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Application of Genetic Algorithm and Fuzzy Sets to Logistic Decision-Making

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Abstract

In many areas, due to situational complexity, conceptual imprecision, or informational imperfection, management accounting is faced with a high degree of uncertainty or ambiguity. Many of these uncertainties spring from emotional and or lingual causes. Until the Fuzzy Set Theory (FST) was introduced, people learned how to model these uncertainties arising from the human mind and the environment. The present study explores the applied potentials of fuzzy sets and Genetic Algorithms (GA) in different areas of management accounting, especially logistic issues. Logistic issues in a dynamic business environment primarily involve allocating specific resources to several corresponding consumption destinations. Each resource supplies certain goods, whereas each destination demands certain quantities. In this type of issue, the goal is to identify the most economical transportation route that meets the demand without violating the supply constraints. This paper suggests using fuzzy sets to supply appropriate information regarding price, demand, and other variables. The suggestions include the calculation method of the shortest route with the least cost prices for the distribution cycle (network). Finally, as a solution for this complex problem, a GA in combination with a well-suited fuzzy function is recommended.

Keywords: Transportation problem, The shortest route, Logistics, Cost minimization, Imprecise information, Fuzzy sets, Genetic algorithm.

1 | Introduction

Many optimization problems can be formulated in terms of networks. For example, a distribution manager would like to find the shortest route from a source to a destination and the cheapest route for connecting all routes (i.e., distribution network), or he wants to obtain the best route for transferring inventories within a network. Network optimization is among the most important areas of management science, and for the

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following reasons, it has received wide recognition [1]. First, networks can be applied to modeling many fundamental and applied cases, such as transportation systems, communication systems, issues of transfer or transmission routes, production planning, and cash flow analysis. Second, since networks provide a realistic picture of the understudy issues, managers are adopting the network approach as rapidly as possible. The special mathematical properties of networks allow managers to develop specific algorithms to enable them to solve more significant problems that other optimization methods could not solve.

In this paper, a new approach to a classical network optimization problem, i.e., transportation problem, which suggests the use of Fuzzy Set Theory (FST) for control of uncertainty [2] and the use of Genetic Algorithm (GA) for the optimization of the distribution network [3], [4]. The main advantage of GA, which makes it one of the best of its kind, is that it does not impose restrictions on us for transforming the problem condition into a special case.

2 | Applications of FST to Accounting

It was in 1965 that Zadeh [2] introduced his FST to cope with uncertainty and inaccuracy (called 'fuzzy' by him) in the real world and decision-making processes. Fuzziness differs from Randomness. In fuzziness, ambiguity regards the event, whereas randomness refers to uncertainty regarding specifically defined events. For instance, a trivial deviation of cost price implies ambiguity or uncertainty because the word "trivial" is vague and inexplicable. However, the probability of an IRR 1000 deviation in cost price implies event randomness. The event itself is clear; it is about a deviation from cost prices to the amount of IRR 1000 or any other amount, and the uncertainty concerns the occurrence or non-occurrence of this event.

Nevertheless, randomness measured from probabilities can be related to fuzzy events. For example, someone may want to find out about the probability of a trivial deviation in cost price. Possible judgment, too, can be both vague and inexplicable. Comments like around 40%, quite likely, or the best case are examples of such judgment [5].

Some researchers employed FST to solve specific decision-making problems. These applications can be classified into two principal groups: normative and descriptive. Normative category concerns topics such as: 1) optimization in the presence of constraints, including linear programming, integer programming, and goal programming, 2) multi-person decision making including group theory, game theory, and team theory, 3) multiple criteria decision making, 4) statistical decision making theory, and 5) multi-stage decision making.

For different reasons, FST can be of great practical value. First, this theory provides a mathematical framework in which accounting fuzzy concepts and conditions (e.g., trivial deviation, material errors, efficient sampling) can be systematically investigated. Therefore, with the knowledge of the FST and its application, management accountants will not have to ignore the otherwise inexplicable uncertainties regarding accounting issues, nor will they be able to deal with them as random events in probability theory.

