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Investment Decision-Making for Textile Design Projects from the Perspective of Financial Management: Risk Control and Return Analysis

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ABSTRACT

Focusing on investment decision-making challenges within the textile industry, this study addresses the significant financial risks arising from high volatility in textile raw material prices and uncertain market demand for textile products. Financial management of textile design projects is enhanced by constructing a dual-objective optimization model to simultaneously maximize net present value (NPV) and minimize conditional value at risk (CVaR). The model utilizes a comprehensive risk index to characterize multisource risk factors specific to textile manufacturing. To solve this complex investment optimization problem in the textile sector, this paper proposes an improved multi-objective particle swarm optimization (R-MOPSO) algorithm with a dynamic risk perturbation and crowding distance guidance mechanism. Validation experiments based on operational data from a large-scale yarn textile enterprise show that the R-MOPSO algorithm achieves a superior Pareto solution set, where the NPV can reach 3.884 million CNY while controlling CVaR within 913,000 CNY. Sensitivity analysis further confirms the model's robustness, revealing that a 15% increase in textile raw material price leads to a 5.9% decrease in NPV and a 9.1% increase in CVaR. Results demonstrate that the proposed R-MOPSO is a robust and effective intelligent decision-making tool specifically tailored for capital investment projects in the highly volatile textile industry.

KEYWORDS

investment risk control, yarn production, multi-objective particle swarm optimization algorithm, textile design project evaluation, textile industry

INTRODUCTION

In recent years, the global textile industry has accelerated its transformation toward green and intelligent development. The fluctuation range of raw material prices has reached as high as 30% to 45%. Coupled with changes in exchange rates and labor costs, the risks of investment decisions have intensified. However, most existing studies focus on traditional financial indicators and lack multisource risk modeling and joint optimization of returns and risks [1-3]. Capital projects face problems such as long cycles, large fluctuations, and complex decisions in the early stages of investment. The traditional single financial evaluation method based on net present value (NPV) or internal rate of return has difficulty meeting the dynamic, flexible, and risk-sensitive requirements of modern textile companies in investment strategy planning [4,5].

At present, in the field of project investment decision-making, increasing attention has been paid to integrating advanced intelligent algorithms for balancing financial returns and risk control under uncertain conditions. Existing studies have applied various optimization and machine learning methods to improve financial risk prediction and decision-making efficiency. For example, Wang and Gao [6] developed a financial risk analysis model for cross-border e-commerce by combining support vector machine with fuzzy theory, which effectively improved the accuracy of identifying high-risk financial data and predicting multiple types of financial risks. Similarly, Shen [7] proposed a financial risk pre-alarm mechanism based on a backpropagation neural network optimized with a genetic algorithm, achieving a prediction accuracy of 97.94% and significantly outperforming other financial risk assessment methods. In the domain of investment portfolio optimization, algorithms such as the non-dominated sorting genetic algorithm (NSGA-II), the strength Pareto evolutionary algorithm (SPEA2), and the standard particle swarm optimization (PSO) algorithm have been widely adopted to enhance decision robustness and efficiency in the presence of complex and volatile environments. However, these methods generally have problems such as slow convergence, uneven solution set coverage, and slow response to local disturbances in the face of complex nonlinear constraints and multisource risk structures in the real investment environment. In particular, they lack the ability to structure modeling of industry-specific risks. Highly volatile industries represented by textile design projects place higher requirements on optimization algorithms, which not only need to take into account the rationality of financial goals but also must adapt to the dynamic disturbance characteristics of risk factors [8-10]. Therefore, on the basis of the traditional optimization model, this study combines the project characteristics and financial sensitivity requirements of the textile industry to construct a multi-objective investment optimization method that is both financially accurate and risk-adaptive, providing a more scientific and efficient decision support framework for the complex manufacturing industry.

