Research Article

Intelligent Gamification Mechanics Using Fuzzy-AHP and K-Means to Provide Matched Partner Reference

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Players in the Small and Medium System (SME) collaboration gamification system need suitable partner references to support the goals of their activities. This study aims to build an intelligent system gamification mechanics model to provide the proper partner reference for players. The following steps are carried out sequentially in carrying out this research. First, analyze needs for a recommendation model that supports partner reference. Second, design an intelligent system formula using the Fuzzy-Analytical Hierarchy Process (Fuzzy-AHP) and K-Means algorithms to obtain partner reference recommendation patterns and segmentation of similarity of interests between partners. Third, compile the scenario of recommendation model mechanics which involves actors and activities involved in the model. Fourth, design use cases and activity diagrams to translate scenarios in the form of program flow. Fifth, code programs related to use cases and activity diagrams. The sixth is to conduct experiment with the prototype results to test all the functions of the proposed model. Fuzzy-AHP produces a weight for each tested data which can be claimed as a ranking, with the highest weight value being 9,980. K-Means produces 3 clusters in which, based on this experimental data, the third cluster has the most members. Both models are realized in the dashboard, and referring to experiments from 63 respondents, the model shows its performance by displaying SME rankings and clusters according to the data and criteria being tested. Intelligent system algorithms are to develop models of gamification mechanics, primarily to support player decisions in determining more effective game steps. This model can work well if sufficient data requirements support it. Therefore, the proposed mechanics depends on game activities, and more data are available to be extracted and produce more precise recommendations.

1. Introduction

Small and Medium Enterprise (SME) is one of the essential components of the country's economy because its existence contributes to the absorption of labour and an increase in per capita income. However, there are many challenges faced [1–3]. Some of the challenges include weak information exchange and low activity and retention and motivation to collaborate [2, 4–7]. Several studies reported that SMEs are reluctant to collaborate because of the lack of information regarding appropriate partner references in collaborating [1, 2] and the lack of effective exchange of information and good knowledge extraction between SMEs [4, 8].

Meanwhile, partner reference recommendations are an important part of collaborating activities [1, 8]. The accuracy of partner references determines the success of the collaboration between SMEs [1, 8]. Appropriate partner references are coming from aspects of similarity of interest,

mutual need, and interdependence [1, 1, 2, 4, 8]. The results of the review study found nine (9) studies that proposed matters relating to extracting data on SME [1, 2, 4, 8–11]. Most of these studies are at the conceptual level (8 studies), where the topics are mostly by the proposed concept of data extraction models for information exchange. It can indicate that SME data extraction research development is mostly still at the conceptual level, which is still broad to be developed, and subsequent research needs to develop further to create more concrete and specific models. Meanwhile, one study proposes extracting data related to collaboration partner references and has become a partner reference model. However, it still has weaknesses in only single criteria and is generated from data that are difficult to calculate, so it is prone to bias [11]. Related to the literature review, there are still few appropriate approaches for presenting references for suitable SME partners in collaborating, and there are not many appropriate mechanisms for collecting and extracting information into new knowledge in exchanging information within the SME network [1, 2, 4, 8].

Concerning collaboration problems that collaboration retention is small, so the collaboration framework approach can be chosen out from how attractive or acceptable the characteristics of the approach are. There is a gamification approach that is currently being developed and has become part of the lifestyle of today's society and aims to increase user participation and motivation and try to influence user behavior [12–14]. Gamification is the process of imitating a fun and even addictive gameplay atmosphere while players complete nongame tasks [14–16]. Gamification seeks to bring together functionality and engagement to increase functionality, productivity, and satisfaction, create more experiences, drive behavior, and generate positive business impact [17]. Showing the principles of the MDE framework model, the essential components of gamification consist of mechanics, dynamics, and emotional where each of these components cannot be separated because the mechanical element (M) will create the dynamics of the game and create its emotional atmosphere for the players [17–19]. The success of the gamified system lies in the application of game mechanics according to the characters of players [19]. Gamification is suitable as an SME collaboration framework platform regarding its characteristics. We expect to make collaboration more exciting and increase retention. So, going from the two problems, a solution is needed by building an intelligent system in a collaborative gamification mechanics model that can provide knowledge extraction to produce a suitable reference partner for SME actors.

Several intelligent systems approaches can be applied in this research. Among them is the fuzzy-analytical hierarchy process (Fuzzy-AHP) which has the potential to provide a more precise weight value in completing the weighting of data with several criteria [20, 21]. Fuzzy-AHP has the advantage of being able to weigh more precisely than data criteria that have more subjective characteristics and are uncertain so that the resulting reference is claimed to be more precise [21–23]. While the K-Means clustering approach has the potential to group objects based on their characteristics [24] so that objects with the same characteristics are grouped in the same cluster and objects with different characteristics are grouped into other clusters [25, 26]. This condition fits the mapping needs and position of each SME to make it easier for them to identify partners who have the same interests.

This study introduces the proposed "Intelligent Gamification Mechanics (IGM)" model. This model embodies gamification mechanics made from an intelligent system to provide knowledgeable recommendations to players. The IGM formula uses the fuzzy-AHP algorithm [24] and K-Means [25] to provide two knowledge recommendations that support each other in providing a suitable partner reference. The fuzzy-AHP formula produces recommendations for ranking suitable SME partners [27]. The K-Means formula produces SME segmentation mapping that provides information on the position of players in groups who have the same interests and potential to collaborate. The model is built in the gamification platform to make the model more attractive and interactive. This model can be included in a collaboration framework to provide recommendations for suitable partner references for collaborators.

This study reports the results of our research on the performance of the IGM model. The experiment used 63 respondent data according to the criteria used in the algorithm. The prototype demonstrates the model's ability to present a suitable ranking of SME partners while at the same time presenting the mapping/positioning of SMEs in groups that have the exact needs and great potential for collaboration. This research resulted in 3 contributions: first, an intelligent system formula in gamification mechanics; second, a leader board prototype that displays suitable partner ranking and SME segmentation mapping. Future research can apply or develop this model to improve collaboration partner references in various fields. The model can be developed by adding criteria and the number of clusters as needed, and the results can be compared and analyzed.

