A Value Approach to Forming a Fuzzy Model for Evaluating Business Models of IT Enterprises in Ukraine

Olga Rybytska, Olena Levchenko and Marianna Dilai

Lviv Polytechnic National University, 12 Stepan Bandera Str., Lviv, 79013, Ukraine

Abstract

The article is devoted to the construction of a fuzzy logic model for evaluating business models of Ukrainian IT enterprises in terms of their value creation for recipients of digital services and products. The model is built using a preliminary clustering of enterprises by the following indicators: the range of industry sectors and the range of services provided by enterprises. The average declared cost per labor hour for project implementation was chosen as the objective function. Groups of enterprises having similar parameters are formed and their complex impact on the value of the objective function is analyzed. A fuzzy logic model for predicting the value of the average cost of an hour of labor for project implementation is built.

Keywords

Fuzzy sets, linguistic terms, fuzzy model, clustering, IT enterprise, enterprise value.

1. Introduction

The purpose of the study is to analyze the models of functioning of IT enterprises in Ukraine, taking into account the range of services provided to the relevant range of industry sectors using cluster analysis methods, and to build a fuzzy logical model of the impact of types of services (and concentration of certain types of services in combination with industry sectors, service providers) on the financial indicator of business model efficiency, i.e., the declared average cost per hour of labor for project implementation.

Obviously, the IT market is largely integrated into global processes. There are virtually no borders between the client base and consumers of digital products. This fact, on the one hand, expands opportunities, and on the other hand, significantly increases competition and complicates the possibility of building an optimal structure: types of services provided – industry sectors (customer base in relation to industry sectors). Therefore, when building a business model [1, 2, 3, 4] for an IT enterprise, the top of the hierarchical tree is its value [5, 6, 7]. In other words, the main task of management is to maximize the ability to meet the needs of the customer base in general, and representatives of a specific industry sector in particular.

Financial performance indicators of IT enterprises that position themselves as Ukrainian (this identification of enterprises is based on the percentage of employees, i.e., team members registered in Ukraine) are not available in open sources. Therefore, the authors chose the cost of an hour of labor for a project as an indicator of the enterprise value, as declared on the Clutch platform [8]. The authors were able to obtain a full set of the studied indicators for 255 enterprises regarding the range of services provided, the range of industry sectors receiving services, and the declared cost of an hour of labor for project implementation.

2. Related Works

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EMAIL: olha.m.rybytska@lpnu.ua (O. Rybytska); olena.p.levchenko@lpnu.ua (O. Levchenko); marianna.p.dilai@lpnu.ua (M. Dilai)
ORCID: 0000-0002-2394-355X (O. Rybytska); 0000-0002-7395-3772 (O. Levchenko); 0000-0001-5182-9220 (M. Dilai)

In the existing publications, the authors have not found a value-based approach to the study of the information technology market and assessment of the effectiveness of the built business model, taking into account the construction "range of services provided – range of customer industries". The cluster analysis of the impact of various technologies on the development results of countries was carried out by Jie Xiong, Sajda Qureshi, Lotfollah Najjar in [9]. It is proposed to use a combination of cluster and logistic regression analysis to study the outflow of clients from consulting services and products [10]. In [11], cluster analysis is used to study how Information Technology (IT) evaluation is carried out among a group of Spanish companies. Attempts to divide Ukrainian IT enterprises into groups by similarity according to various indicators, including the percentage of specialists registered in Ukraine, the scale of enterprises, the scale of enterprises-customers of services, and the range of services provided, were made in [12]. The cluster Analysis of Motivational Management of Personnel Support of IT Companies was conducted in [13].

The mathematical framework of the theory of fuzzy sets and fuzzy logic is being increasingly used to build models for forecasting and supporting decision-making under conditions of uncertainty. In particular, in [14], it is proposed to use this apparatus to forecast economic trends and processes. Real-Life Applications of Fuzzy Logic are described in detail in [15]. The construction of the fuzzy model assessing the contribution of products to the United Nations' sustainable development goals (a methodological proposal) is presented in [16]. The construction of a fuzzy knowledge base on the factors influencing the growth rate of the IT market of Ukraine is discussed in [17, 18]. In addition, [19] illustrates the successful application of this theory in building a model for forecasting the product balances of a certain trading enterprise based on selected input factors.

3. Methods

In order to identify the common features of groups of enterprises, given the similarity of business model segments, which are considered to be characteristic features of enterprise value, it is proposed to apply clustering methods and to calculate the number of clusters using the k-means (elbow) method and the method of simplified silhouette estimation [20, 21, 22].

