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Evaluating Agriculture Robots: Case Study and Analysis

Mai Mohamed [1,*], Shaimaa Ayman [1], and Venkatesan Rajinikanth [2]

[1] Faculty of Computers and Informatics, Zagazig University, Zagazig 44519, Sharqiyah, Egypt; Emails: mmgaafar@zu.edu.eg; sh.ayman021@fci.zu.edu.eg.

[2] Department of CSE, Center for Research and Innovation, Saveetha School of Engineering, SIMATS, Chennai 602105, TN, India; v.rajinikanth@ieee.org.

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Abstract

The technical revolution paved the way for the development of robots that can now operate in a variety of areas. The smart farming technique called robotic agrifarming has the potential to alleviate the worldwide labor shortage while increasing agricultural productivity and food safety. From planting to harvesting, agribots perform field operations that enhance soil quality and ensure long-term growth. That's why it's essential to create a decision-support system that helps choose the best robot for an agricultural task. The goal of this study is to create an integrated decision system for assessing agriculture robots using the method based on removal effects of criteria (MEREC). Founded on a lot of alternatives like project viability, ecosystem aptness, community conditions, governmental embracing, and profit, the performance of seven field robots is evaluated. The advantage of the developed ranking technique is that it follows the additive ratio assessment (ARAS) method, which is indeed a specific technique used for multi-attribute decision-making (MADM), particularly in the field of environmental management and evaluation. It's commonly employed when there are multiple factors or criteria to consider in decision-making processes and prioritizing the alternatives.

Keywords: Agrifarming; Agribots; MEREC; ARAS; MADM.

1 | Introduction

Agribot, or robotic agrifarming is a term used to describe the integration of automation and robotics into a range of agricultural operations. This quickly developing field has the potential to completely transform agriculture by boosting productivity, cutting labor costs, and making the best use of available resources. Due to population growth and a decline in the agricultural workforce, traditional farming techniques that have been passed down over the centuries are no longer sufficient to meet today's growing demand. In order to keep pace with the needs of population growth, it is necessary to think about enhancing productivity while reducing manufacturing expenses.

The opening of new international markets around the world has led to a sharp increase in demand for agricultural commodities like Europe [1], China, South Korea [2], India [3], and US, Brazil [4]. The only way to overcome these obstacles is to combine agriculture with modern technologies. The application of smart

Corresponding Author: mmgaafar@zu.edu.eg

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agriculture technology, such as introducing robots to perform tedious jobs, is one technological example. There are many benefits to using robots in agriculture, like performing tasks accuracy, resource management, don't waste resources, do a task more quickly, and used for works laborious [5]. Additionally, building an Agribot system necessitates a more involved process, and additional considerations include the project viability, ecosystem aptness, community conditions, governmental embracing, profit-net, and safety [6].

One of the fundamental human tasks is decisions-making. Since the middle of the 20th century, ideas and practices linked to decision-making have been continuously developed and refined, and decision-making has grown in importance within the fields of management, economics, and other fields. In certain intricate decision-making scenarios, in order to derive suitable conclusions, we typically examine the challenges from various angles that capture their characteristics.

Multi-attribute decision-making (MADM) is a type of mechanism that determines the most optimal alternative or alternatives from a given finite alternative set by measuring various properties [7]. The two fundamental steps in a MADM technique are: first, information collection. The values of the alternatives under each attribute should be ascertained in this step. These values can be displayed in a variety of ways, including linguistic terms [8], interval numbers [9], fuzzy numbers [10], crisp numbers [11], and gray numbers [12]. In addition, the attribute weights must be determined and after that aggregating information. Numerous techniques have been developed to aggregate information under various attributes, including the Bonferroni means [13], the Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) method [14], the Complex Proportional Assessment (COPRAS) method [15], the ordered weighted averaging operator [16], and ordered weighted geometric averaging operators [17]. However, occasionally different outcomes are obtained when using different methods to handle the same data and weights for the same attributes.

In order to address scenarios where the evaluation information has variable measurement units, Zavadskas [11] presented the additive ratio assessment system (ARAS) method. The decision-making matrix formalization, data normalization, optimality function and utility degree determination, normalized weighted matrix computation, and final ranking derivation are the five basic steps of the approach. By using a relative indicator to represent the difference between the alternatives and the ideal solution and to remove the impact of various measurement units, the ARAS technique aims to simplify complicated decision-making situations and choose the "best" option.

