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Cargo Company Recommendation Study Based on Probabilistic Linguistic Term Set

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Abstract
The global economic structure is the main reason for changes in consumption habits and consumer behavior. Developing information technologies direct producers and consumers to e-commerce. Cargo services are an important link in the chain in the fast and effective operation of e-commerce. The growth in e-commerce has a driving force in the development of cargo services and cargo companies. Cargo companies can survive in global competition by being preferred by customers and increasing their number of customers. The change in the number of customers occurs by communicating the satisfaction or dissatisfaction with the cargo company to potential customers. This study deals with the preference levels of cargo companies serving in Turkey according to customer suggestions. The data obtained from the survey evaluations are processed and recommendation ranking calculations are made for cargo companies. Probabilistic Linguistic Term Sets (PLTS) are used to eliminate customer ambiguities in survey evaluations. Alternative cargo company recommendations are ranked based on the customers' past service experiences from cargo companies. Aras Cargo, MNG Cargo, PTT Cargo, Surat Cargo, UPS Cargo, Yurtiçi Cargo companies are evaluated according to price, personnel, speed, reliability and network attributes. The maximum deviation optimization method based on the Lagrangian function is used to calculate the weights of the cargo companies' attributes. The probabilistic linguistic cosine similarity method compares cargo companies pairwise under attributes and a similarity matrix is obtained for six cargo companies. The similarity matrix defines the alternative cargo company recommendation ranking based on customers' past experiences. UPS, SURAT and MNG cargo companies stand out as the most prioritized companies according to the evaluation results. The effects of attribute weights are observed by designing six different scenarios and it is observed that the differentiating attribute weights affect the recommendation ranking. Spearman correlation coefficient evaluation based on recommendation rankings indicates a high relationship between attributes.

1. Introduction

Consumer behavior keeps up with the changes in the globalizing economic system. E-commerce, which is a part of the global change process, helps customers to access products and services economically and quickly [1]. Recommendation systems enable consumers to reach the right service and product with past experience transfers. Collaborative filtering, content-based and hybrid recommendation methods are the most used methods in the traditional recommendation system. Collaborative filtering is the most common recommendation method and bases its evaluations on the similarities among items or users [2].

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Recommendation systems in the literature deal with user preference movements based on offline and online data. Hwangbo et al. proposes a new called K-RecSys model based on the collaborative filtering recommendation system and applies this system on the click and sales data of a fashion product [3]. Zihayat et al. introduces the two-stage benefit-based news recommendation system and examines whether users' news clicks reflect users' real interests [4]. Lin et al.'s study applies a recommendation system in students' course selection based on course registration data in Chinese universities [5]. Abbasi-Moud et al. studies on the tourism recommendation system and reveals user preferences based on social network comments [6]. Liu et al. design a multi-modal transportation recommendation system in the perspectives of users, travel modes, time and location, and this model is promoted as a superior method of providing navigation service [7]. Cui et al. propose a new recommendation model developed with cuckoo search to provide faster and more accurate advice to users [8]. Nitu et al. develop an integrated personalized travel recommendation system with time-sensitive innovation weighting based on tweet data [9]. Wang et al.'s study proposes a collaborative filtering recommendation algorithm for hotels, and the validity of the model is checked with data collected from the website for ten hotels [10].

Cargo services, which have an important place in e-commerce, allow customers to reach products and services effectively, efficiently and with high satisfaction [11]. Customers are affected by the evaluations of their relatives or online users when choosing a company for cargo service, and their preferences are determined by these effects. Evaluations based on past experience are difficult to define by users with precise measurements and expressions. In addition, evaluations expressed in linguistic terms cause information to contain vagueness and fuzziness [12]. In this study, the importance and frequency levels of users' evaluations are expressed by using a set of PLTSs. Single and multiple linguistic term models have been developed to solve linguistic definition problems. Single linguistic terms that reflect the unhesitant expression of opinions are inadequate to describe hesitant and uncertain real-life expressions. Therefore, multiple linguistic terms are used to describe uncertain real-life expressions and resolve ambiguities in expressions. Hesitant Fuzzy Linguistic Term Set (HFLTS) is one of the widely used multi-linguistic methods for expressing ambiguous and complex evaluations [13]. PLTS proposed by Pang et al. assigns probabilities to linguistic terms of HFLTS to more accurately describe ambiguities [12]. The PLTS method used in different computing with words studies has proven its validity [10], [14], [15]. In this study, PLTS helps reflect the different importance of possible recommendation statements. PLTS is chosen as the mathematical tool to deal with hesitant and ambiguous statements in recommendation problems based on multiple attribute evaluations [12].

This identification method helps to reduce the level of incomplete and incorrect expression of hesitant information. PLTSs used in individual and group assessments have found application area in education, health and project studies [10], [14]. PLTSs method, which also finds application areas in recommendation studies, generates a solution in film and hotel recommendation problems [2].

The main motivation of this study is to create an alternative cargo company to meet the expectations of the users in the provision of cargo services, which constitute an important stage of e-commerce. This study aims to make a comparative evaluation for six common cargo companies in Turkey based on five key attributes in the evaluation and to develop a recommendation ranking for users. Linguistic evaluations of the users based on their past experiences are collected through an online survey and the linguistic evaluations of the users are converted into Probabilistic Linguistic Term Elements (PLTE). Evaluation expressions converted to PLTEs are used in the probabilistic linguistic cosine similarity method to calculate similarity between cargo companies. Cargo companies are compared according to their similarity values and recommendations are ranked according to the past usage characteristics of the users. The difference in the range of linguistic terms used by the probabilistic linguistic term method and the first use of this method in the cargo company recommendation study are determined as the original contributions of the study to the literature.