Clustering makes it possible to divide a set of objects into relatively homogeneous groups (clusters), i.e., into N groups of elements that are most "similar" according to a certain similarity criterion. In this case, the elements included in different clusters should differ as much as possible. The purpose of the k-means method is to solve this type of problem. The hypothesis can be based on theoretical considerations, the results of previous studies, or guesswork [3]. The optimal choice of the number of clusters is made by solving the problem several times for different N and comparing the quality and correctness of the solutions obtained. The study begins with an arbitrarily chosen (according to the expert's judgment) number of clusters and the calculation of deviations (distances of elements from the centroids within the clusters). By changing the number of clusters, the variability within clusters is minimized and the variability between clusters is maximized. The algorithm randomly assigns the centers of future clusters (centroids) in space. Then it calculates the distance between the cluster centers and each object, and the object is assigned to the cluster the centroid of which is the closest. After all the objects are distributed, the algorithm calculates the mean values for each cluster. The number of mean values corresponds to the number of variables used in the analysis – k. The set of means represents the coordinates of the new position of the cluster center. This process is repeated until the centers of gravity stop "migrating" in space. Often, the input data is not clearly distributed among the clusters, and as a result, the division obtained by using the elbow method will not meet the highest quality assessment of the division. Therefore, it is proposed to combine the elbow method with the simplified silhouette estimation method.

The known methods of multicriteria analysis involve the transformation of a vector of partial criteria to a scalar integral criterion. A significant disadvantage of this approach is that it is poorly adapted to qualitative criteria that are inherent in systems with subjective uncertainty.

Fuzzy expert methods [22-27] show good results in such tasks, but due to the formation of a fuzzy knowledge base, the construction of membership functions, and fine-tuning of the fuzzy knowledge base, they require painstaking and cumbersome work.

Fuzzy statistics methods are easy to use, transparent, and allow for a variety of approaches through the choice of fuzzy measures and integrals. These methods ensure the implementation of all currently known decision-making strategies.

In order to estimate the output value using fuzzy statistics, several parameters are first selected. For each parameter, the "weight" is calculated. In order to obtain a comprehensive estimate of the value under study, the problem of summing all heterogeneous parameters is solved.

One of the solutions to this problem is fuzzy integration. This method weakens the summability conditions used in arithmetic operations and introduces a formalization based on monotonic estimates. This approach brings the method closer to human subjective reasoning. Therefore, a fuzzy integral is called a fuzzy expected value (FEV, Fuzzy Expected Value) [23].

The fuzzy integral is a non-additive procedure for aggregating fuzzy information and, under different conditions, can have several options for the physical interpretation of the result, in particular:

- in the task of comparison, the fuzzy integral is interpreted as the definition of a complex assessment that reflects the degree of compliance of the input information with some reference value, which is represented as a distribution of fuzzy measures;
- in the task of assessing the certainty of an event, a fuzzy integral through the subintegral distribution of a fuzzy probability measure determines the degree of possibility of this event;
- in the problem of multi-criteria selection, the fuzzy integral provides a solution that corresponds to the concept of median and is analogous to the mean in ordinal scales.

The fuzzy Sugeno integral of a certain function $f: X \to [0, 1]$ by a fuzzy measure m, X is defined as follows

$$S(f, m, X) = \max_{\alpha \in [0,1]} min(\alpha, m(F_\alpha)), \tag{1}$$

where $F_\alpha = \{x \in X: f(x) \geq \alpha\}$.

For the discrete case, the integral (1) will have the form

$$S = \max_{\alpha \in [0,1]} (\alpha \wedge m_\alpha), \tag{2}$$

where the Tsukamoto measure [15]:

$$m_\nu = (1 - \nu) \bigvee_{i \in \Theta_\alpha} m_i + \nu \sum_{i \in \Theta_\alpha} m_i\ ,\ \Theta_\alpha = \{i | f(x_i) \geq \alpha\}. \tag{3}$$

with the condition of rationing

$$(1 - \nu) \bigvee_{i \in n} m_i + \nu \sum_{i=1}^{n} m_i = 1 \tag{4}$$

In formulas (3) and (4), the symbol "∨" means taking the maximum.

Given $\nu = 0$, the measure is a measure of possibility; given $\nu = 1$, the measure is a measure of probability; given $\nu > 1$, it is a measure of fuzzy confidence; and given $0 < \nu < 1$, it is a measure of plausibility.

