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Enhancing business analytics predictions with hybrid metaheuristic models: a multi-attribute optimization approach

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ABSTRACT

This approach aims to optimize business analytical predictions through multiattribute optimization using a hybrid metaheuristic model based on the modified particle swarm optimization (MPSO) and gravitational search optimization (GSO) algorithms. This research uses a variety of data, such as revenue, expenses, and customer behavior, to improve predictive modeling and achieve superior results. MPSO, an interparticle collaborative mechanism, efficiently explores the search space, whereas GSO models' gravitational interactions between particles to solve optimization problems. The integration of these two algorithms can improve the performance of business analytical predictions by increasing model precision and accuracy, as well as speeding up the optimization process. Model validation test results, precision 95.60%, recall 96.35%, accuracy 96.69%, and F1 score 96.11%. This research contributes to the development of more sophisticated and effective business analysis techniques to face the challenges of an increasingly complex business world.

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1. INTRODUCTION

In the current digital and highly competitive environment, firms require precise analytical forecasts in order to make prompt and efficient business decisions. Precise forecasts of customer behavior, market trends, and overall business performance are crucial for a company's success [1]. Nevertheless, making analytical forecasts can be challenging due to the intricate nature of the company data at hand. Business data frequently encompasses numerous dimensions and qualities, and can exhibit significant dynamism and lack of organization [2], [3]. An effective method to enhance analytical predictions involves the utilization of optimization techniques, namely metaheuristics. Metaheuristics are search algorithms that employ heuristics to efficiently solve complex optimization problems, often yielding optimum or nearly optimal solutions [4], [5]. Combining multiple metaheuristic strategies can result in more potent and effective models for solving optimization challenges. By combining approaches such as modified particle swarm optimization (MPSO) and gravitational search optimization (GSO), it is possible to create models that exhibit more adaptability and improved capability in handling complex data.

Previous research [6] found service quality factors that influence customer satisfaction, promotional efforts undertaken by retailers, and customer perceptions of the organized retail sector using the random grasshopper optimization algorithm (RGOA) for optimal sample selection, and the selected optimal instances were fed to a deep neural network model (DNN) for prediction of future customer behavior. Research was also carried out [7], optimizing a forecasting model using an extreme learning machine (ELM) combined with the Harris Hawks optimization algorithm (HHO) to estimate product demand in e-commerce companies. The results show that the proposed approach is superior to traditional product demand forecasting models in terms of prediction accuracy and can be applied in real-time to predict future product demand based on the previous week's sales data.

By combining approaches such as MPSO and GSO, it is possible to create models that exhibit more adaptability and improved capability in handling complex data. The aim of this research is to utilize MPSO to find the most effective solutions to complex optimization problems, especially in optimizing parameters for business prediction models. Modified to improve performance and stability, the MPSO algorithm is a variation of the particle swarm optimization (PSO) algorithm [8], [9]. MPSO starts by creating a set of particles in a specified search space, with each particle representing a potential solution. The particles navigate the search space by considering the impact of the best-performing particles around them, as well as the most successful particles ever discovered by the total population. MPSO also optimizes business prediction models' parameters, including analytical models that estimate customer behavior or company performance. GSO is a computational technique that takes inspiration from gravitational interactions between celestial bodies in the cosmos [10]. The GSO algorithm works by initializing a set of agents in the search space and iteratively exploring potential solutions by moving these agents. Gravitational pull governs the movement of agents, determined by the distance and mass between them [11]. Both algorithms overcome their respective limitations and produce more optimal solutions. MPSO and GSO represent an innovative approach to managing the complexity of business data and improving the quality of analytical predictions to support better business decision-making.

2. METHOD

First, the research starts with the collection of pertinent business data, which serves as the primary basis for conducting the business analysis. We then implement the MPSO and GSO algorithms in a computing environment to optimize the parameters in the business model. MPSO while GSO adjusts parameter values based on particle gravitational interactions, MPSO searches a wide parameter space with respect to convergence speed and global exploration [12]. Furthermore, a hybrid model integrates the results of the two algorithms, combining the advantages of each algorithm. Model generates more accurate and stable predictions for the business variables you want to predict. Finally, the prediction results from the hybrid model will be evaluated using data testing performance evaluation metrics using accuracy, precision, and F1 score, and cross-validation will be carried out to ensure model robustness and avoid overfitting [13], [14] should be seen in Figure 1.

