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Financial optimization modeling on asset liability management with weighted goal programming

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A B S T R A C T

Asset Liability Management (ALM) can be overseen using financial ratios derived from financial statements. These statements provide a comprehensive picture of a company's status and necessitate analysis to evaluate performance. This research aims to analyze financial ratios to describe the financial condition, measure business development over time, and evaluate the achievement of the company's objectives. An optimization analysis of financial ratios is performed using the Weighted Goal Programming (WGP) model, which addresses multiple objectives by applying weights based on their priorities. The Best-Worst Method (BWM) was used to determine the priority weights of deviation variables from each financial ratio target. Financial ratios were selected based on their impact on profit using factor analysis. The constructed WGP model aims to minimize deviations in Return on Assets, Operating Ratios, Operating Income Ratio, Total Assets Turnover, and Current Ratio. Computational calculations to solve the WGP model are performed using Python, with pseudocode provided. A case study on a company in the garment and textile sector was conducted and found that the Operating Ratio, Return on Assets, Operating Income Ratio, and Current Ratio still need improvement by developing strategies to achieve the targets. Sensitivity analysis was also employed to assess the resilience of the model in response to alterations in data.

1. Introduction

Asset Liability Management (ALM) can be managed through financial ratios generated from financial statements. Financial statements offer a comprehensive depiction of the company (Pelekh et al., 2020). The company's financial statements are prepared to reflect all activities undertaken by the company. The evaluation of financial statements in achieving the company's targets is an important component, serving as the initial step in determining the company's success strategy. Financial ratios, extracted from financial statements, are key metrics used to evaluate a company's financial health. Ratio analysis is a crucial technique for evaluating a company's financial performance and identifying strengths and weaknesses relative to other companies (Dalessandro, 2013). The main objective of a company is to increase profit (Bărbută-Misu et al., 2019), so it is important to identify the financial ratios that exert the most significant influence on the company's profit by analyzing financial statements. Subsequently, assessing the attainment of these targets provides insight into the company's performance. The results of the evaluation are followed up by determining strategies to increase the company's profit. Research in financial statement analysis generally revolves around two main issues: augmenting fundamental analysis and detecting market inefficiencies within financial statement data (Yohn, 2018). Enhancing fundamental analysis is crucial for enhancing profitability forecasts and achieving more accurate company valuation predictions.

From the problems described, several financial ratios that affect profit can be set as company objectives, making the multi-

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objective goal programming model suitable for application in determining the optimal achievement of targets. It can estimate an organization's financials to optimally utilize available funds for its improvement goals (Lakshmi et al., 2021). The aim of goal programming is to minimize the degree of deviations from the predefined objectives (Hussain & Kim, 2020).

Goal Programming (GP) is a popular method for concurrently addressing multiple objective issues and achieving all objectives (Alarjani & Alam, 2021). In its development, the GP model can be a model with a priority (Preemptive GP) and a weighted (Weighted GP) model. The Preemptive GP model sorts all objective functions based on the priority (Hasbiyati et al., 2023). Meanwhile, the Weighted GP model assigns weights to each deviation variable based on their relevance of importan ce (Banik & Bhattacharya, 2018). Siew et al. (2020) have undertaken the GP optimization approach without weights for managing assets and liabilities in the telecommunications firm Telekom Malaysia Berhad in Malaysia. The study incorporates financial statement parameters focused on maximizing earnings, equities, assets, profits, optimal management elements, and minimizing liabilities. Wijayanti et al. (2023) utilizes GP model without weights to optimize Asset Liability Management (ALM). The five elements of financial statements, namely maximizing assets, minimizing liabilities, maximizing equity, maximizing income, and minimizing financial expenses, are optimized to achieve the company's expected targets. Financial statement analysis is conducted on seven garment companies located in West Java, Indonesia. Tanwar et al. (2020) conducted a study on optimizing assets and liabilities in Indian banks, utilizing a blend of GP models and Analytical Hierarchy Process (AHP). The model devised in this research offers advantages to bank managers in their planning and forecasting endeavors. It is crafted in alignment with the practical goals and constraints of the bank, meticulously addressing the challenges confronted by bank officials. BWM was utilized to assess the relative influence (weight) of each criterion in selecting stocks for the evaluation and ranking of Saudi Arabian banking stocks based on their performance (Alamoudi & Bafail, 2022). Their research results produced a weight order of financial indicators consisting of five criteria, namely profitability, market, valuation, liquidity, and others.

In this study, efforts were made to optimize financial ratios that support company profit by employing a blend of Weighted Goal Programming (WGP) and Best-Worst Method (BWM). This model aims to see the condition of a company's financial statements further and optimize financial statements while obtaining maximum profit with minimal risk or expenditure. BWM is employed in determining weights for the goal function that represents the priorities of each financial ratio objective. BWM is a multi-criteria decision-making approach that uses a pairwise comparison system to improve the consistency and reliability of outcomes. One of the main benefits of the BWM method is its need for fewer pairwise comparisons while achieving higher consistency (Sotoudeh-Anvari et al., 2018). In Rezaei (2015), the comparison between BWM and AHP, the widely used method, across various evaluation criteria showed that BWM excels over AHP. BWM possesses several essential characteristics that render it a robust and compelling method. GP is designed to reduce deviations from the targets of the financial ratios. There has been no research using the WGP model and BWM method to analyze company financial ratios, making this study a novelty in this research. In a study by Tanwar et al., WGP and AHP are used to analyze financial statements, but differ in the decision variables, which do not consider the financial statement values in specific time periods. In determining financial ratio parameters in the model, factor analysis is used to select financial ratios that affect the company's profit. Sensitivity analysis is also conducted to determine how changes in the parameter values of the model affect the optimal solution.

This paper consists of six (6) sections. Section 1 provides the introduction, serving as the background of the research. Meanwhile, Section 2 offers an overview of the review of literature from prior studies which are relevant to the current research. Section 3 explains the theories utilized in the research. Section 4 presents a case study on a company. Section 5 provides the results and discussions, categorized into BWM stages, WGP formulation, solution analysis, and sensitivity analysis. The final section, Section 6, draws the conclusions from the conducted research and provides insights for future studies.