2. Materials and Methods

There are five method steps (Figure 1). First, analyze the need for a recommendation model that supports the provision of appropriate partner reference information. Second, design an intelligent system formula using the fuzzy-AHP and K-Means algorithms to obtain partner reference recommendation patterns and segmentation of similarity of interests between partners. Third, develop a scenario of recommendation model mechanics by involving the actors and activities involved in the model. Fourth, design use cases and activity diagrams to translate scenarios in the form of program flow. Fifth, code programs containing use cases and activity diagrams. The sixth is to experiment with the prototype results to test all the functions of the proposed model.

The first stage is to build an intelligent system formula to produce two recommendation models.
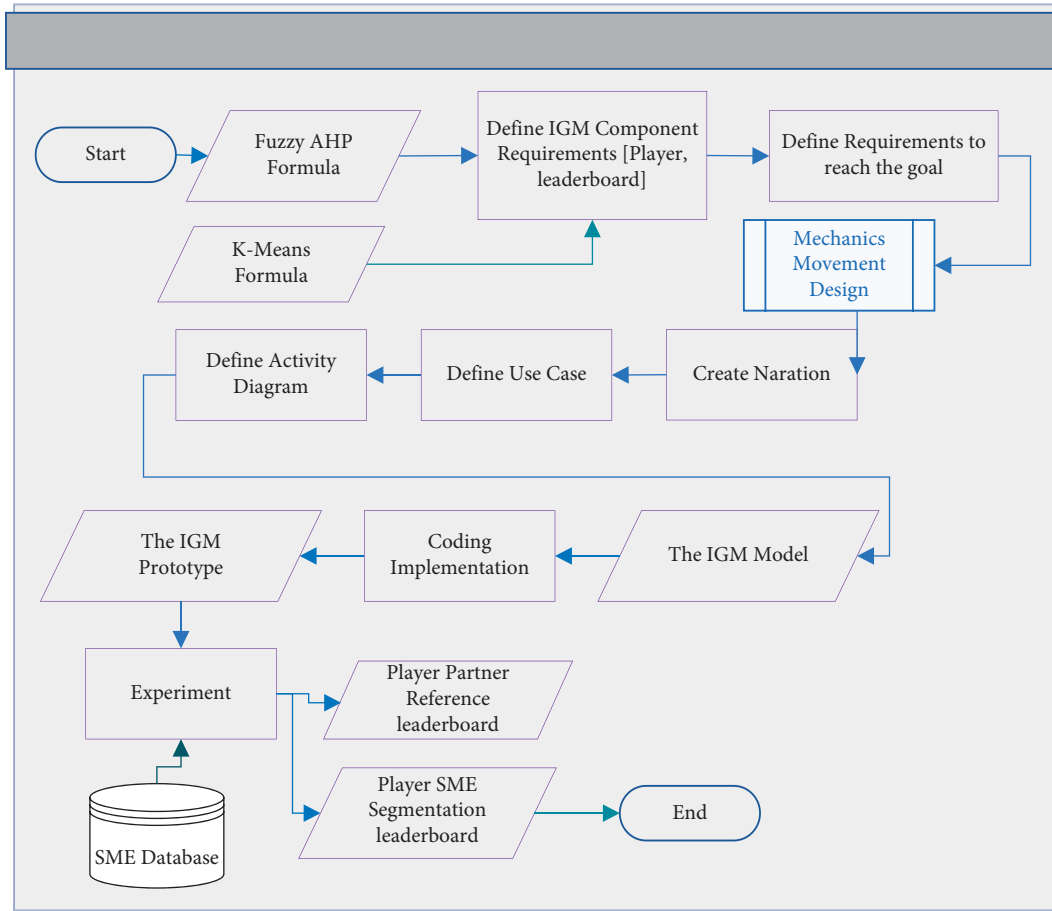
Figure 1: Research method.

2.1. Fuzzy-AHP Algorithm.

Fuzzy-AHP was first proposed by Chang which is a direct development of the AHP method which consists of matrix elements represented by fuzzy numbers [20, 21]. Fuzzy-AHP is a combination of the AHP method with fuzzy concept approach. Fuzzy-AHP covers the weaknesses found in AHP, namely, problems with criteria that have more subjective characteristics [20, 21, 26]. A scale order represents the uncertainty of numbers. The Fuzzy-AHP method uses a fuzzy ratio called triangular fuzzy number (TFN) and is used in the fuzzification process. TFN consists of three functions. The membership consists of the lowest score (l), the middle grade (m), and the highest grade (u) [21, 26].

The steps of the FAHP method are as follows [20, 21]:

(1) Arrange problems in a hierarchical form

(2) Compile a comparison matrix between all elements/criteria

(3) Calculating the value of the consistency ratio from the results of the comparison matrix, calculation with the condition that the CR value is 0.1

(4) Change the weighted results into fuzzy numbers using the TFN scale

(5) Calculate the fuzzy geometric mean and fuzzy weight

(6) Determine the fuzzy priority for each alternative using linguistic variables

In this study, SME partner ranking recommendations apply the fuzzy-AHP algorithm with four criteria: scope, market, product, and marketplace. All fFuzzy-AHP steps and formulas are compiled and tested with dummy data to ensure correct calculations.

2.2. K-Means Algorithm.

The K-Means algorithm is unsupervised machine learning algorithm. In the data analysis process, K-Means clustering is a method that performs data grouping with a partition system [24–26]. K-means clustering is also a non-hierarchical cluster analysis method that seeks to partition existing objects into one or more clusters or group objects in regard to their characteristics. Objects with the same characteristics are grouped in the same cluster. Objects that have different characteristics are grouped into other clusters [26, 28]. K-Means steps are as follows [28–30]:

(1) Perform data preprocessing followed by data transformation; then, determine the number of clusters (Number of K)

(2) Choose a centroid at random as many as the specified number of K

(3) Calculates the rarity of the centroid to the object and grouping connected with the minimum distance

(4) Check if the object moves; then, the iteration process continues

(5) If the object does not move, the last cluster is recorded as the result of the cluster formed

In this study, recommendations SME segmentation applies the K-Means clustering algorithm by determining three clusters and the centroid at random. K-Means calculates data containing four criteria (scope, market, product, and marketplace). After the K-Means step is declared, the formula is tested with dummy data to ensure the correctness of the formula calculation.