FINANCIALLY DRIVEN PROJECT RISK AND RETURN MODELING

In the investment decision-making of textile design projects, the key to risk control and return evaluation lies in building a quantitative model with financial sensitivity to capture the impact of multisource heterogeneous risk factors on the project's NPV and cash flow stability. On the basis of the uncertainty of project cash flow in reality and the volatility of the market environment, the traditional return and risk calculation model needs to be improved structurally to adapt to the cyclical, raw material dependence and innovation-driven characteristics of textile industry projects [11-13]. First, the calculation model of the expected NPV of the project is adjusted, and a volatility weighted correction factor and an elastic discount rate are introduced to adapt to the risk adjustment needs of highly sensitive industries. The improved expected NPV formula is defined as follows:

$$NPV = \sum_{t=1}^{T} \frac{(C_t - O_t)(1+\delta_t)}{(1+r_t+\lambda \cdot \sigma_t)^t} - I_0 \tag{1}$$

where C_t represents t the operating income in the year, O_t represents the operating expenses in the same period, δ_t is the output growth adjustment coefficient, r_t is the benchmark σ_t discount rate, λ is the return volatility of the period, t is the risk aversion coefficient, and I_0 is the initial investment cost. This model reflects the sensitive response of the project to financial risks by introducing a volatility risk adjustment item in the discount rate. A multifactor weighted comprehensive risk index (CRI) is constructed to accurately measure the multisource risk exposure faced by the project. This model integrates key risk dimensions such as raw material price fluctuations, market demand elasticity, exchange rate changes, labor cost fluctuations, and equipment depreciation. The specific improved risk function is expressed as follows:

$$CRI = \sum_i w_i \cdot Z_i + \sum_i \sum_{j=i} \rho_{ij} \cdot w_i \cdot w_j \cdot Z_i \cdot Z_j \tag{2}$$

where ρ_{ij} represents the covariance coefficient between the i-th risk source and the j-th risk source, and Z_i and Z_j are the standardized risk values of each risk source, respectively. Introducing the covariance term can better reflect the interdependence among risk sources. Table 1 shows the main factors and attributes that constitute the financial risks of textile design projects.

Table 1. Main factors of financial risk in textile design projects

Risk Factor	Code	Measurement Method	Data Source	Impact Direction
Raw Material Price Volatility	R_1	Standard Deviation/Mean Ratio	Cotton Yarn Futures Market	Cost Increase
Market Demand Elasticity	R_2	Month-on-Month Sales Change Rate	Market Sales Records	Revenue Fluctuation
Exchange Rate Volatility	R_3	Daily Volatility	National Exchange Rate Data	Cost Uncertainty
Labor Cost Fluctuation	R_4	Annual Wage Growth Rate	Human Resources Data	Cost Increase
Equipment Depreciation Rate	R_5	Annual Depreciation Rate	Fixed Asset Ledger	Net Value Decrease

Through the construction of the above model and factor identification, a quantitative basis is provided for subsequent investment decisions based on multi-objective optimization algorithms so that the investment plan can achieve a structural balance between risk control and return acquisition.

MODELING OF INVESTMENT DECISION OPTIMIZATION PROBLEM

In investments in textile design projects, decision-making optimization issues not only involve maximizing economic benefits but must also take into account the risk tolerance of the project under an uncertain environment and the realistic constraints of resource allocation. The traditional single-objective investment model cannot effectively balance the dynamic relationship between benefits and risks. Thus, building a multi-objective optimization model is a key path to achieve scientific decision-making. The model should consider the robustness of financial returns and the minimization of risk exposure, and embed multidimensional constraints such as resources and production capacity to reflect the complexity of investment in the real project environment [14-16]. In the construction of the objective function, the expected return maximization of the project NPV is defined as the main objective, and the return adjustment is made in combination with the sensitivity function of cash flow fluctuations. The following return objective function is proposed:

$$\max f_1(x)=\sum_{t=1}^{T}\frac{\left[C_t(x)-O_t(x)\right]\cdot\left(1-\kappa\cdot CV_t\right)}{(1+r_t)^t} \tag{3}$$

where r_t represents the annual rate of return of the project. $C_t(x)$, $O_t(x)$ are t the expected income and cost of CV_t the investment plan in the first period, x represents the coefficient of variation of cash flow, and κ is the risk adjustment factor. This formula explicitly embeds the adverse impact of risk on income into the expected return structure and more truly reflects the quality of financial returns under high volatility through the adjusted income expression. At the same time, in terms of risk objective function, the generalized conditional value at risk (CVaR) model is introduced, and combined with the risk factor weight matrix, the improved CVaR model that is designed especially for the textile industry is constructed as follows:

$$\min f_2(x)=CVaR_\alpha(x)=\frac{1}{1-\alpha}\int_{Z(x)>VaR_\alpha(x)}Z(x)\cdot w(x)dF(x) \tag{4}$$

where $Z(x)$ is the investment loss function, $VaR_\alpha(x)$ is the risk value threshold at $w(x)$ the confidence level, and α is the weight function composed of various risk factors, reflecting x the sensitivity of a specific investment plan to different sources of risk. This risk function not only describes the expected value of extreme losses but also realizes risk structuring for industry characteristics through the introduction of risk weights. On this basis, the model introduces a set of realistic constraints to limit the feasible solution space, including budget constraints, production capacity constraints, technical personnel configuration constraints, and project cycle constraints.

As shown in formula (5),

$$\begin{cases}\sum_{i=1}^{T}I_i\le B\\ P_i\le C_i,\quad \forall i\in\{1,2,3,\cdots T\}\\ \sum_{j=1}^{n}X_{ij}\le L_i\\ \sum_{i=1}^{T}D_i\le P\end{cases} \tag{5}$$

where I_i represents the investment amount of phase i, T is the total number of phases of the investment cycle, B is the total budget limit, P_i is the production volume corresponding to the phase, C_i is the upper limit of the production capacity corresponding to the phase, X_{ij} is the number of type i technical personnel required for phase j, L_i is the total number of technical personnel for phase i, D_i is the estimated working hours for the phase, and P is the time limit of the total project cycle.

INVESTMENT STRATEGY OPTIMIZATION BASED ON MULTI-OBJECTIVE PARTICLE SWARM OPTIMIZATION ALGORITHM

In textile design investment projects, traditional single-objective optimization methods cannot simultaneously meet the dual requirements of risk control and return maximization, especially in an environment with a large number of nonlinear constraints and uncertainty interference. Therefore, a multi-objective PSO (MOPSO) algorithm is introduced to achieve the Pareto optimal solution set of the investment portfolio on the two objective functions of NPV and CVaR. The basic idea of the MOPSO algorithm is to approximate the optimal solution of multiple objective functions by simulating the iterative movement of "particles" in swarm intelligence in the search space. In this study scenario, the position of the particle represents different investment portfolio vectors X, while the speed reflects the direction and amplitude of the scheme adjustment. Compared with the standard PSO algorithm, mechanisms such as crowding distance sorting, external archive management, and elite guidance strategy are introduced to enhance the diversity and convergence of solutions [17-19]. The adaptability of the algorithm to complex investment environments is improved by structurally improving the speed update formula and introducing a dynamic inertia factor and a risk-driven disturbance term, as shown in formula (6).

$$v_i^{t+1} = w^t \cdot v_i^t + c_1 \cdot r_1 \cdot (p_i^{best} - x_i^t) + c_2 \cdot r_2 \cdot (g^{best} - x_i^t) + \eta \cdot \Delta R_i^t \quad (6)$$

where w^t is t the dynamic inertia factor of the generation; $\eta \cdot \Delta R_i^t$ which represents i the guiding term of the particle in the direction of risk disturbance and is used to enhance its response to the CVaR gradient; and ΔR_i^t is the sensitive change rate of the current scheme on the risk objective function compared with the previous generation. The position update follows the standard accumulation mechanism [20].

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{7}$$

The crowding distance is introduced to update the external elite archive and thus maintain the stability of the Pareto frontier solution. In each iteration, representative particles are selected from the current set of non-dominated solutions to form the archive AA, and the selection criteria are the non-dominance and spatial distribution of the solution. The calculation of the crowding distance is defined as follows:

$$CD_k = \sum_{m=1}^{M} \frac{f_m^{k+1} - f_m^{k-1}}{f_m^{\max} - f_m^{\min}} \tag{8}$$

where CD_k represents k the congestion of the solution, and f_m^{k+1} and f_m^{k-1} are the function values of the adjacent individuals on the objective function f_m. The solution with smaller congestion is more likely to be replaced. In addition, a probabilistic perturbation strategy is used to perform local mutation operations on some particles and thus prevent particles from falling into local optima. The specific perturbation mechanism combines the risk exposure of the current particle and the breadth of investment resource distribution to improve the jumping and stability of the search. The local mutation formula is defined as follows:

$$x_i^{t+1} = x_i^{t+1} + \phi \cdot \left(\frac{1}{1 + CRI_i^t} \right) \cdot f(x) \tag{9}$$

where ϕ is the coefficient of variation, CRI_i^t is the comprehensive risk index of the current particle (see the above definition), and $f(x)$ represents the Laplace distribution. This mechanism ensures that particles in high-risk areas have greater variation potential, which helps fully explore the solution space. Therefore, combined with Chapter 1, the overall algorithm modeling is shown in Figure 1.