When normalized, the measure m_ν does not require solving a high-order algebraic equation (as in the case of the Sugeno measure), since equation (4) is linear.

Let us point out the most important properties of the integral (1), (2):

- the fuzzy integral has the property of not accumulating errors when processing fuzzy data;
- the fuzzy integral has the properties of the median, which allows us to speak about the stability of the obtained solutions;
- the fuzzy integral, depending on the choice of the fuzzy measure used for integration, ensures the implementation of all currently known decision-making strategies.

The set X does not necessarily have to be a set of physical indicators; it can be a set of opinions, criteria, etc.

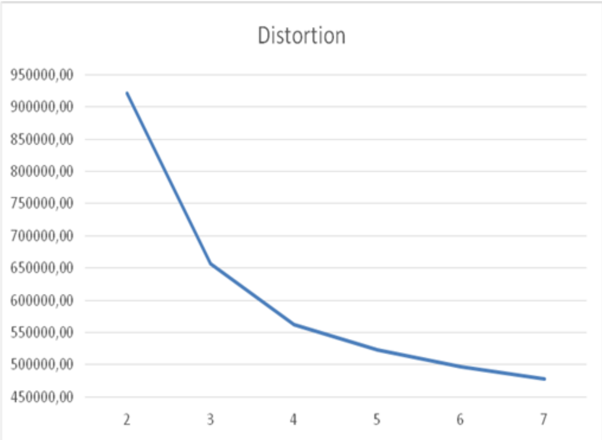
4. Results

4.1. Distribution of IT enterprises in Ukraine by industry focus on the basis of clustering

4.1.1. Industry focus spectrum

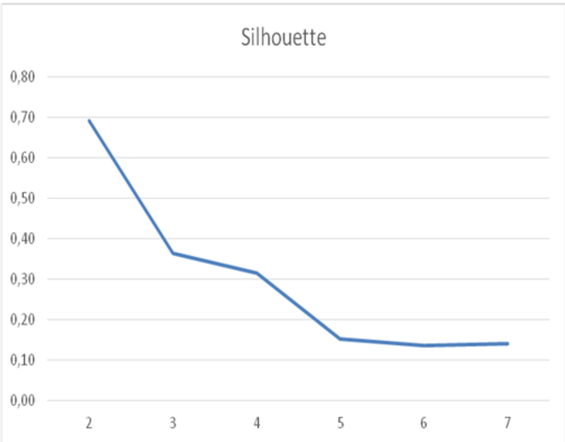
According to the data in the personal profiles of IT companies in the Clutch network, Ukrainian IT companies provide services and create products for the following major industries: Ga (Gaming); FS (Financial Services); CPS (Consumer Products & Services; IT (Information Technology); BS (Business Services); Re (Retail); Me (Medical); E-c (e-commerce); Ed (Education) and others (not specified due to the small share).

The data obtained on the spectrum of industry focus (as a percentage of the total client base) and the amount of dispersion (a measure of concentration in certain industries) were clustered.



Distortion	Number of clusters	Distortion value
	2	321954,07
	3	147535,00
	4	69769,52
	5	53718,04
	6	39639,02
	7	29627,74

Figure 1: Determining the number of clusters relative to the focus industry using the elbow method



Silhouette	Number of clusters	Distance value
	2	0,92
	3	0,78
	4	0,79
	5	0,79
	6	0,67
	7	0,68

Figure 2: Determination of the number of clusters in relation to the focus industry by the silhouette method

In accordance with the division into five clusters (see Figure 1-2), the following clustering was obtained in terms of the focus of IT enterprises on the main sectors of the economy for which they produce products or provide services (see Figure 3-6):

- **Cluster 0** – 68 companies with a very wide range of industries with an even distribution into 6-10 areas: financial services, information technology, medical, business services, e-commerce, retail, education, media, and other industry.
- **Cluster 1** – 78 companies with a wide range (4-6) of industries; specialization in certain areas is no more than 40%; the main areas are financial services, business services, medical, education, retail, information technology, e-commerce, and other industry.
- **Cluster 2** – 50 companies with an average specialization of up to 60%, focusing on 3-5 positions in the following areas: financial services, medical, information technology, other industry, education, and e-commerce.

- **Cluster 3** – 12 narrowly focused companies with the highest concentration on 2-3 industries, in particular: financial services, e-commerce, information technology, gaming, and other industry.
- **Cluster 4** – 9 companies that have a very narrow range of industries, concentrating 90-100% of their customer base on one industry: e-commerce, information technology, financial services, education), gaming, CO (Manufacturing), and other industry.