The second stage is to define the mechanical components, including the player and the leader board. The player is defined by definition, status, and access rights, while the leader board is defined by description, user interface, and access pattern. Then, the third step is to define the rules and requirements to reach the goal, namely, player rankings and segmentation are displayed on the leader board accurately. Then, the second and third steps produce a mechanics movement module. The fourth step is to compose a mechanics narrative according to the mechanics movement module completed. In this stage, the mechanics are equipped with detailed steps of each path from actor to system or vice versa and from system to system or actor to actor. This narrative also explains the origin of the data processed in the intelligent system.

The fifth stage is to complete the mechanics with use cases and activity diagrams that serve to translate the program flow and all activities in mechanics. After this stage is complete, the model is ready to be implemented in the coding program at the next stage. The fifth stage is coding this program using a web programming language with the coding flow following what has been described in the use case and activity diagram. Then, the completion of the fifth stage means the IGM prototype is ready to be tested. The last stage is to experiment by entering data from 63 respondents with the condition that the data have been preprocessed and transformed. Respondent data include general identity and four criteria used in the intelligent system formula. Experiments were carried out to observe all prototype functions and the performance results of the IGM model.

3. The Proposed Model

This section reports the details of the proposed model related to the method steps described in Figure 1. Figure 2 describes the general flow of the IGM model. The model is built on a gamified platform that adopts a leader board and dashboard to showcase the mechanics of the intelligent system.

From Figure 2, the model is detailed to the following steps to describe the flow of the proposed model.
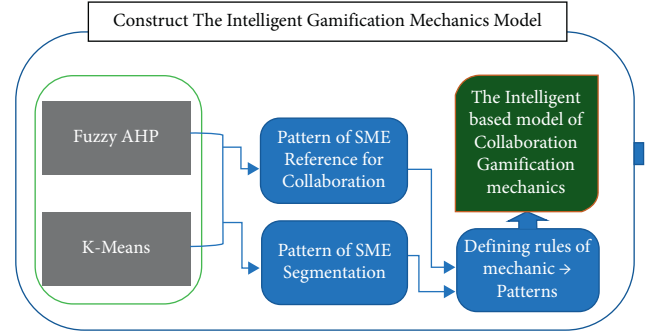

Figure 2: IGM model.

3.1. SME Reference Formula with Fuzzy-AHP. This section describes the flow of the player reference formula with fuzzy-AHP using dummy data. The first step in the fuzzy-AHP process is to tabulate the data using dummy data (Table 1) as an experiment to ensure the model works correctly. In Table 1, dummy data are presented in the form of 4 data on SME players who will be ranked as reference partners along with four criteria possessed by players, namely, SME, scope, market, product, and marketplace. These four criteria were chosen by considering the analysis of the needs and availability of SME data, which of course can change if applied to data in different situations and fields.

Triangular fuzzy number (TFN) is used in the fuzzification process which consists of three membership functions, namely, the lowest value (l), the middle value (m), and the highest value (u) [20, 26]. Determination of TFN is guided by linguistic variable and triangular fuzzy number (Table 2).

Step 1: define a priority comparison of criteria using the TFN scale (Table 2). Previously, the following were the guidelines for determining the TFN scale out from the weight of each criterion in reference to expert opinion and literature review [2, 3] in the SME sector by adjusting the TFN value guidelines (Table 3). Then, determining the priority value between criteria (Table 4) is to determine the value of 1 for two criteria that have the same value and find the difference for the two criteria that have different values.

Step 2: determine the comparison of paired matrices between criteria with the TFN scale in the decimal value (Table 5).

Step 3: determine the fuzzy synthesis (S_i) limit value referring to the FAHP calculation step fuzzy formula (S_i):

$$S_i = \sum_{j}^{m} m_i^j X \left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^i \right]^{-1}, \qquad (1)$$

where

$$\sum_{j=1}^{m} M_{gi}^j = \sum_{j=1}^{m} l_j, \sum_{j=1}^{m} m_j, \sum_{j=1}^{m} u_j. \qquad (2)$$

TABLE 1: Dummy data of SME identity.

Alternative	Criteria			
	C1	C2	C3	C4
A1-SME Player-1	2	1	1	1
A2-SME Player-2	2	1	3	3
A3-SME Player-3	1	2	3	3
A4-SME Player-4	1	1	2	3

TABLE 2: TFN table [20, 26].

Intensity	Linguistic variable	TFN number	Reciprocal
1	Equally strong	(1,1,1)	(1,1,1)
2	Intermediate of 1 to 3	(1/2, 1, 3/2)	(2/3, 1, 2)
3	Very strong	(1, 3/2, 2)	(1/2, 2/3, 1)
4	Intermediate of 3 to 5	(3/2, 2, 5/2)	(2/5, 1/2, 2/3)
5	Strong	(2, 5/2, 3)	(1/3, 2/5, 1/2)
6	Intermediate of 5 to 7	(5/2, 3, 7/2)	(2/7, 1/3, 2/5)
7	Moderately strong	(3, 7/2, 4)	(1/4, 2/7, 1/3)
8	Intermediate of 7 to 9	(7/2, 4, 9/2)	(2/9, 1/4, 2/7)
9	Equally strong	(4, 9/2, 9/2)	(2/9, 2/9, 1/4)

TABLE 3: Weight of criteria based on expert perspective.

Criteria	Weight
C1-scope of SME	5
C2-market	3
C3-product	9
C4-market place	7

TABLE 4: Comparison of priorities between criteria with TFN scale.

	C1	C2	C3	C4
C1-scope of SME	1	2	1/4	1/3
C2-market	1/2	1	1/6	1/7
C3-product	4	6	1	2
C4-market place	3	7	1/2	1

TABLE 5: Determine the comparison of paired matrices between criteria with TFN.

