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A data-driven decision framework for selecting the best location to establish a manufacturing centre based on Industry 5.0 dimensions

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Abstract

The current study addresses one of the main strategic challenges of logistics managers relevant to selecting the best location for the establishment of manufacturing sites using a data-driven approach. In this regard, by considering the elements of the recently introduced industrial revolution called Industry 5.0 (I5.0), this research first identifies the major criteria of the research problem based on experts and literature. Then, their importance is measured using the Fuzzy Best-Worst Method (FBWM). In the next step, the potential points to establish the manufacturing centers are evaluated based on the I5.0 dimensions applying the Light Gradient Boosting Machine (LightGBM) method. The achieved results show that “Land Cost”, “Infrastructure for making facility smart”, “Impact on ecological landscape”, and “Easy commute for workers” are the most significant indicators among the criteria of the research problem.

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Keywords: Location Problem; Industry 5.0; Supply Chain Management; Data-Driven Decision-Making.

1. Introduction

The location problem is a critical aspect of supply chain management, as it involves determining the optimal placement of facilities, such as warehouses, manufacturing plants, and distribution centers, to maximize efficiency and minimize costs. This strategic decision significantly influences transportation costs, service levels, and overall operational effectiveness, making it essential for managers to carefully evaluate various factors, including proximity to suppliers and customers, labor availability, infrastructure, and regulatory environments [1–4]. However, practical

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managers face several challenges in addressing the location problem, such as fluctuating market demands, evolving consumer preferences, geopolitical uncertainties, and environmental considerations. Additionally, the advent of new technologies and the push for sustainability further complicate decision-making processes. Balancing these dynamic elements requires a comprehensive understanding of both quantitative models and qualitative insights, making it imperative for managers to adopt a holistic approach to location strategy that aligns with their organization's long-term goals while remaining adaptable to changing conditions.

Recently, to enhance the attributes of Industry 4.0 and fix its drawbacks, researchers have introduced Industry 5.0 (I5.0) [5]. Overall, I5.0 represents a transformative shift in the manufacturing and production landscape, emphasizing the collaboration between humans and advanced technologies, such as artificial intelligence, robotics, and the Internet of Things (IoT). Unlike its predecessor, Industry 4.0, which focused primarily on automation and efficiency, I5.0 seeks to reintroduce human creativity and craftsmanship into the production process, fostering a more sustainable and personalized approach to manufacturing. In today's competitive world, where consumer expectations are rapidly evolving and environmental concerns are paramount, I5.0 is crucial for driving innovation and resilience. It not only enhances productivity and operational efficiency but also prioritizes the well-being of workers and the planet, ensuring that businesses can adapt to changing market demands while promoting social responsibility. In general, I5.0 has four main pillars: digitalization, resilience, human-centricity, and sustainability [6].

In this study, we focus on the location problem to select the best location for the establishment of the manufacturing centers based on I5.0 pillars. To do this, at the outset, the main criteria are extracted and then the potential locations are evaluated by developing an effective data-driven method based on FBWM and LightGBM, In general, this work contributes to the literature by investigating the location problem based on I5.0 indicators using a data-driven approach for the first time. Moreover, the main objectives of this article are as follows: (i) determining the main indicators of I5.0 to select the best location for establishing manufacturing centers and (ii) developing an effective data-driven approach to assess the potential locations.

2. Literature Review

This section provides a review of studies in the field of facility location assessment, as well as the use of data-driven models in site evaluation. For example, Zhang and Wei [7], in their study, proposed a hybrid method for selecting locations for electric vehicle charging stations. Focusing on four criteria—distance from high-traffic centers, main roads, the city center, and suburban areas—they used Spherical Fuzzy Sets (SFSs) for evaluation and the Combined Compromise Solution (CoCoSo) method for prioritization. The results of this study indicate the high accuracy and efficiency of the employed model. Razeghi et al. [8], in a study aimed at selecting suitable locations for solar power plant installation in Iran, used the AHP method for weighting the criteria and VIekriterijumsko KOmpromisno Rangiranje (VIKOR) for evaluating the options. The criteria considered included installation cost, distance to urban centers, and environmental impacts. Krishankumar and Ecer [9] presented a multi-criteria framework for selecting electric vehicle charging station locations, which considered criteria such as serviceability, land cost, traffic density, and environmental impact. They reported high accuracy in identifying optimal locations using a hierarchical and multi-stage method.