Recently, some applications of fuzzy sets have been made to solve accounting issues and problems. These studies can be divided into two categories. The first category deals with auditing problems such as evaluation of internal control [6] and audit sampling [7]. The second category addresses management accounting issues and problems such as capital budgeting, handling deviations of cost price, and strategic planning. Cooley and Hicks [6] applied fuzzy sets to an internal control system consisting of two subsystems of shipment control and cash receipts. These subsystems were considered in three respects: goals, risk, and procedures. The importance of goals, Probability of risk, and reliability of practices were evaluated as fuzzy variables based on three preliminary, qualitative fuzzy valuations (i.e., strong, weak, and moderate internal control system) and two combined fuzzy valuations (very strong and very weak internal control system). Each fuzzy value was described by a membership function, which defines the meaning of the terms in the collective set and is scaled from zero to nine. For example, the term 'weak' can be represented by a membership function that decreases from one to zero or increases from one to five.

Some of the researchers, including Bailey and Jensen [8] and Kaplan [9], suggested that Bayesian analysis can be employed in audit sampling (content test and compliance test). In this regard, the expression of quality (such as satisfactory or unsatisfactory presentation of accounts) must be correctly assumed as well-defined. In response to this shortcoming, Lin [7], drawing on fuzzy sets and fuzzy probability models, develops an audit model based on Bayes' theorem, which enables qualitative phrasing of the content and compliance testing and the results thereof.

3 | Application of Fuzzy Sets in Management Accounting

Today, management accounting is recognized as the scientific paradigm of the 21st century. This branch of science, profiting from various tools developed in other scientific fields such as mathematics, especially modern mathematics theories, and concepts like fuzzy sets, has been trying to make rapid growth and progress. For example, scholars have proposed several models to address price deviation. Several researchers, have raised the question of when deviations in cost price ought to be handled. This question is usually answered based on individual judgment. Many of the proposed models need to be applied in important business areas since they do not fit in the cost-benefit framework, or the models with a cost-benefit approach fail to allow for the issue of ambiguity in random situations or under uncertainty. Therefore, the fuzzy approach can be recommended for dealing with these issues.

Ijiri and Jaedick [10] consider the difference between main products and by-products to be fuzzy. Also, social responsibility accounting and government regulations involve ambiguities that can further affect the accounting system and business decisions. For instance, Stephens et al. [11] observed that ambiguity in accounting statements could affect firm operations. Similarly, ambiguity in government laws and regulations may affect management decisions in firms. Consider clarity in the analysis of accounting decisions to ensure the analysis is effective and even defective. For instance, March [12] points out that disregard for the existing ambiguities in the choice of information systems (including accounting) can result in work deficiency and misleading [5].

Kaplan [9] says, "performance measures are primarily focused on short-term operational outcomes, and it is dispensed with the long-term impact, the measurement of which is more difficult." He also believes that the benefits of decentralization should be addressed in agency models, which can be misleading compared to the more complex environments of large firms. Decision-makers should choose the best system from among the possible systems. The best system is usually one that satisfies specific constraints and criteria. As an example of such constraints and criteria, it can be referred to as a system where, in addition to putting some limitations on the purchase budget, it should be fast, flexible, quickly changeable, reliable, easy to use, cost little, and with large storing capacity. At any rate, the weights and relationships between constraints and criteria are unclear. The words such as 'very important' and 'fair' are often used to describe the significance of a particular criterion.

4 | Logistic Business Problem

Consider the problem of finding the minimum cost price for transporting raw materials from several destinations. The departure points can be a factory, storehouse, or any other point from which the materials are carried. Destinations are any place the materials are held to. Which routes should the distributor (the truck) take to minimize the transportation cost? This problem, traditionally, is rephrased into two different sub-decisions. One finds quantities of materials that should be carried from each source to any of the destination points to minimize costs. The demands are met (the transportation problem).

The other determines the shortest route through which the truck reaches all destinations (the shortest route problem), which is also known as the Traveling Salesman problem. To obtain the optimum solution whereby the distribution costs and the covered route are minimized, the two sub-problems should be combined into one problem. It is a logistic problem with many solutions (and occasionally infinite solutions) and several simple sub-solutions. In addition, some information items could be clearer since even by complex numerical calculations, the costs, supply, and demand may not be determined [13]. Hence, in the case of imprecise logistic problems, fuzzy sets can provide satisfactory solutions.