	C1			C2			C3			C4		
	L	M	U	L	M	U	L	M	U	L	M	U
C1	1.00	1.00	1.00	0.50	1.00	1.50	0.40	0.50	1.50	1.00	1.50	2.00
C2	0.67	1.00	2.00	1.00	1.00	1.00	0.29	0.33	0.40	0.25	0.29	0.33
C3	1.50	2.00	0.67	2.50	3.00	3.50	1.00	1.00	1.00	0.50	1.00	1.50
C4	0.50	0.67	1.00	3.00	3.50	4.00	0.67	1.00	2.00	1.00	1.00	1.00

While

$$\left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^{j}\right]^{-1} = \frac{i}{\sum_{j=1}^{n} u_j \sum_{j=1}^{n} m_j \sum_{j=1}^{n} l_j}, \quad (3)$$

calculates the total lower value in each column, and here is an example of C1:

$$\sum_{j=1}^{n} l_j = 1 + 0.5 + 0.4 + 1 = 2.9. \quad (4)$$

For the total value of lower, $c_2 = 2.20, \cdot c_3 = 5.50$, and $c_4 = 5.17$, using the same method according to the data in Table 5,

$$\sum_{i=1}^{n}\sum_{j=1}^{m} l_j = 2.9 + 2.20 + 5.50 + 5.17 + 15.77. \quad (5)$$

Calculate the total median value in each column and here is an example of C1:

$$\sum_{j=1}^{n} m_j = 1 + 10.50 + 1.50 = 4. \quad (6)$$

For the total value of the median, C2 = 2.62, C3 = 7, and C4 = 6.17, using the same method according to the data in Table 5,

$$\sum_{i=1}^{n}\sum_{j=1}^{m} m_j = 4 + 2.62 + 7 + 6.17 + 19.79. \quad (7)$$

Calculate the total upper value in each column and here is an example of C1:

$$\sum_{j=1}^{n} u_j = 1 + 1.5 + 1.5 + 2 = 6. \quad (8)$$

For the upper total value, C2 = 3.73, C3 = 6.67, and C4 = 8, use the same method according to the data in Table 5:

$$\sum_{i=1}^{n}\sum_{j=1}^{m} u_j = 6 + 3.73 + 7 + 6.67 + 8 = 24.40. \quad (9)$$

Calculating fuzzy synthesis value at lower, we obtain

$$S_i = \sum_{j=1}^{n} l_j X \frac{1}{\sum_{i=1}^{n}\sum_{j=1}^{m} u_j}, \quad (10)$$

$$s_1 = 2.90 x \frac{1}{24.40} = 0.119.$$

To calculate S_2, S_3, and S_4, use the same formula as the data reference in Table 6.

Calculate the value of Fuzzy synthesis on the median:

TABLE 6: Total of lower, median, and upper for each criteria.

	$\sum_{j=1}^{n} l_j$	$\sum_{j=1}^{n} m_j$	$\sum_{j=1}^{n} u_j$
C1	2.90	4.00	6.00
C2	2.20	2.62	3.73
C3	5.50	7.00	6.67
C4	5.17	6.17	8.00
Total	15.77	19.79	24.40

$$S_i = \sum_{j=1}^{n} m_j X \frac{1}{\sum_{i=1}^{n}\sum_{j=1}^{m} m_j}, \quad (11)$$

$$S_1 = 4 x \frac{1}{19.79} = 0.20.$$

To calculate S_2, S_3, and S_4, use the same formula as the data reference in Table 6.

Calculating the value of fuzzy synthesis on upper, we obtain

$$S_i = \sum_{j=1}^{n} u_j X \frac{1}{\sum_{i=1}^{n}\sum_{j=1}^{m} l_j}, \quad (12)$$

$$S_1 = 6 x \frac{1}{15.77} = 0.38.$$

To calculate S_2, S_3, and S_4, use the same formula as the data reference in Table 6.

Step 5: determine the value of the fuzzy-AHP's priority vector (V) using the FAHP calculation step, specifically in equation (12). Determine the vector's value using the following equation:

$$V(M_2 \geq M_1) = \begin{cases} 1, & \text{if } m_2 \geq m_1, \\ 0, & \text{if } l_1 \geq m_2, \\ \dfrac{l_1 - \mu_2}{(m_2 - \mu_2) - (m_1 - l_1)}, & \text{other,} \end{cases} \quad (13)$$

m_i is triangular fuzzy number of Ci criteria.

Calculating the vector value (C1) containing Table 7 data, we obtain as follows:

$$V(C_1 \geq (C_2, C_3, C_4, C_5, C_6, C_7, C_8)),$$

$$V(C_1 \geq C_1) = 1 \text{ as value } m_1 = m_1 \longrightarrow 1 = 1,$$

$$V(C_1 \geq C_2) = 1 \text{ as value } m_1 \geq m_2 \longrightarrow 0.20 \geq 0.15,$$

$$V(C_1 \geq C_3) = \frac{l_3 - u_1}{(m_1 - u_1) - (m_3 - l_3)} \text{ as value } m_1 \leq m_3 \longrightarrow 0.20 \geq 0.35,$$

TABLE 7: Synthesis value limit.

	S_i		
	l	m	U
C1	0.119	0.20	0.38
C2	0.090	0.13	0.24
C3	0.225	0.35	0.42
C4	0.212	0.31	0.51

$$V(c_1 \geq c_3) = \frac{(0.225 - 0.38)}{((0.20 - 0.38) - (0.35 - 0.225))} = 0.506,$$

$$V(c_1 \geq c_4) = \frac{l_4 - u_1}{(m_1 - u_1) - (m_4 - l_4)} \text{ as value } m_1 \leq m_1 \longrightarrow 1 = 1,$$

$$V(c_1 \geq c_4) = \frac{(0.012 - 0.38)}{((0.20 - 0.38) - (0.31 - 0.012))} = 1.579,$$

$$V(c_2 \geq c_1) = \frac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)} \text{ as value } m_1 \geq m_2 \longrightarrow 0.13 \geq 0.20,$$

$$V(c_2 \geq c_1) = \frac{(0.119 - 0.24)}{((0.15 - 0.24) - (0.20 - 0.119))} = 0.628,$$

$$V(C_2 \geq C_2) = 1 \text{ as value } m_2 \leq m_2 \longrightarrow 1 = 1,$$

$$V(c_2 \geq c_3) = \frac{l_3 - u_2}{(m_2 - u_2) - (m_3 - l_3)} \text{ as value } m_2 \leq m_3 \longrightarrow 0.13 \leq 0.35,$$