Liang et al. [10], using a fuzzy best-worst method involving multiple stakeholders, evaluated the location of an internal terminal. According to their findings, market capacity was identified as the most important criterion in the evaluation process, and the opinions of various stakeholders were incorporated into the decision-making. Mishkina et al. [11], in a study aimed at optimizing the location of electric vehicle charging stations, developed a machine learning-based model that analyzes geographic maps and factors such as population density and transportation routes to identify suitable sites. This model, trained using neural networks on urban data, was implemented on the map of Moscow, and its results demonstrated the practical effectiveness of machine learning in developing sustainable urban infrastructure. Noferesti and MirzaHossein [12], aiming to improve residential location choice prediction, introduced an innovative machine learning-based approach. By analyzing household travel survey data and comparing the performance of various algorithms, they found that eXtreme Gradient Boosting (XGBoost) and gradient boosting models, with an accuracy of around 42 percent, outperformed traditional methods. This study provides effective strategies for optimizing urban planning and land use. Karbassi Yazdi et al. [13], in a study aimed at identifying the best locations for implementing green energy projects in India, used a hybrid multicriteria decision-making (MCDA) approach under uncertainty. They employed the Delphi method for identifying criteria, the Fermatean Fuzzy Weighted Aggregated Sum Product Assessment (WASPAS) technique for prioritization, and the MEthod based on the Removal Effects of Criteria (MEREC) method to analyze the impact of criterion removal, conducting a comprehensive evaluation of candidate sites. The results indicated that NP Kunta in Andhra Pradesh was the optimal location for implementing a green energy project, with political strategies and objectives ranked as the most influential factors.

Although previous studies have used machine learning algorithms in certain aspects of location analysis, they have mostly been limited to case-specific analyses, evaluation of selected criteria, or prediction in a single domain. In fact, a comprehensive model that can evaluate, classify, and prioritize locations simultaneously in a data-driven and multi-criteria manner has not yet been developed. The present study, by designing a hybrid model based on feature weighting and machine learning, takes a novel step toward comprehensive location assessment with the potential for generalization and application in various siting problems.

3. Methodology

3.1. Case study and Indicators

In this case study, one of the counties located in the northern region of Iran has been selected as the target area. The objective is to evaluate and identify suitable locations for establishing a smart facility, taking into account the climatic, geographical, and social conditions of the region. For this purpose, a set of surrounding areas has been considered as initial location candidates. A structured dataset was then compiled using data collected from these locations, aligned with the specific environmental characteristics of northern Iran. This dataset includes key site selection indicators such as land cost, accessibility to markets and suppliers, smart infrastructure, security level, and local development potential. Subsequently, using the LightGBM machine learning algorithm, these locations were classified based on their suitability levels to identify the optimal sites for decision-making.

Based on the literature and experts, the following indicators can be considered for the research problem (See Table 1).

Table 1. Indicators of the research problem

Indicator	Category	Reference
Land Costs	General	[14,15] + Experts
Distance to market	General	[15,16] + Experts
Distance to suppliers	General	[15,16] + Experts
Infrastructure for making facility smart	Digitalization	[17] + Experts
Capacity expansion	Resilience	[15,16] + Experts
Security	Resilience	[15] + Experts
Environmental protection level	Sustainability	[18,19] + Experts
Local development	Sustainability	[18] + Experts
Impact on ecological landscape	Sustainability	[18,20] + Experts
Potential for creating a place for workers to rest and exercise	Human-centricity	Our team + Experts
Easy commute for workers	Human-centricity	Our team + Experts

3.2. Fuzzy BWM

One of the effective methods to calculate the weights of the indicators is fuzzy BWM that was proposed by Guo and Zhao [21]. This method has several advantages, such as enhancing the reliability and reducing the computational burden. To implement this method, the following steps have been defined.