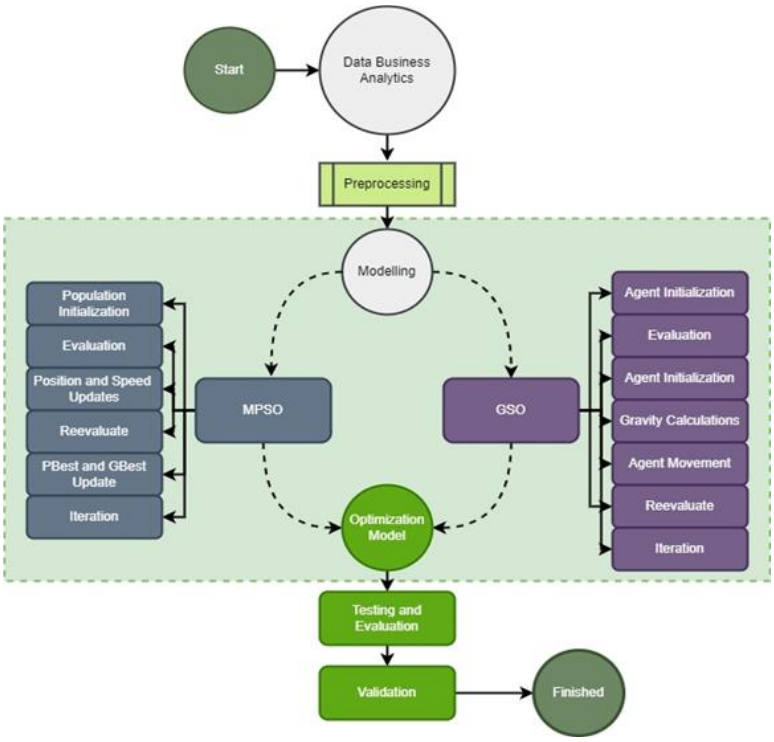


Figure 1. Research method

2.1. Business analytics understanding

Using data for business analytics understanding is key to understanding and optimizing business performance [15]. This research utilizes various types of data, such as sales, inventory, and financial data, to provide a picture of business performance and operational efficiency. Analysis of this data can help identify trends, measure product or service performance, and make decisions based on evidence [16]. Use of market data and economic data helps in understanding the macroeconomic context in which they operate. This includes understanding consumer behavior, market competition, and industry trends that influence business performance [17]-[19]. And using customer data can provide insights into customer preferences, behaviors, and needs. Analyzing customer data allows you to identify potential market segments, improve the customer experience, and expand your customer base [20]. Optimized research on business lifecycle analytics should be seen in Figure 2.