The study is organized under the following sections. Section Preliminaries discusses the basic concepts of PLTSs, the methods used in the recommendation model, and the recommendation model based on the PLTS approach. With the case study in Section Application, the recommendation model is applied in the courier recommendation ranking case study. The Discussion Section mentions comparative information about similar studies. In the Section Conclusion, evaluations are made about the validity of the model and the order of cargo proposals, and future studies are also mentioned.

2. Preliminaries

This section describes the PLTSs, which is the main assessment tool used in the study, the basic concepts of the study and the computational processes applied in the recommendation ranking study.

2.1. Probabilistic Linguistic Term Sets

PLTSs were developed by Pang [12] in order to reduce information fuzziness by including ambiguities and hesitancies in commonly used linguistic expressions in the decision-making process. A set of linguistic terms is defined as S= $\{s_\alpha \mid \alpha=-\tau,\ldots,0,\ldots,\tau\}$ where s_α defines the possible value of linguistic variable and τ is a positive integer. For example if τ is 1, linguistic term set can be defined as S={s_{-1} =very low, s_0 = medium, s_1 = very high}. The set of probabilistic linguistic terms is defined as [12]:

$$L(p) = \left\{L^i(p^i) | L^i \in S, p^i \geq 0, i = 1, \ldots, \#L(p), \sum_{i=1}^{\#L(p)} p^i \leq 0\right\} \tag{1}$$

where L^i corresponds to the ith term of the linguistic term set defined by #L(p) terms, and the probability of the ith term is denoted by p^i. If the sum of the probability values of the elements of the linguistic term set is equal to one, this set is called full PLTS. If the evaluation has complete information about the probabilistic distribution of possible linguistic terms, $\sum_{i=1}^{\#L(p)} p^i$ is calculated as 1. Otherwise, $\sum_{i=1}^{\#L(p)} p^i = 0$ indicates that no information is available about the probabilistic distribution of possible linguistic terms. This situation prevents the calculations and evaluation process. The realization of the $\sum_{i=1}^{\#L(p)} p^i < 0$ situation indicates that information loss will occur in the evaluation and that deviations will occur in the decision results. This is avoided by normalizing probabilities before computational operations as follows:

$$L\acute{L}(p) = \left\{L^i(\acute{p}^i) | i = 1, \ldots, \#\mathrm{L(p)}\right\} \tag{2}$$

$$\acute{p}^i = \mathrm{p^i} / \sum_{\mathrm{i=1}}^{\mathrm{\#L(p)}} \mathrm{p^i} \tag{3}$$

If the term numbers of the two PLTSs are different $(\#L_1(p) \neq \#L_2(p))$, equality is established between the term numbers of the set. The number of missing elements is added to the set with the smallest number of elements, and the probability values of these added elements are accepted as 0.

The distance between two PLTSs, $L_1(p) = \{L_1^i(p_1^i) | \; i = 1, \ldots, \#L_1(p)\}$ and $L_2(p) = \{L_2^i(p_2^i) | \; i = 1, \ldots, \#L_2(p)\}$, is calculated as follows [12]:

$$\mathrm{d}(\mathrm{L_1(p), L_2(p)}) = \sqrt{\sum_{\mathrm{i=1}}^{\mathrm{\#L(p)}} \left(\mathrm{p_1^i r_1^i - p_1^i r_2^i}\right)^2 / \mathrm{\#L(p)}} \tag{4}$$

r_1^i and r_2^i refer to the sub-index values of the linguistic terms L_1^i and L_2^i, respectively. The distances satisfy the conditions $d(L_1(p), L_1(p)) = 0$ and $d(L_1(p), L_2(p)) = d(L_2(p), L_1(p))$. The similarity measure is used to define the level of similarity between elements. Cosine similarity value (SIM), which is used as an important tool in decision-making problems, calculates the similarity measure between two vectors. The cosine similarity value between L_1 and L_2 PLTSs is calculated as follows [13], [16]:

$$SIM(\mathrm{L_1(p), L_2(p)}) = \frac{\sum_{i=1}^{\mathrm{\#L(p)}} \left(\tau^{(L_1^i p_1^i)/\tau} * \tau^{(L_2^i p_2^i)/\tau}\right)}{\sqrt{\left(\sum_{i=1}^{\mathrm{\#L(p)}} \left(\tau^{\frac{L_1^i p_1^i}{\tau}}\right)^2\right)\left(\sum_{i=1}^{\mathrm{\#L(p)}} \left(\tau^{\frac{L_2^i p_2^i}{\tau}}\right)^2\right)}} \tag{5}$$

Cosine similarity values between PLTSs satisfy the conditions SIM(L_1(p), L_1(p))=1 and SIM(L_1(p), L_2(p))=SIM(L_2(p), L_1(p)).