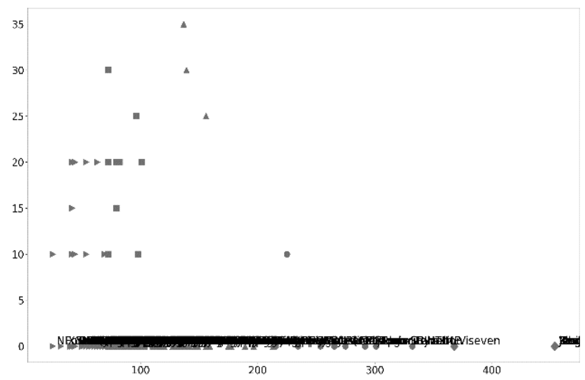


Figure 3: Industry focus: X – Disp, Y% – Costumer Products &Services (■ – cluster 0; ▶ – cluster 1; ▲ – cluster 2; ● – cluster 3; ♦ – cluster 4)

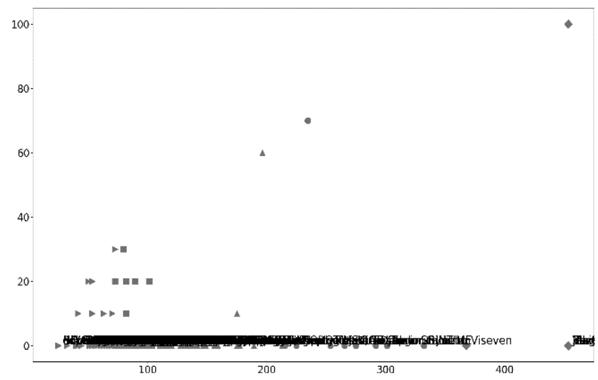


Figure 4: Industry focus: X – Disp, Y% – Gaming (■ – cluster 0; ▶ – cluster 1; ▲ – cluster 2; ● – cluster 3; ♦ – cluster 4)

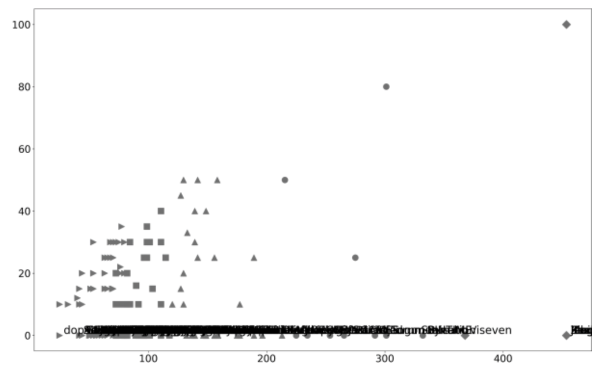


Figure 5: Industry focus: X – Disp, Y% – IT (■ – cluster 0; ▶ – cluster 1; ▲– cluster 2; ● – cluster 3; ♦ – cluster 4)

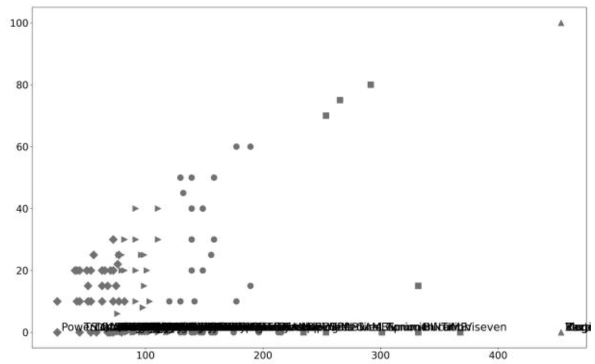


Figure 6: Example figure Industry focus: X – Disp, Y% – Financial Services (♦ – cluster 0; ▶ – cluster 1; ● – cluster 2; ■ – cluster 3; ▲ – cluster 4)

4.1.2. Focus service clustering

According to the data presented in the personal profiles of IT companies in the Clutch network, Ukrainian IT companies provide the following types of services: AR/VR (Augmented and Virtual Reality Development); AI (Artificial Intelligence); MaD (Mobile app Development); CSD (Custom Software Development); WDS (Web Design); BC (Blockchain); WD (Web development); UX, UI design; other services (combined due to their mostly small share in the total spectrum), including EC (e-commerce development), BsC (Business consulting), AT (Application testing); CM (Content marketing), IT Staff Augmentation, IoT development; CC (Cloud Consulting); CRM, ERP consulting and SI; IT managed services; IT strategy consulting; BI & Big Data Consulting & SI; Digital Strategy; Enterprise App Modernization; Product design; Branding; Cybersecurity; Social Media Marketing; Search Engine Optimization; Advertising; Public Relations and other unique services.