2. Related Work

Peykani et al. (2023) introduced a Linear Programming (LP) model that integrates constraints to attain optimal values for parameters within the balance sheet. This model is consistent with the goals of ALM, taking into account constraints related to the system, balance sheet, and regulations. The design of the model emphasizes adherence to the most practical approach with minimal adjustments and seeks to minimize the dimensions or scale of the balance sheet. Lam et al. (2021) utilized the GP model to enhance the financial statements of shipping companies, targeting objectives such as asset, liability, equity, earning, profit, and optimum management items. Khazri et al. (2018) developed a mathematical model to optimize assets and liabilities for an Iranian bank using multi objective GP. Their research took into account the bank's objectives, as well as structural, ideological, and legal constraints to create an ideal planning model. They employed fuzzy hierarchical analysis to define goals, determine priorities, and establish their order of significance. Alam (2022) has devised and implemented a goal programming methodology to evaluate financial planning, utilizing the annual financial statements of the Saudi Basic Industries Corporation, playing a role in the establishment of a framework for financial planning. Through this research, he outlined specific objectives, including lowering costs, increasing fixed assets, enhancing equity share participation, boosting revenue, raising net profit, and decreasing debt. Hoe et al. (2021) conducted a study aiming to enhance the financial management of publicly listed electronic companies. The goals encompassed the maximization of assets, minimization of liabilities, maximization of equity, profit, and earnings, as well as the optimization of key management aspects, by employing a GP model. In study by Emin Öcal et al. (2007), factor analysis was used on financial data from Turkish construction companies over a five-year period to identify financial indicators that can analyze the industry's financial trends. They identified five independent factors which are, liquidity, capital structure and profitability, activity efficiency, profit margin and growth, and assets structure, as being responsive to economic changes in the country. Avakh Darestani et al. (2022) introduced a model aimed at choosing the optimal maintenance strategy for a manufacturing company in Iran. They sought to combine two methods, GP and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), to prioritize maintenance strategies. Initially, they identified all factors that impact maintenance and used the BWM to assess the relative importance of each factor. A summary of several relevant articles is presented in Table 1.

Table 1
Literature Review

References	Model	Financial Statement Analysis	Bank	BWM	Factor Analysis
Siew et al. (2020)	GP	✓	×	×	×
Wijayanti et al. (2023)	GP	✓	×	×	×
Tanwar et al. (2020)	WGP	✓	✓	×	×
Peykani et al. (2023)	LP	✓	✓	×	×
Lam et al. (2021)	GP	✓	×	×	×
Khazri et al. (2018)	WGP	✓	✓	×	×
Alam (2022)	GP	✓	×	×	×
Hoe et al. (2021)	GP	✓	×	×	×
Emin Öcal et al. (2007)	-	✓	×	×	✓
Alamoudi & Bafail (2022)	-	✓	✓	✓	×
Avakh Darestani et al. (2022)	WGP	×	×	✓	×
This research	WGP	✓	×	✓	✓

From the literature discussed, GP can be used to analyze financial statements in both banking and non-banking institutions. Most literature utilizes the AHP method for determining weights in the GP model. None of the relevant studies have used factor analysis in determining the parameters in the model. In this study, factor analysis is performed on the financial ratios that affect profit. These financial ratios are then used as parameters in the WGP model. Furthermore, the literature reviewed has not yet utilized the GP and BWM models in the analysis of a company's financial ratios, making this study innovative in its approach.

3. Materials and Methods

3.1 Asset Liability Management (ALM)

Asset Liability Management (ALM) is a process of planning, organizing, and monitoring that functions as an integrated control of assets and liabilities, which are interrelated in the effort to achieve company profits (Hastings, 2009). ALM refers to the process when a company tries to optimize assets and liabilities to achieve the desired levels of profit and liabilities (Abdollahi, 2020). The purpose of ALM is to ensure proper coordination between assets and liabilities to reach financial targets at a certain level of risk and within predetermined constraints (Bhat, 2020). Asset liability management can be managed through financial ratios generated from financial statements. Financial statements serve as a diagnostic tool for assessing financing, investment, and operational activities within a company (Hasanaj & Kuqi, 2019). Financial reports are generally prepared in annual periods, but some institutions compile financial reports in monthly, quarterly, or semester periods (Mashkour, 2020). A company owns assets to conduct its business or its economic resources, which include costs due to previous transactions and benefits in the future. Assets can be categorized into various types, including current assets, long-term investments, fixed assets, intangible assets, and other assets. Operating Ratio is an economic sacrifice the company must make in the future. This sacrifice for the future occurs due to commercial activities in the previous period (Xu et al., 2020). Operating ratios are categorized as short-term or long-term on the balance sheet, depending on the length of the contract with the individual or agency with whom the billing is agreed. Long-term agreements can emerge as a balanced result (Roy et al., 2022). Equity is the obligation of a business entity to its owner. Equity is obtained by subtracting the total operating ratio from the total assets. In addition, equity represents the residual interest in the owner’s business (Otaka, 2020). Revenue is the income earned by a company over a certain period (Jayathilaka, 2020). Financial expenses (expenses) are economic sacrifices incurred in one accounting period (Karagul, 2018).

The nine (9) financial ratios used in this study are: Return on Asset (ROA) is a measure indicating a company's capacity to generate earnings, encompassing its entire range of operations (Ciptawan & Frandjaja, 2022). Operating Ratio (OR) measures operating costs per rupiah of sales; the smaller the ratio, the better the performance (Lumbantobing et al., 2020). Operating Income Ratio (OIR) describes what is commonly referred to as pure profit received for every rupiah from the sales made by a company (Harinurdin, 2022). Total Asset Turnover (TATO) is an activity index (efficiency index) gauges a company's capacity to generate income from its overall assets by comparing net revenues to the average total assets (Aidi et al., 2022). Current Ratio (CR) assesses a company's working capital position by comparing total current assets to current liabilities, indicating if current assets significantly exceed short-term debts. (Ciptawan & Frandjaja, 2022). Debt to Total Asset Ratio (DAR) is employed to assess a company's capability to fulfill its long-term financial commitments (Lumbantobing et al., 2020). Debt to Equity Ratio (DER) is a financial metric that evaluates the proportion of debt relative to equity (Harinurdin, 2022). Working Capital to Total Asset (WCTA) is a net assessment comparing a company's current assets to its working capital. WCTA represents the disparity between current assets and current liabilities (Aidi et al., 2022). Company Size reflects the magnitude of a company's total assets; the greater the assets, the larger the company's size. The Company Size metric is determined by applying the natural logarithm formula to total assets (Azaro et al., 2020).

3.2 Factor Analysis

Factor analysis is a statistical method based on the correlation analysis of multiple variables. Its goal is to condense numerous variables into a smaller set of underlying factors that these variables measure. This is achieved by clustering variables that are correlated with one another. The process generally involves four main stages (Emin Öcal et al., 2007).