$$V(c_2 \geq c_3) = \frac{(0.225 - 0.24)}{((0.15 - 0.24) - (0.35 - 0.225))} = 0.049,$$

$$V(c_2 \geq c_4) = \frac{l_4 - u_2}{(m_2 - u_2) - (m_4 - l_4)} \text{ as value } m_2 \leq m_4 \longrightarrow 0.13 \leq 0.35,$$

$$V(c_2 \geq c_4) = \frac{(0.212 - 0.24)}{((0.15 - 0.24) - (0.31 - 0.51))} = 0.122,$$

$$V(C_3 \geq C_1) = 1 \text{ as value } m_3 \leq m_1 \longrightarrow 0.35 \geq 0.20,$$

$$V(C_3 \geq C_2) = 1 \text{ as value } m_3 \leq m_2 \longrightarrow 0.35 \geq 0.13,$$

$$V(C_3 \geq C_3) = 1 \text{ as value } m_3 \leq m_3 \longrightarrow 1 = 1,$$

$$V(C_3 \geq C_4) = 1 \text{ as value } m_3 \leq m_4 \longrightarrow 0.35 \geq 0.31,$$

$$V(C_4 \geq C_1) = 1 \text{ as value } m_4 \leq m_1 \longrightarrow 0.31 \geq 0.20,$$

$$1V(C_4 \geq C_2) = 1 \text{ as value } m_4 \leq m_2 \longrightarrow 0.31 \geq 0.13,$$

$$V(c_4 \geq c_3) = \frac{l_3 - u_4}{(m_4 - u_4) - (m_3 - l_3)} \text{ as value } m_4 \leq m_3 \longrightarrow 0.31 \leq 0.35,$$

$$V(C_4 \geq C_3) \frac{(0.225 - 0.51)}{((0.31 - 0.51) - (0.35 - 0.225))} = 0.870,$$

$$V(C4 \geq C4) = 1 \text{ as value } m_4 = m_4 \longrightarrow 1 = 1. \tag{14}$$

To calculate the vector in the next cells, we use the same equation, where all the priority vector results have been presented in Table 8.

Step 6: determine the defuzzification-ordinate (d') value related to the FAHP calculation step equation (5). Determining the value of the defuzzification ordinate is

TABLE 8: Fuzzy-AHP priority vector (V) value.

	C1	C2	C3	C4
C1	1.000	1.000	0.506	1.579
C2	0.628	1.000	0.049	0.122
C3	1.000	1.000	1.000	1.000
C4	1.000	1.000	0.870	1.000

to find the minimum value of the vector value of each criterion:

$$d' A_i = \min V (S_i \geq S_k), \tag{15}$$

for $k = 1, 2, \ldots, n$, $k \neq i$; then, this process produces a vector weight.

Then, the application is $d' (C_1 = \min(C1, C2, C3, C4))$ so that it produces data as in Table 9.

Step 7: normalize the value of the fuzzy vector weight (W) going from the FAHP calculation step in equation (6).

Normalization of fuzzy vector weight value (W) is

$$W' = (d' (A_1), d' (A_1) \ldots, d (A_n))^T, \tag{16}$$

where $A_1 = 1, 2, \ldots, n$ is the decision element.

After the normalization of the W' equation, the normalized value of the vector weight (see Table 10) is like equation (7):

$$W = (d' (A_1), d' (A_1) \ldots, d (A_n))^T, \tag{17}$$

where is W is nonfuzzy number and value of $\sum W = 1$,

$$W' = (0.505, \ 0.049, \ 1.000, \ 0.870)^T,$$

$$\sum W = (0.505 + 0.049 + 1.000 + 0.870) = 2.424, \tag{18}$$

$$W = \frac{(0.505, \ 0.049, \ 1.000, \ 0.870)}{2.424} = (0.209, 0.020, 0.412, 0.359).$$

Step 8: determine the vector weight value of each criteria using equation (8):

$$b_{ij} = \frac{a_{ij} - a_j^{\min}}{a_j^{\max} - a_j^{\min}}, \tag{19}$$

where $a_j^{\max} = \max (a_{1j}, a_{1j}, a_{1j}, \ldots, a_{mj})$ and $a_j^{\min} = \min (a_{1j}, a_{1j}, a_{1j}, \ldots, a_{mj})$, $i = 1, 2, \ldots, m$ and $j = 1, 2, \ldots, n$.

Then, carry out the process of normalizing the weight vector of each criterion that represents the weight of each alternative with the total number of weight values equal to 1. Then, rank decision results by calculating the total score with equation (9).

$$S_j = \sum (S_{ij}) (W_i), \tag{20}$$

where S_j = score, S_{ij} = the weight of each criterion which represents the weight of S_j, and W_i = weight of every criteria. The outputs of these calculations determine which score is the highest. The score with the greatest recommendation is the best. Table 11 contains the maximum and minimum values for each criterion.

Considering the vector weight on the criteria (W) using equation (9), the following procedure is used for C1:

For C2, C3, and C4 using the same equation formula, then the overall result of the weight vector value is shown in Table 12.

Determine the score by multiplying the weight vector (w) (Table 9) by the weight vector (w) for each criterion (Table 12), which represents the weight of each, as shown in equation (9). The overall score in alternative 1 (A1) is calculated as follows:

$$A1 = (1 \times 0.209) + (0 \times 0.020) + (0 \times 0.412) + (0 \times 0.359) = 0.209,$$

$$A2 = (1 \times 0.209) + (0 \times 0.020) + (1 \times 0.412) + (1 \times 0.359) = 0.980,$$

$$\tag{21}$$

$$A3 = (0 \times 0.209) + (1 \times 0.020) + (1 \times 0.412) + (1 \times 0.359) = 0.791,$$

$$A4 = (0 \times 0.209) + (0 \times 0.020) + (0.5 \times 0.412) + (1 \times 0.359) = 0.565.$$

TABLE 9: Defuzzification (d') ordinal value.