2.2. Problem Definition and Data Processing

The set $X = \{x_i | x_1, x_2, \ldots, x_m\}$ is used to define the six common cargo companies in Turkey that are covered in the cargo company recommendation study. The set of attributes that customers use to define the service they receive from shipping companies is defined as $A = \{a_j | a_1, a_2, \ldots, a_n\}$. Customers who want to receive cargo service are guided by the experience and evaluations of other customers.

Users are requested to evaluate their experiences with cargo companies through a survey created with a Google form. Users make their evaluations by considering price, personnel approach, service speed, reliability and service network attributes [17], [18]. The seven-dimensional linguistic term set, S={s_{-3}=very bad, s_{-2}=bad, s_{-1}=somewhat bad, s_0=moderate, s_1=somewhat good, s_2=well, s_3=very good}, is used to convey users' past experience. Probabilistic linguistic term set transformations are performed to statistically describe the linguistic views obtained from users' evaluations [19]. The number of repetitions of the expression in each evaluation of each service attribute expression $O^j_{s_\alpha}$ and the total number of repetitions of each attribute a_j are counted as O_{a_j}. Thus, the probability value (P^α) of the sub-index α of the linguistic term s_α, which defines the attribute terms, is calculated as [2], [15].

$$P^{\alpha} = O^{j}_{s_\alpha}/O_{a_j} \tag{6}$$

A probabilistic set of linguistic terms is obtained by calculating the probability values of all expressions. The view set of the i^th cargo service according to the j^th attribute is represented as L_{ij} (p). The implementation steps of the cargo company recommendation method are as follows:

Step 1: Formation of evaluation matrices of cargo companies: Cargo companies' factor-based evaluation information is explained with PLTS and the evaluation matrix is obtained.

$$P = \begin{bmatrix} L_{11}(p) & L_{12}(p) & \cdots & L_{1n}(p) \\ L_{21}(p) & L_{22}(p) & & L_{2n}(p) \\ \vdots & & \ddots & \vdots \\ L_{m1}(p) & L_{m2}(p) & \cdots & L_{mn}(p) \end{bmatrix} \tag{7}$$

where L_{ij} represents the evaluation information of cargo company x_i (i=1,2,…,m) according to the factor a_j (j=1,2,…,n).

Step 2: Determination of attribute weights: The attribute weights are determined using the maximum deviation method. The large deviation value of the attribute, which reflects the power of the discrimination ability, indicates that the weight of the attribute is also large. The degree of deviation, with w={w_j| j=1, 2,…, n} being the set of attribute weights, is calculated based on the distance between PLTS formula (Eq.4). The degree of deviation between the x_i cargo company and other cargo companies according to the a_j attribute is calculated as follows [20]:

$$d_{ij} = \sum_{k=1,k\neq i}^{m} d\left(L_{ij}(p), L_{kj}(p)\right) = \sum_{k=1,k\neq i}^{m} \sqrt{\sum_{l=1}^{\#L(p)} \left(p^l_{ij} r^l_{ij} - p^l_{kj} r^l_{kj}\right)^2 / \#L(p)} \tag{8}$$

The total degree of deviation for the a_j attribute is defined as:

$$d_j = \sum_{i=1}^{m} d_{ij} \tag{9}$$

The total degree of deviation between attributes according to the evaluation matrix is shown as follows [2], [21]:

$$d_P = \sum_{j=1}^{n} w_j d_j \tag{10}$$

The maximum deviation optimization model is created as follows:

$$\begin{gathered} mak\ d_P = \sum_{j=1}^{n} w_j \sum_{i=1}^{m} \sum_{k=1,k\neq i}^{m} d\left(L_{ij}(p), L_{kj}(p)\right) \\ \sum_{j=1}^{n} w_j^2 = 1, w_j \geq 0 \end{gathered} \tag{11}$$

The Lagrangian function is used to solve the maximum deviation optimization model:

$$L(w,\lambda) = \sum_{j=1}^{n} w_j \sum_{i=1}^{m} \sum_{k=1,k\neq i}^{m} d\left(L_{ij}(p), L_{kj}(p)\right) + \frac{\lambda}{2}\left(\sum_{j=1}^{n} w_j^2 - 1\right) \tag{12}$$

The normalized attribute weights are calculated as:

$$w_j = \frac{\sum_{i=1}^{m}\sum_{k=1,k\neq i}^{m} d\left(L_{ij}(p), L_{kj}(p)\right)}{\sum_{j=1}^{n}\sum_{i=1}^{m}\sum_{k=1,k\neq i}^{m} d\left(L_{ij}(p), L_{kj}(p)\right)} \tag{13}$$

Step 3: The similarity matrix is created: Similarities between cargo companies are calculated by weighted similarity calculation method. First of all, the pairwise similarities between the cargo companies under each attribute are calculated according to the cosine similarity method (Eq.5) as follows:

$$SIM\left(L_{ij}(p), L_{kj}(p)\right) = \frac{\sum_{l=1}^{\#L(p)}\left(\tau^{(L_{ij}^{l}p_{ij}^{l})/\tau} * \tau^{(L_{kj}^{l}p_{kj}^{l})/\tau}\right)}{\sqrt{\left(\sum_{l=1}^{\#L(p)}\left(\tau^{\frac{L_{ij}^{l}p_{ij}^{l}}{\tau}}\right)^{2}\right)\left(\sum_{l=1}^{\#L(p)}\left(\tau^{\frac{L_{kj}^{l}p_{kj}^{l}}{\tau}}\right)^{2}\right)}} \quad (14)$$

where $\#L(p)=\#L_{ij}(p)=\#L_{kj}(p)$. The pairwise weighted similarity values between x_i and x_k cargo companies are calculated as follows according to the weights of the attributes:

$$SIM(x_i, x_k) = \sum_{j=1}^{n} w_j SIM\left(L_{ij}(p), L_{kj}(p)\right) \quad (15)$$