1. Initial Solution: The initial solution involves selecting variables and creating an inter-correlation matrix that includes all of them. This matrix, which is a $k \times k$ array (where k denotes the number of variables), contains the correlation coefficients for each pair of variables. When variables have a weak correlation, it's improbable that they share a common factor. Therefore, their correlation is not analyzed further. The Kaiser-Meyer-Olkin (KMO) test and Bartlett's Test of Sphericity are used to assess the suitability of variables for factor analysis. A KMO value above 0.5 is required for satisfactory analysis. Moreover, Bartlett's Test of Sphericity should produce a significant value below 0.001, this indicates that the correlation matrix is not an identity matrix.
2. Factors Extraction: Extracting the factors concerns determining the appropriate number of components from the correlation matrix based on the initial solution. Initially, each variable is standardized to have a mean of 0 and a standard deviation of 1. Consequently, a factor necessitates an eigenvalue of at least 1 for extraction.
3. Factors Rotation: Rotating the factors is essential to tackle scenarios where one or more variables may load similarly on multiple factors, leading to ambiguity in factor interpretation. Factor rotation enhances the clarity of relationships between variables and factors. Among the various methods, Varimax is the most commonly used.
4. Results Interpretation: The last stage involves analyzing the factor loadings of each variable to derive results. The factor loadings need to be analyzed to interpret the underlying meaning of each factor. Subsequently, each factor is assigned an appropriate name (labeling) based on the variables with high loadings on that factor.

3.3. Best-Worst Method (BWM)

The Best-Worst Method (BWM) is a new multi-criteria decision-making (MCDM) method proposed by Rezaei (2015). This method derives weights based on pairwise comparisons between the best and worst criteria/alternatives with other criteria/alternatives. A consistency ratio is also developed to verify the reliability of the results. In this study, BWM was employed to determine the weights of each predetermined financial ratio through factor analysis. These weights were subsequently utilized in the WGP model. Here are the 6 steps in the BWM method (Rezaei, 2015).

1. Identify the set of evaluation criteria $\{C_1, C_2, C_n\}$ as determined by decision-makers.
2. Identify the best (most important or influential) and worst (least important or influential) criteria as selected by decision-makers.
3. Assign preference values ranging from $\{1,2,3, \dots, 9\}$, can be seen in Table 2, to indicate the preference of the best criterion over each of the other criteria. Formulate the Best-to-Others vector as $A_{BO} = (a_{B1}, a_{B2}, \dots, a_{Bn})$, where a_{Bj} represents the preference of the best criterion C_B over criterion $C_j, j = 1, \dots, n$.

Table 2
Preference Value for BWM (Alamoudi & Bafail, 2022)

Value	Verbal Assessment
1	Equally Important
3	A little more important than others
5	Considerably more important than others
7	Highly important compared to others
9	Of utmost importance than others
2,4,6,8	The magnitude between two consecutive ratings

4. Assign preference values ranging from $\{1,2,3, \dots, 9\}$ to indicate the preference of each criterion over the worst criterion. Formulate the others-to-worst vector as $A_{OW} = (a_{1W}, a_{2W}, \dots, a_{nW})$,, where a_{jW} represents the preference of criterion C_j over the worst criterion $C_W, j = 1, \dots, n$.
5. Calculate the weights W_1^*, W_2^*, W_n^* using the specified model:

$$\underbrace{Min\ Max}_{j} \left\{ \left| \frac{W_B}{W_j} - a_{BJ} \right|, \left| \frac{W_j}{W_W} - a_{JW} \right| \right\} \quad (1)$$

s.t

$$\sum_{j=1}^{n} W_J = 1, W_J \geq 0, for\ all\ j$$

Model (1) can be transformed into Model (2) in the following way:

$$\begin{aligned} & min\ \xi \\ & \text{s.t.} \\ & \left|\frac{W_B}{W_j} - a_{BJ}\right| \leq \xi, for\ all\ j \\ & \left|\frac{W_j}{W_W} - a_{JW}\right| \leq \xi, for\ all\ j \\ & \sum_{j=1}^{n} W_J = 1, W_J \geq 0, for\ all\ j \end{aligned} \tag{2}$$

By solving Model (2), the optimal weights W_1^*, W_2^*, W_n^* and ξ are obtained.

6. Assess the consistency ratio (CR) according to the method outlined in Rezaei (2015). CR can be calculated using the following formula.

$$CR = \frac{\xi}{CI} \tag{3}$$

The consistency index (CI) is presented in Table 3.

Table 3
Consistency Index

A_{BW}	1	2	3	4	**5**	6	7	8	9
CI	0	0.44	1	1.63	2.3	3	3.73	4.47	5.23

A consistency ratio close to 0 indicates higher consistency in the evaluation matrix, while values closer to 1 suggest lower consistency. As previously noted, the outcome of BWM is always consistent. However, Rezaei (2015) highlighted that in AHP, the CR is utilized to validate the comparisons, whereas in BWM, the CR is employed to assess the degree of reliability.

3.4 Goal Programming

Goal programming (GP) is a decision-making method designed to help decision-makers choose options that most effectively meet their objectives to the highest possible degree (Goh, 2019). The fundamental method in GP involves establishing a target quantified for each goal, formulating an objective function formula for each goal, and then seeking a solution to minimize the deviation between the objective function and each specific goal. Thus, GP or multi-objective optimization is one of the mathematical models used as a foundation for intricate decision-making to analyze and solve problems that involve many goals so that alternative solutions to optimal problem-solving are obtained (Omrani et al., 2019). Saaty, in 1987, presented the AHP (Kara, 2019) to deal with problems with several criteria and some alternatives. This method makes it possible to divide and organize problems and sort them hierarchically graphically. Through pairwise comparisons, the hierarchy and influence of fractions are established. They make up the problem and show contrasting value reflections using fundamental scales and quantitative and qualitative criteria. WGP is employed to identify the optimal solution, aiming to minimize the total deviations between goals; weighted optimality criteria enable an experimenter to articulate hierarchical preferences across estimable functions using a succinct weighting system (Allen-Moyer & Stallrich, 2022). WGP is designed for problems where all goals are quite important, where modest differences in importance are measured by assigning weights to the goals. A decision-making can set relative weights for undesired deviation of the goals, which reflect the decision-maker's preferences between different goals. For example, Ho (2019) presents the formulation for WGP as follows:

$$\begin{aligned} & min(\alpha_i d_i^+ + \beta_i d_i^-) \\ & f_i(x) - d_i^+ + d_i^- = g_i \\ & d_i^+, d_i^- \geq 0, \\ & i = 1,2,\ldots,m, x \in F \end{aligned} \tag{4}$$

where F is the set of feasible regions, the weights α, β are assigned to deviation d_i^+, d_i^- in their respective objective functions. x is variable $x_1, x_2, \ldots, x_n$ the function $f(x)$ is linear with respect to $x_1, x_2, \ldots, x_n$, d_i^+, d_i^- each is an advantage and disadvantage of achieving the target. The achievement of the deviation variable is defined in Table 4.