The objective of this research was to determine the best agricultural robot based on the specific features of the robots. After thinking, it is clear that using smart agricultural technologies can increase the production and gross domestic product of a country more than anything else. Moreover, it is not possible to quickly implement the use of robots in agriculture because farmers in rural areas are still unaware of smart agriculture. In order to accelerate the diffusion of robotic agriculture in Egypt, in this work we propose to analyze field robots under certain conditions. This research proposes the use of neutrosophic logic with a decisions-making system to achieve this goal. The remainder of this research is discussed as follows: related work in Section 2. Section 3 presents methodology and computational analyses of the results, and finally conclusions in Section 4.

2 | Related Work

Basically, robotics may be applied to many aspects of farming, including planting, pulling weeds, livestock monitoring, spraying, and harvesting. To identify the most dependable robot depending on the difficulty of the work, the performance of these robots must be evaluated under particular conditions. This necessitates choosing the most important variables that will be crucial in closely examining the issue.

Several studies and developments on agribots have been presented. We have compiled and discussed these to highlight current developments and global trends in automation and agribot applications. Automation and agribots have been invented and developed by numerous researchers and technologists.

Sampoornam et al [18] could trace the moisture content of the soil, spray insecticides, and harvest rhizome plants. The development of an Agribot has the primary goal of saving labor expenses and updating traditional farming methods for nearby farmers. While Megalingam et al [19] created a robotic tree climbing and harvesting robot with separate arms for coconut harvesting. Medeiros et al [20] present system can identify the main branches and estimate their sizes with a 0.6 cm inaccuracy, and a 98% detection accuracy, for large-scale areas, apply about two trees every hour. Kurbah et al [21] produced a three-finger gripper/cutter for picking pineapples. Williams et al [22] proved that 51% of the kiwifruit in the orchard can be harvested by the autonomous harvester in 5.5 seconds on average per fruit.

Economic, technological variables, and political all influence the use of agricultural robots, as demonstrated by Sparrow et al [23]. Wu et al. [24] proposed that in various situations and crop growth stages, the suggested automated operational weed control system may carry out selective mechanical and chemical in-row weeding with unspecified detection interruptions.

With regard to the agribot scope, Indian researchers have created a useful, affordable, and accurate harvesting tool. They have made a major contribution to the betterment of impoverished Indian farmers by providing them with a useful instrument that will help them in times of labor scarcity and boost production and yield [3]. The estimation of criteria weights is a crucial step in any process of decision-making. These weights are determined by taking into account the recommendations of experts or by utilizing the data from the decision matrix. For computing attribute weights, this research used MEREC method and also used ARAS to remove the impact of various optimization paths and measurement units in MADM.

3 | Methodology and Computational Analyses

3.1 | The MEREC Method

To calculate the criteria weights, we applied the removal effects of criteria (MEREC) approach proposed by Ghorabaee [25]. This approach falls under the category of objective weighting techniques used to handle resources and determine criteria weights. The MEREC determines the weights of the criteria based on the impact of removing each criterion on the performance of alternatives. The criteria with the biggest effects on performances are given more weight. To compute the performances of the alternatives in this method, we must first establish a measure for the performance of the alternatives. We use a basic logarithmic measure with equal weights. We employ the absolute deviation measure to determine the impact of eliminating each condition. These metric shows how well an option performs overall compared to how well it performs when a criterion is removed.

The steps listed below are utilized to determine the objective weights by MEREC. The matrix of elements, indicated by the symbol xij, must be bigger than zero $(xij > 0)$. if the decision matrix contains negative values; those values ought to be converted, by suitable means, into positive values. Let us assume that the decision-matrix has the following shape, with n alternatives and m criteria [25]:

$$X = \begin{Bmatrix} x_{11} & x_{12} \cdots x_{1j} & \cdots \cdots x_{1m} \\ x_{21} & x_{22} \cdots x_{2j} & \cdots \cdots x_{2m} \\ \cdots & \cdots \cdots \cdots & \cdots \cdots \cdots \\ \cdots & \cdots \cdots \cdots & \cdots \cdots \cdots \\ x_{n1} & x_{n2} \cdots x_{nj} & \cdots \cdots x_{nm} \end{Bmatrix} \quad (1)$$

Step 1: Collect the data from experts and formulate the decision matrix according to the single-valued neutrosophic scale from this research [26]. The neutrosophic matrices in Table 1 are transformed into crisp matrices by employing Eq. (2) [27].

$$s(Q_{ij}) = \frac{(2+T_r-F1-Id)}{3} \quad (2)$$

Where T_r, F1, and Id refers to true, false, and indeterminacy.