The similarity matrix between the cargo companies according to the pairwise weighted similarity values is defined as follows:

$$M = \begin{bmatrix} SIM(x_1,x_1) & SIM(x_1,x_2) & \cdots & SIM(x_1,x_m) \\ SIM(x_2,x_1) & SIM(x_2,x_2) & \cdots & SIM(x_2,x_m) \\ \vdots & & \ddots & \vdots \\ SIM(x_m,x_1) & SIM(x_m,x_2) & \cdots & SIM(x_m,x_m) \end{bmatrix} \quad (16)$$

$SIM(x_i, x_i)=1$ and $SIM(x_i, x_k)=SIM(x_k, x_i)$ conditions are met in the similarity matrix showing the similarity between the two cargo companies.

Step 4: Ranking of alternative cargo company recommendations for users. A recommendation ranking is created for past cargo company users based on customer expectations. The similarity matrix between companies that exceed the threshold value is taken into account in the recommendation ranking formation.

A case study is carried out by following the steps mentioned in this section. The flow chart of the application steps is shown in Figure 1.

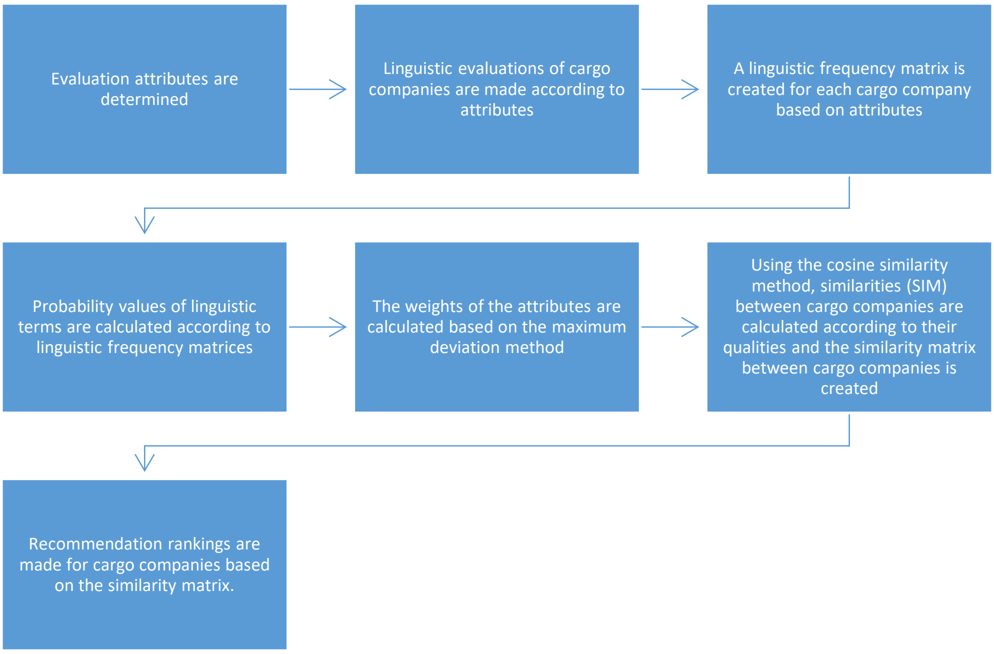

Figure 1. Flow diagram of the application steps

3. Case Application

In this section, a recommendation study is made for five common cargo companies in Turkey, taking into account the evaluations made by users based on the basic characteristics of cargo service. Common cargo companies covered in the study are as follows: Aras Cargo, MNG Cargo, PTT Cargo, Surat Cargo, UPS Cargo, Yurtici Cargo. The participants are asked to evaluate the cargo companies based on their experiences on price, personnel approach, speed, reliability and service network attributes with the survey defined in Google forms. The evaluation attributes of cargo companies are defined by considering the studies in the literature. The descriptions of the attributes are as follows:

- Price (a1): All service fees incurred in the process of receiving, safe transport and delivery of the cargo. Price varies according to delivery time, product sensitivity, product size and product weights [22]–[24].

- Personnel approach (a2): Verbal and nonverbal communication of the personnel in charge of the product delivery and purchase stages with the customer [23], [25], [26].
- Speed (a3): Cargo delivery is realized within the shortest time promised [22], [24], [27].
- Reliability (a4): The expectation that the product will be delivered in desired conditions, durable and clean [22], [27], [28].
- Service network (a5): Existence of a widespread branch network that facilitates the process of receiving and returning the product [17], [24], [27].

The set of cargo companies is shown as $X = \{x_1, x_2, x_3, x_4, x_5, x_6\}$ and the set of attributes is defined as $A= \{a_1, a_2, a_3, a_4, a_5\}$. A linguistic term set as $S=\{s_{-3}, s_{-2}, s_{-1}, s_0, s_1, s_2, s_3\}$ is defined for customers to evaluate cargo companies according to attributes. The number of evaluation terms for each cargo company is indicated by $Q^j_{s_\alpha}$ and the total number of evaluations by Q_{a_j} for each attribute a_j.