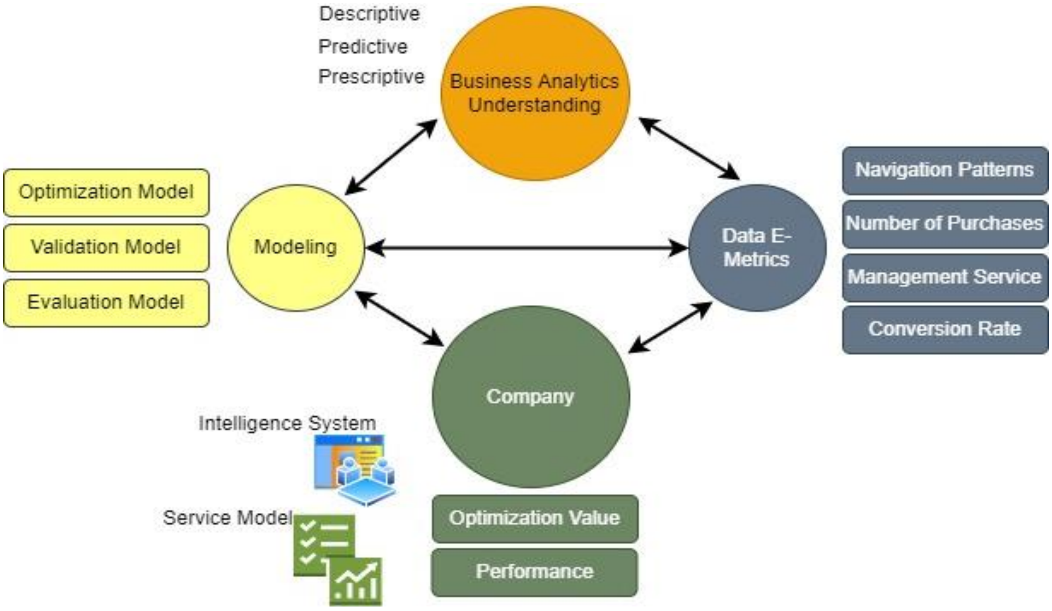


Figure 2. Optimized research scope

2.2. Modified particle swam optimization

The MPSO method is an optimized version of the PSO algorithm that incorporates principles of group behavior observed in nature, specifically the coordinated movement of bird or fish flocks. MPSO utilizes a group of particles within a search space to systematically investigate and take advantage of possible solutions. Each particle corresponds to a single solution within the search space and navigates around it by incorporating both local and global knowledge. The following equation represents the MPSO formula [21]-[23]:

Particle initialization:

$$x_i^0 = rand\ (LB, UB) \tag{1}$$

$$v_i^0 = rand(-V_{max}, V_{max}) \tag{2}$$

Fitness evaluation:

$$f_i^0 = f(x_i^0) \tag{3}$$

Update PBest and GBest:

$$\begin{gathered} PBest_i = x_i^0\ if\ f_i^0 < f(PBest_i) \\ GBest = \min(PBest_i) \end{gathered} \tag{4}$$

Update position and speed:

$$v_i^{t+1} = w.v_i^t + c_1.rand().(PBest_i - x_i^t) + c_2.rand().(GBest - x_i^t) \quad (5)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (6)$$

where: x_i^t particle position i on iteration i. v_i^t particle speed i on iteration t. $PBest_i$ best position of the particle i. $GBest$ global best position. w inertia factor. c_1, c_2 cognitive and social learning factors. LB, UB, V_{max} lower limit, upper limit, and maximum speed limit respectively. $rand()$. generates a random number between 0 and 1. f_x objective function to be optimized. If the maximum number of iterations is reached or a satisfactory solution is found, stop.

2.3. Gravitational search optimization

The GSO algorithm is an optimization technique that draws inspiration from the gravitational forces that exist between things in the cosmos. The GSO algorithm uses gravity to improve the efficiency of finding optimal solutions within the search space [24], [25]. Particle position initialization:

$$x_i^0 = rand\ (LB, UB) \quad (7)$$

Fitness evaluation:

$$f_i^0 = f(x_i^0) \quad (8)$$

Update $PBest$ and $Gbest$

$$PBest_i = x_i^0 \ if \ f_i^0 < f(PBest_i)$$
$$GBest = \min(PBest_i) \quad (9)$$

Particle mass calculation:

$$m_i = \frac{f_i^0 - f_{min}}{f_{max} - f_{min}} \quad (10)$$

Gravity calculations:

$$F_i = G.\frac{m_i - m_j}{r_j^2 + \epsilon} \quad (11)$$

Update particle position:

$$a_i = \frac{\sum_{j-1}^{N} F_i}{m_i} \quad (12)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (13)$$

where: x_i^t particle position i on iteration i. f_i^t particle fitness value i on iteration t. $PBest_i$ best position of the particle i. $GBest$ global best position. m_i particle mass i. G gravitational constant. r_{ij} distance between particles i and j. ϵ, small value to avoid division by zero. $LB, UB,$ lower limit, upper limit, and maximum speed limit respectively. $rand()$. generates a random number between 0 and 1. f_x objective function to be optimized. If the maximum number of iterations is reached or a satisfactory solution is found, stop.

3. RESULTS AND DISCUSSION

3.1. Data preparing

This data set is based on e-metrics for all customer activities divided into 8 clusters. Cluster C1-C2: this cluster focuses on user navigation patterns in apps, including metrics for the most frequently visited pages, the most common navigation routes, and the length of user sessions. Cluster C3-C4: this group highlights user purchasing behavior, including the number of purchases by each user, the total value of purchases, or the frequency of purchases in a certain time period. Cluster C5-C6: this group is related to the use of management services by users and includes types of account management services and customer service. Cluster C7-C8: this cluster focuses on user conversion rates, which are measured by conversions from visitors to customers, conversions from leads to sales, and conversions from ad clicks to desired actions. These clusters are shown in the Table 1.