Similarly, taking into account the variance, the measure of dispersion of the services provided (in %) by type of service, the optimal division of enterprises into 5 clusters was obtained. A graphical representation of the clustering results in two-dimensional space by some types of services is presented in Figures 7-10.

The following clustering of Ukrainian IT enterprises by focus services was obtained:

- **Cluster 0** – companies that have a wide range of focus services (from 5 to 16 services) with an emphasis on one of the services (up to 50%): custom software development, web development, mobile application development;
- **Cluster 1** – companies that have a fairly wide range of focus services (2 to 4 services) with an emphasis on one of the following services (up to 60%): web development or custom software development, mobile application development, artificial intelligence, blockchain, augmented and virtual reality development, web design, e-commerce development;
- **Cluster 2** – companies specializing in the provision of 2-4 ancillary services with a concentration of up to 85% on one of the following services: web development, custom software development, web design, blockchain, artificial intelligence, mobile application development;
- **Cluster 3** – companies with a high concentration of focus service, which is 90-100%, specializing in augmented and virtual reality development, application testing, artificial intelligence, mobile application development, blockchain, e-commerce, web development, business consulting, content marketing;
- **Cluster 4** – companies that are 100% focused on interface design.

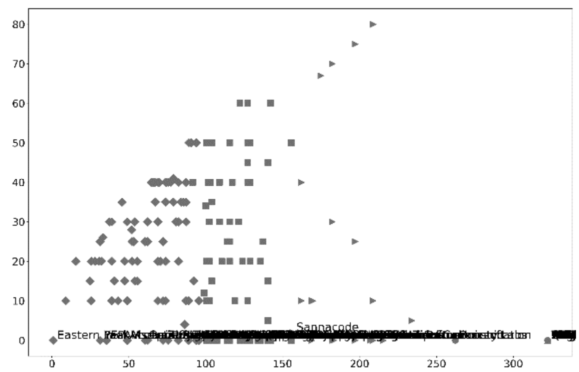


Figure 7: Focus Service X – Disp, Y% – Custom Softvare Development (♦ – cluster 0; ■ – cluster 1; ► – cluster 2; ● – cluster 3; ▲ – cluster 4)

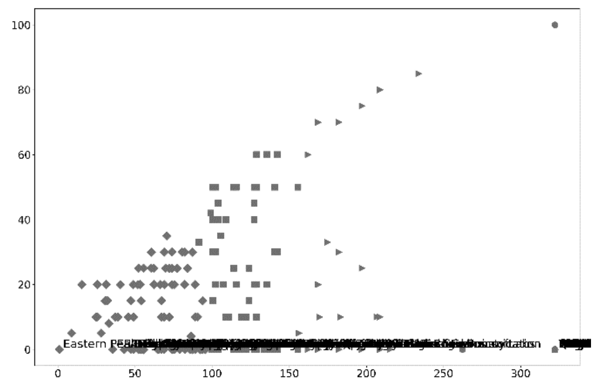


Figure 8: Focus Service X – Disp, Y% – Web Development (♦ – cluster 0; ■ – cluster 1; ► – cluster 2; ● – cluster 3; ▲ – cluster 4)

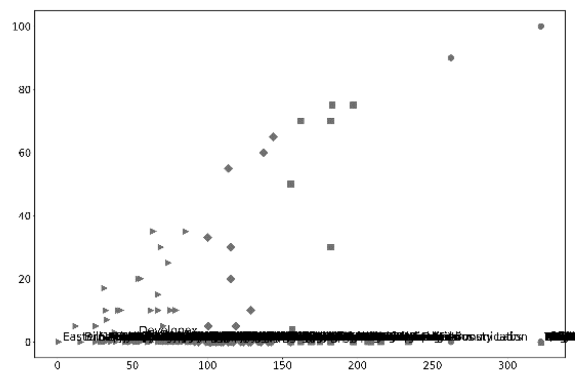


Figure 9: Focus Service X – Disp, Y% – Artificial Intelligent(♦ – cluster 0; ■ – cluster 1; ► – cluster 2; ● – cluster 3; ▲ – cluster 4)