5 | Fuzzy Logistic Model

Companies need to know how many goods are supplied from a source to a destination using this method. The fuzzy method best lends itself to instances of imprecise information by organizing and representing it as effectively and intelligibly as possible. The required information for solving these problems is specified below:

Destination or customer demands

The company should meet the customer demands. Sometimes, this information is unknown, so a more realistic assessment is required regarding fuzzy sets. Thus, for n destinations, we have $\tilde{C}=\{\tilde{c}_1,\tilde{c}_2,...,\tilde{c}_n\}$.

Number of sources and supply capacity of each one

We assume each source has a specific supply capacity, which can be determined accurately. Thus, for m source, we have $F=\{F_1,F_2,...,F_m\}$.

Truck capacity

The company has one truck per supply source for the distribution of the goods. Now, truck capacity needs to be specified since transportation frequency depends on each truck's capacity truck. For the mentioned m sources, the capacity of trucks is given as follows $V=\{V_1,V_2,...,V_m\}$.

Transportation cost of the empty (unloaded) truck

There are occasions when a truck has to return to its respective source to get reloaded. Hence, the transportation cost of the unloaded truck has to be calculated. This cost depends on the distance the truck covers (the route length). Thus, for m sources, the transportation cost of an empty truck is as follows $cv=\{cv_1,cv_2,...,cv_m\}$.

Transportation cost for each extra unit of the transported goods

When the trucks distribute goods, the transportation cost for each extra unit is added. This added cost price also depends on the covered distance. Considering that this figure cannot be accurately calculated, fuzzy sets are employed to modify the obtained results. Thus, for m sources, the extra costs are calculated as follows: $\tilde{\Delta}cv=\{\tilde{\Delta}cv_1,\tilde{\Delta}cv_2,...,\tilde{\Delta}cv_m\}$.

Distance between sources and destinations

Transportation is done from a source to a destination or customer, and the distance between them is obtained from the following matrix:

$$D=\begin{Bmatrix} D_{11},D_{12},...,D_{1n} \\ D_{21},D_{22},...,D_{2n} \\ \vdots \\ D_{m1},D_{m2},...,D_{mn} \end{Bmatrix}.$$

Distance between destinations

As mentioned earlier, a truck from a source, which is a distributing source, may go to several destinations. Hence, the distance between destinations should be known, which is obtained from the following matrix:

$$D = \begin{Bmatrix} -, D'_{12}, \ldots, D'_{1n} \\ D'_{21}, -, \ldots, D'_{2n} \\ \vdots \\ D'_{n1}, D'_{n2}, \ldots, - \end{Bmatrix}.$$

Based on this modeling procedure, we approach a real-world distribution problem. However, in addition to fuzzy sets, other complementary tools are needed to find a solution or at least a justifiable solution for this complex problem. To this effect, we choose the GA to be used with a fuzzy function. Although fuzzy sets are actually considered in this paper, the authors recommend representing all fuzzy information as Trapezoidal Fuzzy Numbers (TFNs).

6 | Genetic Algorithm and Fuzzy Logistic Issues

Some researchers apply GA to transportation issues [14]. They often solve problems by manipulating and reducing their size and complexity or using exact numbers for their variables. In this study's proposed approach, the TFN method based on the available information is recommended, whereby a model with fewer restrictions is provided. For this purpose, the quantities supplied from each source to each destination and truck transportation routes should be determined through GA. The same measure is used to obtain both quantities, that is, minimization of distribution costs.

6.1 | Genetic Algorithm

GA is one of the optimization methods, other than derivation principles, based on evolutionary concepts and the principle of natural selection, first introduced by John Holland [15] at Michigan University. Inspired by natural genetics principles, GA looks for solutions to problems. The core idea in GA is the control of the chromosomal populations, which determines the selected solutions (volunteers) for specific issues. Over time, there appears to be a controlled competition and variation in the population. GA provides an essential criterion for successfully researching solutions and optimizing problems. In this method, a set of points called population is considered the starting optimization point in place of the initial point. Next, a population of new generations is built using racial crossover and reproduction. The stages of producing the latest generation are as follows:

Step 1. Each point is transformed into a bit string, which is called a chromosome. Each bit in this string is called a gene.

Step 2. The optimization criterion defines a fitness degree for each population point.