Table 1. Linguistic evaluation results of the survey

Cargo company	Attributes	Linguistic terms						
		s_{-3}	s_{-2}	s_{-1}	s_0	s_1	s_2	s_3
ARAS	a_1	6	8	2	15	7	13	6
	a_2	4	3	3	14	7	16	10
	a_3	5	2	4	11	8	15	12
	a_4	3	4	4	14	4	14	14
	a_5	3	2	5	12	8	15	12
MNG	a_1	4	6	2	15	12	14	4
	a_2	3	3	6	10	9	17	9
	a_3	3	0	6	14	12	16	6
	a_4	0	2	8	13	7	19	8
	a_5	0	2	7	12	10	18	8
PTT	a_1	12	5	9	10	6	12	3
	a_2	10	6	8	9	7	12	5
	a_3	22	8	9	9	5	3	1
	a_4	10	4	8	13	8	8	6
	a_5	8	7	5	11	10	9	7
SURAT	a_1	6	10	6	17	8	7	3
	a_2	4	7	7	13	8	11	7
	a_3	4	3	8	13	13	11	5
	a_4	2	5	5	17	10	12	6
	a_5	2	7	6	14	8	13	7
UPS	a_1	4	1	3	17	3	15	14
	a_2	1	0	2	15	8	18	13
	a_3	2	1	2	15	8	11	18
	a_4	0	0	2	13	10	13	19
	a_5	1	3	4	15	7	15	12
YURTICI	a_1	5	4	3	6	9	17	13
	a_2	1	1	2	9	11	16	17
	a_3	1	1	3	8	6	11	27
	a_4	0	1	1	12	5	14	24
	a_5	0	1	2	7	11	14	22

Step 1: Users making evaluations are expected to have past cargo usage experience. Experiences may have been gained from direct or indirect interaction with the cargo service. Users' personal information such as age, gender, education or income level is not requested when evaluating cargo companies. Users make their evaluations based on the linguistic terms as $S=\{s_{-3}$: very bad, s_{-2}: bad, s_{-1}: little bad, s_0: not bad/good, s_1: a little good, s_2:good, s_3:very good$\}$. The evaluation results of 57 users according to the seventh linguistic term scale are collected and shown in Table 1.

Step 2: According to the survey data obtained in Table 1, the probability value of the related linguistic term of each cargo company is calculated according to Eq.6 and PLTSs are defined for linguistic terms. For example, the probability values of the linguistic terms of the evaluations made for the price attribute (a_1) of ARAS Cargo Company (x_1) are calculated as $P^{-3}=6/57=0.105$, $P^{-2}=0.140$, $P^{-1}=0.035$, $P^0=0.263$, $P^1=0.123$, $P^2=0.228$, $P^3=0.105$.

The PLTS of the linguistic assessments of x_1 determined by a_1 is defined as: $L_{11}=\{s_{-3}(0.105), s_{-2}(0.140), s_{-1}(0.035), s_0(0.263), s_1(0.123), s_2(0.228), s_3(0.105)\}$. The PLTS of the linguistic evaluations of the cargo companies are calculated according to the qualifications and the evaluation matrix of the cargo companies is obtained as follows:

$$P = \begin{bmatrix} \left\{\begin{matrix} s^{-3}(0.105), s^{-2}(0.140), \\ s^{-1}(0.035), s^{0}(0.263), \\ s^{1}(0.123), s^{2}(0.228), s^{3}(0.105) \end{matrix}\right\} & \cdots & \left\{\begin{matrix} s^{-3}(0.05), s^{-2}(0.04), \\ s^{-1}(0.09), s^{0}(0.21), \\ s^{1}(0.14), s^{2}(0.26), s^{3}(0.21) \end{matrix}\right\} \\ \left\{\begin{matrix} s^{-3}(0.07), s^{-2}(0.11), \\ s^{-1}(0.04), s^{0}(0.26), \\ s^{1}(0.21), s^{2}(0.25), s^{3}(0.07) \end{matrix}\right\} & \cdots & \left\{\begin{matrix} s^{-3}(0), s^{-2}(0.04), \\ s^{-1}(0.12), s^{0}(0.21), \\ s^{1}(0.18), s^{2}(0.32), s^{3}(0.14) \end{matrix}\right\} \\ \vdots & \ddots & \vdots \\ \left\{\begin{matrix} s^{-3}(0.09), s^{-2}(0.07), \\ s^{-1}(0.05), s^{0}(0.11), \\ s^{1}(0.16), s^{2}(0.30), s^{3}(0.23) \end{matrix}\right\} & \cdots & \left\{\begin{matrix} s^{-3}(0), s^{-2}(0.02), \\ s^{-1}(0.04), s^{0}(0.12), \\ s^{1}(0.19), s^{2}(0.25), s^{3}(0.39) \end{matrix}\right\} \end{bmatrix}$$

Since the probability values of linguistic terms are obtained by normalizing in the evaluation matrix, there is no need to make a new normalization over the probability values.