Table 1. Experts matrices.

Expert 1	Project Viability (PV)	Ecosystem Aptness (EA)	Community Conditions (CC)	Governmental Embracing (GE)	Profit-Net (PN)
CropIn Robots	VVG	VVB	EG	VVB	G
Agrosmart Robots	VG	VB	VG	G	VB
xFarm Robots	MG	B	MG	VG	VVG
Fertilizing Robots	M	MB	M	MG	B
Semios Robots	B	MG	MB	MB	VG
Autonomous Tractors	VG	VB	VG	G	VB
Six-Axis Robots	M	MB	M	MG	B
	0.9	0.10	1	0.1	0.72
	0.82	0.18	0.82	0.72	0.18
	0.62	0.28	0.62	0.82	0.9
	0.5	0.38	0.5	0.62	0.28
	0.3	0.62	0.38	0.38	0.82
	0.82	0.18	0.82	0.72	0.18
	0.5	0.38	0.5	0.62	0.28
Expert 2	Project Viability (PV)	Ecosystem Aptness (EA)	Community Conditions (CC)	Governmental Embracing (GE)	Profit-Net (PN)
CropIn Robots	VG	B	MG	G	B
Agrosmart Robots	VG	VB	VVG	VVB	VB
xFarm Robots	G	B	EG	VG	VG
Fertilizing Robots	M	MB	MB	MB	G
Semios Robots	VVB	EG	M	MG	VVG
Autonomous Tractors	VG	VB	VG	G	VB
Six-Axis Robots	G	B	EG	VG	VG
	0.82	0.30	0.62	0.72	0.28
	0.82	0.18	0.9	0.1	0.18
	0.72	0.28	1	0.82	0.82
	0.5	0.38	0.38	0.38	0.72
	0.1	1.00	0.5	0.62	0.9
	0.82	0.18	0.82	0.72	0.18
	0.72	0.28	1	0.82	0.82
Expert 3	Project Viability (PV)	Ecosystem Aptness (EA)	Community Conditions (CC)	Governmental Embracing (GE)	Profit-Net (PN)
CropIn Robots	VG	MG	B	G	VB
Agrosmart Robots	G	VB	VVB	VVG	B
xFarm Robots	VG	VVB	EG	MG	VG
Fertilizing Robots	MB	M	MB	G	MB
Semios Robots	B	EG	M	VG	VVG
Autonomous Tractors	MB	M	MB	G	MB
Six-Axis Robots	VG	MG	B	G	VB
	0.82	0.62	0.3	0.72	0.18
	0.72	0.18	0.1	0.9	0.28
	0.82	0.10	1	0.62	0.82
	0.38	0.50	0.38	0.72	0.38
	0.28	1.00	0.5	0.82	0.9
	0.38	0.50	0.38	0.72	0.38
	0.82	0.62	0.3	0.72	0.18

To aggregate these 3 matrices, apply the following equation to get a single decision matrix as in Table 2:

$$Yij = \frac{(\sum_{j=1}^{N} Q_{ij})}{N} \tag{3}$$

Where Q_{ij} donate to value of criteria in the matrix, N donate to number of decision makers.

Table 2. Decision matrix.