Step 3. For the production of the next generation, a couple is chosen from among the chromosomes of the present generation according to their degree of fitness.

Step 4. Crossover occurs on the selected chromosomes, whereby a number of the genes of the two chromosomes are replaced by one another.

Step 5. Since crossover alone does not improve chromosomes, certain genes of the chromosomes are directly modified. This change through intervention is called mutation.

Steps 2-5 continue until the new population is completed. To prevent the fitness quality of the new population from declining, a number of the chromosomes with the highest fitness degree, called elites, in the current generation are transferred to the new generation. The production process of new populations or generations, as explained above, will be pursued until a halting criterion is satisfied.

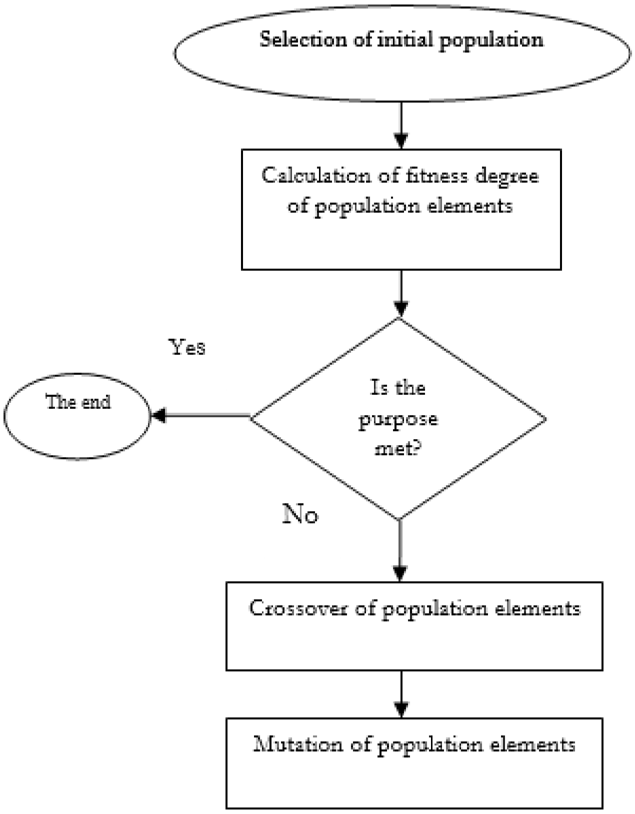

Fig. 1. Flowchart of GA.

A GA with a regularly produced chromosomal population (possible solutions) is started, and using the genetic operators modeled after the natural genetic process, it moves towards improving the chromosomes. By successfully repeating this process, the chromosomes used as solutions in society are ranked (evaluated) based on a new population of chromosomes through a selective mechanism and employing certain genetic operators like crossover and mutation. An evaluation or a suitable function should be considered for each problem to solve it correctly. Consider a chromosome (a homogenous solution); a suitable (justified) function provides a single justified figure that is supposed to be fit for the use or formulation of the proposed solution by the respective chromosome.

GA may be successfully applied to a wide range of issues, especially in managerial applications, which is quite evident. The main reasons for this success are: 1) GA's ability to quickly and reliably solve complex problems, 2) GA's simpler connection with the existing models, 3) it is expandable, and 4) it is easy to combine. All these reasons can be gathered in one single reason, GA is huge. It works powerfully in tough environments, usually with large spaces, no sequence, complex, and somewhat ambiguous. However, it only guarantees the production of overall optimum solutions. At any rate, its solutions are generally good, and it has proved to be quick and successful in finding excellent and acceptable solutions. The positive and satisfactory GA results also indicate the recent growing interest in its applications in various areas.

6.2 | A Genetic Algorithm for Fuzzy Logistic Problems

The following components are recommended for the solution of fuzzy logistic issues.

6.2.1 | Genetic display

The set of solutions for the mentioned problems is a set of transported distribution quantities from a source to a destination and the routes taken by the truck from each source. The following two matrices are used for coding these solutions: one comprises the quantities distributed from each source to each destination, and another provides the covered distances by several trucks.

Table 1. The coding of the matrix of values, comprising five sources and four destinations.