Step 3: The weights of the attributes are calculated using the maximum deviation method. First, the distances between the PLTSs of the attributes are calculated using Eq.4 to observe the relationships between the cargo companies. For example, the distance for PLTSs L_{11} and L_{21}, which are defined according to the price (a_1) nature of Aras (x_1) and MNG (x_2) cargo companies, respectively, is calculated as follows:

$$d(L_{11}(p).L_{21}(p))$$

$$= \sqrt{\frac{\begin{matrix} ((-3)*(0.105-0.07))^2 + ((-2)*(0.140-0.105))^2 + \\ ((-1)*(0.035-0.035))^2 + ((0)*(0.263-0.263))^2 + \\ ((1)*(0.123-0.211))^2 + ((2)*(0.228-0.246))^2 \\ +((3)*(0.105-0.07))^2 \end{matrix}}{7}}$$

$$= 0.072$$

Relative deviation degrees and total deviation degrees of attributes According to Eq.8 and Eq.9 for each cargo company are shown in Table 2. The total degree of deviation between attributes according to Eq.10 is defined as:

$$d_P = 5.341w_1 + 4.701w_2 + 9.812w_3 + 7.029w_4 + 5.357w_5$$

Table 2. Deviation degrees of attributes

Attributes	Aras	MNG	PTT	Surat	UPS	YURTICI	d_j
Price	0.678	0.774	1.013	0.912	1.038	0.926	5.341
Personnel	0.572	0.596	1.060	0.766	0.745	0.962	4.701
Speed	1.190	1.338	2.500	1.346	1.389	2.049	9.812
Reliability	0.899	1.093	1.412	1.096	1.091	1.438	7.029
Network	0.662	0.807	1.069	0.792	0.659	1.368	5.357

The maximum deviation optimization model based on the total deviation degree is defined as:

$$maks\ d_P = 5.341w_1 + 4.701w_2 + 9.812w_3 + 7.029w_4 + 5.357w_5$$
$$w_1^2 + w_2^2 + w_3^2 + w_4^2 + w_5^2 = 1$$

The optimization model is solved by defining the Lagrangian function (L (w, λ)):

$$L(w.\lambda) = 5.341w_1 + 4.701w_2 + 9.812w_3 + 7.029w_4 + 5.357w5 + \frac{\lambda}{2}(w_1^2 + w_2^2 + w_3^2 + w_4^2 + w_5^2 - 1)$$

The partial derivatives of the Lagrangian function are taken according to the weights of the attributes and the Lagrange parameter λ:

$$5.341 + \lambda w_1 = 0$$
$$4.701 + \lambda w_2 = 0$$
$$9.812 + \lambda w_3 = 0$$
$$7.029 + \lambda w_4 = 0$$
$$5.357 + \lambda w_5 = 0$$
$$\frac{1}{2}\left(w_1^2 + w_2^2 + w_3^2 + w_4^2 + w_5^2 - 1\right) = 0$$

The solution of the Lagrangian function gives the Lagrangian parameter λ=-15 and the attribute weights 0.356, 0.313, 0.654, 0.469 and 0.357, respectively. Normalized values are defined as w_1=0.166, w_2=0.146, w_3=0.304, w_4=0.218, w_5=0.166.

Step 4: Similarities between cargo companies for each attribute are calculated using the cosine similarity method and a similarity matrix is created. For example, the cosine similarity values of Aras Cargo with other cargo companies under all attributes are defined in Table 3.

The weights of the attributes are included in the calculation process and the weighted similarity matrix is generated using Eq.15. For example, the weighted similar value between ARAS (x1) and MNG (x2) cargo companies is calculated as follows:

$$SIM(x_1, x_2) = 0.9997 * 0.166 + 0.9999 * 0.146 + 0.9986 * 0.304 + 0.9980 * 0.218 + 0.9991 * 0.166 = 0.9989$$

Table 3. Cosine similarity degrees for Aras Cargo Company

SIM(L_{ij} (p), L_{kj} (p))	MNG	PTT	Surat	UPS	YURTICI
	0.9997	0.9992	0.9995	0.9981	0.9988
	0.9999	0.9992	0.9996	0.9997	0.9987
ARAS	0.9986	0.9949	0.9985	0.9984	0.9916
	0.9980	0.9978	0.9979	0.9992	0.9970
	0.9991	0.9990	0.9992	0.9999	0.9970

The similarity matrix between all cargo companies is defined as:

$$M = \begin{array}{r} ARAS \\ MNG \\ PTT \\ Surat \\ UPS \\ Yurtici \end{array} \begin{bmatrix} 1 & 0.9989 & 0.9975 & 0.9988 & 0.9990 & 0.9959 \\ 0.9989 & 1 & 0.9974 & 0.9996 & 0.9967 & 0.9915 \\ 0.9975 & 0.9974 & 1 & 0.9980 & 0.9951 & 0.9900 \\ 0.9988 & 0.9996 & 0.9980 & 1 & 0.9967 & 0.9915 \\ 0.9990 & 0.9967 & 0.9951 & 0.9967 & 1 & 0.9982 \\ 0.9959 & 0.9915 & 0.9900 & 0.9915 & 0.9982 & 1 \end{bmatrix}$$

The similarity matrix shows high similarity among cargo companies. A value of 1 in the matrix indicates the user's previous cargo preference. The matrix defines cargo company recommendations based on users' past preferences. For example, the order of recommendation for the customer using Aras Cargo Company is determined as UPS> MNG> Surat> PTT>Yurtiçi. The recommendation ranking table for all cargo companies is shown in Table 4.