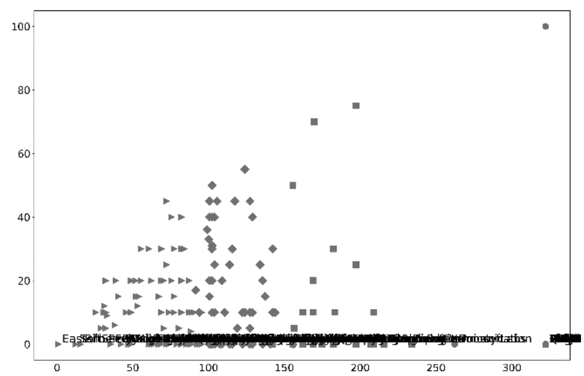


Figure 10: Example figure Focus Service X – Disp, Y% – Mobile App Development (♦ – cluster 0; ■ – cluster 1; ► – cluster 2; ● – cluster 3; ▲ – cluster 4)

Based on the clustering, we grouped companies by similarity. Companies are considered to be similar if they are included in the same cluster by various parameters. As a result of this similarity grouping, 22 groups of companies were obtained, three of which have more than 20 companies in the group, 8 groups with 5-19 member companies, and 11 groups with up to 4 members.

The following conclusions were drawn based on the results of the companies belonging to a particular cluster. The most numerous are the groups of enterprises that provide a very wide range of services to a wide and very wide range of industries, i.e., they belong to clusters 0 and 1 in terms of industry focus and clusters 0 and 1 in terms of focus service. A considerable number of enterprises provide the widest range of industries with the narrowest range of services and vice versa (clusters 0-3, 1-3, 0-4, 3-0, 3-1, 4-1). However, for the most part, the average declared cost per labor hour is higher for companies that provide a fairly wide range of services, with a predominant emphasis on AI, MaD, and CSD, and lower for UX and UI design services. Clustering results, including those in works [12, 13], allowed us to note certain regularities regarding the impact of combinations of the range of services provided to the relevant industries. This made it possible to formulate logical rules in a fuzzy model.

4.2. Building a fuzzy model

4.2.1. Formation of linguistic terms for input and output parameters and membership functions for fuzzy term series

Methods of fuzzy logic and fuzzy set theory are widely used in modern mathematical economics. Fuzzy sets and fuzzy logic have been applied virtually in all branches of science, engineering, and socio-economic sciences [14, 16-19, 25, 26, 28]. The principal notion of the theory is that of a linguistic variable.

In order to apply methods of fuzzy logic, we shall have the fuzzy variables and turn them into linguistic terms. For all seventeen input values, the universal sets are the same $X = [\underline{x}, \overline{x}] = [0; 100]$ and for the output $R = [\underline{r}, \overline{r}] = [0; 150]$. Five linguistic terms were chosen as input variables: A_1 – *low* (L), A_2 – *below average* (PA), A_3 – *average* (A), A_4 – *above average* (AA), A_5 – *high* (H).

For each term $a \in A_i$ from the term set A_i, we define a trapezoid membership function $\mu_a: X_i \to [0; 1]$ (Figures 11, 12). Three linguistic terms were formed for the output value: R_1 – *low* (L), R_2 – *average* (A), R_3 – *high* (H) with membership functions$\mu_r: R \to [0; 1]$, as shown in Figures 11, 12.