	C1	C2	C3	C4	Defuzzification
C1	1.000	1.000	0.506	1.579	0.506
C2	0.628	1.000	0.049	0.122	0.049
C3	1.000	1.000	1.000	1.000	1.000
C4	1.000	1.000	0.870	1.000	0.870

TABLE 10: Normalization of fuzzy vector weight value (W).

C_i	W
C1	0.209
C2	0.020
C3	0.412
C4	0.359

TABLE 11: Maximum and minimum value.

Alternative	Criteria			
	C1	C2	C3	C4
A1-SME 1	2	1	1	1
A2-SME 2	2	1	3	3
A3-SME 3	1	2	3	3
A4-SME 4	1	1	2	3
Max	2	2	3	3
Min	1	1	1	1

TABLE 12: Vector weight value (w) specification criteria.

Alternative	Criteria			
	C1	C2	C3	C4
A1-SME 1	1	0	0	0
A2-SME 2	1	0	1	1
A3-SME 3	0	1	1	1
A4-SME 4	0	0	0.5	1

From the fuzzy-AHP ranking results, the SME ranking is generated according to the criteria set in the fuzzy-AHP calculation (Table 13). The ranking results in this model use dummy data to ensure that the process input and output

TABLE 13: Vector weight value (w) specification criteria.

Alternative	Criteria				Vector weight value	Weight score
	C1	C2	C3	C4		
A1-SME 1	1	0	0	0	0.209	0.209
A2-SME 2	1	0	1	1	0.020	0.980
A3-SME 3	0	1	1	1	0.410	0.791
A4-SME 4	0	0	0.5	1	0.359	0.565

functions have been running according to the target. The value of the weight score determines the ranking results. The higher the value, the higher the ranking of an alternative. This model is devoted to ranking SME players according to suitable criteria for collaborating with a player. The higher the weight score is, the higher the ranking of SME partners chosen to be suitable partners. From testing with dummy data, the ranking of the data is shown in Table 14.

3.2. SME Segmentation Formula with K-Means

Step 1: tabulate the data using dummy data. Then, determine the number of clusters in the first iteration, wherein determining the number of clusters and the position of the cluster (denoted K) in the first iteration is determined randomly [29]. In this model design, 3 $(K = 3)$ clusters are determined by choosing randomly from the data with the details of the data centroid in Table 15. Then, it can be notated as C1 (2,1,1,1), C2 (3,3,3,3), and C3 (2,2,4,2).

Step 2: calculate the distance value of the data to the centroid using the Euclidean distance formula (equation (10)):

$$D(a,b) = \sqrt{\sum_{k=1}^{n} (a_k - b_k)^2}. \tag{22}$$

Showing the data in Table 14, the data distance from the centroid of each criterion is as follows

To get (S_n, C_1),

$$\begin{aligned}
D(S_1, C_1) &= \sqrt{(S_{1a} - C_{1a})^2 + (S_{1b} - C_{1b})^2 + (S_{1c} - C_{1c})^2 + (S_{1\,d} - C_{1\,d})^2}, \\
D(S_1, C_1) &= \sqrt{(2-2)^2 + (1-1)^2 + (1-1)^2 + (1-1)^2} = 0, \\
D(S_2, C_1) &= \sqrt{(S_{2a} - C_{1a})^2 + (S_{2b} - C_{1b})^2 + (S_{2c} - C_{1c})^2 + (S_{2\,d} - C_{1\,d})^2}, \\
D(S_2, C_1) &= \sqrt{(2-2)^2 + (1-1)^2 + (3-1)^2 + (1-3)^2} = 0.828.
\end{aligned} \tag{23}$$

Furthermore, the data $D(S_n, C_1)$ use the same method as the calculation results in Table 11 column Cr1. We use the same formula to get $D(S_n, C_2)$ and $D(S_n, C_3)$, and the result is described in Table 16.

Step 3: group the data according to the centroid by grouping the data according to the shortest distance of each item. This process can be calculated by finding the smallest value among the values, $D(S_n, C_1)$, $D(S_n, C_2)$, and $D(S_n, C_3)$. The cluster is determined containing the smallest value obtained by one of the Euclidean distance values in each item set. The results of determining the cluster can be seen in Table 17.

TABLE 14: Ranking of SME reference on fuzzy-AHP.

Alternative	Weight score	Ranking
A1-SME 1	0.209	Rank 4
A2-SME 2	0.980	Rank 1
A3-SME 3	0.791	Rank 2
A4-SME 4	0.565	Rank 3

TABLE 15: Cluster data in the first iteration.

SME player (S)	Cr1	Cr2	Cr3	Cr4	Centroids
SME Player-1	2	1	1	1	
SME Player-2	2	1	3	3	C1
SME Player-3	1	2	3	3	
SME Player-4	1	1	2	3	
SME Player-5	3	3	3	3	
SME Player-6	1	2	4	2	C2
SME Player-7	2	2	4	2	
SME Player-8	1	1	5	1	
SME Player-9	1	1	2	1	C3
SME Player-10	2	2	2	1	

TABLE 16: Euclidean distance in the first iteration.

SME player (S)	Cr1	Cr2	Cr3	Cr4	$D(S_n, C_1)$	$D(S_n, C_2)$	$D(S_n, C_3)$
SME Player-1	2	1	1	1	0.000	3.606	3.317
SME Player-2	2	1	3	3	2.828	2.236	1.732
SME Player-3	1	2	3	3	3.162	2.236	1.732
SME Player-4	1	1	2	3	2.449	3.000	2.646
SME Player-5	3	3	3	3	3.606	0.000	2.000
SME Player-6	1	2	4	2	3.464	2.646	1.000
SME Player-7	2	2	4	2	3.317	2.000	0.000
SME Player-8	1	1	5	1	4.123	4.000	2.000
SME Player-9	1	1	2	1	1.414	3.606	2.646
SME Player-10	2	2	2	1	1.414	2.646	2.236

Step 4: determine the centroid for iteration 2, by calculating the average of the results of the sum of data for each cluster group (Table 18).

With the results of the average data value for each cluster group (Table 18), the centroid value with the

TABLE 17: Cluster group in first iteration.