Table 4
Achievement Deviation Variable

Minimize	Goal	If Goal Achieved
d_i^-	Minimize under achievement	$d_i^- = 0, d_i^+ \geq 0$
d_i^+	Minimize over achievement	$d_i^+ = 0, d_i^- \geq 0$
$d_i^- + d_i^+$	Minimize both under and over achievement	$d_i^- = 0, d_i^+ = 0$

Table 4 demonstrates that achieving the objective of minimizing the negative deviation variable is realized when the deviation variable equals zero, or when the positive deviation variable's value exceeds zero. The goal of the positive deviation variable is achieved if the positive variable of the i-th goal equals zero or the negative deviation variable is greater than zero. The goal of adding the positive and negative variables to objective function is accomplished if the negative and positive deviation variables are equal to zero (Alam, 2022; Prasad & Reddy, 2018).

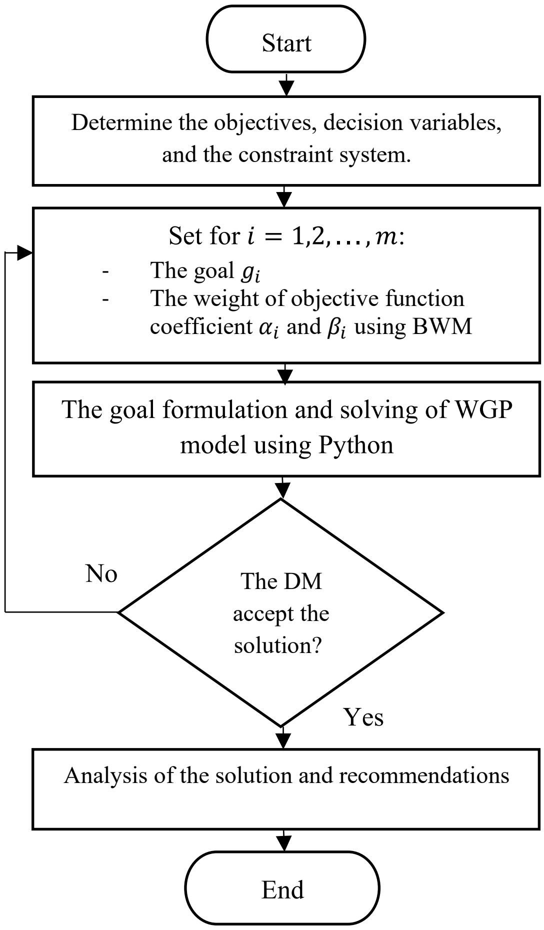

Fig. 1. Flowchart of the WGP Algorithm

Fig. 1 presents the steps for formulating the GP problem, beginning with determining the decision variables, the objective function, the objective function with top priority, the weighting, the achievement function, and completing the GP model (Omrani et al., 2019). After obtaining a solution model, the decision-maker (DM) determines whether the results obtained are acceptable or not. If they are acceptable, the process continues with analyzing the solution and providing recommendations. If not, the process returns to goal setting and weighting. The weighting factor assigned to a specific goal serves dual purposes, encompassing both 'normalization' and 'evaluation'. The ‘normalization’ role drives all deviations to a uniform scale according to their degree of closeness, whereas the ‘evaluation’ role reflects the preference structure of DM (Ho, 2019).

3.5 Sensitivity Analysis

Sensitivity analysis generally examines how variations in a model's input data influence its output data (Schulte & Nissen, 2023). Inputs, commonly termed as "factors" in sensitivity analysis, encompass model parameters, forcing variables, boundary and initial conditions, structural configuration choices, assumptions, and constraints. Outputs consist of functions derived from model responses, varying across spatial and temporal domains, encompassing objective functions such as production or cost functions in cost-benefit analysis, or error functions in model calibration.

Sensitivity analysis primarily focuses on assessing how variations in constraints and other model parameters impact the optimal solution. It serves several key purposes in systems analysis and modeling (Razavi et al., 2021): (a) in scientific exploration, sensitivity analysis is employed to investigate causal connections and understand the impact of different processes, hypotheses, parameters, scales, and their interactions on a system, b) dimensionality reduction aims to identify insignificant factors within a system that may be redundant and can be addressed or eliminated in subsequent analyses, (c) data worth assessment is used to pinpoint the processes, parameters, and scales primarily influencing a system, identifying areas where acquiring new data can most effectively reduce targeted uncertainty, and (d) decision support involves evaluating the sensitivity of expected outcomes to various decision options, constraints, assumptions, and uncertainties.

4. Case Study

Data utilized in this study was gathered and subjected to selection for use in the analysis process. The research utilized secondary data obtained from the official website of the Indonesia Stock Exchange. The selection of companies followed a purposive sampling method, focusing on garment companies located in the West Java region with comprehensive financial records spanning from 2019 to 2021. Based on these criteria, financial statements from 12 garment companies in the West Java region for the years 2019-2021 were obtained. The financial ratios used in this study are Total Asset Turnover, Current Ratio, Working Capital to Total Assets, Debt to Assets Ratio, Debt to Equity Ratio, Company Size, Return on Assets, Operating Ratio, Operating Income Ratio. Figure 2 below presents the data from 12 garment companies.