In this process, decision-makers initially identify the criteria deemed best (most favourable or significant) and worst

Step 1. Specifying the worst and the best indicators based on expert opinion.

Step 2. Forming the fuzzy comparison vectors. Suppose that $\tilde{A}_B = (\tilde{a}_{B1}, \tilde{a}_{B2}, \dots, \tilde{a}_{Bn})$ is the BO (Best-to-Other) border and $\tilde{A}_W = (\tilde{a}_{1W}, \tilde{a}_{2W}, \dots, \tilde{a}_{nW})$ demonstrates the OW (Other-to-Worst) border. Table 2 shows the relevant linguistic variables to form these borders (taken from [21]).

Table 2. Linguistic variables form BO and OW vectors [21].

Linguistic terms	EI (Equally important)	WI (Weakly important)	FI (Fairly important)	VI (Very important)	AI (Absolutely important)
Membership function	(1, 1, 1)	(2.5, 3, 3.5)	(1.5, 2, 2.5)	(0.667, 1, 1.5)	(3.5, 4, 4.5)

Step 3. Measuring the importance of indicators applying Model (1)

Where:

$\tilde{a}_{Bj} = (l_{Bj}, m_{Bj}, u_{Bj})$ and
$\tilde{a}_{jW} = (l_{jW}, m_{jW}, u_{jW})$
respectively demonstrates the BO and OW borders.

Moreover, $\tilde{w}_j = (l_j^w, m_j^w, u_j^w)$ is the fuzzy weights of the criteria. Additionally,

$\tilde{\xi}^* = (k^*, k^*, k^*)$ and $R(\tilde{a}) = \frac{l+4m+u}{6}$.

$$
\begin{aligned}
&\text{minimize } \tilde{\xi}^* \\
&\text{subject to:} \\
&\left|\frac{(l_B^w, m_B^w, u_B^w)}{(l_j^w, m_j^w, u_j^w)} - (l_{Bj}, m_{Bj}, u_{Bj})\right| \le (k^*, k^*, k^*) && \forall j, \\
&\left|\frac{(l_j^w, m_j^w, u_j^w)}{(l_W^w, m_W^w, u_W^w)} - (l_{jW}, m_{jW}, u_{jW})\right| \le (k^*, k^*, k^*) && \forall j, \\
&\sum_{j=1}^{n} R(\tilde{w}_j) = 1, \\
&l_j^w \le m_j^w \le u_j^w && \forall j, \\
&l_j^w \ge 0 && \forall j.
\end{aligned} \tag{1}
$$

Step 4. Checking the consistency ratio based on Table 3 and Equation (2).

$$CR = \frac{\xi^*}{\text{Consistency Index}} \tag{2}$$

Table 3. Consistency ratio for fuzzy BWM [21]

	(AI)	**(VI)**	**(FI)**	**(WI)**	**(EI)**
$\tilde{a}_{BW}$	(3.5, 4, 4.5)	(2.5, 3, 3.5)	(1.5, 2, 2.5)	(0.667, 1, 1.5)	(1, 1, 1)
Consistency Ratio	8.04	6.69	5.29	3.80	3.00

3.3 Light Gradient Boosting Machine (LightGBM) Algorithm

The LightGBM (Light Gradient Boosting Machine) algorithm is an advanced and efficient decision tree-based boosting method that performs exceptionally well, particularly in classification problems involving structured data and multiple features. By utilizing optimization techniques such as leaf-wise tree growth (instead of level-wise) and histogram-based learning, LightGBM achieves high training speed and low memory consumption without compromising model accuracy [22–24].

