4 > A5 > A2 > A1 > A3.

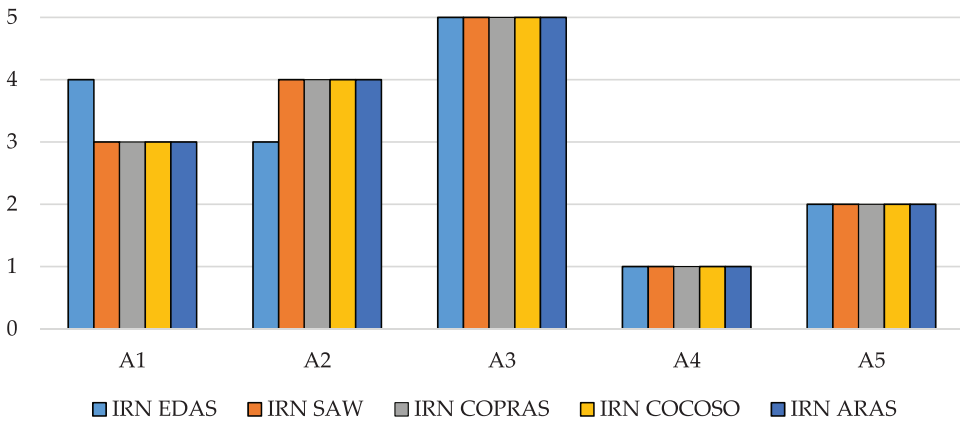
## 5. Sensitivity and Comparative Analyses

### 5.1. *Checking the robustness of the solution in comparison to other IRN MCDM methods*

This part of the paper presents the verification of the Fuzzy FUCOM–IRN EDAS model through several phases. First, a comparative analysis of the obtained results was performed with already developed methods: interval rough SAW.[87] Interval rough CoCoSo,[34] interval rough ARAS (additive ratio assessment), and interval rough COPRAS[88] methods. The results of the comparative analysis are shown in Fig. 2, while the ranks in the comparative analysis are shown in Fig. 3.

According to Fig. 2, A3, A4, and A5 remain in their ranking places according to the five IRN MCDM methods. Only A1 and A2 have different ranking places in terms






of IRN EDAS method apart from other four IRN MCDM methods. Results of comparative analysis show stability of the proposed integrated Fuzzy FUCOM–IRN EDAS model. Also, it can be concluded that analysis shows a high correlation between the proposed model and other MCDM methods.

## 6. Discussion

The technological transformation resulting from the effects of Logistic 4.0 notwithstanding, smart logistics applications experienced various barriers during the COVID-19 pandemic leading to reduced levels of service, productivity and competitive power for businesses. This study was aimed at examining the barriers to smart logistics applications and selecting the most ideal demand forecasting methods for firms that recieve and/or provide logistics services during the COVID-19 period. According to the results of the study, technological barriers were found to be the most significant barriers to smart logistics applications. Economical barriers were ranked second while political and legal risks were found to be the least significant barrier to smart logistics applications. The results also show that logistics firms need to emphasize the role of technological infrastructure, smart services, hardware, equipment, and qualified workforce in smart logistics/smart logistics applications. The study also finds that the government could help with the economical barriers and could provide some incentives to projects that prioritize smart logistics. The firms need to be transparent with their shareholders concerning their smart logistics applications such as the technological components. Also, study (Ref. 89) confirms the critical lesson learned from COVID-19 in agile companies must plan for a range of incomprehensible contingencies to ensure business continuity and growth.

The study found the requirement for integration between the technologies used, cyber-attacks on the firm (data-related problems, service frustration, etc.), and lack of specialized personnel for smart logistics technology (there is a need to provide continuous education) as the most important three subcriteria are barriers to smart

logistics applications. National climate, the negative effects of corporate culture on smart logistics applications, and lack of incentives were to be the least important three subcriteria in terms of barriers related to smart logistics applications. The simulation method, which takes into account the weights of criteria related to the barriers of smart logistics applications, was found to be the most ideal demand forecasting method.

Demand forecasting methods will make a great contribution to firms that receive and/or provide logistics services and represent remarkable portion in national economy. Accurate demand forecasting in providing nonstop service at desired level leads to improve the firms' efficiency, productivity, and performance levels. Besides the accuracy and reliability of every other activity, plannings based on demand variable will increase too. While the results show parallels with the studies of Jain,[90] Constantino *et al.,*[91] Xie,[14] Khaldi *et al.,*[92] Karagöz and Doyduk,[18] Liu *et al.,*[93] and Kodym *et al.*[20]; it differs from Law and Au,[94] Bulut,[95] and Barczak *et al.*[17] regarding the barriers of smart logistics applications. This differentiation is caused by the uncertainty and complexity of logistics sector.

## 7. Conclusions

Technological investments have become critical components in most organizations due to globalization in the digitalized world. Businesses are in a race to keep up with the digital trends occasioned by the increased technological investments that result from Industry 4.0 transformation in various areas. To the enterprise, the digital trends hold a promise of low operating costs, high profitability, customer satisfaction, and high productivity hence technological investments in these areas become necessary. Smart logistics applications refer to the technological investments made in line with the demands of Logistic 4.0.

Infrastructure of the technological transformations can be reinforced through smart logistics applications with sights set on achieving high performance in logistic operations, efficient and productive transportation by cyber-physical systems, and sensors all while ensuring customer satisfaction at the desired level and strengthening competitive advantage especially during the COVID-19 period. Smart logistics applications could also be integrated into demand forecasting to eliminate challenges associated with the inventory such as declining accuracy and deviation levels.

There were several limitations to this study. First of all, the study was restricted by time constraints and the inability of the researchers to increase the number of experts in the study due to the COVID-19 pandemic. Second, the study was limited only to the determined provinces and sectors, and the scope only focused on the implementation of and barriers to smart logistics and demand forecasting methods. The subject grouping made in the study was subjective at some points. The study was also impacted by the absence of any criteria set regarding the theme of barriers to smart logistics applications and the choice of a demand forecasting method in both the interviews with the expert group and the literature review.

Just as technological and economic factors could be considered as the main barriers to smart logistics practices in logistic firms, they could also be thought as the main challenges to the technological transformation endeavors of businesses in general. Smart logistics could be used as a platform for technological transformation through the allocation of more resources to Logistics 4.0 and its practices in general by businesses, and the support of the government. Smart logistics practices could also be included as one of the essential parameters in the comparison of successful business applications. Future studies, by evaluating smart logistics practices, barriers to smart logistics, factors that affect demand forecasting, could examine issues surrounding the performance of smart logistics, capacity, level of competition, economic, technological, social, ecological, and political issues on smart logistics on a wider business network as opposed to only logistics businesses.

Different criteria/factors could also be considered and a comparison done on the barriers related to smart logistics applications and the demand forecasting levels. Different group decision-making models[51,96,97] can be considered. Also, different MCDM-based methods such as MABAC,[19] DEMATEL,[98] BWM,[99,100] ROMETHEE (Preference Ranking Organization METHod for Enrichment Evaluation),[101] TOPSIS (Technique for Order Preference by Similarity to Ideal Solution),[102–104] GRA,[105] MEREC (Method based on the Removal Effect of Criteria),[106] MAIRCA,[29,114] MARCOS,[107] and MACBETH[108] in various environments such as interval type-2,[109] pythagorean,[110] spherical,[111] fermatean,[112] and q-rung orthopair[113] can be applied for future studies too.

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