While users' past preferences put forward Surat and UPS cargo companies as the most recommended companies, the least recommended cargo companies are determined as Yurtici and PTT.

Table 4. Recommendation rankings for cargo companies

Rank	Aras (x_1)	MNG (x_2)	PTT (x_3)	Surat (x_4)	UPS (x_5)	Yurtici (x_6)
1	UPS	Surat	Surat	MNG	Aras	UPS
2	MNG	Aras	Aras	Aras	Y.ici	Aras
3	Surat	PTT	MNG	PTT	Surat	Surat
4	PTT	UPS	UPS	UPS	MNG	MNG
5	Y.ici	Y.ici	Y.ici	Y.ici	PTT	PTT

3.1. Sensitivity Analysis

Sensitivity analysis is applied for cargo companies in different scenarios to observe the effects of the weights of the attributes (a1: price, a2: personnel, a3: speed, a4: reliability, a5: network) on the recommendation system (Table 5). Weights are defined as 1/5 to consider attributes equal, and weight values are assigned as 1 to prioritize each attribute weight.

Table 5. Recommendation rankings for cargo companies in different scenarios

Aras (x_1)							MNG (x_2)							PTT (x_3)						
w_{Lagr}	1/5	a1	a2	a3	a4	a5	w_{Lagr}	1/5	a1	a2	a3	a4	a5	w_{Lagr}	1/5	a1	a2	a3	a4	a5
x5	x5	x2	x2	x2	x5	x5	x4	x4	x1	x1	x4	x4	x4	x4	x4	x1	x4	x4	x4	x4
x2	x2	x4	x5	x4	x2	x4	x1	x1	x4	x4	x1	x1	x5	x1	x1	x2	x1	x2	x1	x1
x4	x4	x3	x4	x5	x4	x2	x3	x3	x3	x5	x3	x3	x1	x2	x2	x4	x2	x1	x2	x5
x3	x3	x6	x3	x3	x3	x3	x5	x5	x6	x3	x5	x5	x3	x5	x5	x6	x5	x5	x5	x2
x6	x6	x5	x6	x6	x6	x6	x6	x6	x5	x6	x6	x6	x6	x6	x6	x5	x6	x6	x6	x6
Surat (x_4)							UPS (x_5)							Yurtici (x_6)						
w_{Lagr}	1/5	a1	a2	a3	a4	a5	w_{Lagr}	1/5	a1	a2	a3	a4	a5	w_{Lagr}	1/5	a1	a2	a3	a4	a5
x2	x2	x2	x2	x2	x2	x2	x1	x1	x6	x1	x1	x1	x1	x5	x5	x5	x5	x5	x5	x1
x1	x1	x1	x1	x1	x3	x5	x6	x6	x1	x2	x6	x6	x4	x1	x1	x1	x1	x1	x1	x5
x3	x3	x3	x3	x3	x1	x1	x2	x2	x2	x6	x4	x4	x2	x4	x2	x2	x2	x4	x2	x3
x5	x5	x6	x5	x5	x5	x3	x4	x4	x3	x4	x2	x3	x3	x2	x4	x3	x4	x2	x3	x4
x6	x6	x5	x6	x6	x6	x6	x3	x3	x4	x3	x3	x2	x6	x3	x3	x4	x3	x3	x4	x2

Since the attribute weights are equal to the attribute weights obtained in the study (w_{Lagr}), there is no change in the recommendation order. Only MNG and Surat cargoes have been replaced in the Yurtici cargo recommendation list. UPS and Yurtici cargo companies are mutually recommended companies based on the price priority evaluation. Aras cargo company is recommended for PTT and MNG, and MNG is the first recommended company for Aras and Surat cargo companies. The priority of personnel behavior is similar to the price priority of the first recommendation firm for Aras, MNG, Surat and Yurtici companies, while the following recommendation orders change. According to personnel priority, Surat is the first recommended company for PTT users, while Aras is the first recommended cargo company for UPS. In the speed-weighted evaluation, MNG and Surat cargo companies are determined as the priority recommendation company, while Aras Cargo Company is defined for UPS users and UPS Company for Yurtici users as the first recommendation. According to the reliability priority weighting, while the UPS Company is the first recommended company to Aras company users, the other company's recommendation rankings follow the speed-weighted recommendation ranking. According to the priority weighting of the service network, Aras is recommended for Yurtici cargo company users, while the recommendation rankings for other cargo companies are similar to the reliability recommendation rankings.

Relationships between attributes are compared with Spearman correlation coefficient values according to priority attributes recommendation rankings (Table 6).

Table 6. Relationship matrix between attributes according to recommendation order

Attributes	Price	Personnel	Speed	Reliability	Network
Price	1	0.9884	0.9848	0.9835	0.9771
Personnel	0.9884	1	0.9920	0.9902	0.9812
Speed	0.9848	0.9920	1	0.9959	0.9810
Reliability	0.9835	0.9902	0.9959	1	0.9846
Network	0.9771	0.9812	0.9810	0.9846	1

In general, the high correlation between attributes indicates that users attach importance to all attributes in service evaluation. According to the relationship matrix, speed attribute is highly correlated with reliability (0.9959) and personnel (0.9920) attributes. The weakest relationship is seen between price and network (0.9771).