In this study, LightGBM was employed to classify locations into three categories: "Selected," "Stored," and "Rejected." The dataset included 11 location evaluation features, such as land cost, distance to market, and security level. To prevent overfitting and maintain model generalizability given the relatively limited dataset size, the parameters num_leaves, max_depth, and min_data_in_leaf were set to 31, 5, and 20 respectively. These metrics evaluate the performance and reliability of a classification model; Accuracy measures the overall proportion of correct predictions, while Precision indicates how many of the predicted positives are actually correct, and Recall shows how many of the actual positives the model successfully identified. F1-score is the harmonic mean of precision and recall, providing a balanced measure especially useful when dealing with imbalanced datasets.

LightGBM's training process is based on the gradient boosting technique, where weak learners (small decision trees) are added sequentially to reduce prediction error. At each step, LightGBM computes the gradient of the loss function for the training samples and constructs a new decision tree to predict these gradients. Unlike similar algorithms that grow trees level-wise, LightGBM uses a leaf-wise strategy, meaning it expands the leaf with the highest potential for loss reduction at each iteration. This approach enhances model accuracy, although parameters such as tree depth and the minimum number of samples per leaf are regulated to avoid overfitting. Ultimately, the final model prediction is formed by aggregating the outputs of all trees, each weighted accordingly.

4. Numerical Results

4.1. Fuzzy BWM's Outputs

To calculate the significance of the considered indicators, a pairwise comparison has been formed based on opinions of three groups of experts. To form this tables, the numbers presented in Table 2 have been employed. In this regard, Tables 3 and 4 respectively, show BO and OW borders. Also, Table 5 demonstrates the weights of indicators that have been calculated by implementing Model (1) in LINGO software. As shown in Table 4, "Land Cost", "Infrastructure for making facility smart", "Impact on ecological landscape", and "Easy commute for workers" are the most important criteria for the research problem. Moreover, the results show that the value of the CR is equal to 0.04317 that confirms the reliability of the achieved results.

Table 3. Best-to-Other (BO) vector

Expert		Land Costs			Distance to market			Distance to suppliers			Infrastructure for making facility smart			Capacity expansion			Security		
1	Land Costs (Best Criterion)	1	1	1	0.67	1	1.5	0.67	1	1.5	1	1	1	1.5	2	2.5	1.5	2	2.5
2		1	1	1	1.5	2	2.5	1.5	2	2.5	0.67	1	1.5	0.67	1	1.5	0.67	1	1.5
3		1	1	1	0.67	1	1.5	0.67	1	1.5	0.67	1	1.5	0.67	1	1.5	0.67	1	1.5
Average		**1**	**1**	**1**	**0.95**	**1.33**	**1.83**	**0.95**	**1.33**	**1.83**	**0.78**	**1.00**	**1.33**	**0.95**	**1.33**	**1.83**	**0.95**	**1.33**	**1.83**

Expert		Environmental protection level			Local development			Impact on ecological landscape			Potential for creating a place for workers to rest and exercise			Easy commute for workers		
1	Land Costs	0.67	1	1.5	0.67	1	1.5	1.5	2	2.5	0.67	1	1.5	0.67	1	1.5
2		0.67	1	1.5	0.67	1	1.5	1.5	2	2.5	0.67	1	1.5	0.67	1	1.5

3	(Best Criterion)	1.5	2	2.5	1.5	2	2.5	1.5	2	2.5	1.5	2	2.5	1.5	2	2.5
Average		**0.95**	**1.33**	**1.83**	**0.95**	**1.33**	**1.83**	**1.50**	**2.00**	**2.50**	**0.95**	**1.33**	**1.83**	**0.95**	**1.33**	**1.83**