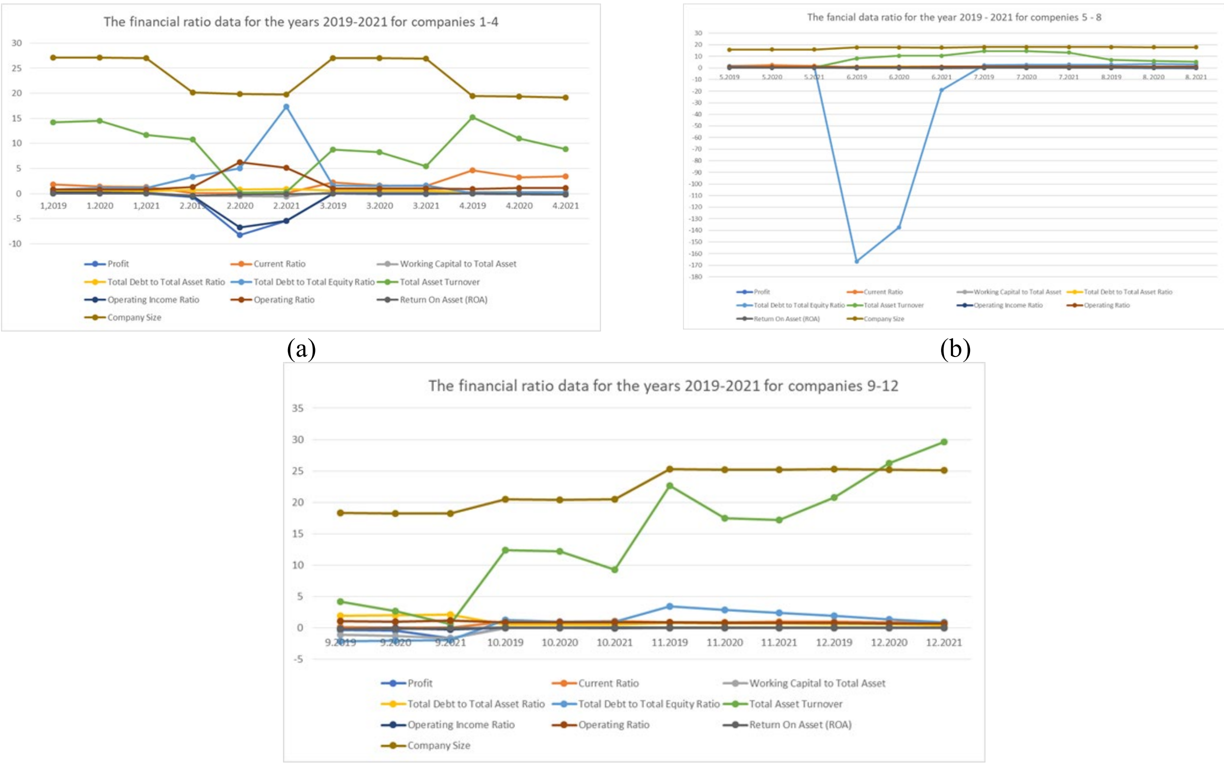

Fig. 2. The financial ratio data for the years 2019-2021 for companies (a) 1-4, (b) 5-8, and (c) 9-12.

Factor analysis on financial ratios that impact the company's profit was used to analyze the data. The following are the results of the factor analysis.

4.1. Initial Solution

Data feasibility testing and variable correlation are assessed through the KMO (Kaiser-Meyer-Olkin) test and Bartlett's test before commencing factor analysis. The outcomes of these tests are presented in Table 5.

Table 5
KMO and Barlett's Test

KMO and Barlett's Test		Value
KMO Measure of Sampling Adequacy		0.522
Barlett's Test	Chi-square	372.284
	Df	36
	Sig.	0

Table 5 shows that the KMO value for this research data is 0.522, which is greater than 0.05. Additionally, Bartlett's test shows a value of 372.284, which is greater than 36 (df), and the significance value (0.0001) is less than the significance level (0.05). Based on these results, factor analysis is deemed appropriate for analyzing the data in the form of a correlation matrix. In the anti-image matrix values, the results of the MSA (Measure of Sampling Adequacy) test are shown in Table 6 as follows.

Table 6
MSA Values in the Anti-Image Correlation Matrix

	CRR	WCTA	DAR	DER	TATO	OIR	OR	ROA	CS
CR	0.703[a]	0.213	0.417	-0.130	-0.017	-0.356	-0.335	0.082	-0.070
WCTA	0.213	0.574[a]	0.944	0.040	0.249	-0.237	-0.205	-0.359	-0.355
DAR	0.417	0.944	0.532[a]	0.041	0.327	-0.201	-0.167	-0.300	-0.320
DER	-0.130	0.040	0.041	0.647[a]	0.083	0.049	0.045	-0.014	-0.220
TATO	-0.017	0.249	0.327	0.083	0.399[a]	0.691	0.714	-0.321	-0.293
OIR	-0.356	-0.237	-0.201	0.049	0.691	0.458[a]	0.999	-0.176	0.158
OR	-0.335	-0.205	-0.167	0.045	0.714	0.999	0.465[a]	-0.177	0.143
ROA	0.082	-0.359	-0.300	-0.014	-0.321	-0.176	-0.177	0.619[a]	0.059
CS	-0.070	-0.355	-0.320	-0.220	-0.293	0.158	0.143	0.059	0.569[a]

Anti-image matrices are valuable tools for identifying and selecting variables appropriate for inclusion in factor analysis. In the anti-image correlation section, Table 5 includes the letter code (a), which signifies the MSA. It is noted that all variables meet the MSA value, thus these variables can be continued for factor analysis.

4.2. Extraction Factor

Eigenvalues are a measure of the amount of variance accounted for by a factor. Thus, the eigenvalues are useful in determining the number of principal factors need to be extracted. An eigenvalue greater than 1 is considered to indicate the presence of an interpretable factor. The count of eigenvalues which are greater than 1 indicates the number of principal factors incorporated (the number of factors to be retained).

Table 7
Extraction factor

Component	Initial Eigenvalues		
	Total	%of Variance	Cumulative %
CR	3.456	38.397	38.397
WCTA	1.869	20.770	59.167
DAR	1.368	15.196	74.363
DER	1.277	9.744	84.107
TATO	1.025	8.061	92.168
OIR	0.400	4.443	96.611
OR	0.283	3.141	99.752
ROA	0.022	0.243	99.995
CS	0.010	0.005	100.000

Table 7 presents the eigenvalues and the percentage of total and cumulative variance of each variable completely using the Principal Component Method. Table 7 shows five extracted factors with eigenvalues greater than one. Sequentially, these factors have eigenvalues of 3.456, 1.869, 1.368, 1.277, and 1.025. For the total variance in percentage, the variance for factor 1 is 38.397%, for factor 2 is 20.770%, and for factor 3 is 15.196%. The percentage variance is obtained by multiplying the ratio of the eigenvalue of each factor by the total original variables and then by 100%. Based on the cumulative percentage variance, the five extracted factors explain a variance of $38.397\% + 20.770\% + 15.196\% + 9.744\% + 8.061\% = 92.168\%$. This cumulative variance exceeds the minimum threshold of 60%, ensuring that these five factors are considered representative of the six original variables. The number of principal factors is also determined by the pattern of eigenvalue decline shown in a scree plot. The scree plot is presented in Fig. 3.

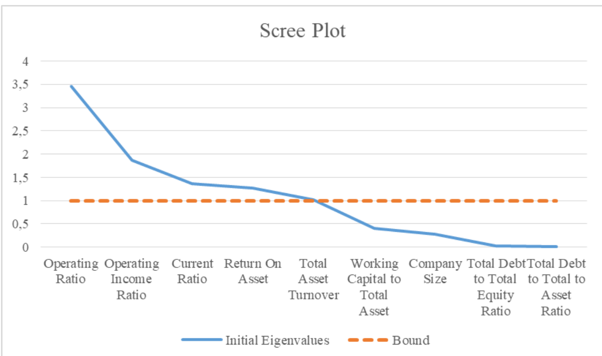

Fig. 3. Scree Plot

The scree plot in Fig. 3 illustrates the eigenvalues of all initially considered factors for extraction. It helps determine the number of factors to be included. The number of selected factors corresponds to those with eigenvalues equal to or greater than one. In Fig. 3, there is a sharp drop in eigenvalue after the first component. The second and third components show a gradual decline but remain above one. Beyond the third component, eigenvalues fall below one. Therefore, the first three factors adequately represent the nine original variables.