Table 1. Cluster parameters

Cluster	Parameters
C1	Navigation patterns
C2	
C3	Number of purchases
C4	
C5	Management service
C6	
C7	Conversion rate
C8	

3.2. Optimization model

In (1) and (2), we assign a random initial position and velocity to each individual in the population. We assess particles using the optimized objective function in (3). In (4), we update the $PBest$ (individual best position) and $GBest$ (global best position) based on the highest fitness value that each particle and the entire population discover, respectively. We adjust and alter each particle's position and velocity to incorporate the influence of the growing $GBest$, along with other parameters like convergence speed in (5), (6). The method terminates when it reaches the maximum number of iterations. The next step assigns each particle a mass directly proportional to the fitness value of (7). As the fitness value increases, so does the particle equation's mass. The remaining particles within the population exert a gravitational pull on each individual particle. Every particle then recalibrates its position, taking into account the gravitational force that comes from (8), (9). Particles gravitate towards greater masses, symbolizing superior solutions. The technique for calculating gravitational force entails determining the parameters of (10). We correctly configure the parameters to ensure convergence in the search for an optimal solution. The repetitive procedure of estimating gravitational force and tracking changes in particle position continues until the number of iterations satisfies (11). As shown in Table 2.

Table 3 explains that variability between clusters varies depending on the dispersion value and range (min-max) of the attributes in each cluster. Clusters with high dispersion have more data variation. Clusters with high averages indicate certain trends in the observed data.

Table 2. MPSO-GSO iteration results

Cluster	Product related	Bounce rates	Revenue	Customers needs	Behavior	Value	Iteration
C1	78.73	637.83	637.83	209.5	356.74	0.025	0.847
C2	64.83	637.73	629.83	183.6	637.83	0.08	0.869
C3	2.66	738.83	652.73	2086.2	567.73	0.0203	0.882
C4	627.5	372.84	172.84	388	762.88	0.0562	0.895
C5	154.216	637.63	479.93	298	122.3	0.0285	0.907
C6	163.838	738.87	272.09	63	37.98	0.071	0.903
C7	167.83	526.38	272.93	482	22.3	0.022	0.889
C8	377.83	626.83	227.73	4084.3	23.23	0.001	0.902

Table 3. Cluster variability

Cluster	Mean	Mode	Median	Dispersion	Min	Max	Missing
C1	2.32	0	1	1.43	0	27	0 (0 %)
C2	808.186	0.00	7.5	218.727	0.00	3398.75	0 (0 %)
C3	0.50	0	0	2.52	0	24	0 (0 %)
C4	344.724	0.00	0.00	408.279	0.00	2549.38	0 (0 %)
C5	31.73	1	18	1.40	0	705	0 (0 %)
C6	1194.75	0.00	598.937	160.167	0.00	63973.5	0 (0 %)
C7	0.0221914	0.00	0.00311247	218.492	0.00	0.2	0 (0 %)
C8	0.0430728	0.2	0.0251564	11.282	0.00	0.2	0 (0 %)

We have grouped the maximum iteration results from each data cluster based on attributes relevant to the business. Each cluster has different values for each attribute, reflecting variations in customer behavior, needs, income levels, and business performance, as shown in Figure 3. It shows the values of the main components for each cluster, as well as the proportion of variance explained by each main component.

Figure 4 provides information about how each cluster contributes to the variation in the data as a whole; in Figure 4(a), clusters with a low proportion of variance have a smaller contribution. While Figure 4(b), with a high proportion of variance, has a significant influence on patterns in the data, it helps understand how each cluster affects the analysis or prediction.