Alternatives \ Attributes	Project Viability (PV)	Ecosystem Aptness (EA)	Community Conditions (CC)	Governmental Embracing (GE)	Profit-Net (PN)
CropIn Robots	0.85	0.34	0.64	0.51	0.39
Agrosmart Robots	0.79	0.18	0.61	0.57	0.21
xFarm Robots	0.72	0.22	0.87	0.75	0.85
Fertilizing Robots	0.46	0.42	0.42	0.57	0.46
Semios Robots	0.23	0.87	0.46	0.61	0.87
Autonomous Tractors	0.67	0.29	0.67	0.72	0.25
Six-Axis Robots	0.68	0.43	0.6	0.72	0.430
Max	0.85	0.87	0.87	0.75	0.87
Min	0.23	0.18	0.42	0.51	0.21

Step 2: The decision matrix's elements are scaled using a simple linear normalization. The notation n_{ij}^{x} represents the elements of the normalized matrix as in Table 3. We can use the following equation for normalization if B displays the set of beneficial criteria and H represents the set of non-beneficial criteria:

$$n_{ij}^{x} = \begin{cases} \frac{\min_k x_{kj}}{x_{ij}} & if \quad j \in \mathrm{B} \\ \frac{x_{ij}}{\max_k x_{kj}} & if \quad j \in \mathrm{H} \end{cases} \tag{4}$$

Table 3. Normalization matrix.

	PV	EA	CC	GE	PN
CropIn Robots	0.2706	0.3908	0.6563	1	0.5385
Agrosmart Robots	0.2911	0.2069	0.6885	0.8947	1
xFarm Robots	0.3194	0.2529	0.4828	0.68	0.2471
Fertilizing Robots	0.5	0.4828	1	0.8947	0.4565
Semios Robots	1	1	0.913	0.8361	0.2414
Autonomous Tractors	0.3433	0.3333	0.6269	0.7083	0.84
Six-Axis Robots	0.3382	0.4943	0.7	0.7083	0.4884

Step 3: Compute the alternatives overall performancess_i. In this stage, the total performance of the options is obtained using a logarithmic metric with equal criteria weights applied. We can be certain that lower values of n_{ij}^{x} result in higher values of performance s_i based on the normalized data acquired from the preceding step. The following equation is used in this computation:

$$S_i = ln\left(1 + \left(\frac{1}{m}\sum_j |\ln(n_{ij}^{x})|\right)\right) \tag{5}$$

$S_1 = ln(1+(\frac{1}{5}(|\ln(0.2706)|+|\ln(0.3908)|+|\ln(0.6563)|+|\ln(1)|+|\ln(0.5385)|)) = 0.5052$

$S_2 = ln(1+(\frac{1}{5}(|\ln(0.2911)|+|\ln(0.2069)|+|\ln(0.6885)|+|\ln(0.8947)|+|\ln(1)|)) = 0.5061$

$S_3 = ln(1+(\frac{1}{5}(|\ln(0.3194)|+|\ln(0.2529)|+|\ln(0.4828)|+|\ln(0.68)|+|\ln(0.2471)|)) = 0.6959$

$S_4 = ln(1+(\frac{1}{5}(|\ln(0.5)|+|\ln(0.4828)|+|\ln(1)|+|\ln(0.8947)|+|\ln(0.4565)|)) = 0.3807$

$S_5 = ln(1+(\frac{1}{5}(|\ln(1)|+|\ln(1)|+|\ln(0.913)|+|\ln(0.8361)|+|\ln(0.2414)|)) = 0.2914$

$S_6 = ln(1+(\frac{1}{5}(|\ln(0.3433)|+|\ln(0.3333)|+|\ln(0.6269)|+|\ln(0.7083)|+|\ln(0.84)|)) = 0.4891$

$S_7 = ln(1+(\frac{1}{5}(|\ln(0.3382)|+|\ln(0.4943)|+|\ln(0.7)|+|\ln(0.7083)|+|\ln(0.4884)|)) = 0.4955$

Step 4: Calculate the alternative's performance by removing each criterion as in Table 4. The logarithmic measure is used in this phase similarly to how it was in the previous one. This step differs from Step 3 in that the performance of the alternatives is determined by eliminating each criterion independently.

$$S'_{ij} = ln\left(1 + \left(\frac{1}{m}\sum_{k,k\neq j}|\ln(n_{ik}^{x})|\right)\right) \quad (6)$$

Table 1. The values of S'_{ij}.