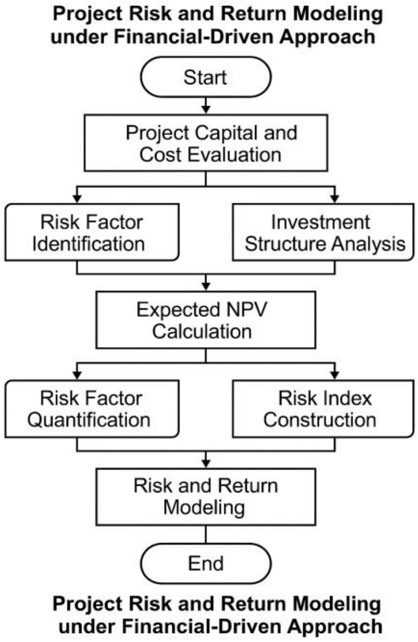

Figure 1. Project risk and return modeling based on financially driven approach

EXPERIMENTAL DESIGN AND DATA ANALYSIS

Experimental Data Sources

This study involved a large textile enterprise in Suzhou City, Jiangsu Province. The enterprise is mainly engaged in the design and production of high-count yarn fabrics, with strong independent research and development capabilities and customized production capabilities. The experimental data cover the cost structure, product returns, risk factor indicators, and related market dynamics in multiple investment cycles from 2020 to 2024. The collected data come from the enterprise's ERP system, monthly financial statements, raw material procurement platform, and the data interface of the National Bureau of Statistics. Table 2 shows the core experimental data of some sampling periods, and the data are given after confidentiality processing. To ensure the consistency of the input data scale, this paper adopts min-max normalization processing for all numerical metrics in Table 2, scaling each feature to the [0, 1] interval to avoid bias in model training caused by different dimensions. In addition, for variables with obvious skewed distribution, logarithmic transformation should be performed first before normalization to ensure a smoother data distribution, which is conducive to improving the convergence speed of the optimization algorithm and the stability of the model.

Table 2. Data of corporate textile design investment experiment (2020–2024)

Year	Total Investment (10,000 CNY)	Annual Revenue (10,000 CNY)	Raw Material Price Index (YoY)	Labor Cost Growth Rate	Exchange Rate Volatility (%)	Equipment Depreciation Rate (%)	Estimated NPV at Year-End (10,000 CNY)
2020	520	1180	102.3	0.038	4.12	11.2	318.5
2021	560	1340	109.8	0.045	5.27	10.7	362.9
2022	600	1280	117.6	0.062	7.41	12.3	331.7
2023	590	1410	114.2	0.059	6.88	11.5	378.2
2024	615	1500	121.9	0.074	9.35	13.1	391.4

Result Analysis

On the basis of the above-mentioned actual data environment, a multiround iterative simulation experiment with the goal of maximizing the NPV and minimizing the CVaR was carried out to verify the convergence performance of the MOPSO in the textile design investment problem. The comparative experiment included four optimization methods. The results are shown in Table 3. The HV and spread values of R-MOPSO increased steadily, demonstrating relatively stable convergence. By contrast, the growth of other algorithms, especially SPEA2 and NSGA-II, gradually slowed down in the later stage. These indicators show that R-MOPSO can effectively avoid particle concentration while maintaining the diversity of the solution set, demonstrating superior optimization ability.