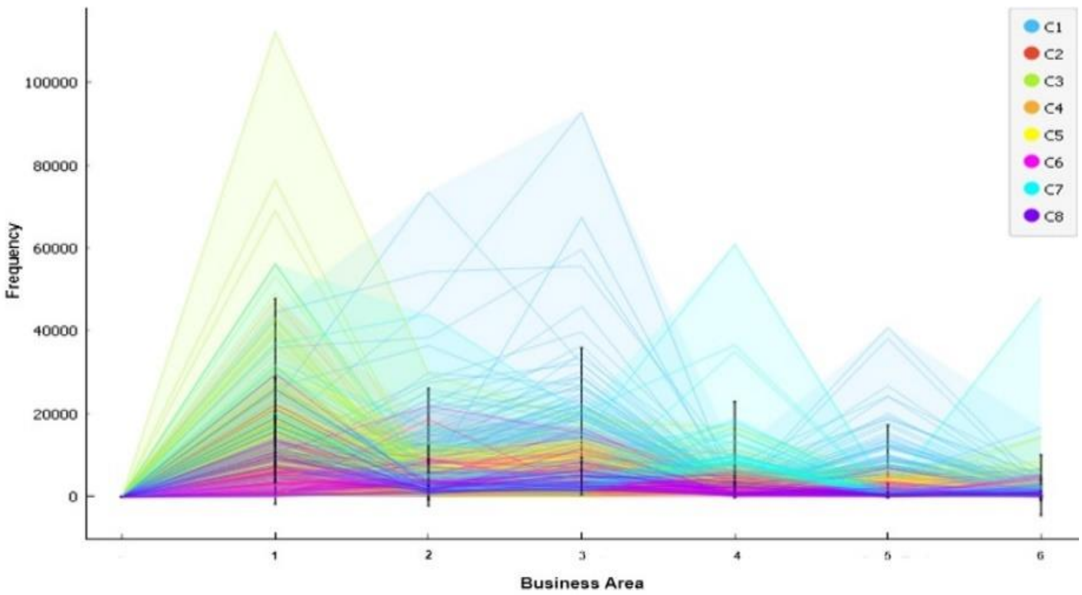
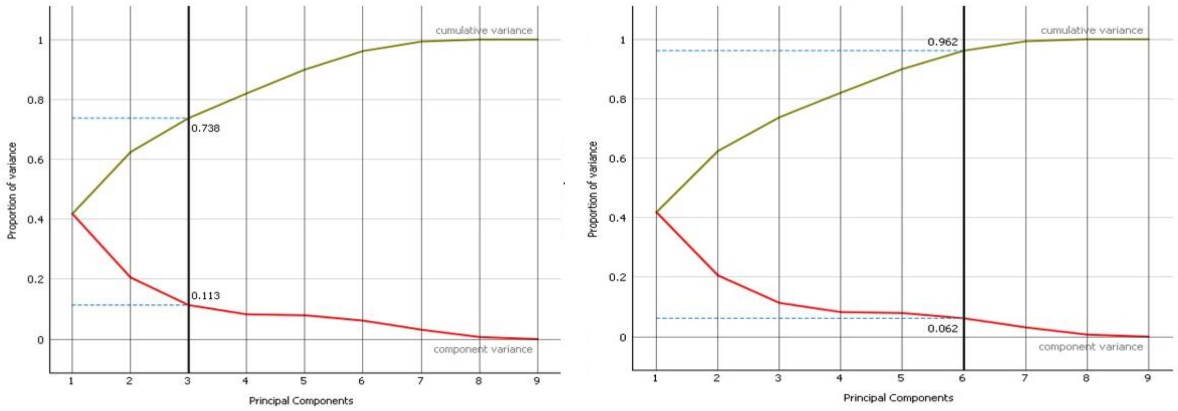


Figure 3. Value of the main components of each cluster



(a) (b)

Figure 4. Cluster contribution information (a) clusters with a low proportion of variance and (b) clusters with a high proportion of variance

3.3. Validation model

Model validation uses criteria such as precision, recall, accuracy, and F1 score. Precision is a measure of the proportion of positive events that the model accurately predicts. This demonstrates the model's precision in accurately identifying positive events. The model's recall is defined as the proportion of accurately detected positive cases. This indicates the model's capacity to precisely detect all relevant occurrences in the positive category. Accuracy is defined as a model's ability to correctly classify all classes in a comprehensive manner. The F1 score, which is calculated as the harmonic mean of precision and recall, offers a full assessment of model performance by taking into account the equilibrium between these two metrics. Here's how we explain the formula [26], [27]:

$$Precision = \frac{TP}{TP+FP} \tag{14}$$

$$Recall = \frac{TP}{TP+FN} \quad (15)$$

$$Accuracy = \frac{number\ of\ correct\ predictions}{total\ amount\ of\ data} \quad (16)$$

$$F1\ Score = 2 \times \frac{Presisi \times Recall}{Presisi + Recall} \quad (17)$$

Where:
TP (true positive) refers to the count of positive cases accurately predicted by the model.
FP (false positive) refers to instances where the model mistakenly predicts negative cases as positive.
FN (false negative) is the number of positive cases that were incorrectly predicted as negative by the model.