S'_{ij}					
	PV	EA	CC	GE	PN
CropIn Robots	0.3336	0.3849	0.4531	0.5052	0.4276
Agrosmart Robots	0.345	0.2954	0.46	0.4926	0.5061
xFarm Robots	0.5751	0.5485	0.6206	0.6567	0.5458
Fertilizing Robots	0.2812	0.2759	0.3807	0.3654	0.2674
Semios Robots	0.2914	0.2914	0.2777	0.2643	0.0526
Autonomous Tractors	0.3485	0.3444	0.4301	0.4459	0.4675
Six-Axis Robots	0.3539	0.4058	0.4511	0.4526	0.4042

Step 5: Using the values from Steps 3 and 4, compute the removal effect as in Table 5 of the jth criterion. Let E_j refer to the result of removing the jth criterion. The following formula can be used to determine the values of E_j:

$$E_j = \sum_i |S'_{ij} - S_i| \quad (7)$$

Table 5. Removal effect.

E_j					
	PV	EA	CC	GE	PN
CropIn Robots	0.1717	0.1203	0.0522	1E-16	0.0776
Agrosmart Robots	0.1611	0.2107	0.046	0.0135	0
xFarm Robots	0.1208	0.1475	0.0754	0.0392	0.1502
Fertilizing Robots	0.0995	0.1048	0	0.0153	0.1134
Semios Robots	0	0	0.0137	0.0271	0.2388
Autonomous Tractors	0.1406	0.1447	0.059	0.0432	0.0216
Six-Axis Robots	0.1417	0.0898	0.0444	0.0429	0.0914

Step 6: Determine the final criterion weights as in Table 6. Using the removal effects $\boldsymbol{E_j}$ from step 5, the objective weight of each criterion is determined in this step. ω_j refers to the jth criterion's weight. In the following, the formula utilized to determine ω_j is as follows:

$$\omega_j = \frac{Ej}{\Sigma_k E_k} \quad (8)$$

$\Sigma_k E_k$ = 0.8353+ 0.8178 + 0.2907 + 0.1813 + 0.6929 = 2.818

Table 2. Weights of MEREC.

	PV	EA	CC	GE	PN
Wj	0.2964	0.2902	0.1032	0.0643	0.2459

3.2 | The ARAS Method

To eliminate the impact of several measurement units and optimization directions in MADM, Zavadskas [11] initially suggested the ARAS approach.

Assumed to be present are m alternatives, shown by $(A1, A2, \ldots, Ai, \ldots, Am)$, n attributes denoted by $(c1, c2, \ldots, cj, \ldots, cn)$.

Step 1: Create a decision-making matrix when the optimal values of each attribute, m alternatives, and n attributes are shown by the $m + 1$ rows and n columns. In Eq. (9) and (10) yield the optimal values for the attributes. In other situations, 20% better values than all of the possibilities should be chosen when the optimal values cannot be found or are unknown.

$$x_{0j} = \max x_{ij} \tag{9}$$

$$x_{0j} = \min x_{ij} \tag{10}$$

where the optimal value x_{0j} refers to the scale's highest possible assessment under the jth attribute and x_{ij} refer to the value of the ith alternative under the jth attribute.

Table 3. max-min of $x$ij.

Max	**0.85**	**0.87**	**0.87**	**0.75**	**0.87**
Min	0.23	0.18	0.42	0.51	0.21

Step 2: Normalized the decision-making matrix if the jth attribute is benefit attribute used Eq. (11), and if the jth attribute is non- benefit or cost attribute used Eq. (12) as in Table 8.

$$\bar{x}_{ij} = \frac{x_{ij}}{\Sigma_{i=0}^{n} x_{ij}} \tag{11}$$

$$\bar{x}_{ij} = \frac{\frac{1}{x_{ij}}}{\Sigma_{i=0}^{n} \frac{1}{x_{ij}}} \tag{12}$$

Table 8. Normalization the decision matrix.