Table 8
Communalities value

Component	Extraction
OR	0.924
OIR	0.920
CR	0.913
ROA	0.910
TATO	0.791
WCTA	0.791
CS	0.739
DER	0.389
DAR	0.317

After the extracted factors are obtained, the communalities are determined, which differ from the variance explained by the extracted factors. The communalities of the six analyzed variables, in descending order, are detailed in Table 8. Table 8 shows the communalities of the nine analyzed variables in descending order. The variable with the highest communality value is "Operating Ratio" with a value of 0.924, meaning that about 92.4% of the variance in the first variable can be explained by the formed factors. Similarly, this applies to the variables with the second, third, and subsequent highest communalities. The larger the communality value of a variable, the stronger its relationship with the formed factors.

4.3. Rotation Factor

Factor loadings can be seen from the correlation values between each factor and variable. Factor loadings provide information about which variables are significantly correlated with a particular factor. Table 9 shows the factor loadings of the factors.

Table 9
Factor Loadings

	Component		
	1	2	3
CR	0.663	0.382	-0.452
WCTA	0.833	0.421	-0.194
DAR	-0.746	-0.584	0.126
DER	0.102	0.462	0.304
TATO	0.598	-0.155	0.598
OIR	0.674	-0.658	-0.183
OR	-0.683	0.663	0.135
ROA	0.548	-0.280	0.105
CS	0.421	0.129	0.773

Table 9 explains the unrotated factor loadings. While the relationships between factors and individual variables are evident, there are overlapping factors that are difficult to identify and interpret. If the loading of the first component is at least $0.5 (\geq 0.5)$, the variable is considered a member of the formed factor. However, if the loading is less than $0.5 (< 0.5)$, the variable is not a member of that factor. If a measurement variable has loadings of ≥ 0.5 across multiple factors, a factor rotation using the varimax method should be performed to ensure that no variable has a loading of ≥ 0.5 on two or more factors. The rotated factor loadings can be shown in Table 10. From Table 10, the Current Ratio with a weight of 0.867 falls into Factor 1, while the WCTA, DAR, OIR, and ROA fall into Factor 2. The DER, TATO, OR, and CS fall into Factor 3. After identifying the variables that form based on their significant weight values within the same factor, the final step is factor interpretation. A total of 9 statement variables were reduced using factor analysis into 3 main factors. Each factor is named according to the variables that comprise it. Each factor consists of 2 to 4 variables

Table 10
Rotated Factor Loadings

	Component		
	1	2	3
CR	0.867	0.168	-0.100
WCTA	0.413	0.408	0.308
DAR	-0.921	-0.007	-0.254
DER	0.234	-0.349	0.374
TATO	0.090	0.386	0.762
OIR	0.140	0.949	0.021
OR	-0.125	-0.951	-0.068
ROA	0.170	0.531	0.280
CS	0.372	0.389	0.486

Considering the results of factor analysis, only the variables Total Asset Turn Over, Current Ratio, Return on Assets, Operating Ratio, Operating Income Ratio have an effect on Company Profits. So, these financial ratios are used in formulating weighted goal programming. In the application of WGP model, financial report from a firm included in the Indonesia Stock Exchange, was utilized for the years 2019 to 2021, then the value of Return on Assets (ROA), Operating Ratio (OR), Operating Income Ratio (OIR), Total Asset Turnover (TATO), and Current Ratio (CR) are calculated as in Table 11.

Table 11
Financial Report Data

Finance Ratio	2019	2020	2021
ROA	0.023	0.025	0.031
OR	0.867	0.828	0.828
OIR	0.026	0.053	0.046
TATO	22.688	17.505	17.223
CR	0.904	0.870	0.982

5. Results and Discussion

5.1. Best-Worst Method (BWM)

The financial ratios obtained through factor analysis are then weighted using the BWM. The criteria for the five financial ratios are defined as $C_1 = ROA, C_2 = OR, C_3 = OIR, C_4 = TATO, C_5 = CR$. Through a questionnaire filled out by experts, it was decided that (C_3) is the best criterion and TATO (C_4) is the worst criterion. Table 12 and Table 13 below provide values ranging from 1 to 9, according to Table 2, based on the opinions of the experts.

Table 12
Pairwise comparison vector for the best criterion

Criteria	C_1	C_2	C_3	C_4	C_5
Best criterion: C_3	3	3	1	6	5

Table 13
Pairwise comparison vector for the worst criterion

Criteria	Worst criterion: C_4
C_1	3
C_2	3
C_3	6
C_4	1
C_5	2

Table 12 presents the pairwise comparison vector for the best criteria. The values in the table indicate the correlations between the best criteria, such as OIR, and other criteria based on the values in Table 2. Meanwhile, Table 13 represents the pairwise comparison vector showing the correlations between other criteria and the worst criterion, TATO. These pairwise comparison values are utilized in Model (2) to produce weight values as shown in Table 14 below.

Table 14
Weights of Goals

Goal	Weight
ROA	0.173
OR	0.173
OIR	0.477
TATO	0.072
CR	0.104

Table 14 presents the weights assigned to different goals or criteria, indicating their relative importance in decision-making. Each goal represents a distinct aspect relevant to the decision at hand. Meanwhile, the weight contains decimal values ranging from 0 to 1, indicating the assigned weights for each goal. These weights reflect the proportionate significance of each goal about the overall decision. Higher weight values indicate greater importance. These weights provide a quantitative measure of the relative importance of each goal, aiding decision-makers in prioritizing and evaluating different criteria effectively.

After obtaining the weight values, a consistency check is performed on the experts' opinions using formula (3), resulting in a CR value of 0.043. This value approaches 0, indicating that the obtained weights are consistent and reliable, then the weight values obtained in Table 14 can be included in the next WGP model.