S_1^1	Source 1	Source 2	Source 3	Source 4	Source 5	Total
Destination 1	15	0	0	70	0	85
Destination 2	0	40	0	0	0	40
Destination 3	25	10	40	0	50	125
Destination 4	0	0	60	0	5	65
Total	40	50	100	70	55	315

Table 2. The coding of the covered distances by trucks.

S_1^1	Source 1	Source 2	Source 3	Source 4	Source 5
Destination 1	1	2	1	4	3
Destination 2	4	3	2	3	2
Destination 3	2	1	3	2	1
Destination 4	3	4	4	1	4

Which indicates the position of each destination in the routes taken by each truck.

In addition, to find useful solutions, the company should decide on meeting each customer's fuzzy demand level. TFN can be defined as all the possible distributions. Also, the company determines the risk of not covering the customer demand. This is done by preparing the matrix of values for solutions available.

6.2.2 | Fitting fuzzy function

A fitting function should allocate more values to these solutions, which are good solutions for the distribution problem [16]. For this purpose, we suggest the total distribution cost, which takes both matrices into account, to be calculated as follows: first, the truck carries all goods from its sources. The first destination shown by the routes in the matrix determines the cost of the first freight. The first destination is supplied by one or more freights, and nothing is given to the second destination.

If the truck along the route is unloaded, it returns empty to the source to get reloaded. It is fine. After completing the job, when all destinations are provided with goods, the truck will return to its initial departure point to complete the covered distance. The sum of all these transportation costs (loaded departure from the source, the effort of the second destination for getting supplied, and returning empty to the source, etc.) is part of the solution to the problem. To obtain the total price, the price of the other distribution routes in the matrix should be calculated, and for other trucks, this process should be drawn.

Given that fuzzy sets can provide some information, we suggest an operation for designing the sets [5]. In addition, in cases where the operation cannot produce a TFN, the results are estimated (by approximation) by assuming a small error [1]. To establish a hierarchy among the solutions, a fuzzy distance called Humming distance is suggested [1]. For this purpose, the distance between the source $\tilde{B}$ (with the sign of 0) and the fuzzy cost price of each solution is defined as follows:

$$d(\tilde{A}, \tilde{B}) = \int_{\alpha=0}^{1} \left(\left| A_\alpha^1 - B_\alpha^1 \right| + \left| A_\alpha^2 - B_\alpha^2 \right| \right) d\alpha.$$

In which $[A_\alpha^2, A_\alpha^1]$ is the confidence interval at significance level α.

More accurate solutions have smaller distances; hence, our desired values can be obtained by calculating the distance for each solution.

6.2.3 | Selection process

We suggest using Roulette Wheel Ranking [4] to select the parents of the next generation.

6.2.4 | Crossover operator

Traditional crossover cannot be used since the solutions are two matrices that should accomplish the restrictions. To do this, we suggest different crossovers for each matrix, such as the following ones.

6.2.5 | Matrix of distribution values

To combine information of these matrices, which are obtained from two parents, it made use of the proposed matrix by Vignaux and Michalewicz [14] for transportation problems.

6.2.6 | Matrix of the truck-covered routes

We need to prepare the route matrix for both parents. To do this, a source is chosen, and the routes of the 'parents' covered by the truck from this source are replaced with one another (matrix transpose).

First, a source (say, source 2) is selected to draw the route matrix in the problem.

Table 3. Draw the route matrix.

S_1^1	**Source 1**	**Source 2**	**Source 3**	**Source 4**	**Source 5**
Destination 1	1	2	1	4	3
Destination 2	4	3	2	3	2
Destination 3	2	1	3	2	1
Destination 4	3	4	4	1	4
S_2^2	**Source 1**	**Source 2**	**Source 3**	**Source 4**	**Source 5**
Destination 1	3	4	4	1	2
Destination 2	4	3	3	2	4
Destination 3	1	2	2	3	3
Destination 4	2	1	1	4	1

Following this, the lists of the covered routes are replaced with one another using matrices (matrix transposes).

Table 4. Matrix transposes.