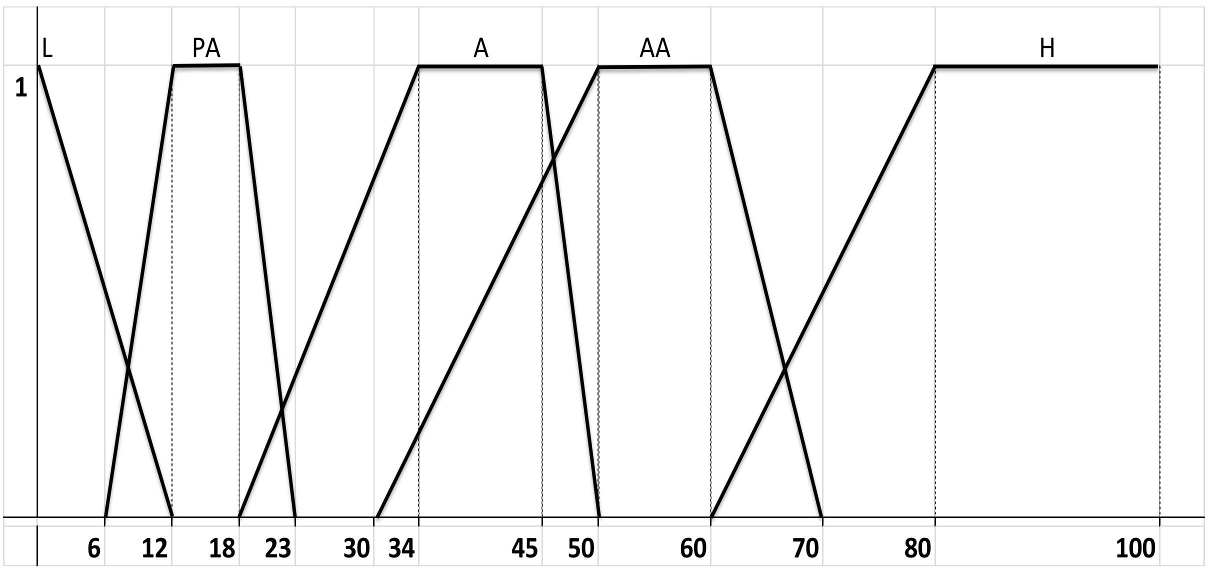


Figure 11: Membership functions for term sets of the input vector

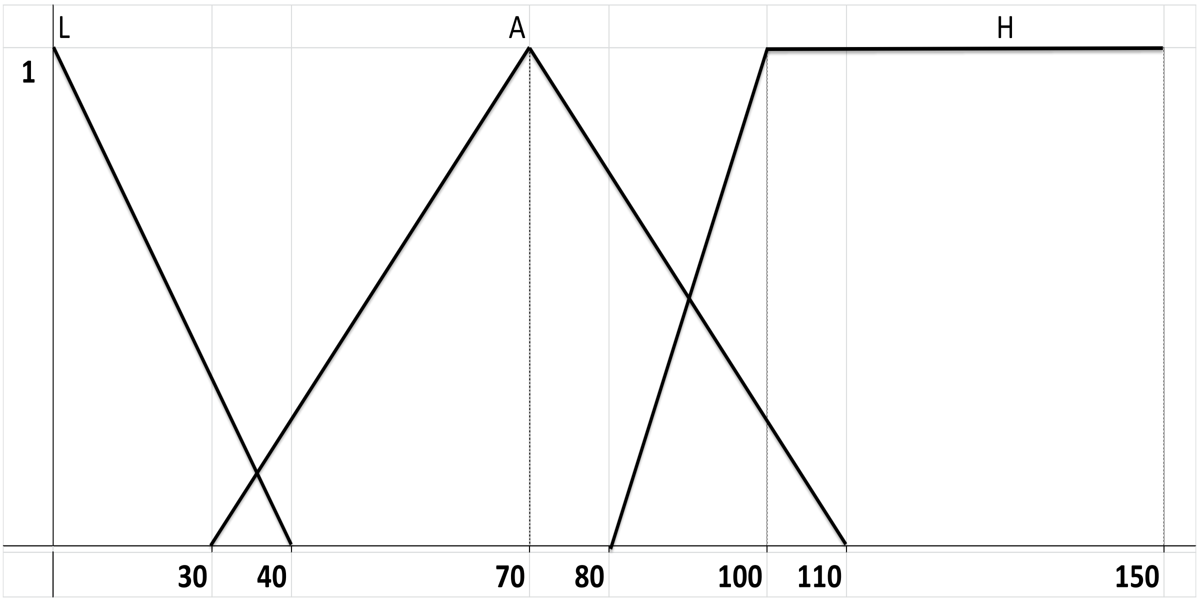


Figure 12: Membership functions for term sets of the original value

The input vectors are $X = (U, V)$, where $U = (u_1, u_2, u_3, u_4, u_5, u_6, u_7, u_8)$ is the percentage in the range of provided services of the corresponding types: u_1– AR/VR (Augmented and Virtual Reality Development; u_2– AI (Artificial Intelligence), u_3 – MaD (Mobile app Development); u_4 – CSD (Custom Software Development); u_5 – WDS (Web Design); u_6 – BC (blockchain); u_7 – WD (Web development); u_8– UX, UI design; and V stands for industry sectors to which services are provided: v_1 – Ga (Gaming); v_2 – FS (Financial Services); v_3 – CPS (Consumer Products & Services); v_4 – IT (Information Technology); v_5 – BS (Business Services); v_6 – Re (Retail); v_7 – Me (Medical); v_8 – E-C (e-commerce); v_9 – OI (Other industry).