Table 4. Other-to-Worst (OW) vector

	Potential for creating a place for workers to rest and exercise (Worst criterion)			
Expert / Criteria	1	2	3	Average
Land Costs	1.5	1.5	1.5	**1.50**
	2	2	2	**2.00**
	2.5	2.5	2.5	**2.50**
Distance to market	1.5	0.67	0.67	**0.95**
	2	1	1	**1.33**
	2.5	1.5	1.5	**1.83**
Distance to suppliers	1.5	0.67	0.67	**0.95**
	2	1	1	**1.33**
	2.5	1.5	1.5	**1.83**
Infrastructure for making facility smart	1.5	0.67	1.5	**1.22**
	2	1	2	**1.67**
	2.5	1.5	2.5	**2.17**
Capacity expansion	0.67	1.5	0.67	**0.95**
	1	2	1	**1.33**
	1.5	2.5	1.5	**1.83**
Security	0.67	0.67	0.67	**0.67**
	1	1	1	**1.00**
	1.5	1.5	1.5	**1.50**
Environmental protection level	0.67	0.67	0.67	**0.67**
	1	1	1	**1.00**
	1.5	1.5	1.5	**1.50**
Local development	0.67	1.5	1.5	**1.22**
	1	2	2	**1.67**
	1.5	2.5	2.5	**2.17**
Impact on ecological landscape	0.67	1.5	1.5	**1.22**
	1	2	2	**1.67**
	1.5	2.5	2.5	**2.17**
Potential for creating a place for workers to rest and exercise	1	1	1	**1.00**
	1	1	1	**1.00**
	1	1	1	**1.00**
Easy commute for workers	0.67	1.5	1.5	**1.22**
	1	2	2	**1.67**
	1.5	2.5	2.5	**2.17**

Table 5. The significance of indicators calculated by the fuzzy BWM

Indicator	Weight
Land Costs	0.1231235
Distance to market	0.08264610
Distance to suppliers	0.08992831
Infrastructure for making facility smart	0.1059525
Capacity expansion	0.08992831
Security	0.07947883
Environmental protection level	0.07947883
Local development	0.09433659
Impact on ecological landscape	0.09629778
Potential for creating a place for workers to rest and exercise	0.06449265
Easy commute for workers	0.09433659

4.2. LightGBM Outputs

In this section, a machine learning model is developed to evaluate and select the best location for establishing a production facility. The dataset consists of 760 records representing various locations for setting up a smart facility. Each record is assessed based on 11 features, such as land cost, distance to market, and security level, and is labeled with one of three categories: “Selected,” “Stored,” or “Rejected.” Of this data, 80% is used for model training and 20% for testing in order to evaluate the model’s performance on unseen data. In the preprocessing stage, features were separated from the label column, and the labels were encoded into numerical values to be processed by the machine learning algorithm. Additionally, the train/test split was performed using stratified sampling to preserve class distribution across both sets, thereby improving the model’s performance in multi-class classification.

In this study, the LightGBM algorithm was used to classify the locations into the three aforementioned categories. LightGBM is a powerful gradient boosting algorithm based on decision trees, known for its high speed and low memory usage, even when applied to datasets of moderate size. To prevent overfitting due to the relatively small dataset, parameters such as `num_leaves=31`, `max_depth=5`, `min_data_in_leaf=20`, and `learning_rate=0.1` were tuned to maintain a balance between accuracy and generalizability. The model's outputs were also used in the form of class probabilities, enabling more precise decision-making regarding whether a location should be stored for later consideration or rejected. With these configurations, the algorithm succeeded in building a robust decision structure based on key features such as land cost, security, smart infrastructure, and local development potential.

Fig 1 illustrates a portion of the structure of one of the decision trees used in the LightGBM model, drawn up to a depth of three levels. In this tree, each node performs a split based on the value of a specific feature, and the path to each leaf reflects the model’s decision-making logic in predicting the location label. For the internal node with Security $\leqslant$ 0.701, we have 102 samples, with 49 classified as "Stored" and 108 as "Selected", resulting in a Gini impurity of 0.429. This node splits the data further into two pure leaf nodes, as indicated by Gini = 0.0 in both children.