5.2. Goal Programming Formulation

The data is compiled as a Weighted Goal Programming model used in determining the order of priority goals in the Company's Asset Liability Management (ALM). The decision variables used are x_1, which is the value of the financial statements in 2019, x_2 is the value of the financial statements in 2020, x_3 is the value of the financial statements in 2021, d_i^- is the negative deviation value from the i-th goal or target, and d_i^+ is the positive deviation value from the i-th goal or target. The first constraint function is the goal constraint function, which calculates the values of the financial ratios used in this study. The determination of the value of the financial ratios is obtained from the calculation of financial ratios from the company's financial statements in the period 2019-2021. The financial statement data fluctuates, so the results of the calculation of financial ratios are taken on average from the data for the year concerned. The target values of each financial ratio are determined through benchmarking with 12 other garment companies over three years, which is determined as the righthand side (RHS) constant in the constraint function. The GP model to optimize the financial ratios consists of the objective function in equation (5), constraint functions (6), (7), (8), (9), and (10), as well as non-negativity constraints (11) as follows.

$$\min Z = 0.173d_1^- + 0.173d_2^+ + 0.477d_3^- + 0.072d_4^- + 0.104d_5^- \tag{5}$$
$$0.022x_1 + 0.025x_2 + 0.031x_3 + d_1^- - d_1^+ = 0.140 \tag{6}$$
$$0.867x_1 + 0.828x_2 + 0.828x_3 + d_2^- - d_2^+ = 2.230 \tag{7}$$
$$0.026x_1 + 0.053x_2 + 0.046x_3 + d_3^- - d_3^+ = 0.637 \tag{8}$$
$$22.688x_1 + 17.505x_2 + 17.223x_3 + d_4^- - d_4^+ = 76.657 \tag{9}$$
$$0.904x_1 + 0.870x_2 + 0.982x_3 + d_5^- - d_5^+ = 11.428 \tag{10}$$
$$x_1, x_2, x_3, d_i^-, d_i^+ \geq 0, \forall i = 1,2,3,4,5 \tag{11}$$

The objective function in the model (5) aims to minimize the deviation variables corresponding to the goals of the constraint functions. The weights of each deviation variable are determined based on the results of calculations using BWM. Constraint (6) maximizes the Return on Assets by minimizing deviations below the target, ensuring that the negative deviation is zero($d_1^- = 0$). Constraint (7) aims to minimize the Operating Ratio by minimizing deviations above the target, ensuring that the positive deviation is zero($d_2^+ = 0$). Meanwhile, Constraint (8) is to maximize the Operating Income Ratio by minimizing deviations below the target, ensuring that the negative deviation is zero ($d_3^- = 0$). Constraint (9) maximizes the Total Asset Turnover by minimizing deviations below the target, ensuring that the negative deviation is zero($d_4^- = 0$) whereas Constraint (10) maximizes the Current Ratio by minimizing deviations below the target, ensuring that the negative deviation is zero($d_5^- = 0$).

5.3. Computational Method Written in the Python Programming Language

The pseudo code of the Python algorithm utilized to solve the WGP model is presented as follows:

First Algorithm : Addressing the Weigh Goal Programming	
Begin	
Step 1:	Specify the problem with the "LpMinimize" syntax and define the variables using the "LpVariable" syntax.
Step 2:	Import the required library (Pulp) to initialize the model.
Step 3:	Define the decision variables.
Step 4:	Create the optimization model.
Step 5:	Set the objective function to minimize the weighted sum of the deviation variables and add the constraints.
Step 6:	Solve the optimization problem.
Step 7:	Display the outcomes using the syntax below:
	For each $i \in 3$ do
	Print x_i
	For each $i \in 10$ do
	Print x_i
	End For
	End For
End	

Besides the algorithm for solving the WGP model, Python is also used in sensitivity analysis. The Python algorithm for sensitivity analysis is as follows.

Second Algorithm : Sensitivity Analysis for Weigh Goal Programming

Begin

Step 1: Conduct sensitivity analysis for the optimization issue.
Step 2: Determine the sensitivity of the objective function coefficients and right-hand side constants.
Step 3: Identify the range of values for which the current solution remains optimal.
Step 4: Print sensitivity analysis results.
Step 5: Display the outcomes using the syntax below:

For each constraint $i \in 3$ do
  Print c_i
  For each constraint right-hand side constant j $\in 10$ do
    Print b_j
  End For
End For

End

5.4. Numerical Simulation

The Weight Goal Programming model that has been formulated is solved using Python. The results obtained from the WGP model optimization indicate that the optimal solution of objective function is 1.194. The value of the objective function indicates the presence of deviation from the optimized financial ratio. The values of decision variables in the WGP model are $x_3 = 4.451$ and otherwise is zero. The optimal solution shows that the financial statement value in the 3rd year is 4.451, which supports the achievement of the financial ratio target. The deviation variables value of the goal constraints for each financial ratio are presented in Table 15 and Fig. 4.

Table 15
Deviation Variables

Goal Constraint	Negative Deviation Variables	Positive Deviation Variables
Maximizing ROA	0.002	0
Minimizing OR	0	1.465
Maximizing OIR	0.432	0
Maximizing TATO	0	0
Maximizing CR	7.057	0

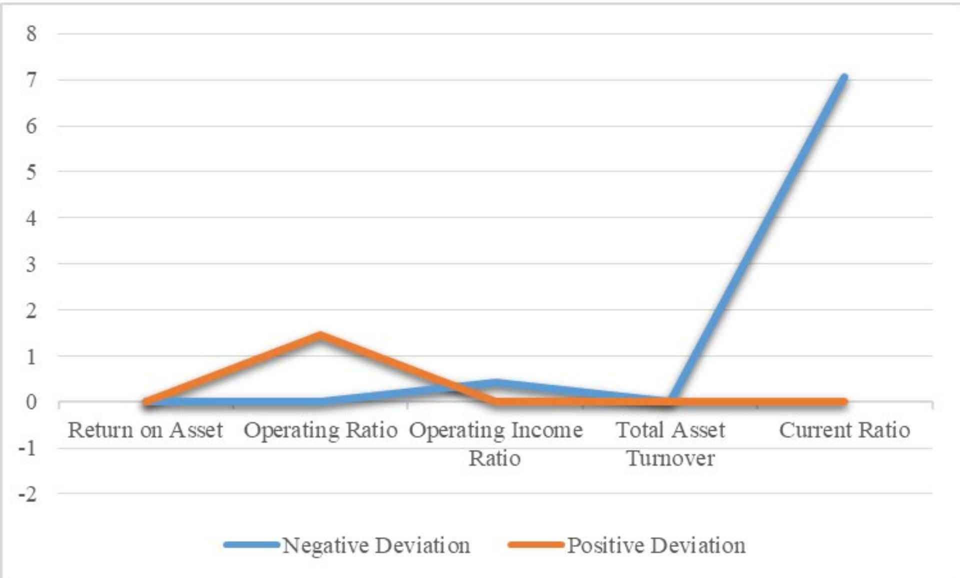

Fig. 4. Deviation Variables

Table 14 and Figure 4 shows that efforts to achieve all objectives through the constituent elements at the same time obtain the optimal solution combination, namely

1. The target of maximizing the Return on Asset (ROA) was not achieved because there was a negative deviation value from the total number of the Company's Return on Asset, i.e. $d_1^- = 0.002$.
2. The target of minimizing the Operating Ratio (OR) was not achieved because there was a positive deviation value from the total number of the Company's Operating Ratio, i.e. $d_2^+ = 1.465$.
3. The target of maximizing Operating Income Ratio (OIR) was not achieved because there was a negative deviation value from the Company's total Operating Income Ratio, i.e. $d_3^- = 0.433$.