Table 3. Comparison of Pareto frontier performance indicators in the iteration process of each algorithm (unit: 10,000 CNY)

Iteration	NSGA-II (HV)	SPEA2 (HV)	MOPSO-Std (HV)	R-MOPSO (HV)	NSGA-II (Spread)	SPEA2 (Spread)	MOPSO-Std (Spread)	R-MOPSO (Spread)
10	0.113	0.086	0.127	0.141	0.425	0.409	0.466	0.541
20	0.212	0.191	0.191	0.22	0.51	0.471	0.541	0.598
30	0.252	0.239	0.25	0.272	0.561	0.538	0.623	0.65
40	0.28	0.253	0.292	0.355	0.636	0.576	0.654	0.743
50	0.287	0.268	0.317	0.381	0.63	0.594	0.681	0.778
60	0.298	0.276	0.345	0.391	0.667	0.627	0.712	0.819
70	0.301	0.285	0.331	0.38	0.672	0.614	0.706	0.851
80	0.337	0.298	0.349	0.377	0.691	0.628	0.742	0.843
90	0.329	0.295	0.355	0.402	0.702	0.632	0.723	0.864
100	0.334	0.291	0.334	0.394	0.697	0.643	0.759	0.865

Note: HV represents the hypervolume index of the Pareto solution set in the target space, and spread represents the boundary extensibility of the solution set.

The larger the HV, the better. The formula for calculating spread is as follows:

$$Spread = \frac{\sum_{i=1}^{n-1} \left| d_i - \bar{d} \right|}{(n-1)\bar{d}} \tag{10}$$

where d_i represents the distance between adjacent solutions, and $\bar{d}$ represents the average distance. The solution sets generated by different algorithms are displayed in two dimensions to evaluate the comprehensive performance of the MOPSO algorithm in the dimensions of investment return and risk control. The data simulation uses the enterprise data collected in 2020–2024 in the previous article and generates 100 non-dominated solutions through each algorithm. Table 4 extracts some representative non-dominated solution data. R-MOPSO exhibits superior performance in multiple solutions, especially in the region where the NPV is higher than 3.65 million CNY and the CVaR is lower than 920,000 CNY, demonstrating its advantages in terms of revenue and risk control. Compared with NSGA-II and SPEA2, R-MOPSO can maintain a higher NPV while having lower risks. R-MOPSO can offer more stable and high-return investment solutions, which are suitable for the risk control requirements in actual investment decisions.

Table 4. NPV-CVaR performance of representative non-dominated solutions of each algorithm (unit: 10,000 CNY)

Solution ID	Algorithm	NPV (10,000 CNY)	CVaR (10,000 CNY)
1	NSGA-II	322.5	97.3
2		338.1	105.6
3		295.4	85.9
4	SPEA2	334.8	101.2
5		307.2	91.7
6	MOPSO-Std	348.3	98.6
7		362.1	108.4
8		339.9	92.5
9	R-MOPSO	375.6	87.2
10		388.4	91.3
11		365.7	83.9
12		379.1	90.1

The robustness and adaptability of R-MOPSO under risk disturbance conditions were evaluated by using one-at-a-time (OAT) sensitivity analysis to conduct single-factor disturbance experiments on major financial risk factors. This method observes the response changes of the objective function (NPV and CVaR) by changing the value of a certain risk factor while keeping other variables unchanged to quantify the sensitivity of the model to each factor. This experiment selected the following four key risk factors: raw material price index

(RMPI), labor cost growth rate (LCGR), exchange rate volatility (ERV), and equipment depreciation rate (DR). The disturbance range was set to ±15%, with an incremental step of 5%. The target variables are the average NPV and CVaR values in the final non-dominated solution. The experimental results are shown in Table 5. R-MOPSO is the most sensitive to fluctuations in RMPI. When RMPI rises by 15%, NPV decreases by 5.9% and CVaR increases by 9%. In addition, changes in LCGR have a significant impact on NPV and CVaR, whereas exchange rate fluctuations and equipment depreciation have a relatively small impact on the results. R-MOPSO has excellent robustness and adaptability under risk disturbances.