SME player (S)	$D(S_n, C_1)$	$D(S_n, C_2)$	$D(S_n, C_3)$	Nearest distance	Cluster
SME Player-1	0.000	3.606	3.317	0.000	C1
SME Player-2	2.828	2.236	1.732	1.732	C3
SME Player-3	3.162	2.236	1.732	1.732	C3
SME Player-4	2.449	3.000	2.646	2.449	C1
SME Player-5	3.606	0.000	2.000	0.000	C2
SME Player-6	3.464	2.646	1.000	1.000	C3
SME Player-7	3.317	2.000	0.000	0.000	C3
SME Player-8	4.123	4.000	2.000	2.000	C3
SME Player-9	1.414	3.606	2.646	1.414	C1
SME Player-10	1.414	2.646	2.236	1.414	C1

TABLE 18: Centroids in iteration 2.

SME	C1	C2	C3	C4
Cluster 1				
SME Player-1	2	1	1	1
SME Player-4	1	1	2	3
SME Player-9	1	1	2	1
SME Player-10	2	2	2	1
Centroid-1	1.5	1.25	1.75	1.5
Cluster 2				
SME Player-5	3	3	3	3
Centroid-2	3	3	3	3
Cluster 3				
SME Player-2	2	1	3	3
SME Player-3	1	2	3	3
SME Player-6	1	2	4	2
SME Player-7	2	2	4	2
SME Player-8	1	1	5	1
Centroid-3	1.4	1.6	3.8	2.2

details of the centroid is notation C1 (1.5, 1.25, 1.75, 1.5), C2 (3, 3, 3, 3), and C3 (1.4, 1.6, 3.8, 2.2).

Step 5: the process of repeating the iteration as before with different data centroids, namely, calculating the distance value of the data to the centroid, using the Euclidean distance formula (10)

Consisting of the data in Table 13, the data distance from the centroid of each criterion is as follows.

To get $D(S_n, C_1)$,

TABLE 19: Euclidean distance in the second iteration.

SME player (S)	Cr1	Cr2	Cr3	Cr4	$D(S_n, C_1)$	$D(S_n, C_2)$	$D(S_n, C_3)$
SME Player-1	2	1	1	1	1.061	3.606	3.162
SME Player-2	2	1	3	3	2.031	2.236	1.414
SME Player-3	1	2	3	3	2.151	2.236	1.265
SME Player-4	1	1	2	3	1.620	3.000	2.098
SME Player-5	3	3	3	3	3.021	0.000	2.408
SME Player-6	1	2	4	2	2.475	2.646	0.632
SME Player-7	2	2	4	2	2.475	2.000	0.775
SME Player-8	1	1	5	1	3.335	4.000	1.844
SME Player-9	1	1	2	1	0.791	3.606	2.280
SME Player-10	2	2	2	1	1.061	2.646	2.280

TABLE 20: Cluster group in second iteration.

SME player (S)	$D(S_n, C_1)$	$D(S_n, C_2)$	$D(S_n, C_3)$	Nearest distance	Cluster
SME Player-1	1.061	3.606	3.162	1.061	C1
SME Player-2	2.031	2.236	1.414	1.414	C3
SME Player-3	2.151	2.236	1.265	1.265	C3
SME Player-4	1.620	3.000	2.098	1.620	C1
SME Player-5	3.021	0.000	2.408	0.000	C2
SME Player-6	2.475	2.646	0.632	0.632	C3
SME Player-7	2.475	2.000	0.775	0.775	C3
SME Player-8	3.335	4.000	1.844	1.844	C3
SME Player-9	0.791	3.606	2.280	0.791	C1
SME Player-10	1.414	2.646	2.236	1.414	C1

$$D(S_1, C_1) = \sqrt{(S_{1a} - C_{1a})^2 + (S_{1b} - C_{1b})^2 + (S_{1c} - C_{1c})^2 + (S_{1\,d} - C_{1\,d})^2},$$

$$D(S_1, C_1) = \sqrt{(2 - 1.5)^2 + (1 - 1.25)^2 + (1 - 1.75)^2 + (1 - 1.5)^2} = 1.061,$$

$$D(S_2, C_1) = \sqrt{(S_{2a} - C_{1a})^2 + (S_{2b} - C_{1b})^2 + (S_{2c} - C_{1c})^2 + (S_{2\,d} - C_{1\,d})^2},$$

$$D(S_2, C_1) = \sqrt{(2 - 1.5)^2 + (1 - 1.27)^2 + (3 - 1.75)^2 + (3 - 1.5)^2} = 2.031.$$

(24)

Furthermore, the data $D(S_n, C_1)$ use the same method as the calculation results in Table 19 column Cr1. We use the same formula to get $D(S_n, C_2)$ and $D(S_n, C_3)$.

Step 6: group the data according to the centroid by grouping the data according to the shortest distance of each item. This process can be calculated by finding the smallest value among the values, $D(S_n, C_1)$, $D(S_n, C_2)$, and $D(S_n, C_3)$; the cluster is determined as concerning the smallest value obtained by one of the Euclidean distance values in each itemset. The results of cluster determination can be seen in Table 20.

From the results of the second iteration, there is no change in the position of the cluster, so the iteration process stops until the second iteration, and the resulting cluster is as presented in Table 21.

4. The Experiment Result and Discussion

The experiment uses SME data of 63 respondents' data inputted into the prototype. Figure 3 shows the results of the recommendations generated from the ranking of SME partners with fuzzy-AHP. The results display the identity of the name, email address, and score of the fuzzy-AHP which aims to provide and facilitate information for players to continue their actions after being recommended by the system. These results are constantly changing according to changes in player data in the game. Rankings are displayed in a dashboard accessible to recommended players and partners. The prototype shows its ability to present SME rankings according to the criteria data that have been used as test material.

Figure 4 shows the results of the recommendations generated from SME segmentation with K-Means. Cluster 1 produces four players, cluster 2 produces 41 players, and cluster 3 produces 18. These results constantly change according to changes in player data in the game. The SME segmentation is displayed on the leader board so that all the players involved can see their position in the cluster. They can continue to collaborate in regard to the cluster recommendations generated by the system, considering that they have many characteristics and interests in common.

Experiments show that the model can provide recommendations for SMEs' knowledge for collaboration.

TABLE 21: Cluster group result of SME segmentation.