4. The target of maximizing Total Asset Turnover (TATO) was achieved because there was no negative deviation from the total amount of the Company's Total Asset Turn Over i.e. $d_4^- = 0$.
5. The target of maximizing Current Ratio (CR) was not achieved because there was a negative deviation value from the total number of the Company's Current Ratio, i.e., $d_5^- = 7.057$.
   The goal achievement can be seen in Table 16.

Table 16
Goal Achievement

Goal Constrains	Goal	Output Value		Goal Percentage
ROA	0.140	$d_1^- = 0.002$	$d_1^+ = 0$	98,57%
OR	2.230	$d_2^- = 0$	$d_2^+ = 1.465$	60,35%
OIR	0.637	$d_3^- = 0.432$	$d_3^+ = 0$	32,18%
TATO	76.657	$d_4^- = 0$	$d_4^+ = 0$	100,00%
CR	11.428	$d_5^- = 7.057$	$d_5^+ = 0$	38,25%

Out of the five established objectives, only TATO has been achieved by the WGP model. However, there are three objectives that have not been achieved, namely the objective of maximizing the ROA, minimizing the OR, maximizing the OIR, and maximizing the CR. Goal achievement is indicated by the Goal Values that the company can achieved based on the WGP model's ideal solution.

In the case of maximizing the goal of -TATO, the negative deviation variable has a value of zero, indicating that the objective constraint of this model is equal to or greater than the established Goal Value. The obtained TATO remains at IDR 76.657 billion due to $d_4^+ = 0$.

For the objectives of maximizing the ROA, the OIR, and the CR, the values of the negative deviation variables are 0.002, 0.432, and 7.057, respectively and the positive deviation variable of the OR is 1.465. These values indicate that the achieved targets are not met because they deviate below the established targets by IDR 0.002 billion for the ROA, IDR 0.432 billion for the OIR, IDR 7.057 billion for the CR, and deviate above the target by IDR 1.465 billion for the OR.

The research found that ROA hasn't met expectations, indicating a need for better asset utilization to increase revenue. Strategies like product differentiation or cost leadership can boost ROA by improving profit margins and asset turnover (Yi et al., 2019). The research also discovered that minimizing the OR goal was not achieved. Operational costs relative to sales can be decreased to reduce the operating ratio. Improving cost efficiency can increase sales levels and boost gross profit by lowering the cost of goods sold (Fajar, 2021). The research found that the OIR, which measures a company's ability to generate operational income from sales, fell short of expectations. Improving this ratio involves maximizing sales to increase operating profit and reducing operational costs relative to sales (Fajar, 2021). The research findings indicate that the CR, which evaluates a company's working capital position, did not meet expectations. Enhancing this ratio requires increasing current assets such as cash, inventory, trade receivables, and VAT receivables, while simultaneously reducing short-term debts to lower the company's liabilities (Dianti & Putri, 2021).

5.5. Sensitivity Analysis

In this study, sensitivity analysis is used to explore how and to what degree changes in the parameters of an optimization problem influence the optimal objective function value and the position of the optimal solution. Sensitivity analysis is conducted on the weight values of the coefficients in the objective function and the target values on the right-hand side. For the coefficients of the objective function, the allowable range of weights to maintain the optimal solution obtained is presented in Table 17.

Table 17
Sensitivity Analysis on Weight in Objective Function

Variable	Coefficient	Allowable Increase	Allowable Decrease
x_1	0	Infinity	0.021
x_2	0	Infinity	0.009
x_3	0	0.009	0.014
d_1^+	0	Infinity	0.173
d_1^-	0.173	0.446	0.173
d_2^+	0.173	0.096	0.017
d_2^-	0	Infinity	0.173
d_3^+	0	Infinity	0.477
d_3^-	0.477	0.300	0.477
d_4^+	0	Infinity	0.001
d_4^-	0.072	Infinity	0.071
d_5^+	0	Infinity	0.104
d_5^-	0.104	0.014	0.055

Based on Table 17, the coefficients of the objective function show that the negative deviation of ROA can vary within the range of 0.173 – 0.446, the positive deviation of OR variable can increase by 0.096 and decrease by 0.017, the negative coefficient of OIR can increase by 0.300 and cannot decrease, the negative deviation coefficient of TATO can increase indefinitely and decrease up to 0.071, the negative deviation coefficient of CR can increase by 0.014 and decrease by 0.055, and other variables with objective function coefficients of 0 can increase indefinitely except for x_1 and x_2 can decrease with varying values.

In the sensitivity analysis for the right-hand side target values, the allowable range of changes is presented in Table 18. The right-hand side values can increase indefinitely except for the constraints OR and TATO, which can increase by 1.455 and 1.124, respectively. The OR constraint can decrease indefinitely, while the constraints for ROA, OIR, TATO, and CR can decrease by 0.002, 0.432, 30.271, and 7.057, respectively.

Table 18
Sensitivity Analysis on The Target based on Right-Hand Side Value

Constraint	RHS	Allowable Increase	Allowable decrease
ROA	0.140	Infinity	0.002
OR	2.230	1.455	Infinity
OIR	0.637	Infinity	0.432
TATO	76.657	1.124	30.271
CR	11.428	Infinity	7.057

6. Conclusion

In this study, optimization analysis of financial ratios is conducted to describe the condition of a garment company. Factor analysis identifies ROA, OR, OIR, TATO, and CR as key factors influencing profitability. These ratios are integrated into the WGP model, which aims to optimize financial performance by assigning weights through the BWM method. Results show that while the company has achieved its target for TATO, the other four ratios have not yet reached their respective targets. The optimal solution of the WGP model indicates that the company has achieved its primary objectives but needs improvement for optimal financial performance, particularly in mitigating operational costs and enhancing asset efficiency. A comprehensive review of cost structure and asset management strategies is crucial to achieve better financial outcomes. The recommended range of weights and target financial ratios for maintaining the optimal solution (company performance) are demonstrated by performing a sensitivity analysis. A limitation of this research is its inability to account for uncertain parameters like financial ratios, which may fluctuate due to uncertain interest rates. Additionally, the weights on each variable deviation from financial ratios are uncertain due to differences in expert and stakeholder perceptions. Future research shall consider incorporating uncertain parameters to better reflect reality, possibly through methods like combining WGP with robust optimization to address uncertainty in financial ratios.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal ties that would have seemed to affect the work reported in this study.

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