Table 5. One-at-a-time risk factor sensitivity simulation results

Perturbation Level	RMPI (Net Present Value, 10,000 CNY)	RMPI (CVaR, 10,000 CNY)	LCGR (Net Present Value, 10,000 CNY)	LCGR (CVaR, 10,000 CNY)	ERV (Net Present Value, 10,000 CNY)	ERV (CVaR, 10,000 CNY)	DR (Net Present Value, 10,000 CNY)	DR (CVaR, 10,000 CNY)
−0.15	402.7	83.1	391.8	86.4	388.5	87.6	395.2	85.9
−0.1	396.2	85.4	387.1	87.9	384.6	88.3	389.7	87.1
−0.05	389.5	87.2	384.2	88.4	382.3	88.9	386.5	87.8
0% (Baseline)	382.4	89.5	382.4	89.5	382.4	89.5	382.4	89.5
0.05	376.1	91.8	379.3	90.6	380.2	90.3	379.1	90.9
0.1	368.9	94.2	375.7	91.7	376.8	91.6	373.6	92.4
0.15	359.8	97.6	370.4	93.5	371.5	93.9	368.1	94.8

Note: NPV - net present value (unit: 10,000 CNY); CVaR - conditional value at risk (unit: 10,000 CNY); RMPI - raw material price index; LCGR - labor cost growth rate; ERV - exchange rate volatility; DR - depreciation rate

Verification of MOPSO Improvement Mechanism and Cross-Industry Generalization Experiment

A comparative experiment was conducted to verify the advantages of R-MOPSO over traditional PSO and explore the generalization ability of the model in non-textile industries. Additionally, investment data of electronic manufacturing projects were selected for a comparative experiment to evaluate the cross-industry applicability of the model. Both industries adopted the same algorithm parameters to compare the optimization performance of NPV and CVaR. The experimental results are shown in Table 6. The calculation method is as follows:

$$NPV = \frac{382.4 - 345.2}{345.2} \times 100\%$$
$$CVaR = \frac{105.8 - 89.5}{105.8} \times 100\% \tag{11}$$

Table 6. Experimental comparison of R-MOPSO and traditional PSO in the textile and electronics industries

Industry	Algorithm	Average NPV (10,000 CNY)	CVaR (10,000 CNY)	Iterations to Convergence	HV Index
Textile industry	Traditional PSO	345.2	105.8	82	0.326
	R-MOPSO	382.4	89.5	60	0.396
Electronic manufacturing industry	Traditional PSO	412.7	121.3	95	0.309
	R-MOPSO	459.5	98.6	68	0.382

R-MOPSO can effectively increase NPV in both the textile and electronic manufacturing industries, significantly reduce CVaR, and outperform traditional PSO in terms of iterative convergence speed and solution set diversity (HV value), demonstrating good cross-industry generalization ability. R-MOPSO is applicable not only to the textile industry but also to other highly volatile manufacturing fields, providing intelligent support for investment decisions.

CONCLUSIONS

To address the difficulty faced by the traditional single financial evaluation method in simultaneously maximizing returns and controlling risks in the investment decision-making of textile design projects, this study constructed a dual-objective optimization model combining NPV and CVaR and introduced the CRI and the improved R-MOPSO algorithm. The experimental results show that, under the same investment conditions, R-MOPSO increases NPV by approximately 10.8% and reduces CVaR by 15.4% compared with the traditional single-objective method, quantitatively verifying its significant advantages in balancing returns and risks. However, this paper still has certain limitations. For instance, the response mechanisms for extreme events (such as raw material disruptions and significant changes in exchange rate policies) have not yet been embedded in the model. In the future, a dynamic risk identification and real-time learning framework can be introduced to enhance the model’s adaptability. In addition, in light of the actual enterprise scenarios, tools such as forward contracts and option hedging for financial fluctuations such as exchange rate risks should be adopted to reduce risk exposure. At the specific application level, the proposed model was simulated and verified in a high-count yarn investment project of a large textile enterprise in Suzhou. The results show that even when the raw material price fluctuates by ±15%, the model can still maintain an NPV of more than 3.7 million CNY and keep the CVaR within 920,000 CNY, proving that it has strong industrial application potential and promotion value. It also provides a feasible path for intelligent investment decision-making in other highly volatile manufacturing sectors.

Availability of Data and Materials

The datasets used and/or analysed during the current study were available from the corresponding author on reasonable request.

Author Contributions

Jing Nie designed, collected and analyzed the data, and drafted the manuscript. Jing Nie conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Jing Nie participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

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Conflict of Interest

The author declares no conflict of interest.

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