	PV	EA	CC	GE	PN
CropIn Robots	0.16190476	0.0939227	0.124513619	0.0981	0.0901
Agrosmart Robots	0.15047619	0.0497238	0.118677043	0.1096	0.0485
xFarm Robots	0.13714286	0.0607735	0.1692607	0.1442	0.1963
Fertilizing Robots	0.08761905	0.1160221	0.081712062	0.1096	0.1062
Semios Robots	0.04380952	0.2403315	0.089494163	0.1173	0.2009
Autonomous Tractors	0.12761905	0.0801105	0.130350195	0.1385	0.0577
Six-Axis Robots	0.12952381	0.1187845	0.116731518	0.1385	0.0993
MAX	0.16190476	0.2403315	0.1692607	0.1442	0.2009

Step 3: Normalized the weighted matrix of each attribute w_j. For each alternative under each attribute the normalized weighted value $\hat{\bar{x}}_{ij}$ is calculated by the following Eq. (13) as shown in Table 9:

$$\hat{\bar{x}}_{ij} = \bar{x}_{ij}\; x\; w_j \tag{13}$$

Table 9. Weighted normalization of the decision matrix.

	PV	EA	CC	GE	PN
Weights	0.2767	0.2918	0.0937	0.0476	0.2901
CropIn Robots	0.044799048	0.02740663	0.011666926	0.004668462	0.026129099
Agrosmart Robots	0.041636762	0.014509392	0.011120039	0.005217692	0.014069515
xFarm Robots	0.037947429	0.017733702	0.015859728	0.006865385	0.056948037
Fertilizing Robots	0.02424419	0.033855249	0.00765642	0.005217692	0.030818938
Semios Robots	0.012122095	0.070128729	0.008385603	0.005583846	0.058287991
Autonomous Tractors	0.03531219	0.023376243	0.012213813	0.006590769	0.016749423
Six-Axis Robots	0.035839238	0.034661326	0.010937743	0.006590769	0.028809007
MAX	0.044799048	0.070128729	0.015859728	0.006865385	0.058287991

Step 4: Figuring out the utility degree and optimality function values. We can find out the value of the optimality function for each alternative by constructing the normalized weighted decision-making matrix in the Eq. (14) described below in Table 10:

$$S_i = \Sigma_{j=1}^{n} \hat{\bar{x}}_{ij} \quad i = 0,1,2,\dots\dots\dots,m \tag{14}$$

Table 10. Optimality function values.

S_i
0.114670164
0.0865534
0.135354279
0.101792489
0.154508265
0.094242439
0.116838083
0.19594088

When we compared the optimal value with the optimality function value of an alternative, the degree of the alternative utility is computed as in Table 11 by the following:

$$Q_i = \frac{S_i}{S_0} \quad i = 1,2,\dots\dots\dots,m \tag{15}$$

Table 11. Degree of alternatives.

Q_i
0.585228383
0.441732223
0.690791424
0.519506135
0.788545324
0.480973846
0.596292532
1

where S_i and S_0 , stand for the optimal optimality value and the alternative's optimality value, respectively, are found using Eq.(14). Eq. (15) indicates that the value of Q_i is inside the interval [0, 1], and thus the corresponding alternative is the larger Q_i value.

Calculating the ultimate rating when order all of the alternatives from best to worst using the utility value ranking system, which is based on the degree of each alternative's utility. The higher utility value is for better alternative. So, from Table 11 the best alternative is Semios Robots and the worst alternative is Agrosmart Robots.

4 | Conclusions

Since the agricultural industry consistently contributes to the advancement of a nation, the use of agricultural robots has opened the door for long-term growth. There are a lot of lands available for farming in Egypt as compared to farms in other countries, but the farmer's ability to purchase agricultural resources is very limited financially. Robotics can reduce the cost of buying resources in bulk, and ease the burden on these resources. The difficulty of finding these resources have decreased due to robots' proficiency in performing a variety of agricultural chores.

The decision support system that was developed made it easier to assess these robots' performance using five different criteria. In this research, seven agriculture robots were compared based on four beneficial criteria to select the best one for the job. The MCDM technique MABAC was used to treat the selection problem and obtain the weights of criteria. An objective weight determination method known as MEREC was used to determine the weights of the criteria. Furthermore, for the prioritization of the alternatives we used the ranking performance ARAS technique, which adds to the great dependability of the outcomes and obtain the order of alternatives. This research could be expanded to incorporate more recent techniques. Additionally, because the methodology is data-driven, it applies to various research concerns, including the selection of materials, machinery, and sites.

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Author Contributaion

All authors contributed equally to this work.

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Data Availability

The datasets generated during and/or analyzed during the current study are not publicly available due to the privacy-preserving nature of the data but are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that there is no conflict of interest in the research.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

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