The main components of the number of accurate predictions corresponds to the number of data points that the model successfully classifies. The model assesses a cumulative amount of data, known as the total data volume. Each cluster has its own respective value.

Validation results based on (14)-(17) can be seen in Table 4, contains detailed prediction results obtained by the MPSO-GSO model on different folds. The study investigates the performance of the MPSO-GSO method on cluster classification C1-C8. The model demonstrates effectiveness in all aspects, achieving precision of 95.90%, recall of 96.35%, accuracy of 95.69%, and an F1 score of 96.11%. Figure 5 explains that each cluster has a different prediction performance. The differences in precision, recall, accuracy, and F1 score values between clusters demonstrate this. While most clusters exhibit relatively high and consistent evaluation metric values, there are notable differences in their performance. This indicates that there are certain factors influencing the model's ability to correctly classify the data in each cluster, but it is not something that can influence the test results. According to the average value of the validation test results, the model can predict well.

Table 4. Validation results

Cluster	Precision	Recall	Accuracy	F1 score
C1	94.73	95.73	97.74	98.64
C2	97.73	96.73	94.73	95.83
C3	97.37	96.73	96.74	96.74
C4	98.63	98.73	95.63	96.73
C5	95.63	94.74	96.63	94.73
C6	93.76	97.73	93.64	95.73
C7	95.63	94.73	94.73	95.78
C8	93.73	95.74	95.73	94.74
Average	95.90	96.35	95.69	96.11

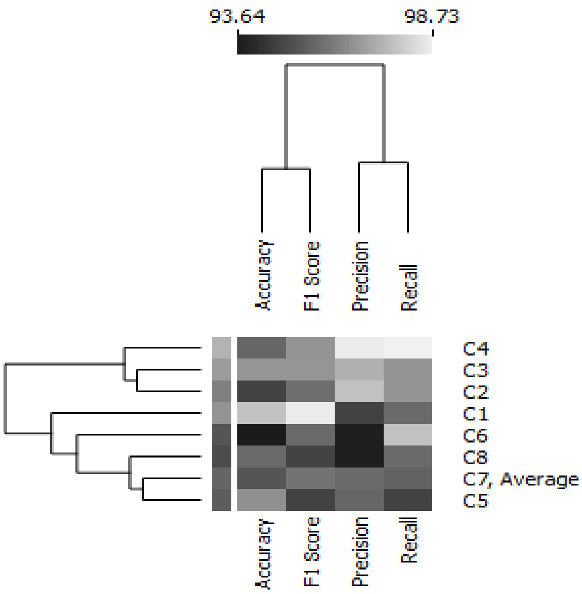


Figure 5. Validation of cluster prediction models

4. CONCLUSION

The study's conclusion is that combining the MPSO and GSO algorithms into a single metaheuristic approach could be very useful for improving business predictions. The results show that the hybrid approach effectively handles data complexity and improves the performance of the prediction model. The validation results of the precision model 95.90%, recall 96.35%, accuracy 96.69%, and F1 score 96.11% support this claim. Thus, this research makes an important contribution to the development of analytical techniques that can help companies optimize their business strategies. In the future, this research can be expanded by testing the hybrid approach in various other industrial domains, such as external factors influencing business predictions, global economic changes, or dynamic consumer behavior, to build more adaptive and responsive models.

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AUTHOR CONTRIBUTIONS STATEMENT

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
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Marischa Elveny		✓	✓	✓		✓		✓	✓	✓	✓	✓		✓
Mahyuddin K. M. Nasution	✓		✓	✓			✓			✓			✓	✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

To ensure fair and objective decision-making, the authors of this manuscript declare any associations that could potentially pose a conflict of interest, whether financial, personal, or professional. Non-financial competing interests include expressions of competing political, personal, religious, ideological, academic or intellectual interests. The authors hereby declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. Therefore, the authors declare no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals involved in this study.

ETHICAL APPROVAL

Research relating to human use has complied with all relevant national regulations and institutional policies in accordance with the principles of the Declaration of Helsinki and has been approved by the authors' institutional review board or equivalent committee.

DATA AVAILABILITY

Data supporting the findings of this study are available from the corresponding author on reasonable request. For further questions or data access, please contact the corresponding author

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