The influence of the interrelationships between the indicators, the factors of influence $U = (u_1, u_2, u_3, u_4, u_5, u_6, u_7, u_8, u_9)$ and $V = (v_1, v_2, v_3, v_4, v_5, v_6, v_7, v_8, v_9)$, on the value of the average declared cost per hour for the project implementation is formulated in a fuzzy logical relationship $R = f_R(U, V, W)$.

Here, the principle of hierarchical knowledge bases is not observed: the number of arguments in each node of the tree exceeds the number 7 ± 2 [27], since the authors were unable to separate the indicators into separate independent or weakly dependent subgroups.

The weights W for each of the logical rules were set with the help of an industry expert. However, certain statistical approaches are also possible in the process of future customization of the knowledge base [24].

It is proposed to determine the calculation of the output value using the Sugeno fuzzy integral [19] according to the Tsukamoto measure [27].

The following evaluation scale $R$is established:

- if the resulting integral by a certain measure m_R according to the indicators U, V, W is determined by a number from the interval$[0; 0{,}2)$, we have the case r_1 −of low average cost;
- if this number is in the interval$[0{,}2; 0{,}7)$, we have the case r_3 −of average cost;
- if this number is in the interval$[0{,}7;\ 1]$, we have the case r_2 −of high average cost.

4.2.2. Building a fuzzy knowledge base

A knowledge table [19, 27] was built for the obtained similarity groups based on the principle of belonging to the same clusters for both groups of clustered values (see Figure 13).

The blank cells in Figure 13 correspond to the linguistic term *low* (L).

№	u_1	u_2	u_3	u_4	u_5	u_6	u_7	u_8	v_1	v_2	v_3	v_4	v_5	v_6	v_7	v_8	v_9	W	R
1	H		A						H									1	
2		H	PA							PA	PA			PA	PA			0,9	
3		H	PA												A			0,9	
4			PA	A			PA				A		PA					0,9	
5					AA			PA		PA		PA	A			PA		0,9	
6			A				A				AA		PA					0,9	H
7			PA	A			PA				AA	PA						1	
8								H							A			0,8	
9					AA		PA							PA	PA			0,8	
10			A	PA			A										H	0,9	
11			A	PA			A										A	0,8	
12			PA	A			PA					A	PA					1	
13		AA	L									A	PA					1	
14			PA	A			PA								A			1	
15		H	PA									A	PA					0,9	
16			A	PA			A								A	PA		0,9	
17			A				A								A			0,8	
18			A				A		H									1	
19			PA	A			PA			AA								1	
20						H				AA								0,8	
21			A				A			AA								0,8	A
22			PA	A			PA			PA				PA	PA			1	
23	H		PA											PA	PA			0,8	
24			A				A							PA	PA			0,8	
25			PA	A			PA									H		1	
26			PA	A			PA			PA		PA	A			PA		0,8	
27		H	PA							PA		PA	A			PA		1	
28						H				PA		PA	A			PA		0,8	
29			PA	A			PA									H		1	
31			A				A			PA		PA	A			PA		0,9	
32								H		PA		PA	A			PA		0,8	L
33			PA	A			PA										A	1	

Figure 13. Similarity groups (all blank cells correspond to the value of L (low)

5. Discussions

The authors see the prospect of further study of internal elements of business models aimed at ensuring the growth of the value of IT enterprises in Ukraine for external customers, as well as the study of external factors in order to improve the fuzzy model in view of reducing the amount of necessary statistical information [19]. The software implementation and testing of the model will allow making adjustments to the construction of membership functions and weighting coefficients.

6. Conclusions

The combined approach to assessing the value of IT enterprises in Ukraine using cluster grouping, similarity groups, and fuzzy inference allowed us to draw the following conclusions. The highest-paid services according to the study were: Artificial Intelligence, Business intelligence & Big Data Consulting, E-commerce development, CRM, ERP consulting and SI, Cloud Consulting. These services can be provided only by specialists with a high level of competence. The authors also found that it is inexpedient to widely disperse the range of services provided. It is optimal to focus on a limited number of services, especially such as Custom Software Development, Web development, Artificial Intelligence, Mobile app Development, or 100% UX/UI Design. Working with a wide range of industries or a narrower range of industries is not significant in terms of cost per hour, but it is worthwhile to give preference to such industries as: Financial services, Medical, E-commerce, Information technology, Business services and Retail. The obtained results allowed us to build a fuzzy logic model for predicting the average cost of a labor hour for a project by a particular enterprise.

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