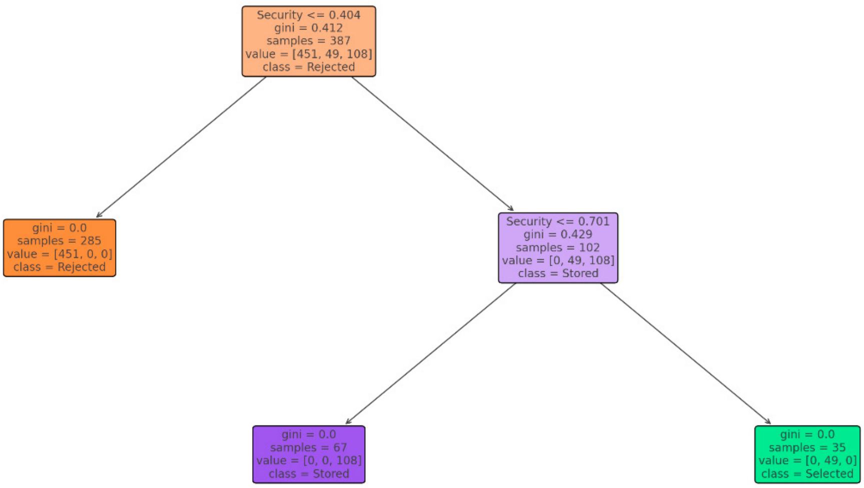

Fig 1. Part of the structure of the LightGBM algorithm

The developed algorithm demonstrates satisfactory performance in identifying and distinguishing between suitable, uncertain, and unsuitable locations, with an overall accuracy of approximately 93%. In addition to this overall accuracy, other key metrics such as F1 Score and Precision also fall within the same range, averaging between 0.92 and 0.94. These results indicate a proper balance between correct classification rates and minimizing Type I and Type II errors. They reflect the model’s ability to make relatively accurate decisions in site selection by incorporating a combination of key features.

Furthermore, Fig 2 presents the confusion matrix, which serves as an additional metric for evaluating model performance. The displayed matrix illustrates how the model classified the three categories: “Rejected,” “Selected,” and “Stored.” As shown, the model achieved high accuracy in predicting the “Rejected” class, correctly identifying 100 out of 108 samples. It also performed well on the “Selected” and “Stored” classes, although a small number of instances were misclassified. This distribution demonstrates the model's ability to effectively differentiate between the three classes with approximately 93% accuracy.

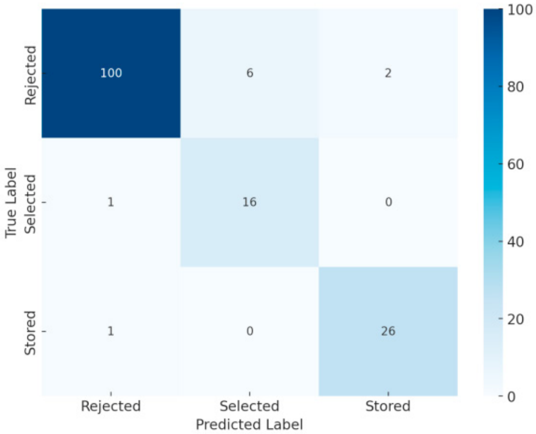

Fig 2. Confusion matrix of the LightGBM model

In line with the developed algorithm, 11 potential locations of case study were evaluated, resulting in 2 locations being selected, 2 stored for further consideration, and 7 rejected.

5. Conclusions

Owing to the importance of selecting an appropriate location for manufacturing center in the logistics systems, this study focused on incorporating Industry 5.0 (I5.0) aspects into the location problem by the simultaneous consideration of sustainability, resilience, digitalization, and human-centricity dimensions. In this regard, the current work has developed a data-driven decision-making model by integrating the fuzzy BWM and LightGBM approaches. In this research, the main criteria have been extracted at the outset. Afterward, their weights were computed using the fuzzy BWM. Then, the potential locations for establishing manufacturing centers were assessed using a machine learning method. Based on the achieved outputs, "Land Cost", "Infrastructure for making facility smart", "Impact on ecological landscape", and "Easy commute for workers" have been selected as the most desirable criteria for the research problem. Future works can focus on incorporating other crucial indicators, such as viability and globalization, into the research problem. Also, investigating the research problem under mixed uncertainty (e.g., fuzzy-scenario) can be another direction for future studies.

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