$S_1^{2'}$	**Source 1**	**Source 2**	**Source 3**	**Source 4**	**Source 5**
Destination 1	1	4	1	4	3
Destination 2	4	3	2	3	2
Destination 3	2	2	3	2	1
Destination 4	3	1	4	1	4
$S_2^{2'}$	**Source 1**	**Source 2**	**Source 3**	**Source 4**	**Source 5**
Destination 1	1	4	1	4	3
Destination 2	4	3	2	3	2
Destination 3	2	2	3	2	1
Destination 4	3	1	4	1	4

6.2.7 | Mutation operator

The purpose of this operator is to introduce diversity into the solutions. To do so, we need to specify the difference between the two types of matrix.

6.2.8 | Mutation of distribution values

We suggest using a method specifically designed to preserve the feasible solutions. It works in the following order:

Step 1. First, a source (source A) and a destination (destination A) from the matrix chosen. This destination should be delivered at a non-zero value from the respective source. For instance, if the first obtained matrix following the crossover process is mutated, the source and the destination can be represented as follows:

Table 5. Source and destination matrix.

S_1^1	Source 1	Source 2	Source 3	Source 4	Source 5	Total
Destination 1	8	0	25	35	17	85
Destination 2	0	40	0	0	0	40
Destination 3	15	5	45	**35**	25	125
Destination 4	17	5	30	0	13	65
Total	40	50	100	70	55	315

Step 2. We produce a random value between zero and the allocated value (say, 20) for this source.

Step 3. In the remaining sources, we look for a value assigned to a different value that is greater than the produced random value in the previous stage (source B and destination B). This can be as follows:

Table 6. Value assigned to a different value.

S_1^1	Source 1	Source 2	Source 3	Source 4	Source 5	Total
Destination 1	8	0	25	35	17	85
Destination 2	0	40	0	0	0	40
Destination 3	15	5	45	35	25	125
Destination 4	17	5	30	0	13	65
Total	40	50	100	70	55	315

Step 4. The random value is reduced to the assigned figures to destination A from source A and to destination B from source B. Next, the random value is added to destination B from source A and to destination A from source B. Hence, the hypothetically mutated matrix can look like the following one:

Table 7. Hypothetically mutated matrix.

$S_1^{1'}$	Source 1	Source 2	Source 3	Source 4	Source 5	Total
Destination 1	8	0	25	35	17	85
Destination 2	0	20	20	0	0	40
Destination 3	15	25	25	35	25	125
Destination 4	17	5	30	0	13	65
Total	40	50	100	70	55	315

In fine, through the above process as a feasible solution, we mutate their matrix of residuals.

6.2.9 | Mutation of the covered routes by truck

For mutation of the route matrix, a transactional (interchange) is provided. For this purpose, a source is randomly chosen, then two destinations are selected, and their position on the covered route by truck is replaced (interchanged) with each other.

6.2.10 | Halt criterion for searching for the best solution

This criterion provides an algorithm that the user determines through several generations until the best solution is found. In the meantime, a characteristic called 'elitism' is introduced into this process, which prevents the deterioration (loss) of good solutions [17]. This supportive action favors preserving the best elements of a society in successful generations (reproduction) unless (and until when) other members appear superior in performing the job. Therefore, the optimum solution for the existing society (population) will remain in force if no better solution undermines it.

In sum, as noted, the proposed model's application in such cases allows for finding solutions for distribution problems under uncertainty.

7 | Conclusion

This paper discussed applying fuzzy sets in different accounting areas, especially logistic decision-making in management accounting. It was said that many issues in accounting (such as accounting of social responsibilities, handling the deviations of cost price, human resource accounting, performance measurement, and decision making) involve certain degrees of ambiguity and need to be reformulated based on fuzzy set logic. As was pointed out in this paper, today, more than anything, there is a need for accounting real-world applications. Upon specification of topics in accounting actual applications, the researcher's fuzzy theory should answer two important questions. The first question concerns the extraction of membership functions since, at this stage, it is more important than analysis and goals. The next issue is the solution of these functions using fuzzy techniques.

This study derived two important conclusions. The first is formulating an approach to logistic problems that can be updated for real settings. The second conclusion demonstrates the GA's capacity to solve complex problems with imprecise information and under uncertainty. Fuzzy sets allow us to present and utilize imprecise information in decisions regarding physical distribution. On the other hand, GAs, when the problems become overly complex, are able, in more familiar and intelligible terms, to provide naturally developed realistic solutions to logistic issues.

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Data Availability

The data supporting the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares no conflicts of interest related to this work.

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