4. Discussion

The recommendation system makes candidate suggestions by analyzing past customer behavior under multiple attributes. Customers can turn to alternative suppliers that suit their usage habits and preferences with the recommendation system. Recommendation systems are also used to solve decision-making problems based on production and service preferences [3], [4], [6]. The selection of alternative methods and vehicles in the transportation sector is considered as a decision-making problem, and studies commonly address air transportation problems [22]–[24], [28]. Additionally, the literature does not include a recommendation study for urban cargo services. Existing studies in the literature focus on cargo company selection problems and address the problems with decision-making methods.

Atmaca and Turgut's study aims to determine customers' selection criteria among cargo companies operating in Turkey [18]. The survey results based on 17 criteria reveal price, safe delivery of cargo, customer service and the company's corporate image as critical factors in customers' preferences for cargo companies. These factors are compatible with the price, reliability and personnel factors discussed in our study. Deste and Savaşkan's study deals with the selection of cargo companies in e-commerce businesses and emphasizes paying attention to price, experience, number of branches, delivery time, number of personnel, number of complaints, resolved complaint rate and reputation criteria [26]. These criteria are similar to the price, personnel, speed and network criteria mentioned in our study. Five cargo companies in Turkey (without specifying their names) are selected in the application part of the study and a preference ranking is made for the companies according to the VIKOR multi-criteria decision-making method. Boz et al.'s study deals with air cargo company selection under chaos conditions with the integrated bayesian BWM (Best-Worst Method) and WASPAS (Weighted Aggregated Sum Product Assessment) method [25]. Five main criteria (economic, social, logistics, location, quality) and 26 sub-criteria are considered for air cargo company selection, and all of the criteria defined in our study are indirectly similar to these sub-criteria. While speed and reliability were determined as the most important criteria in our study, in this study speed emerges as the most important criterion together with service cost, but the reliability criterion has a medium level of importance as product reliability. Asoğlu and Eren handle cargo company selection studies with Analytic Hierarchy Process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) decision-making methods [17]. They evaluate ARAS, PTT, METRO, MNG, SURAT, UPS and YURTICİ cargoes with on-time delivery, personnel approach, customer relations, reliability, solution generation, reasonable pricing and fast operation criteria. AHP analysis determines the most important criteria as appropriate pricing and on-time delivery, while the least important criteria are customer relations and personnel approach. While the on-time delivery criterion, which has the highest importance, overlaps with the speed criterion in our study, the customer relations and personnel approach criteria, which have the lowest importance, overlaps with the personnel criterion in our study. Although YURTICI is ranked first in the alternative cargo company ranking in this study, it appears as the last recommended company in our study. Differences arise from identifiable or latent effects such as the characteristics of the evaluation groups, the number of samples, and experience variability. However, UPS, ARAS and MNG companies, which follow YURTICI in the rankings, are determined as the first three most recommended companies in our study.

5. Conclusion and Suggestions

The change in global trade causes rapid changes in consumer expectations and behaviors. Especially, the corona pandemic period has caused a rapid and inclusive transformation in remote procurement and supply behaviors. This global change reveals the necessity of observing and evaluating user behavior of cargo service companies. This study aims to develop a method that enables users to rank alternative cargo companies based on their evaluations based on their past experiences. In addition, study evaluations allow cargo companies to be compared with each other on the basis of defined attributes.

In this study, Aras, MNG, PTT, Surat, UPS and Yurtici cargo companies are determined as the most preferred cargo companies by users in Turkey. User evaluations of cargo companies according to price, personnel behavior, speed, reliability and network characteristics are collected with the Google form survey tool. Linguistic assessments collected from 57 participants are converted into PLTS and used in calculations. The attribute weights are calculated using the maximum deviation method and the Lagrangian function. Similarity values between cargo companies are calculated using PLTSs and using the cosine similarity method. A similarity matrix is created between the cargo companies by including the attribute weights in the similarity values calculations. The similarity matrix enables the identification of similarity between cargo companies and the order of priority for recommendation.

The primary recommended cargo companies for Aras, MNG, PTT, Surat, UPS and Yurtici companies are determined based on the similarity matrix as UPS, Surat, Surat, MNG, Aras and UPS, respectively. While Surat and UPS companies stand out in the recommendation list, PTT and Yurtici companies are not included in the primary recommendation. In addition, recommendation rankings are created in six different scenarios to observe the effects of attribute weights on recommendation rankings. Weightings that prioritize attributes change the recommendation order, while equal weighting does not show any significant change. Considering the recommendation rankings based on the scenarios that prioritize the attributes, the relations between the attributes are examined with the Spearman correlation coefficient values. While the results indicate high correlations among all attributes, speed appears to have higher associations with reliability and personnel behavior.

The insufficient number of questionnaires emerges as the most important limitation for this study. Improvement of the study with the increasing number of questionnaires and attributes may be included in the future study plans. In addition, the development of surveys with methods that allow users to make more clear evaluations can reduce the loss of information in the evaluation and calculation process. The method applied in the study can also be extended for different service sectors (such as accommodation, banking, and consultancy).

Contributions of the authors

Author 1 contributed to the study in the sections of definition of the problem, determination of evaluation and solution methods, survey study, evaluation of the data and explanation of the results; Author 2 contributed to the study in defining the problem and developing solution suggestions, evaluating the data obtained from the surveys and interpreting the results.

Conflict of Interest Statement

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

The study is complied with research and publication ethics

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