SME	C1	C2	C3	C4
Cluster 1				
SME Player-1	2	1	1	1
SME Player-4	1	1	2	3
SME Player-9	1	1	2	1
SME Player-10	2	2	2	1
Cluster 2				
SME Player-5	3	3	3	3
Cluster 3				
SME Player-2	2	1	3	3
SME Player-3	1	2	3	3
SME Player-6	1	2	4	2
SME Player-7	2	2	4	2
SME Player-8	1	1	5	1
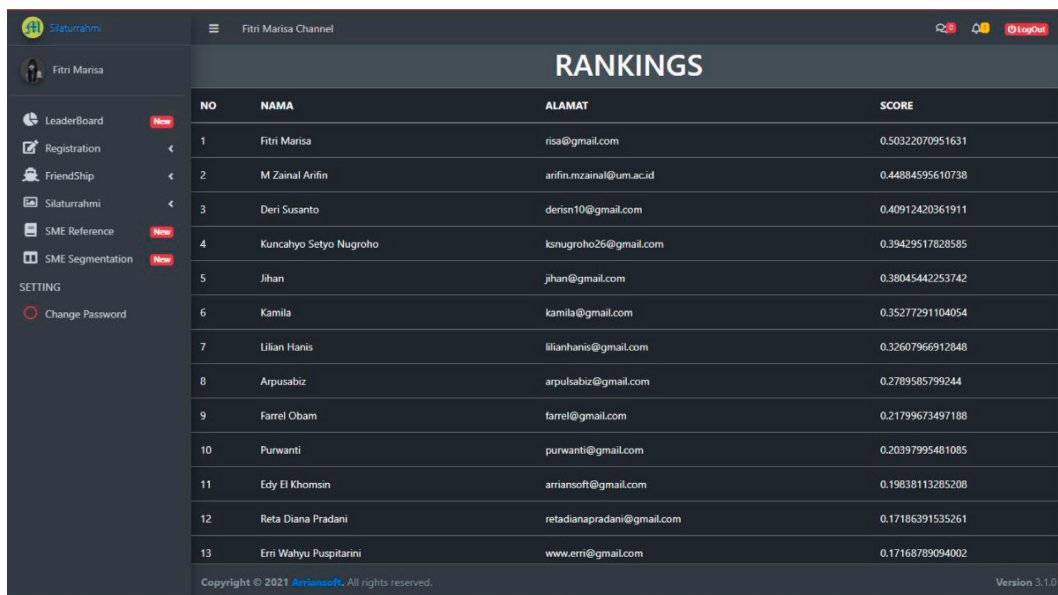
FIGURE 3: SME ranking using fuzzy-AHP.
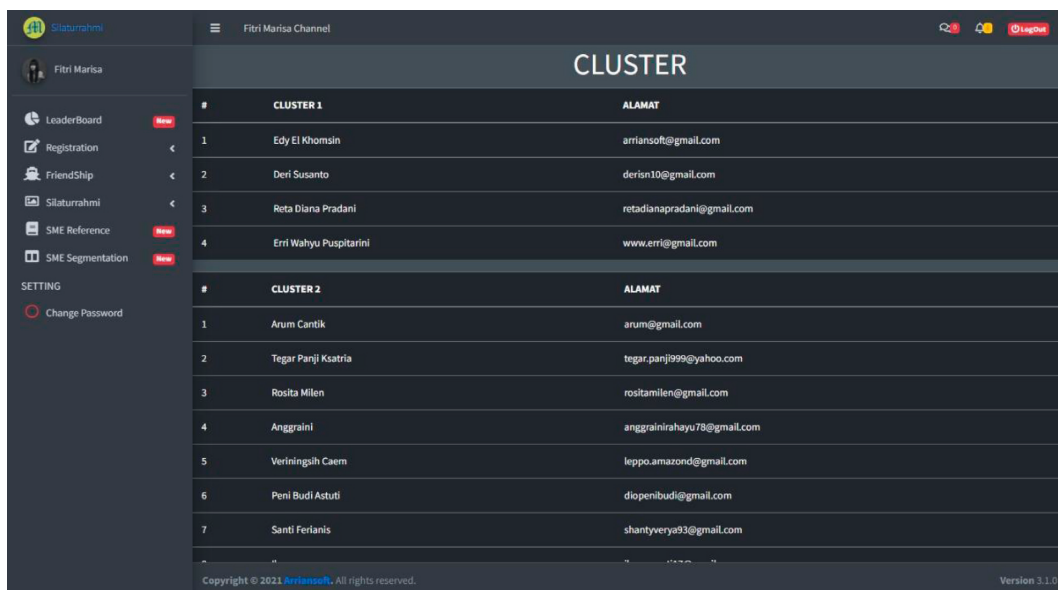
FIGURE 4: SME segmentation using K-Means.

However, this result depends on the adequacy of the data processing. The extensive and valid data affect the accuracy of this model in the analysis. For this reason, anticipation needs to be considered in the prototype to ensure that the data inputted by players are correct and consistent.

5. Conclusion

The Intelligent Gamification Mechanics (IGM) model makes essential recommendations for SME actors to collaborate to provide the proper reference for SMEs to establish cooperation to make it more useful and on target. SME ranking and SME segmentation work complementarily to support players' decisions in cooperating. The proposed intelligent system mechanics model has demonstrated its proper function using the experimental test of SME actor respondent data. At the same time, the dashboard and leaderboard function well and can present the mechanics of the intelligent system in a gamification-based prototype specification. The availability of data will determine the results of the IGM analysis. In line with that, the characteristics of the data and the expected solution of the problem raised also determine the weighting criteria in the fuzzy-AHP model and also determine the number of clusters in the K-Means. Therefore, further research needs to be developed and anticipated changes in respondent data that are up to data and sustainable so that IGM performance can be optimal. This study can also be the initiation of future research on the development of gamification mechanics based on intelligent systems. Gamification in presenting partner references is needed in other fields, and it is necessary to test the performance of this model in solving these problems. For this reason, the implementation and development of this proposed model is still wide open.

Data Availability

The data are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there were no conflicts of interest regarding the publication of this article.

Authors' Contributions

All authors contributed equally to the preparation of this manuscript.

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